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EVOLUTION OF THE CORRELATION BETWEEN BOND AND STOCK MARKET RETURNS: EMPIRICAL STUDY FROM THE EUROPEAN MARKET

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“EVOLUTION OF THE CORRELATION BETWEEN BOND AND STOCK MARKET RETURNS: EMPIRICAL STUDY FROM THE EUROPEAN MARKET”

Abstract

The goal of this master’s thesis is to assess and understand the drivers of the dynamic correlation between stock and bond returns. More precisely, we conducted our empirical analysis on European market for the last two decades on a monthly and daily basis. The chosen time-frame is characterized by particularly high financial stress periods in order to understand the correlation behaviour in time of crisis. We used a DCC-GARCH multivariate model in order to estimate the conditional correlation. Besides, we selected most important factors driving this stock-bond relationship and used statistical tool to determine their significance.

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Master Thesis

Foreword

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1. Introduction

Over past decades, the empirical relationship between stock and bond markets has been a widely covered topic within the financial market academic studies. Indeed, it pulled a considerable interest from economists, researchers, investors and policymakers due to its impact on investment decisions, asset allocation, risk management and portfolio optimization. The main stake of the stock-bond return relationship is the understanding of the mechanisms linking both markets. Indeed, bonds are considered as a safe or conservative investment since it provides fixed but small income with low risks. On the contrary, stocks are considered as riskier investment but tend to provide higher returns to reward the risk. These opposite properties allow investors to diversify their portfolio and adjust the allocation in a dynamic environment (Ilmanen (2003) and Baker and Wurgler (2011)).

The recent crisis period highlighted even more the investor's need for a comprehensive understanding of the stock-bond correlation. This is probably the main driver behind our master thesis choice. More precisely, we focus our research on the European market and as European citizens; we observed the emergence of a two-speed economy landscape in the European Union (EU) due to the European sovereign debt crisis. Indeed, the EU has a unique political and economic structure throughout the world and it faces several challenges due to its country member's diversity. On the other hand, it offers great opportunities to observe dynamic correlation patterns varying from country to country. Finally, we both had a personal incentive to conduct such a research since we both aspire to build a career in asset or risk management in the near future.

The first goal of this master thesis is to get a precise overview of the time-varying stock-bond correlation pattern in several European countries over the past two decades. The main implied assumption is that the correlation between stock and government bonds is dynamic. The second goal is to assess the impact of the different crisis episodes on the correlation. The implied assumption is that crisis or financial stress implies a flight to quality phenomenon best described by a temporary negative stock-bond correlation during bad financial conditions. Finally, this thesis aims at assessing the influence of a set of macro-economic variables on the correlation. Since these variables are mostly time-varying, an influence on the correlation would be consistent with our two first assumptions.

The first assumption is the time-varying evolution of the stock and bond returns correlations. This is not a strong assumption since over the last forty years, it has been widely proven (Barsky, R.B., (1989); Gulko (2002); Ilmanen (2003); Andersson, Krylova and Vähämaa (2006); Scruggs and Glabadanidis, 2003 Chiang and Li (2009); Baele, Bekaert and Inghelbrecht (2010) and Johnson, Naik, Page, Piedersen and Sapra (2013)) that the stock-bond correlation is varying through time. The literature is nearly unanimous on the dynamic effect of the correlation. Nevertheless, researchers often emphasized that the correlation shows a slightly positive long-term average.

The second assumption is the negative impact of crisis and financial stresses on the correlation. This impact has also been widely studied overt the past decades. Hartman, Straetmans and de Vries (2001) Baur and Lucey (2009) Baele et al. (2012, 2014) and Ashgarian, Christiansen and Hou (2014) focused their researches on the FTS phenomenon best described by a switch in the sign of the stock-bond correlation. Outcomes were often similar: FTS events generally coincide with market crisis.

Despite agreement on the time varying aspect and the FTS principle, it does not seems to exist a consensus on the drivers of this correlation. Indeed, Ilmanen (2003) attributes a positive relationship to the inflation level and the flight to quality phenomenon. The flight to quality or Flight To Safety (FTS) principle can be best described as investors moving their capital from risky to safer investments mainly due to increasing uncertainty in the financial markets. For their part, Baele et al. (2010) studied the drivers of the Fight to safety. They mainly attribute FTS effects to the consumer confidence, industrial production, market uncertainty, ted spread or liquidity level that are good proxies for the business conditions. On the same path, Aslanidis and Christiansen (2013) studied the economic stance through the market volatility, interest rates and the yield curve. Similarly, Ashgarian et al. (2014) used a different set of factors since they mainly studied the business cycle through proxies such as inflation, consumer sentiment, industrial production, unemployment, interest rate, term spread and the liquidity level. On the contrary, Gusset and Zimmermann (2015) and Dimic, Kivihao, Piljak and Äijö (2016) oriented their research on the monetary influence. This is just an overview of the set of drivers influencing the stock-bond relationship that we will consider in this master thesis.

To compute the stock-bond correlation over the past two decades, we use a multivariate Dynamic Conditional Correlation - Generalized Auto-Regressive Condition Heteroscedasticity (DCC-GARCH) model that was first introduced by Engle (2001) and then developed in several researches such as Engle (2002), Orskaug (2009) and Ding and Schwert (2010). Actually, there are plenty of approaches to estimate conditional covariances and correlations such as moving average specification of variances and covariances or derived dynamic conditional correlation estimation models. However, the DCC has the advantage to directly parametrize conditional correlation while keeping a relatively simple set up.

We study monthly stock-bond relationship across six countries: Germany, France, Great Britain, Portugal, Spain and Italy. We run the empirical study through daily frequency. The period under review includes 219 monthly observations starting on the 1^{st} January 1999 and ending on the 28^{th} April 2017. The sample period is characterized by highly time varying economic situation providing good insights to our research. We use country-specific and European Stock indices as proxy for stock market and country-specific and European government Treasury Bills with 10-years maturity as proxy for bonds. We firstly determine and compare the sign, the amplitude and the variation of the stock-bond return correlation. Then we regress the macro-economic drivers to assess impacts on correlation.

The structure of the thesis is as follows: Chapter 2 provides a wide overview of the existing literature on the stock-bond relationship and its drivers. It firstly introduces the European market and reviews the existing work on the dynamic feature of the correlation and the flight to quality phenomenon. Besides, the chapter covers the different macro-economic drivers affecting the correlation as well as our underlying assumptions. Afterwards, Chapter 3 covers the theoretical framework of the DCC GARCH used in this thesis. It precises the mathematical development as first introduced by Engle (2001) as well as the estimation procedure and the underlying statistical issues. Subsequently, the practical methodology is discussed in Chapter 4. Then, Chapter 5 interprets and discusses the empirical analysis results. Finally, some conclusions as well as limitations to the research are presented in Chapter 6.

2. Literature review

The analysis of stock-bond correlation as well as its macro-economic factors has been widely covered over the past decades. Therefore, our research highly beneficiates from a large number of authors publishing their outcomes in scientific journal. We will provide here a wide but concise review needed to put in perspective our researches. However, due to the countless work on the topic, it does not claim to be totally comprehensive.

As far as researches have been addressing returns, risk premiums, required returns, correlation and other financial market topics, the relationship between bond and equity market has been the cornerstone of a comprehensive study. Indeed, when it relates to the equity return behavior, the key element is the risk premium that is the reward-to-risk every investor requires. The basic and well-known Capital Asset Pricing Model based on the work of Markowitz already considers the risk premium as the difference between the market return and the risk-free rate. Long-term government bonds are generally used as a proxy for risk-free asset. This is just an example amongst others of the stock-bond relationship importance. Indeed, Eugene Fama and Kenneth French multifactor model (1996), Pastor and Stambaugh fourth factors model and Chen, Roll, and Ross (1986) macroeconomic factors model were all considering the equity-bond relationship playing an important role in the estimation of their factors. The presence of the stock-bond relationship in the pioneering financial models enhances the importance of the topic.

As a result, the correlation between stock and bond markets was a widely covered topic over the past decades within the financial market academic studies. These researches are spread in two main areas. Studies highlighting the time-varying component of the stock-bond correlation thanks to empirical studies and studies emphasizing on the analysis on factors influencing the correlation evolution.

2.1. European Union

The European Union has a unique political and economic structure throughout the world and it faces several challenges due to its country member's diversity. In this section, we will underpin the current European economic context. The initial goal of the E.U. is the integration of its members tending to an international, monetary, and domestic policy more converging. The best example is the implementation of the Euro currency for a large part of the Euro members in 2002 creating the Eurozone. It takes its root in the European Maastricht Treaty of 1992 on the economic and monetary union. However, this alliance tends to stumble on many difficulties. Indeed, the biggest issue lies in deep imbalances throughout the different countries. This issue has been even more enhanced with the European sovereign debt crisis especially affecting south and east countries (more known as periphery countries) in high budgetary difficulties due to the level of debt and the skyrocketing cost of debt. The two-speed economic landscape finds its roots in the great recession of 2008 that enhanced Eurozone financial imbalances. Indeed, such imbalances had a doping effect on the debt crisis 3 years later. Aware of the issue, the E.U. has been working on the single market improvement enhancing economic integration across its members for a few years. Eurostat (2016) provides a good overview of the aforementioned two-speed economic landscape (See Appendix I).

Most of the academic literature is conducted on the U.S Stock market because it is often considered as one of the leading economic indicator. However, the European market becomes more and more fascinating. Indeed, Europe faces several challenges and its capacity to handle and manage the different issues will be key for the future health of the financial market. Due to its country member’s diversity, Eurozone offers great opportunities to conduct cross-country empirical analyses. In this context, we found highly interesting to conduct our DCC model on the European stock-bond relationship on the one hand, and compare potential different DCC patterns between periphery countries (Italy, Spain, Portugal) and central countries (France, Germany, UK).

Kim, Moshirian and Wu (2005) examined the dynamic relationship across stock and bond returns. More precisely, they studied the influence of the European Monetary Union (EMU) on the time-varying integration or segmentation of the financial markets. They explain that economic integration without currency risk leads to financial market integration. However, their main conclusion is that the EMU has played a significant role in the investor confidence level on economic conditions in Europe. They concluded that this uncertainty has led to segmentation and has been a source of flight to quality events.

Similarly, Perego and Vermeulen (2013) conducted a similar research studying the determinants of the stock-bond correlation in a two-side European economic stance. They conducted a Dynamic Conditional Correlation at asset-region level in order to provide an overview of the integration divergence that we previously highlighted. Besides, they regrouped Eurozone countries in two group (North and South) and they computed six dynamic correlations at cross-region and cross-asset levels. They provided good insights about the heterogeneity of the stock-bond correlation evolution across domestic European markets. Indeed, they demonstrated that in time of high market uncertainty or market turmoil such as 2008, south bonds that were used to be considered as safe asset began to be positively correlated to the north stock that are risky assets. Moreover, they were able to explain cross-asset and cross-region correlations with macro-economic variables such as uncertainty and balance of payments between countries. This is where their research is interesting and provides an added value to the literature that usually observe solely cross-asset movements.

Finally, we should notice that in response to the bad shape of the economic stance and the underlying dangerous risks for some European countries (mainly Greece, Portugal, and Italy); the European Central Bank (ECB) decided to rethink its monetary policy. Indeed, since 2012, the ECB has used multiple conventional and unconventional monetary policy tools. The main one is the short-term interest rates that is currently at the zero-lower bound. The second one, less conventional, is the Quantitative Easing (QE) further developed in section 2.4.7. The key mission of the European Central Bank is to keep an inflation rate throughout Eurozone steady and around 2 percent. The European Central Bank has been widely criticized for its supportive decisions but seems to reach its goal in the beginning of 2017. However, the last 5 years experienced eventful period. Inflation has been falling since 2011 and went below 1% around October 2013. Core inflation followed the same trajectory and dropped significantly. Major advanced economies in the Eurozone such as Germany or France have seen their inflation rate lower than 2% for more than 4 years. A major concern for policymakers is to succeed in raising the aggregate level of inflation in both core and periphery area. Therefore, our research contributes in understanding different evolutions of the stock-bond market correlation depending on countries.

2.2. Asset allocation and risk management

The main goal of this thesis is to provide significant insights on the dynamic nature of the stock and bond return correlation in stress periods. The correlation has a major role to play in asset allocation and risk management. Indeed, asset allocation and diversification are the cornerstones of financial markets and each investment decision. Over the last century, economic researches on the field have continuously grown in line with financial markets growing interest. The main implied goal of each investor is to constitute an efficient portfolio in line with the risk he is willing to take.

According to Ilmanen (2003), stocks and government bonds are known to be the main assets constituting a portfolio. He also highlighted the importance of understanding correlation of main assets to optimize asset allocation and risk management. Besides, Baker and Wurgler (2011) stated that the empirical relationship between stock and bond markets is a widely covered topic. Indeed, a considerable interest from economist, researchers, investors and policymakers has risen over the last decades. The main underlying goal is to understand mechanisms linking both markets.

2.3. Stock-bond correlation

In this master thesis, we deeply analyze the evolution of the stock-bond correlation meaning that both assets under review are respectively the stock market and the bond market. To assess the value change of these markets, we compute the return based on indexes acting as proxies for the stocks and on 10-years government Treasury bill acting as proxies for bonds. To compute the correlation, we use the DCC GARCH model developed by Engle (2001) and explained in Chapter 3. It will provide a dynamic value of the correlation coefficient through time between the stock returns and bond returns.

2.3.1. Correlation definition

The correlation measures the level to which two assets move in relation to the other. The correlation coefficient value always ranges between -1 and 1 and can never exceed these values. A correlation coefficient of 1 means a perfect positive relationship between two assets meaning that a value change of asset number one will be replicated on the other. A correlation of 0 means that both assets are totally independent and there is no replicated impact due to asset value changes. Finally, a correlation of -1 means a perfect negative relationship between both assets meaning that a value change of an asset negatively and proportionally impacts the other. In both finance and investment industries, the correlation statistical measure is widely spread.

2.3.2. Time-varying correlation

First fruits of correlation investigation probably arrived with the work of Lintner (1975), Nelson (1976) and Fama and Schwert (1977) providing evidences of negative correlation between common stocks and expected inflation rates. At the time, authors already used Treasury bills considering it as hedging instruments against expected inflation rate. Their finding already highlighted different evolution patterns and time varying opposite movements.

However, some authors had different outcomes on the co-movement of stock and bond markets. Indeed, Shiller and Beltratti (1992) used annual data of the United States and United Kingdom. Using a dynamic present value model, they concluded that observed stock-bond return correlation is too high to be theoretically justified. Campbell and Ammer (1993) used a similar framework to decompose monthly variances and covariances of stock and bond returns. They addressed several offsetting factors such as: the real interest rate that drives a positive correlation due to same sensitivity to discount factor; the expected inflation variation driving a negative correlation and the common future expected return promoting a low positive correlation. To sum up, both authors concluded that the time variation of correlation was not significant.

Despite these contributions, time passing, it has been widely accepted that correlation of stock and bond returns is time varying. This is also the main assumption of this thesis. Many authors firstly conducted their researches on the empirical analysis on the correlation variation through time. Most of them concluded that this relationship is time-varying (Barsky, (1989); Gulko (2002); Ilmanen (2003); Andersson et al. (2006); Chiang and Li (2009)).) Barsky (1989) was, to our knowledge, the first to provide empirical insight on the dynamic nature of the stock-bond return correlation. He used the real risk and productivity growth to rationalize the behaviour of the stock and bond markets.

Then, Ilmanen (2003) found a slightly positive correlation over time with punctual period of intermittence of negative relationship. His findings showed that during easing monetary policy, the correlation tended to be positive and on the contrary, in time of contracting monetary policy, the correlation was turning negative due to outperforming bond market. The author identified main factors affecting the stock-bond correlation: Inflation rate, GDP growth and market uncertainty. We will more precisely review his finding on the correlation drivers in the next sections. His research is one of the most quoted contribution on stock-bond correlation due to the clear, straightforward and interesting conclusion on intuitive macro-economic drivers.

Later, it has been proven using an asymmetric dynamic covariance model that conditional correlation between US bond and stock returns had considerably varied through time since the Second World War (Scruggs and Glabadanidis, 2003). Indeed, their findings show that market variance are asymmetrically affected by shocks in stock and bond returns. Similarly, de Goeij and Marquering (2004) used a DCC model to show the time-varying correlation. More precisely, they focused on the asymmetric leverage effect of the market news. Indeed, bad releases in the stock market and good news in the bond market tend to lower the correlation of stock and bond returns.

A comprehensive research from Baele et al. (2010) showed that stock-bond correlation ranged from 0.6 to -0.6 over the last forty years using a bivariate DCC model. Their investigation mainly focused on the elements driving stock-bond correlation and emphasized on different factors around risk aversion and illiquidity such as interest rates, inflation, cash-flow growth, uncertainty measures and more fundamental economic growth measures. These variables are addressed in the following sections.

More recently, Johnson et al (2013) provided interesting evidence of US asymmetric co-movements between stock and bond returns. Indeed, their econometric model explained the historical relationship between equities and Treasury bill. From 1927 to 2012, correlation between S&P 500 and long-term T-bill has changed 29 times and ranged from -0.93 to +0.86 based on monthly data.

Finally, the study of stock and bond return correlation is a wide topic and most of researcher worked on index-level relationship using benchmark. However, Baker and Wurgler (2011) analysed cross section of stock returns instead of indices. It allowed them to uncover interesting facts regarding stocks and bonds correlation. To summarize their research, they observed highly differentiated relationship of stock-bond depending on the stock nature. Large cap, long listed, low volatility and low growth stocks have an overall higher correlation with government bonds than small cap, young, highly volatile and high growth opportunities stocks. It is intuitive and in line with Fama and French work on their multiple factors model using HML and SMB factors.

2.3.3. Flight to safety phenomenon

To analyze the correlation evolution that we expect to be dynamic, the intuitive assumption is the following: depending on several factors, the correlation should tend to be positive in healthy economic frameworks and negative during bad economic conditions. The concept behind this assumption is the flight to quality phenomenon or flight to safety (FTS). Indeed, it perfectly represents the switch from positive to negative of the correlation sign. FTS can be defined as the change of the investor appetite from risky investments to safer investments. For instance, it takes the form of large capital movements from stock market to bond market. More precisely, as Baele et al. (2012, 2014) explain in several FTS researches, the investor asset allocation is characterized by lower volatility, lower downside risk, lower default and higher liquidity preference. This flight to quality is usually occasioned by market uncertainty and economic development weakening.

Baele et al. (2012, 2014) are to our knowledge the biggest contributor of the FTS researches. Indeed, they identified FTS over time and across several countries and looked more precisely on the switch from equities to government bonds. Besides, they investigated several financial and macro-economic variables that could influence FTS periods. They began to mention the FTS phenomenon as a driver of the correlation (Baele et al. (2007, 2010)) and then focused their research on this concept in most recent papers. They used stock and bond returns data from 1980 until 2012 across 23 different countries. The major outcomes of their studies are that: FTS events generally coincide with market crisis; FTS episodes more country-specific than global and FTS events are characterized by high stock volatility and lower confidence sentiment.

Besides, in their wishes to analyze financial stability, Hartman et al. (2001) provided a new perspective to the relationship between asset classes in time of crisis. More precisely, they studied co-movements of different asset types using a bivariate extreme value theory. They were able to identify the flight to quality defined as a stock market crash combined with a Treasury bond market boom. The main outcome of their studies is that general market turmoil is highly slowed down thanks to the flight to quality system. The main advantage of their model was the unnecessary reliance on correlation that is often based on ARCH-type models. Indeed, the bivariate methodology enabled the searchers to identify dependence structure of distributions far away from the center thanks to statistical extreme value mean. Therefore, the joint return probability law is left unspecified since the estimator is non-parametric.

Moreover, Baur and Lucey (2009) formalized the main components of a dynamic evolution of the stock-bond correlation. They estimated dynamic conditional correlation and analyzed the movement of the correlation through time without specifying any crisis period. Their findings showed that asset classes correlation experience large fluctuations. More precisely, they identified the flight to quality principle as the main driver of large negative correlation periods. Then, they examined more precisely the flight to quality concept between stocks and bonds. They have shown that flights exist especially in stressed periods and are international. This outcome is also consistent with the assumption that business cycle plays a major role in the correlation of stocks and bonds.

Finally, Ashgarian et al. (2014) also highlighted the existence of flight to quality phenomenon showing that when the economic stance is weak, the stock-bond correlation is negative. They attribute the FTS events to several factors that will be developed in the next section.

2.3.4. Price determinants

The second aim of this thesis is to determine the different factors affecting the time-varying correlation of stock and bond returns. In this context, we find important to make a quick reminder of both asset valuation formulas. Indeed, factors moving both asset prices in the same direction are expected to have a positive relationship with the dynamic correlation while factors driving asset price in opposite direction should have a negative impact. We use a simple present value model meaning that the price of the asset is the present value of future incomes generated until bond maturity or stock holding period. Therefore, the stock price formula is the following:

$$P_t = \frac{D_1}{1+r} + \frac{D_2}{(1+r)^2} + \frac{D_3}{(1+r)^2} + \cdots + \lim_{n\to\infty} \frac{D_n + P_n}{(1+r)^n}$$

Where:

P_t	the stock price at time "t"
D_n	the future dividend expected
r	the risk-free rate

The formula shows clearly that the price of the stock mostly depends on its cash flow and the level of the risk-free rate used as discount factor. On the contrary, the bond price is mostly determined through the discount rate. Indeed, cash-flows are represented by the coupons that are fixed and the maturity is also fixed. Therefore, the bond price formula is the following:

$$P_t = \sum_{n=1}^{N} \frac{C}{(1+r)^n} + \frac{M}{(1+r)^n}$$

Where:

D_n	the bond price at time "t"
D_n	the future coupons
r	the risk-free rate

The present value model of both assets provides good insights on stock-bond correlation drivers. Indeed, it seems clear that variables influencing the discount factor will have a positive impact on the correlation. For instance, a decrease in the interest rate will similarly increase both stock and bond prices. On the contrary, factors influencing the expected dividend should have a negative impact on the correlation since it only affects the stock price. However, despite the interesting insights these formulas are providing, it stays a theoretical framework. This is why we review the different researches providing statistical evidences of macro-economic variables influence on the correlation in the next section.

2.4. Macro-economic drivers

Researches on macro-economic factors driving the stock-bond price correlation attracted a lot of interest over the last 2 decades. In this section, we will review the economic factors that should influence the co-movements of bond and stock returns. Due to the large number of studies, we do not claim to cover all the work that has been done. However, we will review the main quoted and famous researches as well as works providing some interesting shades to the previous outcomes.

For example, Li (2002) studied the correlation of stock and bond returns in the G7 countries. They studied several macro-economic variables and their empirical results indicated that the uncertainty about inflation plays a major role in the stock-bond co-movements. For his part, Ilmanen (2003) identified three main factors influencing the stock-bond return correlation: Inflation rate, GDP growth and market uncertainty. Differently, Yang, Zhou, and Wang (2009) used a Smooth Transition Conditional Correlation (STCC) and observed that stock-bond correlation is positively linked to short-term interest rates and inflation.

One of the key concept that most researchers used to explain the stock-bond correlation is the business cycle. Indeed, Ilmanen (2003), Guidolin and Timmermann (2006) and Aslanidis and Christiansen (2013) all have observed that the state of the macro economy provides good insight of the future stock-bond co-movements. Based on these results, Ashgarian et al. (2014) used a Dynamic Conditional Correlation Mixed Data Sampling (DCC-MIDAS) model in order to decompose both the long-term and short-term impact of macro-economic variables on the stock-bond correlation. It was necessary to take into account the lagged realized correlation in the model. In addition to evidences of the flight to quality event, they provided further precisions on the usefulness of smoothing operations such as MIDAS in order to predict long-term component of stock and bond co-movements. Indeed, the Midas techniques introduced by Ghysels, Santa-Clara and Valkanov (2004) and Ghysels, Sinko and Valkanov (2006) enabled them to explain daily stock and bond returns with macro-economic variable at quarterly frequency. Ashgarian et al. (2014) studied several variables such as short-term interest rates, inflation, liquidity variables, equity uncertainty variables and state of the economy variables. These different drivers are deeper presented in the following sections.

Besides, Aslanidis and Christiansen (2001) figured out that major determinants of the relationship are the short interest rates, the yield spread and the VIX volatility Index. They used a Smooth Transition Regression model to analyze the correlation evolution. The advantage of this model is that it enables to describe realized correlation in regime-switching context. Therefore, it highlights economic variables significantly influencing smooth correlation change between two extreme regimes.

Moreover, Dimic et al. (2016) conducted their researches on 10 emerging markets and examined the financial market uncertainty as well as the macro-economic influence on the stock-bond correlation. The most significant result of their work is the particularly time-varying pattern of the correlation. Besides, they demonstrated that the factor mostly influencing the short-term correlation is the domestic monetary policy while inflation has a bigger influence on the long-term horizon.

While some researchers were focusing on the study of macro-economic factors, others were interested in macro-finance variable. However, both macro-economic and asset-specific factors were generally considered by the literature. For instance, Connolly, Stivers and Sun (2005) identified market volatility index as an important determinant of stock-bond correlation. Differently, both Pastor and Stambaugh (2003) and Baele et al. (2010) denoted that changes in stock-bond return correlation depend more on liquidity than on macro-economic fundamentals.

2.4.1. Business cycles

Macroeconomic conditions studies often provided similar outcomes on the time varying patterns and the underlying drivers of stock-bond correlations. The most intuitive factor as driver of correlation movements is the economic stance. Indeed, in time of low risk aversion due to expansion and accommodative economic period, both stock and bond returns are expected to be positive. However, in recession period appears the flight to quality phenomenon implying risk aversion and a switch in asset allocation going from equities to treasury bonds.

Business cycles affect the stock-bond correlation with a lower relationship in time of recession that those of expansion (Ilmanen (2003); Boyd, Hu and Jagannathan (2005); Andersen, Bollerslev, Diebold and Vega (2007)). Indeed, both Boyd et al. (2005) and Andersen et al. (2007) conducted news announcement studies in time of recessions and expansions. They observed a higher cash-flow effect during contraction and a higher discount rates effect during expansions. These effects lead to a positive correlation in positive economic environment and a lower or even negative correlation in an unstable economy.

Christiansen and Ranaldo (2007) conducted events studies through investigation of the macro-economic announcement effects on the realized stock-bond return correlation in the US market. They figured out that announcement impacts are significant and vary across the economic business cycles. Indeed, in expansion, macro-economic releases tend to improve the correlation. On the contrary, in recessions, the market reactions will highly depend on the kind of announcement. They notice that while the sign of the stock-bond co-movements is considered, the announcement effect is highly significant.

Andersson et al. (2006) found that economic growth expectation has no significant impact on stock and bond return correlation. On the contrary, Ilmanen (2003) examined the impact of GDP growth changes. Findings showed that high change in GDP growth trigger market uncertainty which negatively impact the stock-bond correlation.

Finally, Viceira (2012) conducted a research on the time variation of the bond beta in the Capital Asset Pricing Model. He compared the beta evolution with the bond return volatility.

The main outcome of the paper is that bond beta and volatility are linked to the intercept and the slope of the yield curve. Besides, the yield curve is itself a proxy of the business cycle. Therefore, he provides evidence that the stock-bond correlation changes significantly based on the business condition.

Based on these studies, our assumption is that business condition is positively influencing the correlation between stocks and bonds.

2.4.2. Major crisis episodes

Major crisis arrived in the studied timeframe. We provide here a concise overview of the different event occurring from 1999 until 2017 and that impacted both stock and bond markets due to its wide financial impact

- Internet bubble (2000-2002)

The dot-com bubble also known as the internet bubble is an historic economic bubble. A bubble is defined as a period of excessive speculation and overconfidence followed by an extreme reversal reaction. The internet bubble started with wild increase of internet usage and its adaptation to the consumer and company needs. Consequently, many internet companies were founded and many retail investors arrived. The peak of the Bubble was in March 2000 when investors began to review their expectations on the technology and it then collapsed. Many companies just shut down while others saw its market stocks plunged and lose 80 percent of their capitalization. Business Insider (2010)

- Subprime crisis (2007-2009)

The subprime crisis is probably the most severe recession in decades. It arrived with the housing boom in the United States combined with low and easy interest rates facilities. Therefore, many institutional lenders began to offer home loans to individuals with poor or no credit. It is the so called “NINJA” loans for no income no job no asset loans. Financial institutions made the most of the situation through financial derivatives such as CDO or CDO square to quote the most famous. Unfortunately, many borrowers were not able to pay their loans, therefore, the house market started to fall and the loans that were part of the financial product lost all their value. The biggest event of the crisis was probably the bankruptcy of Lehman brother triggering a huge market downfall. This crisis inspired many authors producing movie such as “The big short” or “Margin Call” that provide a good understanding of the situation and the atmosphere at that time.

- European sovereign debt crisis (2009-2014)

The Eurozone debt crisis was a huge event in the European financial market. The crisis started in 2009 when investors began to realize that Greece could default on its debt. The lack of confidence then spread to other peripheral countries such as Portugal, Italy, Ireland or Spain. Central countries such as Germany and France struggled to help and support its European Union members. Fortunately, the 7 points Merkel plan has been initiated since 2012 allowing strong support to the suffering countries. However, they still suffer from the crisis due to strong austerity plan put in place. Besides, the particular economic context previously described probably gets things worse.

- China market crash (2015)

The Chinese stock market turbulence started with a stock market bubble in June 2015 and ended in February 2016. In China, the market is composed of 80 % retail investors. Therefore, falling borrowing cost and lowering stock market regulation boosted investment. Analysts explain the crisis by a slow of the economic pace combined with an overvaluation of the stock market due to momentum with a decrease of the Chinese monetary accommodation. Shanghai Stock Exchange lost a third of its capitalization in one month. More precisely a huge decrease occurred in July and August 2015. The Guardian (2015)

We also took into account minor crisis compared to the others. However, due to the globalization of financial markets, the European market was affected. We refer to the Turkish crisis in 2002, the Argentinian crisis from 1998 to 2002, the Brazilian crisis in 2002 or the Russian crisis of 2014.

2.4.3. Inflation rate

Inflation is probably the most intuitive macro-economic market driver. It is the measure of an average price change of goods and services market basket bought by householders. The basket includes food, clothing, electricity, transportations, fuel and other goods and services. A steady inflation is often seen as a sign of healthy economic environment as soon as it is accompanied with a similar income growth. This is therefore the most monitored economic factor by the central banks and it is highly determinant in the monetary policy decisions.

The main European indicator of inflation is probably the harmonized index of consumer prices (HICP). Eurostat computes it on a monthly basis. This entity is a directorate-general of the European Commission in charge of providing precise statistical information to the institutions of the European Union. Besides, one of its main goals is the harmonization of statistical methodology across different member states. In this context, The HICP is a set of European Union Consumer Prices Indices computed according to specific and harmonized approaches defined and explained in detail by Eurostat. HICP has a legal basis and a large part of the methodology uses elements that are legally binding to regulations from the European Union. For further information on the exact methodology to compute this index, we refer to Eurostat website proposing a clear and precise description of its construction. (Eurostat, 2017)

Ilmanen (2003) used inflation rates amongst others as explanatory variable of the stock-bond correlation. According to simple asset pricing models, asset value should represent the present discounted value of its expected future cash flows. This is why Ilmanen (2003) defines a general pricing formula of a stock as follows:

$$P_S = E\left[\sum_{t=1}^{\infty}\left(\frac{1+G}{1+\ R_F +\ \text{Risk Premium}}\right)^t \times D\right]$$

As a result, he concluded that inflation level has a large impact on the price correlation. On the one hand, high inflation rates tend to move stock and bond markets together due to similar change in the discount rate. Indeed, high inflation rates implies a lower discount rate for both stock and bonds. On the other hand, low inflation or deflation periods tend to increase the stock risk premium but the effect on the bond discount factor is less sensitive or may even be positive due the flight to quality aspect. Some authors brought shade to this statement such as Rankin and Idil (2014) claiming that high and positive inflation or inflation changes do not have a clear impact on stock prices since it also drives the dividend component in the previous formula.

On the same path, Andersson et al (2006) studied the impact of inflation, growth expectation and perceived market uncertainty on the stock-bond correlation. They found a positive relationship between inflation expectation and the stock-bond co-movements. Besides, they highlighted the previously discussed flight to quality phenomenon occurring in time of high stock market uncertainty.

Furthermore, Yang, Zhou and Wang (2009) statistically demonstrated the predictability of the stock-bond correlation by two macro-economic indicators being the inflation and the short interest rates. Indeed, they have shown that higher stock-bond co-movements tend to follow high inflation rates. Finally, Ashgarian et al (2014) indicated that inflation amongst other variables had a significant impact on the long-run stock-bond co-movements. Indeed, the influence of the Inflation variable on the long-run correlation is significant and positive.

Our assumption is that inflation level has a significant influence on the stock-bond return correlation. Intuitively, since inflation is time-varying, we do not expect the correlation to remain stationary. Besides, policymakers and analysts use stock-bond correlation researches to assess the economic stance. A negative correlation would provide insights on stressed economic situation represented by a low level of inflation. On the other hand, a positive correlation would mean that the business condition is improving thanks to higher level of inflation.

2.4.4. Consumer Confidence

The consumer confidence level is a good proxy for the health of the economy from a consumer point of view. In this master thesis, we use a European index called the Consumer Confidence Index (CCI) available on Bloomberg. The definition proposed in the database is the following "*Consumer confidence tracks sentiment among households or consumers. The results are based on surveys conducted among a random sample of 23.000 households*." (Bloomberg platform, 2017)

More precisely, the CCI is built on the "Joint Harmonized EU Program of Business and Consumer Surveys" which aims to realize and provide surveys on judgements and sentiments concerning several economic topics. Indeed, that kind of survey are essential information for economic turnover forecasting. The CCI data are published monthly by the

Directorate-General for Economic and Financial Affairs (DG ECFIN) set up in 1961. For more information on the data collection methodology, we refer to the user guide published by the European Commission (2017) that provides a deep and comprehensive description of the surveys and the methodology used by the Commission to produce its different survey-based indexes.

The Consumer Confidence is one of the state of the economy variable studied by Ashgarian et al. (2014). They used a US consumer confidence proxy since they worked on the US market. They observed that the consumer confidence variable appears to explain the evolution of the long-run stock-bond correlation when jointly considered with the lagged realized correlation.

Besides, Baele et al. (2014) have made an international research on the flight to safety drivers. They found a clear evidence of correlation between the consumer sentiment and the switch of the stock-bond correlation sign to negative. They used the Michigan consumer sentiment index for the US market. But more interestingly, they used the IFO business climate indicator which measures the consumer sentiment in Germany and the results were unanimous. Indeed, using that index on 23 countries on a daily basis, they figured out that only two countries were inconclusive. It provides a good insight on the links between consumer confidence and the correlation between stocks and bonds across the world.

Similarly, Skintzi (2017) used the consumer confidence as a state of the economy variable. He used a Consumer Confidence Indicator from the OECD and observed that it slightly but significantly influences the stock-bond correlation. He also affirms that such variable as well as the unemployment rate better capture the state of the economy than the growth rate does.

Based on these researches, we assume the consumer confidence variable to be positively linked to the stock-bond correlation.

2.4.5. Industrial Production

The Industrial Production index (IPI) is a macro-economic variable that Eurostat defines as the following: *« The industrial production index is a business cycle indicator which measures monthly changes in the price-adjusted output of industry. This article takes a look at the* *industrial production index as it is calculated in the European Union (EU) as well as in some EFTA and candidate countries. »* (Bloomberg platform, 2017). It is sometimes called industrial output index or industrial volume index and it is one of the most important short-term statistics indicators. Indeed, it is widely used to predict economic developments turning points in order to assess future GDP growth.

The Industrial Production is one of the state of the economy variable studied by Ashgarian et al. (2014). As explained, they worked on the US market. Therefore, the authors used an US Industrial production index. They observed that the Industrial production variable appears to explain the evolution of the long-run stock-bond correlation when jointly considered with the lagged realized correlation. Besides, the sign of the influence of the Industrial production is positive and significant.

Moreover, Baele et al. (2010 and 2014) tested the ability of the flight to safety phenomenon to predict future economic development. To do so, they used the cumulative year on year growth of the GDP, inflation and industrial production. They regressed it on the fraction of days exhibiting a FTS. They observed a clear positive relationship between FTS and industrial production growth. It means that a negative stock-bond correlation would trigger negative industrial production growth.

Finally, Dimic et al. (2016) used the Industrial Production Index as a proxy for the business cycle pattern. The business cycle appeared to be significant in eight different emerging markets for the long-run stock-bond correlation. Therefore, positive economic growth represented by high industrial production causes a positive effect on the correlation.

2.4.6. Unemployment

Ashgarian et al. (2014) used Unemployment rate as a state of the economy variable. They used the publication of the United States unemployment level. They observed that unemployment variable explains the evolution of the long-run stock-bond correlation when jointly considered with the lagged realized correlation. However, the sign of the influence is negative. This result is consistent with the flight to quality concept meaning that a weak economy tends to decrease the risk appetite of investors inducing a negative stock-bond correlation.

Skintzi (2017) also used the unemployment as a state of the economy variable. He used the unemployment rate provided by Eurostat. Similarly to the Consumer Confidence, he observed that this factor significantly but slightly influences the stock-bond correlation.

Both studies provide a good insight of the unemployment rate influence. Therefore, we assume a negative relationship between the level of unemployment and the stock-bond correlation.

2.4.7. Market uncertainty

The influence of market uncertainty on stock-bond correlation is mainly driven by the flight to quality phenomenon previously explained. Several authors analyzed its empirical impact on the stock-bond relationship. Connolly et al. (2005) observed several sustained times of negative correlation between 1986 and 2000 in the US stock and Treasury bond markets. They focused their researches on two measures of stock market uncertainty: implied volatility of stock index option, more precisely the Volatility Index (VIX) and abnormal stock turnovers. The volatility of a variable is the standard deviation of the return provided by the variable per unit of time when the return is expressed using continuous compounding (Hull, 2015). Although it is possible to calculate volatility variables based on historical data, the volatility used in black and Scholes model is not observed directly. Therefore, when the volatility is substituted in the pricing model, we get the implied volatility. This is how the Chicago Board Options Exchange (CBOE) published implied volatility indices. The most famous one is probably the VIX that is an index of implied volatility based on S&P 500 30-days option and calculated from different calls and puts.

Baele et al. (2014) studied the market uncertainty through the VIX for the US market, through the VDAX for the European market and through the VFTS for the United Kingdom market. They found evidences of positive correlation between the volatility index and the flight to safety episodes. They made a regression on 23 different countries on a daily basis. The results were impressive since the US market volatility index is significantly impacting FTS in 19 countries while the German volatility index is significant in every studied countries at the 5 percent level. On the same path, Aslanidis and Christiansen (2001) observed that the higher the VIX is, the most likely the correlation is negative.

Furthermore, both Andersson et al. (2006) and Kim et al. (2005) researches focused on the stock market uncertainty role in explaining stock-bond correlations. Indeed, similarly to Connolly et al. (2005) and Baele et al. (2014), they used implied volatility deducted from option indexes as proxy for the stock market uncertainty. They discovered that changes in implied volatility highly affect risk aversion of investors. Therefore, it influences the stock-bond correlation and affects the flight to quality that aforementioned studies are widely covering.

Based on these researches, we assume that high market uncertainty would trigger a lower stock-bond correlation.

2.4.8. Monetary policy

As we previously detailed, numerous researches have been conducted on the different factors underpinning stock and bond market relationship. Factors such as inflation, business cycle and market uncertainty are the most intuitive and were widely studied. Actually, this subset of factors refers to the economic stance that is the first input for asset allocation. More precisely, analysis of monetary policy on the European stock market has received considerable attention over the last 10 years. Indeed, since the 2008 financial crisis, Eurozone has known multiple financial imbalances and European Monetary policy decisions have been very accommodative, driving interest rate close to zero percent.

Since the European debt crisis, European economy has gone through a period characterized by particularly low euro exchange rate and supportive monetary policy measures. The main goal of the quantitative easing is to level up the inflation rate in order to maintain a sustainable economic environment. As well as conventional interest rates policy, quantitative easing influences macroeconomic developments through several channels such as asset purchasing or forward guidance thanks to ECB announcements. (Deutsche Bundesbank, June 2016)

In addition to interest rates decreasing, the ECB Governing Council announced in October 2014 the beginning of an Asset-Backed Securities Purchase Program “ABSPP”. Since then, the ECB extended the QE program on multiple occasions in order to support the economic stance as stated by Claeys, Leandro and Mandra (2015). The quantitative easing consists in buying European governments securities or other securities in order to increase the money supply. Indeed, with flows arriving in financial institutions, it promotes lending capacity and liquidity.

Besides, other unconventional channels emerged from the economic situation and the monetary policy. Indeed, 2016 was characterized by a considerable importance given to the ECB communication channel. For instance, industrial production or unemployment rate announcement are highly covered and followed factors. Therefore, there are some expectations before releases. If the indicator level matches investor and market expectations, the market does not adjust much. On the contrary, if real economic value of the announcement differs from the market expectations, stock prices will largely be affected. However, during 2016, we have observed an inversion in the market reaction to economic news. Indeed, due to ECB monetary policy expectations, a bad economic release would mean a more likely accommodative policy with lower rate and higher quantitative easing. On the contrary, a good economic indicator announcement would trigger a reduction of the easing monetary policy.

On a pure price point of view, monetary policy is key. Indeed, it influences interest rates since it decreases or increases short-term interest rates depending on inflation target. While effects of interest rates changes on stocks and bonds are intuitive, QE effects are less precise. Nevertheless, on a simple economic thinking, the Central Bank buying paper should increase demand and therefore boost price of assets. Dimic et al. (2016) highly emphasized the role of the monetary policy especially on the short-term component of the stock-bond correlation. Indeed, they claim that the monetary policy easing has a positive impact both on stocks and bonds which implies a positive influence on the dynamic correlation.

Gusset and Zimmermann (2015) used a Constant Conditional Correlation (CCC) GARCH model to test either monetary interventions can have an impact on the stock-bond correlation. They start with the assumption that correlation is dynamic and experiences a dramatic shift over the last 20 years. More particularly, they investigate the role of the monetary policy on this abnormal correlation move. To measure the monetary effects, they use the Overnight Index Swap (OIS) as monetary indicator. They discovered that positive monetary policy shocks trigger negative reactions of stock-bond correlation. Their finding is intuitive and they mainly attribute the negative correlation between monetary policy and stock-bond co-movements to the context involving positive macro-economic decisions. Indeed, positive monetary decisions generally occur when the stock market is deteriorating. Since the central banks react with a lower policy rate, it increases bond prices that lead to a lower stock-bond correlation.

Our assumption is that the monetary policy represented by the Quantitative Easing is positively correlated to the stock-bond correlation.

2.4.9. Interest rates

Interest rates underpin financing principles composing both stock and bond markets. It is the most intuitive and leading economic factor. Indeed, low interest rates imply better borrowing facilities for consumers. It increases their purchasing power and incentivizes to spend money instead of sparing it. It irremediably boosts economic growth and inflation. On the contrary, high interest rates implies expensive borrowing. It decreases the consumer purchasing power and increases sparing incentives. Of course, it reduces economic growth as well as inflation.

Interest rates and inflation have a direct link. Fischer (1930) was the first to suggest that the nominal interest rate is the sum of real interest rate and expected inflation rate. The formula is the following:

$$R = r + E\left(\frac{dP}{dt} * \frac{1}{P}\right)$$

Where P is an index of economy price level.

Due to its major impact on finance, interest rate is the most intuitive studied macro-finance driver. As we saw previously, the real interest rate is in the discount factor of both stock and bond theoretical valuations. Therefore, we expect a positive influence on the dynamic correlation.

Campbell and Ammer (1993) found results consistent with this assumption. They figured out that the correlation tends to increase in case of real interest rates change. However, they did not find significant influence on the stock and bond returns. Actually, changes in the real interest rates mostly influence the yield curve and the short-term nominal interest rate. They explain the modest influence of the real interest rate by its low volatility and a market much more reactive to news affecting inflation or future excess return of both assets. On the same path, Li (2002) found a low relationship between the real interest rate and the stock-bond co-movements.

Besides, Aslanidis and Christiansen (2001) found out that one of the major determinant is the short-term interest rates. More precisely, both authors discovered that the higher the short-term interest rates are, the most likely is the correlation positive. Yang et al. (2009) statistically demonstrated the same interest rates influence. Indeed, they have shown that higher stock-bond co-movements tend to follow higher short-term interest rates. For their part, Addona and Kind (2006) found a positive relationship between the volatility level of the real interest rate and the stock-bond return co-movements. They justify this relationship by the similar impact on the discount factor of both assets. Finally, Ashgarian et al. (2014) indicated that short-term interest rates have a significant impact on the long-run stock-bond co-movements. Indeed, the influence of the short interest-rates variable on the long-run correlation is significant and positive.

2.4.10. Term Spread

It is commonly accepted in the literature that the denomination “term spread” refers to the difference of a 10-year Government Treasury bill and a 3-month Government Treasury bill. The slope of the curve is determined by the term spread. It is the difference between the yield of the long-term maturity and the yield of a short term-maturity. At each point in time, the yield of a debt instrument with a long-term maturity is supposed to be higher than the same instrument with a short-term maturity. Consequently, the yield curve is expected to be positive. However, Wheelock and Wohar (2009) have shown that this assumption does not always holds. Indeed, they produced a literature review of the term spread predictability power. They affirmed that the ability of the spread to forecast future recessions is high and is still efficient. For example, they demonstrated that the spread turned negative a few times during the last six decades. These negative spreads occurred just before recession periods. According to both authors, the relationship between the yield curve and the economic condition depends on the monetary regime responsiveness.

This outcome is consistent with Viceira (2012) researches that demonstrated that the yield spread is a reliable proxy for business conditions. Furthermore, he empirically concluded that the yield spread forecast the stock-bond co-movements. Indeed, an increased yield spread implies a negative relationship between stock returns and discount rates. This implies a positive stock-bond correlation since a decrease (increase) in the bond discount rate increases (decreases) bond returns.

In addition to the short-term interest rates, Ashgarian et al. (2014) and Aslanidis and Christiansen (2001) showed that one of the major correlation driver is the term spread. Indeed, both researches demonstrated that the higher the yield spread is, the most likely is the correlation high and positive.

Based on the literature, we assume that the term spread is a good predictor of the economic stance. Therefore, lower or negative term spread should have a similar impact on the stock-bond relationship. This is why the correlation of the term spread with the dynamic conditional correlation should be positive.

2.4.11. Euro Ted Spread

The ted spread is the difference between interbank loan interest rates and short-term US T-bill rates. While for the common Ted spread we calculate the difference between 3-month Libor rate and 3-month T-bill rate, for our Euro Ted spread, we calculate the difference between the 3-months Euribor rate and the 3-month Euro T-bill rate. This spread can be viewed as a credit risk indicator. Indeed, government bonds are considered as risk-free while the Euribor rate reflects the credit risk of corporate borrowing. If the credit risk is high due to a poor economic condition, the ted spread will be higher due to a bigger Euribor rate. The Euro Interbank Offered Rate (Euribor) is the interest rates benchmark of the euro money market. Indeed, it is the rate offered to biggest bank on euro interbank term deposit. It is computed based on an average of approximately fifty banks lending and borrowing money to each other.

According to Yang et al. (2009), the Ted spread is perceived as a confidence indicator in the banking system. When the spread narrows, it strengthens both stock and bond markets. However, higher spread corresponds to higher credit risk and a weakening economy. Yang et al. (2009) used the Ted spread as a proxy of short-term liquidity. Their empirical researches concluded that it has a negative relationship with the stock-bond correlation reflecting the FTS phenomenon. Indeed, short-term liquidity crisis tend to increase the spread that is itself linked to a negative stock-bond relationship.

On the same path, Baele et al. (2014) considered the Ted spread in their study of the flight to safety phenomenon. In time of negative correlation, they observed that the Ted spread is on average 27 basis points higher. However, the results are less convincing internationally since there is a significant and negative correlation between the Ted spread and the FTS only in 5 out of 23 countries.

According to the literature on Ted spread, we expect our Euro Ted Spread variable to be negatively correlated to the stock-bond co-movements.

2.4.12. Liquidity

Several authors studied the role of the market liquidity on the stock-bond correlation. As explained in an article of the ECB (2011), global liquidity has a high influence on the financial stability of the market. Indeed, facilities provided by the European Central Bank are led by the monetary policy. The ECB sees the liquidity as a multifaceted concept that can best be defined as “Ease of financing”. There are two main sources of liquidity: on the one hand, the public liquidity provided by the central banks and on the other one, the liquidity provided through private institutions.

On a public liquidity point of view, the liquidity is the amount of money available to settle claims through central banks. On the stock market point of view, the liquidity is the degree to which a financial instrument is easily and quickly traded in the market without affecting its value. Intuitively, cash is a liquid asset and real estates are illiquid assets. In financial markets, the spread between the bid-ask and the trading volume are both often considered as good indicators of market liquidity.

Literature has often stressed the importance of liquidity effects on asset price. For example, there is a consensus on the positive relationship between excess stock returns and illiquidity as demonstrated by Amihud and Mendelson (1986). There are two main ways the liquidity level can affect bond and stock pricing. Firstly, it can influence the asset’s beta. Indeed, in illiquid markets, economic shocks will not directly affect asset returns but more the risk reward that will itself drive the price. This is a factor exposure effect as explained by Baele et al. (2010). Secondly, liquidity can directly affect price meaning that economic shocks improving liquidity affect asset returns. Therefore, the impact of liquidity on stock-bond correlation depends on the co-movements of the liquidity shocks across stock and bond markets.

The flight to safety phenomenon has a high influence on the market liquidity. Indeed, several authors such as Ashgarian (2014), Amihud (1986, 2002), Amihud and Mendelson (1991), Pastor and Stambaugh (2003), Baele et al. (2010) and Chordia, Sarkar and Subrahmanyam (2002) emphasized the fact that economic stress periods drive investors from less liquid stocks to highly liquid bonds. Therefore, FTS events result in a price pressure leading to negative stock-bond correlation coinciding with a lower aggregate market liquidity.

One of the big differentiation between liquidity studies is the method used to assess the liquidity. Indeed, liquidity is unobservable and requires the use of proxies. The most intuitive measure of liquidity is the transaction cost. However, it is difficult to assess these costs in practice since it depends on many factors such as the trade size, timing, counterparties and others. Another widely used measure is the trading volume since widely traded financial instruments are more liquid. Others will prefer trading frequency that is the number of trades executed regardless of the volume. The issue is that both volume and frequency are correlated to the market volatility. The last widely spread measure is the bid-ask spread which measures small trade costs. It is the difference between the bid price and the bid-ask midpoint price. The trade size, the price impact coefficient and the quote size are other examples of liquidity proxies.

Baele et al. (2010) conducted their research using a DCC model to compute the correlation and studied several factors whose liquidity. They used transaction cost based measures of illiquidity for both stocks and bonds. The outcomes of their research showed little or no significance of the macro-economic factors while liquidity proxies seem to have high impact on the stock-bond co-movements.

Besides, Ashgarian et al. (2014) examined the liquidity factor as well. As a measure of liquidity, they used the trading volume of the S&P500 future contract. Their empirical outcomes demonstrated that the larger the trade volume of the S&P500 is, the larger and positive are co-movements of stock and bond returns. These results are consistent with the research of Baele et al. (2010).

Moreover, Pastor and Stambaugh (2003) conducted a research to investigate whether market liquidity is an important variable for asset pricing. In this context, they observed that when the level of market liquidity drops significantly, stocks and fixed income assets tend to move in opposite way and exhibit a negative correlation. It means that there is a positive correlation between liquidity and stock-bond co-movements. They constructed a liquidity proxy that took their name. However, this measure is constructed based on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). Therefore, using this metric in our master thesis on European market would not be consistent.

Finally, Chordia et al. (2002) conducted an empirical analysis on both stock and bond market liquidity levels. In the context of this master thesis, the most interesting outcomes of their researches is firstly the positive correlation of unexpected liquidity shocks between stock and bond markets. Besides, they highlighted a positive effect of the monetary policy on the liquidity as well as the flight to quality represented by large funds inflows for government Treasury bill and large funds outflows for stocks in time of crisis. The flight to safety aspect was even more obvious in their work of 2001 (see Chordia et al. (2001)) where they studied the determinants of the bid-ask spreads and trading volume over the period of 1991-1998.

Being exhaustive on the liquidity factor is highly challenging due to the impressive amount of researches on the topic. Analysis of the liquidity impact on the stock-bond correlation could be master thesis topic itself. However, we decided to examine the European Central Bank liquidity impact on the European stock-bond return co-movements. Indeed, we think that due to its close link with the monetary policy, it will provide a good insight on the level of the European economic confidence and will probably show divergence in its influence depending on the European countries as explained in the monetary policy factor. Therefore, we decided to work with the excess liquidity of the ECB. The assumption is that liquidity level is positively correlated to the stock-bond correlation.

2.5. Asset return properties

The father of the famous "Brownian motion" model, louis Bachelier (1900), stated that successive differences of asset returns are assumed to be independent, normally distributed with zero mean random variables and a variance proportional to the differencing interval. Despite this contribution to the econometric finance modelling, several authors such as Mandelbrot (1963), Plott and Sunder (1982), Cont (1995), Hull and White (1998) and Kirchler and Huber (2007) proved that asset returns are not following a Gaussian curve and tend to exhibit fat tails and excess kurtosis.

We will review the main relevant asset returns properties mainly based on the work of Mandelbrot (1963) and Cont (2001) providing a clear and comprehensive overview of the different empirical asset return properties.

2.5.1. Asset return normality

A common assumption in financial theory is the normality of asset return. However, it has been proven (Mandelbrot (1963), Plott and Sunder (1982), Cont (1995), Hull and White (1998) and Kirchler and Huber (2007)) that this assumption does not hold and that financial variables are often likely to exhibit bigger moves than a Gaussian distribution would suggest. Amongst all these authors, we decided to present here the work of Hull and White (1998) that provided a simple and straightforward evidence on this property. They used a simple normality test using daily movements on 12 exchange rates over a 10-year period. The table below reports their results:

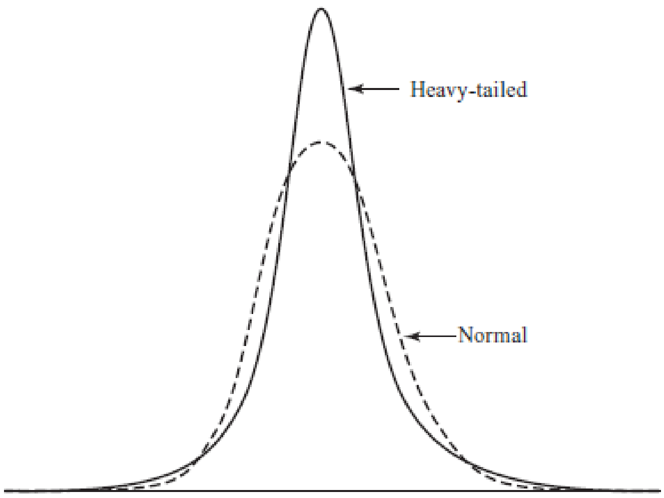
Table 1: Asset return distribution compared to a Gaussian curve

	Real World (%)	Normal Model (%)
> 1 S.D.	25.04	31.73
> 2 S.D.	5.27	4.55
> 3 S.D.	1.34	0.27
> 4 S.D.	0.29	0.01
> 5 S.D.	0.08	0.00
> 6 S.D.	0.03	0.00

Hull and White (1998)

They compared their results with the normal model. As you can see, daily percentage changes exceed normal value except for 1 standard deviation. It clearly supports the fact that returns exhibit fat tails. Besides, there is a lower number of observations in the real world in the one standard deviation range enhancing the highly-peaked distribution.

Plot 1: Asset return distribution compared to a Gaussian curve



Hull and White (1998)

2.5.2. Volatility clustering

Volatility clustering is a time series property exhibiting large return changes followed by large return changes and small changes are often likely to follow small changes. The first author to demonstrate that kind of financial asset returns trend is Mandelbrot (1963). According to him, amplitudes of price changes tend to cluster together implying volatility correlation. He showed that despite negative correlation in asset return itself, absolute returns display a small but positive correlation.

While some authors such as Plott and Sunder (1982) report excess kurtosis and a lack of autocorrelation in asset return without providing explanation on the factor implying that trend; Kirchler and Huber (2007) focused their research on factors impacting fat tails and volatility clustering. They found a significant and positive link between heterogeneity of intrinsic information and return co-movements. According to them, the main driving force of trading activities lies in fundamental information leading to fat tails. However, in the context of this master thesis, we do not further investigate on the driving component of the volatility clustering phenomenon. Nevertheless, it is an important input for the choice of our model.

2.5.3. Asset return unpredictability

The random walk process first introduced by Pearson (1905) is a stochastic or random process that consist in a succession of random outcomes in mathematical series. Random walk combined with a normal distribution are widely used assumptions in financial modelling such as share price or option price of Black and Scholes (1973). Some empirical studies demonstrated convincing predictability of asset return evidences.

However, efficient market hypothesis (EMH) is a theory stating that it is impossible to beat the market. Indeed, it means that asset prices directly incorporate flows of information. However, EMH is a highly controversial theory that has been confirmed and invalidated by many opposite researches. However, this investment theory suggests that asset returns are exclusively dependent on the underlying risk of the financial instrument. It is consistent with CAPM theory and exhibits evidences of return predictability using risk based models.

2.6. Stock-bond correlation assumptions

Based on the literature we detailed in this chapter, we constructed several assumptions that we assess thanks to different regression models. The main assumptions are threefold. Firstly, we expect the correlation of stock and bond returns in European Union to be dynamic. Secondly, we expect to observe FTS phenomenon with different patterns at country level due to its specific conditions. Thirdly, several macro-economic variables should influence the time-varying component of the DCC. Besides, these variable have different impact depending on the economic stance.

In this context and based on the literature, we depicted several sub-assumptions linked to macro-economic variables. Therefore, we have the following assumptions:

- Business conditions should be positively correlated to the DCC;
- Crisis period should negatively influence the DCC;

- Inflation level should be positively correlated to the DCC;
- Consumer confidence level should be positively correlated to the DCC;
- Industrial production level should be positively correlated to the DCC;
- Unemployment should be negatively correlated to the DCC;
- Market uncertainty should be negatively correlated to the DCC;
- Monetary policy represented by QE should be positively correlated to the DCC;
- Interest rates level should be positively correlated to the DCC;
- Term Spread level should be positively correlated to the DCC;
- Euro Ted Spread level should be negatively correlated to the DCC;
- Liquidity level should be positively correlated to the DCC.

3. DCC-GARCH Multivariate model

Correlation is the most important input of this master thesis. Fortunately, the need for reliable estimations of covariance between financial data created large craving of researchers and practitioner to produce studies on the topic. Actually, estimates and forecasting of future correlation is the cornerstone of most pricing equations. Most intuitive finance is built on the assumption that return of different asset depend on their fundamental and are identically and independently distributed (IID) over time. However, as we explained in Chapter 2, most of time-series variable display dynamic means, variances and covariances through time.

Different approaches to estimate conditional covariances and correlations exist such as moving average specification of variances and covariances or dynamic conditional correlation estimation with GARCH process. The latter has the advantage to directly parametrize conditional correlation. As previously explained, to estimate the dynamic correlation of the stock and government bond returns, we use a multivariate DCC-GARCH model. This framework was first introduced by Engle (2001) and then developed in several researches such as Engle (2002), Orskaug (2009), Ding and Schwert (2010) and Fobe (2015). In this chapter, we will review the different works and assumptions that lead to the construction of this more and more spread model.

3.1. Basics of the model

The econometric challenge lies in the specification of how information is impacting mean and variances of returns linked to past information. Somehow, many practitioners have made specification for the mean return. On the contrary, in the eighties, most traditional econometric and time series models were run under constant variance assumption. A primary tool used to describe heteroscedasticity was the rolling standard deviation. We should also mention exponential smoothers models considering weighting past squared returns to compute return at time t. This is why we will first introduce the EWMA model to then derive on the ARCH model we are concerned with.

3.1.1. EWMA model

The exponentially weighted moving average (EWMA) model to estimate volatility was interesting in its ability to easily track updating volatility changes. The formula for the variance model is the following:

$$\sigma_n^2 = \lambda\, \sigma_{n-1}^2 + (1-\lambda)\mu_{n-1}^2$$

The variance estimate σ_n^2 is a function of variance estimate of day n-1, σ_{n-1}^2, and μ_{n-1}^2 which is the most recent daily change. The model used a parametrization denoted λ that allow recent observation to have bigger impact on the estimation of the variance. λ must range between 0 and 1. The main advantage of the model is that it considers asset return property of volatility clustering since it gives more weight to recent observations. Besides, it enables the data storage requirements to be low since we mainly need the recent observations of the variable. Indeed, the parametrization being exponential, we can easily ignore long-range observation. This is a difference with ARCH models developed in the next sub-section.

3.1.2. ARCH model

The first real alternative to EWMA and look alike models is the well-known ARCH stochastic process introduced by Engle (1982). The model takes the following form:

$$\sigma_n^2 = \gamma V_L + \sum_{i=1}^{m} \alpha_i\, \mu_{n-1}^2$$

The ARCH model allows the conditional variance component to be time-varying depending on past errors and lets unconditional variance constant. In such process, "*the recent past gives information about the one-period forecast variance*" (Engle (1982)). In the regression model, Engle introduces disturbance term following an ARCH process:

$$y_t = \varepsilon_t * \sqrt{h_t}$$

$$With\ \varepsilon_t \sim \aleph\ (0,1) and\ h_t = \alpha_0 + \alpha_1 * y_{t-1}^2$$

The ARCH regression model proposed by Engle allows the conditional variance to depend from past observations. It is highly attractive for econometric application and several researches proved its efficiency in predicting future variance. The main advantage comes from parametrization of lag return weights than can be estimated. However, it was fast obvious that taking only one lag of past squared return would not be enough. For readability reasons, we will not go further in detail on ARCH model and we refer to the work of Engle (1982) and Gouriéroux (1997) for more precision on the model and its applications.

3.1.3. Univariate GARCH model

In 1986 the Danish economist Bollerslev proposed the Generalized ARCH (GARCH) model. Compared to previous ARCH model (Engle, 1982), such a model goes one step further by assuming an ARMA model for the conditional variance equation h_t.

Then, the GARCH (q,p) model is defined as (Orskaug, 2009):

$$r_t = \mu_t + a_t$$

$$a_t = h_t^{1/2} * z_t$$

$$h_t = \omega_0 + \sum_{i=1}^{q} \alpha_i a_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$$

Where

r_t	log return of an asset at time t
a_t	mean-corrected return of an asset at time t
μ_t	the expected value conditional r_t
$\{z_t\}$	sequence of iid standardized, random variables
h_t	the conditional variance at time t, conditioned on the history
ω_0, α_i and β_i	parameters of the model
p,q	orders of the GARCH model

As stated in the specification, GARCH models are characterized by orders *p* and *q* where *q* represents the lag orders of the ARCH term (a_{t-i}^2) and *p* the lag orders of the GARCH term (h_{t-j}).

Even if we do not go further in detail concerning GARCH model literature, an important assumption is the stationarity of $\{a_t\}$. This condition is fulfilled when each parameter is non-negative and their sum is strictly less than unity $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i < 1$.

3.1.4. MGARCH models

A few years after the rising of different types of GARCH models focusing on conditional variance of a single asset returns, economists developed more complex models in order to better understand the co-movements between several assets. Such models are defined as Multivariate GARCH models (MGARCH).

The multivariate GARCH models are described as (Orskaug, 2009):

$$r_t = \mu_t + a_t$$

$$a_t = H_t^{1/2} * z_t$$

Where

r_t	$nx1$ vector of log returns of n assets a_t time t
a_t	$nx1$ vector of mean-corrected returns of n assets at time t, i.e. $E[a_t]$ = 0 and $COV[a_t] = H_t$
μ_t	$nx1$ vector of the expected value conditional r_t
$\{z_t\}$	$nx1$ vector of iid errors such that $E[z_t]$ = 0 and $E[z_t z_t^T] = 1$
H_t	nxn matrix of conditional variances of a_t time t
$H_t^{1/2}$	Any nxn matrix at time t such that H_t is the conditional variance matrix of a_t

In such a model, the matrix of conditional variances (H_t) remains to be specified and many different specifications exist. Nonetheless, the number of parameters in H_t quickly raises as the number of observed assets increases. Consequently, any computation of such a matrix is complex (unless this number of assets remains small). Therefore, "*an important goal in constructing the MGARCH models is to make them parsimonious enough, but still maintain the flexibilit*y" (Orskaug, 2009). Depending on the approach one model could develop in order to solve this concern, one can classify them into four categories (Silvennoienen and Teräsvirta, 2007):

- Models of the conditional covariance matrix;
- Factor models;
- Models of conditional variances and correlations;
- Nonparametric and semi parametric approaches.

For the purpose of this master thesis, we are only interested in the third category (models of conditional variances and correlation) in which we can classify the DCC-GARCH model. Such models are built on the idea of modelling conditional variances and correlations instead of straightforward modelling the conditional covariance matrix. Then, H_t is decomposed into conditional standard deviations and a correlation matrices as:

$$H_t = D_t R_t D_t$$

Where $D_t = diag\left(h_{1t}^{1/2}, \dots, h_{nt}^{1/2}\right)$ is the conditional standard deviations matrix and R_t is the correlation matrix (Orskaug, 2009).

3.2. DCC-GARCH model

First introduced by Engle (2001), the Dynamic Conditional Correlation GARCH (DCC-GARCH) model is based on the Constant Conditional Correlation GARCH (CCC-GARCH) model introduced by Bollerslev (1990). Nonetheless, the major difference between those two models lies on the respective specifications concerning the correlation matrix H_t. Indeed, even if the CCC-GARCH model integrates time-varying standard deviations matrix, the correlation matrix R_t remains constant. On the other hand, DCC-GARCH specification proposes time-varying standard deviations matrix and correlation matrix.

As stated in the section 3.1, the DCC-GARCH model is part of the MGARCH models and belongs to the group of "models of conditional variances and correlations" (Silvennoienen, Teräsvirta, 2007).

The DCC-GARCH model presents some advantages compared to general MGARCH models. Indeed, a major critic of the latter is the dramatic complexification of the computation of their covariance matrix when the number of assets increases (Orskaug, 2009). Thanks to a two-steps approach for the parameterization, the number of parameters estimated through the DCC-GARCH model remains independent of the number of assets (Engle, 2001).

3.2.1. The model

The DCC-GARCH model is defined as (Orskaug, 2009):

$$r_t = \mu_t + a_t$$

$$a_t = H_t^{1/2} * z_t \sim \mathcal{N}(0, H_t)$$

$$H_t = D_t R_t D_t$$

Where

r_t	$nx1$ vector of log returns of n assets a_t time t
a_t	$nx1$ vector of mean-corrected return of n assets a_t time t, i.e. $E[a_t]$ = 0 and $COV[a_t] = H_t$
μ_t	$nx1$ vector of the expected value conditional r_t
z_t	$nx1$ vector of iid errors such that $E[z_t]$ = 0 and $E[z_t z_t^T] = 1$
H_t	nxn matrix of conditional variances of a_t time t
$H_t^{1/2}$	Any n x n matrix at time t such that H_t is the conditional variance matrix of a_t
R_t	nxn conditional correlations matrix of a_t at time t.
D_t	nxn diagonal matrix of conditional standard deviations of a_t at time t.

As previously stated, the most important inputs of the DCC-GARCH model are the R_t and D_t matrices, namely the conditional correlations matrix and the diagonal matrix of conditional standard deviations of the mean-corrected returns matrix a_t at time t.

On the one hand, the diagonal matrix of conditional standard deviations, D_t, is composed by square roots of the particular values of the conditional variance equations h_{it} that we can obtain for each asset through Bollerslev's Univariate GARCH (p,q) model (1986) developed in section 3.1.3. Same conditions are imposed on the parameters (non-negative and strictly less than unity sum).

On the other hand, assuming that the residuals ε_t are standardized by its specific standard deviation and are multivariate normally distributed, the conditional correlation matrix R_t is, more specifically, the conditional correlation matrix of the standardized residuals $\varepsilon_t = D_t^{-1} * a_t \sim \mathcal{N}(0, R_t)$ (Orskaug, 2009). As for the Univariate GARCH model, several conditions exist:

- H_t, the conditional covariance matrix, has to be positive definite. Considering that D_t is positive definite by definition (all of its elements are square roots, hence positive), the conditional correlation matrix R_t has to be positive as well;
- By definition of a correlation, all the elements of the conditional correlation matrix R_t have to be less or equal to unity.

In order to respect both of these conditions, we transform the matrix R_t into its decomposition:

$$R_t = Q_t^{* -1} * Q_t * Q_t^*$$

Where

$$Q_t = (1 - a - b) * \overline{Q_t} + a\varepsilon_{t-1}\varepsilon_{t-1}^T + bQ_{t-1}$$

Then, the conditions are transposed on the values of the parameters *a* and *b*. As a consequence, both parameters have to be positive and their sum has to be strictly less than unity (Orskaug, 2009). The following sub-section describes parameters estimation of the DCC-GARCH model.

3.2.2. Parameters estimation

As previously stated, the DCC-GARCH parameters are computed using a straightforward two-steps process. With the first step, we obtain the specific Univariate GARCH parameters estimates $\phi_i = (\omega_{i0}, \alpha_{i1}, \dots, \alpha_{iq}, \beta_{i1}, \dots, \beta_{ip})$ for each of the n assets. Then, we construct D_t by gathering specific conditional covariance equations and use it to calculate standardized residuals ε_t. Finally, those standardized residuals are used in the second step of the process in order to define the parameters $\psi = (a, b)$ and the conditional correlation matrix R_t.

Assuming multivariate Gaussian distributed standardized errors, the log-likelihood function of the correlation estimator R_t can be formulated as (Orskaug, 2009):

$$ln(\mathcal{L}(\theta)) = -\frac{1}{2}\sum_{t=1}^{T}(n\, ln(2\pi) + ln(|H_t|) + a_t^T H_t^{-1} a_t)$$

Then, substituting the conditional variance matrix by its expression $H_t = D_t R_t D_t$ we can write:

$$ln(\mathcal{L}(\theta)) = -\frac{1}{2}\sum_{t=1}^{T}(n\, ln(2\pi) + ln(|D_t R_t D_t|) + a_t^T D_t^{-1} R_t^{-1} D_t^{-1} a_t) \ (1)$$

$$ln(\mathcal{L}(\theta)) = -\frac{1}{2}\sum_{t=1}^{T}(n\, ln(2\pi) + 2ln(|D_t|) + ln(|R_t|) + a_t^T D_t^{-1} R_t^{-1} D_t^{-1} a_t) \ (2)$$

Step one

In the first step, we do not consider the conditional correlation matrix R_t which is substituted by the identity matrix I_t in (2). We obtain the quasi-likelihood function:

$$ln(\mathcal{L}_1(\phi)) = -\frac{1}{2}\sum_{t=1}^{T}(n\, ln(2\pi) + 2ln(|D_t|) + ln(|I_n|) + a_t^T D_t^{-1} I_n^{-1} D_t^{-1} a_t)$$

Given $ln(I_n) = 0$, we rewrite the expression:

$$ln(\mathcal{L}_1(\phi)) = -\frac{1}{2}\sum_{t=1}^{T}\left(n\, ln(2\pi) + \sum_{i=1}^{n}\left(ln(h_{it}) + \frac{a_{it}^2}{h_{it}}\right) + k\right)$$

$$ln(\mathcal{L}_1(\phi)) = \sum_{i=1}^{n}\left(-\frac{1}{2}\sum_{t=1}^{T}\left(ln(h_{it}) + \frac{a_{it}^2}{h_{it}}\right) + k\right)$$

Such an expression is the sum of the log-likelihood functions of the Univariate GARCH models for n assets. As a consequence, the parameters $\phi_i = (\omega_{i0}, \alpha_{i1}, \dots, \alpha_{iq}, \beta_{i1}, \dots, \beta_{ip})$ of the different assets may be separately estimated. Then, the conditional covariance equations h_{it} are computed for each asset, implying that $\varepsilon_t = D_t^{-1} * a_t$ and $\bar{Q}_t$ can be estimated (Orskaug, 2009).

Step two

Thanks to the estimated parameters from step one, the second step of the process focuses on correlation parameters $\psi = (a, b)$ estimation through the correctly specified log-likelihood function. Given $\varepsilon_t = D_t^{-1} * a_t$, (2) can be rewrite as:

$$ln(\mathcal{L}_2(\psi)) = -\frac{1}{2}\sum_{t=1}^{T}(n\, ln(2\pi) + 2ln(|D_t|) + ln(|R_t|) + \varepsilon_t^T R_t^{-1}\varepsilon_t)$$

Since D_t is constant after the estimation of its parameters in step one, we can eliminate the constant terms of the equation. Then, correlation parameters $\psi = (a, b)$ are estimated by maximizing the following expression (Orskaug, 2009):

$$ln(\mathcal{L}_2(\psi)) = -\frac{1}{2}\sum_{t=1}^{T}(ln(|R_t|) + \varepsilon_t^T R_t^{-1}\varepsilon_t)$$

3.3. Statistical estimation issues

Statistical analysis of asset return faces several issues. These issues are important for the choice of the model as well as for results interpretations and conclusions. In this thesis, we will use Ordinary Least Square (OLS) estimators for our models. As Gauss-Markov theorem states, the OLS estimators are the Best Linear Unbiased Estimators of a linear regression model if a set of assumptions hold. For readability reason, we will not provide further detail of this theorem here. However, to ensure the reliability and quality of our model, we have to review the different issues relating to the parameters and the error term linked to the Gauss-Markov assumptions that could occur in our estimations. This section is mainly inspired by the work of Michael Kutner, Christopher Nachtsheim, John Neter and William Li (2004) in the Applied Linear Statistical Models book as well as by the econometrics and forecasting course provide by professors Leonardo Iania and Nguyen Anh at the Louvain School of Management.

3.3.1. Stationarity

Stationary time series can be defined as series with time-invariant statistical properties (mean, variance and covariance). Mathematically, it means that joint distribution of return at each time "t" is the same as the joint distribution of return at "t+1". In order to product reliable and relevant regressions, time series data must be stationary. Indeed, Granger and Newbold (1974) provided evidences that regression between non-stationary series lead to spurious or meaningless relation.

A good tool to ensure time series stationarity is the Augmented Dickey-Fuller (ADF) unit root test. Such a test assumes that the series follow an AR(p) process by including in the right-side of its regression p lagged difference terms of the dependent variable y.

$$\Delta y_t = \alpha y_{t-1} + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \cdots + \beta_p \Delta y_{t-p} + \varepsilon_t$$

Where $\alpha = \rho - 1$

The ADF test tests whether $|\rho|$ is strictly less than unity. Its null hypothesis states that $|\rho| = 1$, hence $\alpha = 0$. In case the null hypothesis is not rejected, we cannot affirm that y is stationary. The non-stationary series are transformed into their first difference to solve the issue.

Due to the fact that ADF statistic does not follow a conventional Student's t-distribution, the null hypothesis is evaluated using the MacKinnon (1991) critical value and p-value computations.

3.3.2. Heteroscedasticity

Heteroscedasticity can be defined as a non-constant variance of the error term for each observation. It violates one of the CLRM basic assumption and implies inefficient estimations meaning that estimators are no longer BLUE. Besides, in case of heteroscedasticity, standard errors are biased and it results in biased statistical tests and confidence intervals. In order to ensure that error terms of our model are homoscedastic, we make a first visual check by plotting residuals against fitted value. Indeed, abnormal pattern exhibiting severe heteroscedasticity are easily detected through correlograms and Q-statistics.

Furthermore, Engle (1982) developed a test that allows to detect the presence of ARCH. Indeed, the ARCH test regresses the squared residuals on the lagged residuals and a constant, with the null hypothesis stating the absence of heteroscedasticity and autocorrelation effects in the error term. Following a Chi² distribution, the Engle's Lagrange Multiplier test statistic is computed as the number of observations times the R^2 from the test regression.

3.3.3. Autocorrelation

Basic regression models of log return generally assume that error terms denoted μ_t are independent and unccorelated random variables. However, this master thesis involves time series data. Therefore, the basic assumption required for CLRM does not hold. A regression with error terms autocorrelation violates one of the Gauss-Markov assumptions and may bias estimators. Whether or not the error term in time *t* depends on the error term in time *t-1* or not is best described by the following equation:

$$\mu_t = \rho * \mu_{t-1} + \varepsilon_t$$

Therefore, when rho is positive, there is a positive autocorrelation of the error term. On the same path, when the rho sign is negative, it exhibits a negative autocorrelation. The first order autoregressive is easily tested with the famous Durbin-Watson test. Durbin and Watson (1950) were the first to provide a useful and simple tool measuring autocorrelation level of error terms. It consists in determining whether or not ρ equals to zero with $H_0: \rho_0 = 0$. The test statistic D is determined through OLS fitting the regression.

$$D = \frac{\sum_{t=2}^{T} (\mu_t - \mu_{t-1})^2}{\sum_{t=1}^{T} \mu_t{}^2}$$

The threshold to assume a positive or negative autocorrelation can be tricky. Fortunately, Durbin and Watson (1950) provided lower and upper bounds respectively d_L and d_U to conclude on autocorrelation.

3.3.4. Multicollinearity

The most intuitive issue occurring in multivariate linear regression is the multicollinearity of regressors. This phenomenon arises when there is particularly high correlation between explanatory variables. Consequently, coefficient estimates will exaggeratedly vary in response to small changes in the model or in the data sample. Multicollinearity is a crucial aspect of the estimation since it allows reducing the number of useful and reliable factors. Due to profuse researches on stock-bond return correlation, testing multicollinearity of the chosen macro-economic factor will be necessary.

As explained by Kutner, Nachtsheim and Neter (2004), the best way to assess the multicollinearity of independent variables is the use of a Variance Inflation Factor (VIF). This indicator measures the collinearity impact amongst explanatory variables on the precision and reliability of estimations. Contrarily to the correlation matrix, the VIF detects higher order multicollinearity. Mathematically, The VIF denotes the diagonal element of the correlation matrix and is equal to:

$$(VIF)_k = (1 - R_k^2)^{-1}$$

Therefore, when R_k^2 is equal to 1, VIF tends to infinite, and when R_k^2 is equal to 0, the Variance Inflation Factor is equal to 1. As stated by Kutner et al. (2004), it is generally accepted that an independent variable with VIF exceeding 10 exhibits to significant multicollinearity. To solve this problem, the variable should be dropped or new uncorrelated variable should be included in the model.

3.3.5. Goodness of fit

The goodness of fit of a statistical model describes how well it fits a set of data. In a classical linear regression model (CLRM) analysis, the most intuitive measure of goodness of fit of the estimated regression line is the coefficient of determination (or R^2). It provides a percentage of the dependent variable variation explained by the explanatory variables. Therefore, this statistic is used in hypothesis testing and the value ranges from 0 to 1. The coefficient equals to the (Explained Sum of Square) divided by the Total Sum of Square (TSS). It is can be represented mathematically as follows:

$$R^2 = \frac{ESS}{TSS} = \sum \frac{\left(\hat{Y} - \bar{Y}\right)^2}{(Y - \bar{Y})^2}$$

Despite its intuitive interpretation, R^2 can be highly tricky and hiding several specification or time series data issues. Firstly, it is dependent on the number of regressors. It means that adding a few explanatory variable to the estimation model always increases the value of R^2 leading to the spurious conclusion that the model is more relevant. However, this problem can be tackled down thanks to the adjusted R^2. Indeed, the latter takes into account the loss of freedom degrees linked to the number of added variables. The formula is as following:

$$\bar{R}^2 = 1 - \left[\left(\frac{n-1}{n-k}\right) * (1 - R^2)\right]$$

With k as the number of regressors and n the number of observations. Therefore, adding variables to the model automatically decreases adjusted R^2. However, both adjusted R^2 and R^2 do not have the same interpretation. Indeed, R^2 is a measure of the goodness of fit whereas adjusted R^2 is a comparative measure of alternative set of regressors.

However, as highlighted by numerous authors and more particularly by Granger and Newbold (1974) in their research on spurious regression, both adjusted R^2 and R^2 with high values do not provide confidence on the reliability of the regression models.

The relative quality of the models can also be measured thanks to the Akaike Information Criterion (AIC) (Akaike, 1973) and the Schwarz Criterion (SC) (Schwarz, 1978). Like adjusted R^2, those two indicators reward the goodness of fit but discourage the incorporation of too much variables by incorporating a penalty term. Compared to the AIC, the SC imposes a larger penalty for added variables. In both cases the preferred model is the one with the lowest indicator.

$$AIC = \frac{-2l}{n} + \frac{2k}{n}$$

$$SC = \frac{-2l}{n} + \frac{(k \log n)}{n}$$

Where n as the number of observations, k the number of parameters and *l* the log-likelihood function.

4. Methodology

4.1. Data collection and sample

This master thesis empirical study is run in two parts. First part concerns the stock-bond correlation estimations and its interpretations on a daily basis. Second part focuses on determining which drivers best explain these correlation evolutions over the sample period. Second part regressions are computed on a monthly basis due to data availability. However, daily data are transformed into monthly data by taking the monthly average when it is necessary. Then, the sample period includes 219 monthly observations and 4760 daily observations starting on the 1st February 1999 and ending on the 28th April 2017. This period is characterized by highly time varying economic situation providing good insights to our research.

We decided to use a Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH(1,1)) model to regress dynamic stock-bond return correlations for the European benchmark (EU) and several European countries: Germany (DE), France (FR), Italy (IT), Spain (SP), Portugal (PT) and United Kingdom (UK). These specific countries have been selected in order to better reflect differences between North (DE, FR, UK) and South (IT, SP, PT) economies of the European Union. For each country, daily DCC are computed based on the country-specific daily observations for stock and bond returns. Then, monthly correlations used for our further regressions are calculated by taking the monthly average of daily correlations.

We used country-specific stock indexes as proxies for stock market returns namely the DAX Index for Germany, CAC40 Index for France, FTSE 100 Index for United Kingdom, FTSE MIB Index for Italy, IBEX 35 for Spain and PSI 20 for Portugal. On the bond side, we collected country government T-bill with 10-year maturity. As benchmark, we selected STOXX 600 Index for stock prices and the Eurozone Sovereign Bond 10+ Year Index for bond yields. Index prices, bond yields, and macro-economic data were extracted from Bloomberg financial platform.

On the one hand, daily stock returns of selected countries are computed as the log difference of daily prices of the respective index. On the other hand, daily bond returns are computed by taking the reverse difference between two daily yields:

$$r_{stock,t} = ln\frac{p_t}{p_{t-1}} \qquad\qquad r_{bond,t} = -yield_t + yield_{t-1}$$

Then, we took several data series in order to best represent the macro-economic drivers that are selected for this master thesis empirical study based on literature review presented in section 2.4.

Business cycle (FINC): We used the Eurozone financial condition index provided on Bloomberg. This is defined as follows: *"This concept tracks overall conditions in a country's financial industry. The Bloomberg Euro Area Financial Conditions Index tracks the overall level of financial stress in Euro area money, bond, and equity markets to help assess the availability and cost of credit. A positive value indicates accommodative financial conditions, while a negative value indicates tighter financial conditions relative to pre-crisis norms".* (Bloomberg platform, 2017) This index can be found under the following Bloomberg ticker: BFCIEU. We also used its British counterpart BFCIGB.

Inflation rate (INFL): We used the Eurozone MUICP All Items Index. It is defined as *"A measure of prices paid by consumers for a market basket of goods and services. It is calculated using the same methodology across countries to allow for comparable measures of inflation. The yearly (or monthly) growth rates represent the inflation rate".* (Bloomberg platform, 2017) This index can be found under the following Bloomberg ticker: ECCPEMUY. We also used country specific consumer confidence indicators that can be found under the following tickers: ECCPDEYY, ECCPFRYY, ECCPITYY, ECCPSPYY, ECCPPTYY and ECCPUKYY.

Consumer Confidence (CC): We used the European Commission Consumer Confidence Indicator Eurozone. It is defined as an index that *"tracks sentiment among households or consumers. The results are based on surveys conducted among a random sample of households. With a target audience of households, a sample size of 23,000 households and the date of survey the first 2 or 3 weeks of the month".* (Bloomberg platform, 2017) This index can be found under the following Bloomberg ticker: EUCCEMU. We also used country specific consumer confidence indicators that can be found under the following tickers: EUCCFR, EUCCDE, EUCCUK, EUCCES, EUCCPT and EUCCIT.

Industrial Production (IP): We used the Eurostat Industrial Production Eurozone Industry Ex Construction SA. It is defined as *"a measure of the output of industrial establishments in the following industries: mining and quarrying, manufacturing and public utilities (electricity, gas and water supply). Production is based on the volume of the output".* (Bloomberg platform, 2017) This index can be found under the following Bloomberg ticker: EUITEMU. We also used country specific industrial production indicators that can be found under the following tickers: EUITFR, EUITDE, EUITUK, EUITES, EUITPT and EUITIT.

Unemployment (UNEMP): We used the Eurostat Unemployment Eurozone SA. It can be defined as "*the rate tracking the number of unemployed persons as a percentage of the labor force (the total number of employed plus unemployed). These figures generally come from a household labor force survey".* (Bloomberg platform, 2017) This index can be found under the following Bloomberg ticker: UMRTEMU. We also used country specific unemployment indicators that can be found under the following tickers: EUMRFR, EUMRDE, EUMRUK, EUMRES, EUMRPT and EUMRIT.

Market Uncertainty (V2X): We used the V2X EURO STOXX 50 Volatility Index (VSTOXX). It is *"based on EURO STOXX 50 realtime options prices and are designed to reflect the market expectations of near-term up to long-term volatility by measuring the square root of the implied variance across all options of a given time to expiration. In compliance with the ESMA requirements, the components weightings of the VSTOXX index are publicly available*". (Bloomberg platform, 2017) This index can be found under the following Bloomberg ticker: V2X.

Monetary Policy (MONPL): There are many proxies to assess the level of the monetary policy. Since in this master thesis, we already study the interest rate and the liquidity as distinct factors, for the monetary policy we will work with the balance sheet of the European Central Bank. We work with the daily movement instead of the absolute amount to get more precise results. The amount of the balance sheet can be found under the following Bloomberg ticker: EBBSSECM.

Interest rates (KEYR): We used the Main Refinancing Operations Announcement Rate. It is defined as *"A target interest rate set by the central bank in its efforts to influence short-term interest rates as part of its monetary policy strategy. This indicator shows the new target interest rate on the date the new rate was announced. The main refinancing rate is the rate for the Eurosystem's regular open market operations (in the form of a reverse transaction) for the purpose of providing the banking system with the amount of liquidity that the former deems to be appropriate. Main refinancing operations are conducted through weekly standard tenders (in which banks can bid for liquidity) and normally have a maturity of one week".* (Bloomberg platform, 2017) This index can be found under the following Bloomberg ticker: EURR002W. We also used its British counterpart BP0001W.

Term Spread (TERM): The term spread that we use in this master thesis is the common 10-year Treasury government bond rate minus the 3-month Treasury government bond rate. The 3-months rate can be found under the following Bloomberg ticker: GECU3M while the 10-years rate can be found under the following Bloomberg ticker: GECU10YR.

Euro Ted Spread (TED): Euro Ted spread is calculated as the difference between the 3-months Euribor rate and the 3-month Euro T-bill rate. The Euribor is short for Euro Interbank Offered Rate. It can be defined as *"the rates that are based on the interest rates at which a panel of European banks borrow funds from one another. In the calculation, the highest and lowest 15% of all the quotes collected are eliminated. The remaining rates will be averaged and rounded to three decimal places. Euribor is determined and published at about 11:00 am each day, Central European Time".* (Bloomberg platform, 2017) This rate can be found under the following Bloomberg ticker: EUR003M. Regarding the 3-months Treasury bond rate, it can be found under the following Bloomberg ticker: GECU3M

Liquidity (EXLIQU): We used the ECB Eurozone Excess Liquidity. The excess liquidity is defined as *"deposits at the deposit facility net of the recourse to the marginal lending facility, plus current account holdings in excess of those contributing to the minimum reserve requirements".* (Bloomberg platform, 2017) This index can be found under the following Bloomberg ticker: ECBLXLIQ.

Finally, all data series were tested for stationarity in order to avoid spurious or meaningless regressions results (Granger and Newbold, 1974) by running the Advanced Dickey-Fuller (ADF) test as presented in sub-section 3.3.1.

Results are available in Appendix II, from Table A.2.1 to Table A.2.3. Numerous tests do not reject the null hypothesis (at a 5% significance level) implying the impossibility to confirm the stationarity of the series. That is the case for FINC (1 test failed out of 2), INFL (7 out of 7), CC (7 out of 7), IP (6 out of 7), UNEMP (7 out of 7), MONPL (1 out of 1), KEYR (2 out of 2), TERM (1 out of 1) and EXLIQU (1 out of 1). Therefore, these series were replaced by its first differences in order to fix the non-stationarity problem. Finally, the macro-economic driver V2X is also transformed in its first difference level for interpretation purpose.

4.2. Construction of dummy variables

Part of the objectives of this master thesis is to differentiate driver impacts on the stock-bond correlation based on the economic stance. In order to reach these targets, we introduced four dummy variables which encompass different types of financial stress periods, namely the economic, financial, currency and debt crisis.

The three first dummy variables are respectively based on the value of the Gross Domestic Product (GDP) Growth Rate (D_GDP), the Eurostoxx Volatility Index (D_V2X) and the EURIBOR-EONIA spread (D_EURIBOR-EONIA). For each variable, criteria were defined in order to evaluate stress period presence. Therefore, the dummy variable is equal to "1" if these criteria are met and "0" otherwise. Finally, the fourth dummy variable D_CRISIS is a combination of the three previous variables: D_CRISIS is equal to "1" when at least one of the three first dummy variables is equal to "1", and "0" otherwise.

4.2.1. Gross Domestic Product (GDP) Growth Rate

Even though GDP growth rate observations do not explain all types of crisis, recession periods can be triggered by economic and global crisis periods (Frankel and Saravelos, 2010). Technically speaking, recession periods occur when an economy presents two consecutive quarters of negative economic growth. Consequently, D_GDP is equal to "1" when it is part of at least two consecutive quarters showing negative GDP Growth Rate and

"0" otherwise. Financial stress periods highlighted by the dummy variable D_GDP are listed in Appendix III, Table A.3.3.

4.2.2. Index Volatility D_V2X

Despite stock market volatility does not entirely depend on financial turmoil, this indicator suits to measure market risk. Indeed, its value tends to rise when investors are concerned about the future volatility and the underlying investing risk (Banerjee, Doran and Peterson, 2007). Based on this statement, D_V2X is equal to "1" when V2X monthly averaged value is superior to 25 and to "0" otherwise. Financial stress periods highlighted by the dummy variable D_V2X are listed in Appendix III, Table A.3.1.

4.2.3. EURIBOR-EONIA spread

According to Thornton (2009), the LIBOR-OIS is assumed to be a good indicator of the banking sector health due to its capacity to reflect risk perception of default associated to lending activities with other banks. The London Interbank Offered Rate (LIBOR) is "*the average interest rate at which leading banks borrow funds of a sizeable amount from other banks in the London market. Libor is the most widely used "benchmark" or reference rate for short term interest rates*" (Federal Reserve Bank of St Louis, 2017). In other words it indicates the rate at which banks are willing to lend to other banks for a specified term of the loan (Thornton, 2009). On the other hand, the Overnight Index Swap (OIS) is an interest rate swap involving the overnight rate being exchanged for a fixed interest rate.

For European countries, this spread is computed as the difference between the EURIBOR and the Euro Overnight Index Average (EONIA) which represents the overnight rate index. Historically, the value of this spread remains around 10-15 basis points. However, such a gap dramatically increases whenever the environment becomes uncertain. This characteristic can be used to determine financial stress periods (Sengupta and Tam (2008), Thornton (2009)). Therefore, D_EURIBOR-EONIA is equal to "1" when the monthly average EURIBOR-EONIA spread is superior to 20 basis points, and "0" otherwise. Financial stress periods highlighted by the dummy variable D_EURIBOR-EONIA are described in Appendix III, Table A.3.2.

4.2.4. Global indicator D_CRISIS

Finally, D_CRISIS is created for each country in order to encompass the different dummy variables previously detailed and to catch effects of the different types of crisis. The country-specific D_CRISIS variable is equal to "1" as soon as either D_GDP, D_V2X or D_EURIBOR-EONIA is equal to "1" and to "0" otherwise.

4.3. Overview of the different variables

Table 2 below exhibit the different independent variables used in our regressions models.

Table 2: List of variables

Indicator	Country	Variable	Source	Code	Frequ.	Transfo.	Sign
Dummy: GDP growth rate	EU	D_GDP (EU)	Bloomberg	EUGNEMUQ Index	Monthly	Dummy	-
	DE	D_GDP (DE)	Bloomberg	EUGNDEQQ Index	Monthly	Dummy	-
	FR	D_GDP (FR)	Bloomberg	EUGNFRQQ Index	Monthly	Dummy	-
	IT	D_GDP (IT)	Bloomberg	EUGNITQQ Index	Monthly	Dummy	-
	SP	D_GDP (SP)	Bloomberg	EUGNESQQ Index	Monthly	Dummy	-
	PT	D_GDP (PT)	Bloomberg	EUGNPTQQ Index	Monthly	Dummy	-
	UK	D_GDP (UK)	Bloomberg	UKGRABIQ Index	Monthly	Dummy	-
Dummy: volatility	Global	D_V2X	Bloomberg	V2X Index	Monthly	Dummy	-
Dummy: EURIBOR-EONIA spread	Global	D_EURIBOR-EONIA	Bloomberg	EURR002W Index EONIA Index	Monthly	Dummy	-
Dummy: globalization indicator	EU	D_CRISIS (EU)	Computation		Monthly	Dummy	-
	DE	D_CRISIS (DE)	Computation		Monthly	Dummy	-
	FR	D_CRISIS (FR)	Computation		Monthly	Dummy	-
	IT	D_CRISIS (IT)	Computation		Monthly	Dummy	-
	SP	D_CRISIS (SP)	Computation		Monthly	Dummy	-
	PT	D_CRISIS (PT)	Computation		Monthly	Dummy	-
	UK	D_CRISIS (UK)	Computation		Monthly	Dummy	-
Business cycle	EU	FINC (EU)	Bloomberg	BFCIEU Index	Monthly	First diff	-
	UK	FINC (UK)	Bloomberg	BFCIGB Index	Monthly	First diff	-
Inflation rate	EU	INFL (EU)	Bloomberg	ECCPEMUY Index	Monthly	First diff	+
	DE	INFL (DE)	Bloomberg	ECCPDEYY Index	Monthly	First diff	+
	FR	INFL (FR)	Bloomberg	ECCPFRYY Index	Monthly	First diff	+
	IT	INFL (IT)	Bloomberg	ECCPITYY Index	Monthly	First diff	+
	SP	INFL (SP)	Bloomberg	ECCPESYY Index	Monthly	First diff	+
	PT	INFL (PT)	Bloomberg	ECCPPTYY Index	Monthly	First diff	+
	UK	INFL (UK)	Bloomberg	ECCPUKYY Index	Monthly	First diff	+
Consumer confidence	EU	CC (EU)	Bloomberg	EUCCEMU Index	Monthly	First diff	+
	DE	CC (DE)	Bloomberg	EUCCDE Index	Monthly	First diff	+
	FR	CC (FR)	Bloomberg	EUCCFR Index	Monthly	First diff	+
	IT	CC (IT)	Bloomberg	EUCCIT Index	Monthly	First diff	+
	SP	CC (SP)	Bloomberg	EUCCES Index	Monthly	First diff	+
	PT	CC (PT)	Bloomberg	EUCCPT Index	Monthly	First diff	+
	UK	CC (UK)	Bloomberg	EUCCUK Index	Monthly	First diff	+

Industrial Production	EU	IP (EU)	Bloomberg	EUITEMU Index	Monthly	First diff	+
	DE	IP (DE)	Bloomberg	EUITDE Index	Monthly	First diff	+
	FR	IP (FR)	Bloomberg	EUITFR Index	Monthly	First diff	+
	IT	IP (IT)	Bloomberg	EUITIT Index	Monthly	First diff	+
	SP	IP (SP)	Bloomberg	EUITES Index	Monthly	First diff	+
	PT	IP (PT)	Bloomberg	EUITPT Index	Monthly	First diff	+
	UK	IP (UK)	Bloomberg	EUITUK Index	Monthly	First diff	+
Unemployment	EU	UNEMP (EU)	Bloomberg	UMRTEMU Index	Monthly	First diff	-
	DE	UNEMP (DE)	Bloomberg	UMRTDE Index	Monthly	First diff	-
	FR	UNEMP (FR)	Bloomberg	UMRTFR Index	Monthly	First diff	-
	IT	UNEMP (IT)	Bloomberg	UMRTIT Index	Monthly	First diff	-
	SP	UNEMP (SP)	Bloomberg	UMRTES Index	Monthly	First diff	-
	PT	UNEMP (PT)	Bloomberg	UMRTPT Index	Monthly	First diff	-
	UK	UNEMP (UK)	Bloomberg	UMRTUK Index	Monthly	First diff	-
Market Uncertainty	Global	V2X	Bloomberg	V2X Index	Monthly	First diff	-
Monetary policy	EU	MONPL (EU)	Bloomberg	EBBSSECM Index	Monthly	First diff	+
Interest rates	EU	KEYR (EU)	Bloomberg	EURR002W Index	Monthly	First diff	+
	UK	KEYR (UK)	Bloomberg	BP0001W Index	Monthly	First diff	+
Term spread	EU	TERM (EU)	Bloomberg	GECU3M Index GECU10YR Index	Monthly	First diff	+
Ted spread	EU	TED (EU)	Bloomberg	EUR003M Index GECU3M Index	Monthly	At level	-
Liquidity	EU	EXLIQU (EU)	Bloomberg	ECBLXLIQ Index	Monthly	First diff	+

4.4. Regression models

As previously stated, the second step of this empirical study consists in determining which drivers best explain stock-bond correlation evolution over the sample period. Then, the studied macro-economic variables are regressed on monthly DCC through the OLS methodology.

Four models are constructed:

Model 1: $C_t = \alpha + \beta_1 C_{t-1} + \beta_2 X_t + \varepsilon_t$

Model 2: $C_t = \alpha + \beta_1 C_{t-1} + \beta_2 X_t + \beta_3 D\_FINSTRESS_t + \varepsilon_t$

Model 3: $C_t = \alpha + \beta_1 C_{t-1} + \beta_2 X_t + \beta_4 (X_t * D\_FINSTRESS_t) + \varepsilon_t$

Model 4: $C_t = \alpha + \beta_1 C_{t-1} + \beta_2 X_t + \beta_3 D\_FINSTRESS_t + \beta_4 (X_t * D\_FINSTRESS_t) + \varepsilon_t$

Where

C_t	Monthly averaged stock-bond DCC at time t
C_{t-1}	Monthly averaged stock-bond DCC at time t-1
X_t	Macro-economic variable at time t
$D\_FINSTRESS_t$	Dummy variable equals to 1 in stress periods and to 0 otherwise

First of all, each model includes one lagged correlation observation to ensure homoscedasticity of residuals as explained in sub-section 3.3.2. Based on Engle's ARCH test (2001) and observations of the correlograms of squared residuals, we conclude that including only one lagged observation is sufficient to avoid heteroscedasticity concerns.

Model 1 is the most parsimonious model. It displays the impact of a specific macro–economic variable X_t on the monthly averaged DCC. Such specification attempts to reflect that the contemporaneous stock-bond correlation is determined by past correlation and new information without taking into account the economic stance. Model 2 considers the influence of financial stress periods by adding the dummy variable $D\_FINSTRESS_t$. Model 3 replaces the previous dummy by an interactive dummy variable in order to catch the incremental margin effect of the variable X_t on the stock-bond correlation during financial stress periods. Finally, Model 4 gathers both fixed effect of $D\_FINSTRESS_t$ and its incremental marginal effect of X_t on the correlation.

5. Results

5.1. DCC-GARCH estimation

Stock-bond correlations are estimated for each country and the European benchmark through a DCC-GARCH (1,1) two-steps model as specified in section 3.2.. First step consists in estimating conditional variance equations $h_{i,t}$ parameters $(\omega_{\mathrm{i}}, \alpha_i, \beta_i)$ from both stock and bond returns. According to Engle and Colacito (2006), including only one ARCH term and one GARCH term is adequate in order to estimate stock or bond conditional variance equation parameters.

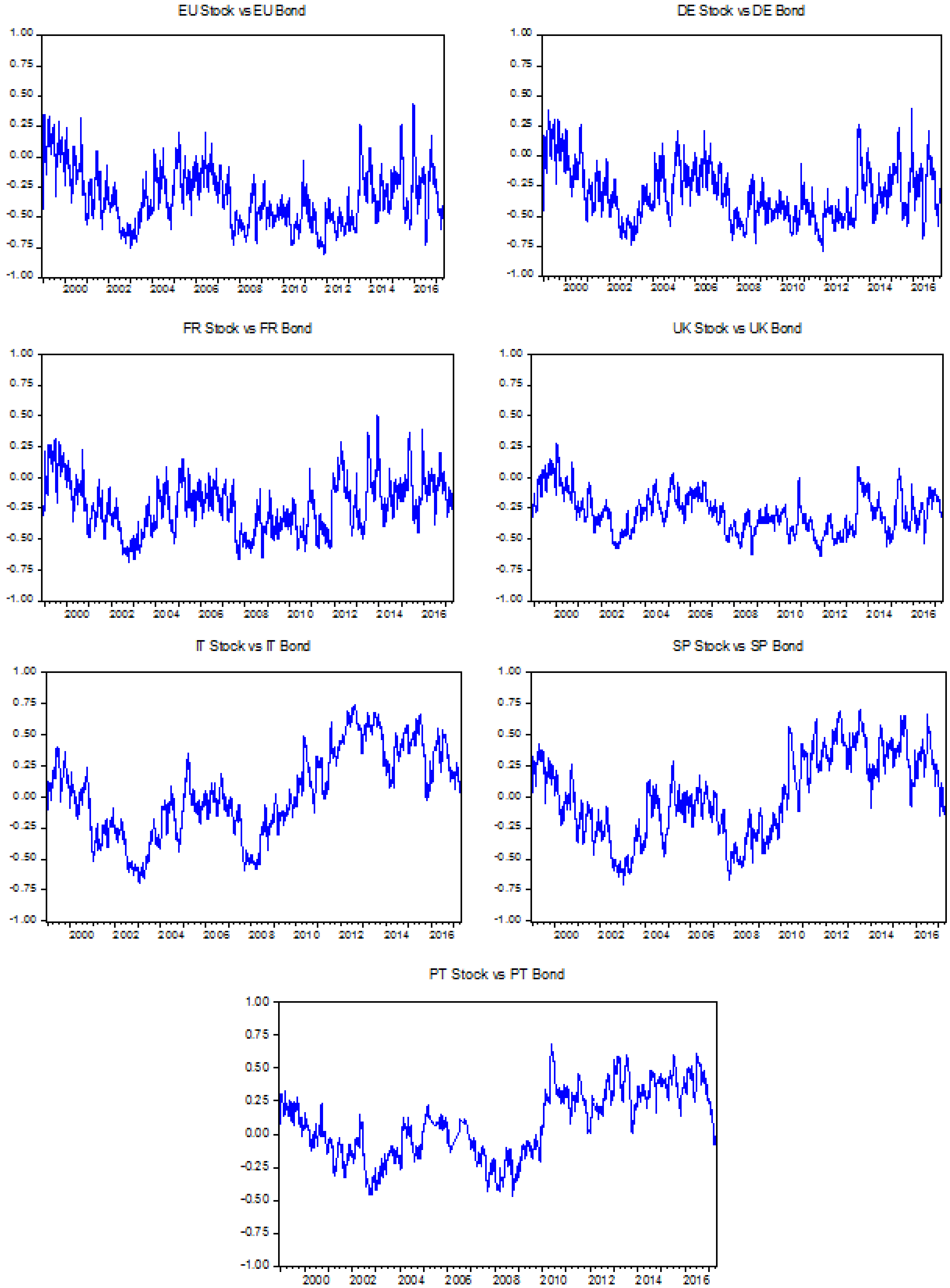
$$h_{i,t} = \omega_{\mathrm{i}} + \alpha_i a_{i,t-1}^2 + \beta_i h_{i,t-1}$$

Then, DCC-GARCH (1,1) parameters *a* and *b* are estimated through a second step based on specific conditional variance equations. Finally, dynamic conditional correlations matrix $R_t = Q_t^{*\,-1} * Q_t * Q_t^*$ is computed through its decomposition $Q_t = (1 - a - b) * \overline{Q_t} + a\varepsilon_{t-1}\varepsilon_{t-1}^T + bQ_{t-1}$.

Each parameter from the two-steps model and their respective dynamic conditional correlation matrices R_t are calculated by running the *Eviews* software for each country and the European benchmark. Results concerning the parameters are available in Appendix IV. Firstly, all parameter estimations are non-negative and sums of both variance equation parameters α_i and β_i and the correlation parameters (*a* and *b*) are strictly less than one. It means that DCC-GARCH conditions on its parameters are fulfilled. Moreover, all results exhibit highly significant parameter estimates at the 1% significance level. Then, one can observe that heteroscedasticity is an important driver of the stock-bond conditional correlation. These observations are highlighted by numerous researchers including Connolly et al. (2005) and Baele et al. (2010). Therefore, it reinforced our decision to include the lagged correlation variable in our regression models as presented in section 4.4.

Figure 1 below plots for each country and the European benchmark daily estimated stock-bond dynamic conditional correlations over the sample period. As one can observe, correlations are time-varying in each case, which is consistent with works provided by Barsky (1989), Gulko (2002), Ilmanen (2003), Kim et al. (2005), Andersson et al. (2006) or Chiang and Li (2009). Moreover, dramatic declines from positive to negative correlation are

Figure 1: DCC estimations graphs for each country and European benchmark



observed during financial stress periods. It mainly occurs in 2000, 2002, 2007, 2010 and 2015 corresponding to the internet bubble collapse, the subprime crisis, the European sovereign debt crisis and the China market crash.

These dramatic downfalls exhibit the presence of FTS events over the sample period as assumed by our second assumption. Nonetheless, second part of our hypothesis suggests that financial stress periods do not affect country specific stock-bond correlations in the same way. A global trend in stock-bond correlations is observed within each studied entity from the beginning of the sample period to the mid of the subprime crisis. Nonetheless, after this point, South (Italy, Spain and Portugal) and North (Germany, France, United Kingdom) countries do not seem to follow the same pattern. On the one hand, North countries estimates tend to remain negative over the post-2008 period and reflect the FTS phenomenon. On the other hand, South countries correlations tend to be positive on the same period and do not show FTS movements.

According to Perego and Vermeulen (2013), this observation is explained by a decorrelation between South- and North-bonds in recent financial stress periods, especially the European sovereign debt crisis. Indeed, both researchers observed the rising of South-bonds/North-stocks correlations, implying that generally accepted South safe assets (bonds) tended to be more correlated with generally accepted North risky assets (stocks). Knowing that South-stocks/North-stocks correlations remained close to one in the same period, investor were not anymore able to reduce investing risks thanks to South-bonds. Therefore, FTS were no longer likely to appear.

Appendix V exhibits results of our cross-area DCC-GARCH (1,1) estimations between North (Germany, France and United Kingdom) and South (Italy, Spain and Portugal) countries included in this master thesis. These results are similar to Perego and Vermeulen (2013) findings. Nonetheless, one can notice constant improvement of the North-stocks/South-bonds correlations since 2014.

In order to run the regression models presented in section 4.4., daily dynamic conditional correlations are averaged on a monthly basis for each country and the European benchmark. As one can observe in Appendix VI, such computation implies a decrease in recognition of extreme events. Nonetheless, our previous observations still hold.

5.2. Descriptive statistics

In this section, we describe and interpret descriptive statistics of the different dependent and independent variables.

5.2.1. Stock-bond return correlations

Over the sample period, the country-specific dependent variables of the stock-bond DCC display different descriptive statistics from one region to another. Indeed, figures exhibit a clear breach between South countries (Italy, Spain and Portugal) on the one hand and North countries (Germany, France and United Kingdom) plus the European benchmark on the other hand. The first ones display higher average values (respectively 0.04, 0.01 and 0.08 at both daily and monthly frequencies) than the second ones (respectively -0.31, -0.23, -0.30 and -0.33 at both daily and monthly frequencies). Such a breach sustains our previous observations based on country-specific correlation graphs.

Firstly, the negative results from North countries reject Ilmanen (2003) and other researchers' findings stating a slightly positive correlation over time. Nonetheless, it is consistent with researches about the FTS phenomenon developed by Baele et al. (2014), Baur and Lucey (2009) and Ashgarian et al. (2014).

Moreover, the clear difference between North and South countries averaged correlations over the sample period is consistent with previous graphical observations and Perego and Vermeulen (2013) findings. The slightly positive values for South countries are mainly driven by post-2008 period where a breach in the FTS phenomenon appears.

Finally, figures confirm our concern about the loss of precision by taking monthly averaged values of the stock-bond correlations as dependent variable. Indeed, even though standard deviations of the respective series remain stable from daily to monthly data, one can observe a systematic deterioration of minimum and maximum values of respective series.

Table 3: Descriptive Statistics of the stock-bond DCC at daily and monthly level

Variable	Transfo.	Frequ.	Obs.	Mean	Median	Std. Dev.	Min	Max
C(EU)	level	d	4760	-0.33	-0.36	0.23	-0.80	0.37
	level	m	219	-0.33	-0.35	0.22	-0.73	0.19
C(DE)	level	d	4760	-0.31	-0.34	0.22	-0.78	0.35
	level	m	219	-0.31	-0.34	0.21	-0.71	0.27
C(FR)	level	d	4760	-0.23	-0.23	0.21	-0.67	0.47
	level	m	219	-0.23	-0.24	0.20	-0.61	0.32
C(IT)	level	d	4760	0.04	0.01	0.34	-0.70	0.75
	level	m	219	0.04	0.02	0.34	-0.66	0.71
C(SP)	level	d	4760	0.01	0.00	0.33	-0.69	0.70
	level	m	219	0.01	0.00	0.33	-0.62	0.66
C(PT)	level	d	4760	0.08	0.07	0.26	-0.47	0.69
	level	m	219	0.08	0.07	0.25	-0.43	0.65
C(UK)	level	d	4760	-0.28	-0.30	0.16	-0.68	0.34
	level	m	219	-0.28	-0.30	0.16	-0.57	0.23

5.2.2. Financial stress variables

The dummy variable D_V2X mean of 0.37 indicates that approximately 37% of the monthly averaged observations based on market volatility indicator V2X stand above 25 basis points. It implies numerous peaks over the sample period. D_EURIBOR-EONIA exhibits similar mean (0.38) and standard deviation (0.49) meaning that 38% of the monthly averaged EURIBOR-EONIA spreads exceeds 20 basis points over the sample period.

Besides, dummy variable D_GDP and its descriptive statistics is country-specific. One can observe that South countries which are the most impacted by recent crisis periods exhibit higher average values. It implies that these countries exhibit more and/or larger recession periods over the selected timeframe. There are significant result differences since Italy, Spain and Portugal show means around 0.26, 0.23 and 0.25 while Germany, France, United Kingdom and the European benchmark show means around 0.11, 0.07, 0.07 and 0.15.

Knowing that dummy variable D_CRISIS is a combination between the three previous variables, results reflect a similar breach between South and both North countries and the European benchmark. Nonetheless, we cannot state at this point of the development which dummy variable is the most accurate for our empirical study. Therefore, we run the regression Model 1 with the three different dummy variables. Results are gathered in section 5.3.1.

Table 4: Descriptive Statistics of the financial stress proxies dummy variables

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min	Max
D_GDP(EU)	dummy	219	0.15	0.00	0.36	0.00	1.00
D_GDP(DE)	dummy	219	0.11	0.00	0.31	0.00	1.00
D_GDP(FR)	dummy	219	0.07	0.00	0.25	0.00	1.00
D_GDP(IT)	dummy	219	0.26	0.00	0.44	0.00	1.00
D_GDP(ES)	dummy	219	0.23	0.00	0.42	0.00	1.00
D_GDP(PT)	dummy	219	0.25	0.00	0.43	0.00	1.00
D_GDP(UK)	dummy	219	0.07	0.00	0.25	0.00	1.00
D_V2X	dummy	219	0.37	0.00	0.49	0.00	1.00
D_EURIBOR-EONIA	dummy	219	0.38	0.00	0.49	0.00	1.00
D_CRISIS(EU)	dummy	219	0.53	1.00	0.50	0.00	1.00
D_CRISIS(DE)	dummy	219	0.53	1.00	0.50	0.00	1.00
D_CRISIS(FR)	dummy	219	0.51	1.00	0.50	0.00	1.00
D_CRISIS(IT)	dummy	219	0.55	1.00	0.50	0.00	1.00
D_CRISIS(ES)	dummy	219	0.57	1.00	0.50	0.00	1.00
D_CRISIS(PT)	dummy	219	0.56	1.00	0.50	0.00	1.00
D_CRISIS(UK)	dummy	219	0.51	1.00	0.50	0.00	1.00

5.2.3. Macro-economic drivers

Business cycles

As one can observe on the graph provided in Appendix VII - Figure A.7.1, indicators of the business cycles across the Eurozone and the United Kingdom, respectively FINC (EU) and FINC (UK) tend to follow a common trend. Indeed, the sample period exhibits a few positive values with downfalls during financial stress periods of 2002, 2008 and 2011.

Nonetheless, FINC (EU) systematically exhibits lower values than its British counterpart FINC (UK) after the 2008 crisis. As a consequence, we observe a slightly lower mean for FINC (EU) (-0.54 against -0.39 for FINC (UK)).

Table 5: Descriptive Statistics of the business cycles indicators

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min		Max	
FINC (EU)	level	219	-0.54	-0.12	1.63	-9.67	10/08	1.22	07/05
	first diff	219	0.00	0.03	0.59	-6.03	10/08	1.69	01/09
FINC (UK)	level	219	-0.39	-0.02	1.73	-9.70	11/08	1.39	02/07
	first diff	219	0.00	0.05	0.56	-5.24	10/08	1.99	01/08

Inflation rate

The indicator of the inflation rate through Eurozone, INFL (EU), exhibits a mean of 1.73 over the sample period. The major drop is observed during the 2008 crisis period; going from a maximum of 4.1 in August 2008 to a minimum of -0.70 one year later. Evolution graphs of country-specific indicators are available in Appendix VII - Figure A.7.2.

Country members of the Euro Area tend to follow the same trend than the European benchmark indicator. Amongst these five countries, three of them namely Italy, Spain and Portugal exhibit higher average values and standard deviations than the European benchmark (respectively 1.91, 2.23, 2.06 against 1.73 for the mean and 1.10, 1.61 and 1.49 against 0.98 for the standard deviation). The major upward drift is observed during the pre-2008 period with Spain and Portugal indicators. On the other hand, Germany and France exhibit lower means (1.45 and 1.53 against 1.73) and standard deviations (0.92 and 0.86 against 0.98) than the European benchmark.

Finally, British indicator INFL (UK) does not follow the European trend as other countries indicators do. However, it is still impacted by the major drifts of 2008 and 2014. We observe a mean of 1.96 and a standard deviation of 1.16, both higher than European benchmark values.

Table 6: Descriptive Statistics of the inflation indicators

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min		Max	
INFL (EU)	level	219	1.73	2.00	0.98	-0.70	08/09	4.10	08/08
	first diff	219	0.01	0.00	0.25	-1.10	12/08	0.70	04/10
INFL (FR)	level	219	1.53	1.70	0.92	-0.80	07/09	4.00	07/08
	first diff	219	0.01	0.00	0.27	-1.10	11/08	0.90	01/02
INFL (DE)	level	219	1.45	1.50	0.86	-0.80	07/09	3.50	07/08
	first diff	219	0.01	0.00	0.34	-1.20	11/08	1.00	12/16
INFL (IT)	level	219	1.91	2.20	1.10	-0.50	01/15	4.30	08/08
	first diff	219	0.00	0.00	0.30	-1.00	01/09	1.40	09/11
INFL (SP)	level	219	2.23	2.70	1.61	-1.50	01/15	5.30	07/08
	first diff	219	0.01	0.00	0.43	-1.30	07/01	2.30	03/10
INFL (PT)	level	219	2.06	2.40	1.49	-1.80	09/09	5.10	03/01
	first diff	219	0.00	0.00	0.39	-1.70	01/13	1.20	01/11
INFL (UK)	level	219	1.96	1.80	1.16	-0.10	10/15	5.20	09/11
	first diff	219	0.01	0.00	0.28	-1.00	12/08	1.00	12/09

Consumer confidence

Country-specific and the European benchmark Consumer Confidence (CC) indicators exhibit similar trends over the sample period. Even though these similarities are not as important as inflation indicator ones, its graphs available in Appendix VII - Figure A.7.3. show significant downturns during the 2002, 2008 and 2012 periods, with a minimum value of -34.60 for in Europe during March 2009.

At the country level, Germany and United Kingdom are the only ones beating the European benchmark with higher means (-5.85 and -7.19 against -11.97). Nonetheless, both exhibit slightly higher standard deviations over the sample period (respectively 9.08 and 8.63 against 7.38). On the other hand, Spain, France and Italy exhibit smaller results (-13.26, -16.66 and -16.84 for their respective means). Finally, Portugal results reflect a systematic downward drift over the sample period with an average value of -25.47.

Table 7: Descriptive Statistics of the consumer confidence indicators

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min		Max	
CC (EU)	level	219	-11.97	-11.50	7.38	-34.60	03/09	2.20	05/00
	first diff	219	-0.01	0.20	1.51	-5.30	10/08	3.80	04/09
CC (DE)	level	219	-5.85	-4.20	9.08	-32.90	04/09	10.90	11/10
	first diff	219	0.00	0.10	2.48	-8.20	08/11	9.60	07/10
CC (FR)	level	219	-16.84	-16.80	8.17	-37.00	03/09	3.30	01/01
	first diff	219	0.00	0.00	2.82	-9.10	10/08	10.10	01/04
CC (IT)	level	219	-16.66	-16.00	9.07	-41.50	06/12	2.50	06/01
	first diff	219	-0.04	-0.20	2.70	-7.00	04/12	13.70	06/13
CC (SP)	level	219	-13.26	-11.40	11.56	-47.60	02/09	5.40	12/15
	first diff	219	-0.01	-0.10	2.86	-10.50	08/12	11.60	05/09
CC (PT)	level	219	-25.47	-25.60	13.28	-53.70	10/12	-0.60	04/17
	first diff	219	0.03	0.10	2.77	-12.00	10/10	7.30	07/09
CC (UK)	level	219	-7.19	-4.60	8.63	-35.20	01/09	7.60	05/14
	first diff	219	0.01	-0.10	2.66	-8.00	07/16	9.50	05/11

Industrial production

Concerning the industrial production indicator (IP), a similar trend is observed in each studied region, except Portugal. Indeed, as one can see on graphs provided in Appendix VII - Figure A.7.4, IP exhibits a small and steady improvement from the beginning of the sample period until subprime crisis. On the contrary, Portugal results reflect a general negative trend over the sample period.

Moreover, all countries except Germany exhibit values above European benchmark from the beginning of the sample to the subprime crisis. Indeed, we observe a switch in the previous relation during 2008.

Table 8: Descriptive Statistics of the industrial production indicators

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min		Max	
IP (EU)	level	219	102.14	101.70	4.65	90.20	04/09	114.90	04/08
	first diff	219	0.05	0.10	1.05	-4.20	11/08	2.30	01/16
IP (DE)	level	219	99.36	100.50	8.69	83.10	02/99	112.50	04/17
	first diff	219	0.13	0.20	1.43	-6.70	01/09	3.70	05/09
IP (FR)	level	219	107.01	109.80	6.75	94.00	04/09	117.30	12/00
	first diff	219	-0.04	-0.10	1.52	-5.60	11/08	4.70	11/05
IP (IT)	level	219	105.60	111.40	10.70	90.00	03/09	121.90	08/07
	first diff	219	-0.08	0.10	1.50	-4.60	12/08	4.40	01/08
IP (SP)	level	219	108.03	113.50	12.68	88.60	11/12	129.70	05/07
	first diff	219	-0.07	0.00	1.52	-6.30	06/08	4.30	08/01
IP (PT)	level	219	106.11	107.40	9.44	90.40	10/12	122.60	04/02
	first diff	219	-0.08	-0.20	2.68	-7.70	03/03	7.10	06/05
IP (UK)	level	219	104.01	106.70	5.65	93.80	10/12	112.60	11/00
	first diff	219	-0.04	0.00	0.98	-5.10	06/02	2.50	07/12

Unemployment rate

Most of country-specific results exhibit means around the European benchmark value (9.58%). This is the case for France (9.18%), Italy (9.25%) and Portugal (9.93%). However, Germany and United Kingdom present better figures with a respective mean of 7.42% and 5.94%. Finally, Spain reflects the worst situation over the sample period with an average value of 15.79% as shown in table 9.

Table 9: Descriptive Statistics of the unemployment rate indicators

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min		Max	
UNEMP (EU)	level	219	9.58	9.30	1.28	7.30	03/08	12.10	05/13
	first diff	219	0.00	0.00	0.09	-0.20	04/07	0.40	01/09
UNEMP (DE)	level	219	7.42	7.70	2.08	3.90	04/17	11.20	08/05
	first diff	219	-0.02	0.00	0.09	-0.20	04/07	0.30	02/04
UNEMP (FR)	level	219	9.18	9.10	0.87	7.30	06/08	10.80	04/99
	first diff	219	-0.01	0.00	0.09	-0.20	01/17	0.30	01/09
UNEMP (IT)	level	219	9.25	8.60	1.99	5.70	04/07	13.00	11/14
	first diff	219	0.00	0.00	0.20	-0.70	12/14	0.70	11/11
UNEMP (SP)	level	219	15.79	13.40	6.04	7.90	05/07	26.30	07/13
	first diff	219	0.01	0.00	0.25	-0.50	02/99	1.10	01/09
UNEMP (PT)	level	219	9.93	9.20	3.44	4.80	12/00	17.50	01/13
	first diff	219	0.02	0.00	0.19	-0.70	08/13	0.50	10/12
UNEMP (UK)	level	219	5.94	5.40	1.21	4.40	04/17	8.40	01/12
	first diff	219	-0.01	0.00	0.10	-0.30	12/13	0.40	04/09

Market uncertainty

The monthly closing average of the V2X was 24.89 over the sample period (with a median value of 23.11). We observe on graphs provided in Appendix XII - Figure A.7.6. that the most important periods characterized by high volatility are clustered around the major crisis periods. Indeed, the maximum of 63.27 is observed in the midst of subprime crisis (October 2008).

Table 10: Descriptive Statistics of the market uncertainty indicator

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min		Max	
V2X	level	219	24.89	23.11	9.06	12.64	02/05	63.27	10/08
	first diff	219	-0.08	-0.59	4.66	-12.14	12/08	32.36	10/08

Monetary Policy

As one can observe in Appendix VII - Figure A.7.7, balance sheet monthly data of the European Central Bank start on June 2009, reducing the number of observations to 94. Over this period, we observe a global increase and a huge rising since end-2014.

Table 11: Descriptive Statistics of the monetary policy indicator

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min		Max	
MONPL	level	94	422.09	250.90	471.92	1.06	06/09	1914.95	04/17
	first diff	94	20.37	4.48	29.83	-7.15	07/14	83.13	06/16

Interest rates

The main refinancing rates delivered by the European Central Bank and the Bank of England tend to follow the same pattern over the sample period. However, as one can observe on the graph provided in Appendix VII - Figure A.7.8, BoE systematically provided refinancing rates above its European counterpart over the pre-2008 period. As a consequence, KEYR (UK) indicator exhibit higher mean. Nonetheless, BoE rates decreased faster than ECB rates during the subprime crisis implying higher standard deviation for KEYR (UK) (2.23 against 1.45).

Table 12: Descriptive Statistics of the interest rates indicator

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min		Max	
KEYR (EU)	level	219	1.97	2.00	1.45	0.00	04/17	4.75	04/01
	first diff	219	-0.01	0.00	0.13	-0.73	12/08	0.43	11/99
KEYR (UK)	level	219	2.87	3.75	2.23	0.25	04/17	6.00	05/01
	first diff	219	-0.03	0.00	0.17	-1.43	01/09	0.71	07/99

Term Spread

Both average and median Term spread amount around 1.37%. The ability of the spread to forecast future recessions (Wheelock and Wohar, 2009) is confirmed by dramatic value decreases in 2000 and 2008. A graph showing the evolution of the European Ted spread over the sample period is available in Appendix VII - Figure A.7.9..

Table 13: Descriptive Statistics of the Term Spread indicator

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min		Max	
TERM (EU)	level	219	1.37	1.37	0.74	-0.06	08/08	2.98	01/10
	first diff	219	0.00	-0.02	0.20	-0.56	11/99	1.25	10/08

Euro Ted Spread

The average European Ted spread level over the sample period is determined at 35 basis points with a corresponding median of 22 basis points. Since higher spreads generally correspond to higher credit risk and a weakening economy (Yang et al., 2009), it is consistent to note major peaks during the midst of the subprime crisis (with a maximum value of 3.18 % on December 2008). A graph showing the evolution of the European Ted spread over the sample period is available in Appendix VII - Figure A.7.10..

Table 14: Descriptive Statistics of the Euro Ted Spread indicator

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min		Max	
TED (EU)	level	219	0.35	0.22	0.50	-0.72	05/00	3.18	12/08
	first diff	219	0.00	0.00	0.19	-0.60	01/02	1.46	10/08

Liquidity

Finally, as one can observe on the graph provided in Appendix VII - Figure A.7.11., the excess liquidity level of the ECB remain stable from the beginning of the sample period to Augustus 2008. It implies a median value around 0 and a low mean around 180k EUR over the sample period. Even though EXLIQU indicator values tend to decrease after each major financial stress period, a steady increase is observed since 2015.

Table 15: Descriptive Statistics of the Liquidity indicator

Variable	Transfo.	Obs.	Mean	Median	Std. Dev.	Min		Max	
EXLIQU (EU)	level	219	0.18	0.00	0.31	-0.01	04/08	1.59	04/17
	first diff	219	0.01	0.00	0.04	-0.18	07/10	0.30	03/12

5.3. Regression results

Results of the four regression models introduced in section 4.4. are presented in this section. For each country and model, the lagged stock-bond DCC variable always reflects a positive impact on the dependent variable with low p-value (below 0.001). It means that heteroscedasticity is an important driver of the stock-bond return correlations. These observations are consistent with, amongst other, Connolly et al. (2005) and Baele et al. (2010) researches. However, β_1 coefficients of these lagged estimated DCC are not discussed in the following sub-section for readability purpose. Complete results of the different regressions are available through Appendices VIII, IX, X and XI.

5.3.1. Model 1 regression results

This sub-section focuses on model 1 and interprets variables with a significant impact on the estimated stock-bond DCC. Tables presenting complete results per country are available in Appendix VIII.

$$\textbf{Model 1}: C_t = \alpha + \beta_1 C_{t-1} + \beta_2 X_t + \varepsilon_t$$

Model 1 regressions results suggest that the following independent variables have a significant impact on the stock-bond correlation for at least one of the specific countries covered by this thesis or the European benchmark: D_V2X (7 out of 7), D_CRISIS (4 out of 7), FINC (6 out of 7), UNEMP (1 out of 7), V2X (6 out of 7) and TERM (4 out of 6).

Dummy variables D_V2X and D_CRISIS

Firstly, none of both dummy variables D_GDP and D_EURIBOR-EONIA seem to be significant drivers of the correlations for any country. On the contrary, D_V2X variable succeeds significance tests (α = 0.01) for all regressions. Finally, the country-specific D_CRISIS variable only exhibits significant results for Germany, France, United Kingdom and Europe. Therefore, the dummy variable D_V2X seems to be the only adequate candidate for model 2 regressions. However, we note that such a choice could create spurious regression with the independent variable V2X itself.

Besides, significant dummy variables coefficients reflect a negative relationship between financial stress periods modelled by these dummies and the estimated stock-bond DCC.

These results would reveal the existence of a flight to safety phenomenon that is consistent with the researches of Baele et al. (2014), Baur and Lucey (2009) and Ashgarian et al. (2014). Moreover, same figures exhibit that South countries (Italy, Spain and Portugal) are less sensitive to these dummies than North countries and the European benchmark. It means that FTS phenomenon is less present in South countries. Such observation is consistent with our previous analysis of DCC-GARCH(1,1) estimations, the descriptive statistics and Perego and Vermeulen (2013) findings.

According to model 1 regression results for the European benchmark, a monthly averaged volatility above 25 implies that stock-bond correlations becomes on average 0.057 (p-value = 0.001) lower, *ceteris paribus*. We observe similar coefficients for Germany (-0.055, p-value = 0.001), France (-0.046, p-value = 0.004), United Kingdom (-0.045, p-value = 0.002), Italy (-0.043, p-value = 0.010), Spain (-0.035, p-value = 0.005) and Portugal (-0.045, p-value = 0.002).

Even though none of the South countries exhibit significant results for D_CRISIS, impacts on the correlation for other ones are quite similar to D_V2X impacts: -0.067 (p-value = 0.000) for the European benchmark, -0.064 (p-value =0.000) for Germany, -0.043 (p-value = 0.005) for France and -0.043 (p-value = 0.003) for the United Kingdom.

Business cycle

Except for Spain, the independent variable FINC (EU or UK depending on the country) has a significant positive impact on the stock-bond correlation, which is consistent with our assumption and, amongst others, Ilmanen (2003), Boyd et al. (2005) and Andersen et al. (2007) researches.

Majority of countries exhibits regression results around the European benchmark. Based on benchmark model 1 regression results, a 1 point improvement in the BFCIEU Index implies an average increase around 0.037 (p-value = 0.009) for the monthly averaged stock-bond correlation, *ceteris paribus*. Similar trends are observed for the other countries: Germany (0.036, p-value = 0.008), France (0.034, p-value = 0.007) and United Kingdom (0.032, p-value = 0.009). However, Portugal (0.029, p-value = 0.004) and Italy (0.024, p-value = 0.075) regression results exhibit a lower impact than Europe.

Unemployment Rate

With a p-value of 0.044, UNEMP(EU) is the only variable showing significant negative impact (-0.195, at 5% significance level) on its dependent variable. The coefficient illustrates that an increase of one percent in the European Unemployment Rate lowers the stock-bond correlation of the European benchmark by 0.195, *ceteris paribus*. This negative relationship is consistent with our assumption based on Ashgarian et al. (2014) and Skintzi (2017) findings stating that a weak economy tends to decrease the investor risk appetite, hence the stock-bond correlation.

Market uncertainty

The V2X variable has a significant negative impact in each country. The negative sign of all coefficients is consistent with our assumption and provides evidence of FTS phenomenon. Indeed, stock-bond correlations tend to decrease due safe asset attractiveness in case of financial stress. Therefore, stocks and bonds become mutual hedge candidates (Baele et al. (2014), Connolly et al. (2004), Andersson et al. (2006) and Kim et al. (2005)). Moreover, regressions of North countries exhibit a stronger impact of the V2X variable than its South counterparts over the global sample period. Such a difference is consistent with our observations of a breach in FTS phenomenon for South countries during the post-2008 period (Perego and Vermeulen, 2013). However, influence remains small: a 1 basis point increase of the V2X variable implies average of 0.006 (p-value = 0.001) DCC decrease for the European benchmark, *ceteris paribus*. We observe similar decreases of 0.006 (p-value = 0.001) for Germany, 0.005 (p-value = 0.001) for France, 0.004 (p-value = 0.024) for Italy, 0.001 (p-value = 0.048), 0.003 (p-value = 0.038) for Spain, 0.003 (p-value = 0.015) for Portugal and 0.005 (p-value = 0.001) for United Kingdom.

Term Spread

The Term Spread variable presents significant positive impacts in four cases. Based on regression outcomes, a 1% increase in the Term Spread should imply on average a 0.102 increase (p-value = 0.014) in the stock-bond correlation of Europe, 0.077 (p-value = 0.058) for Germany, 0.084 (p-value = 0.026) for France and 0.076 (p-value = 0.055) for Italy, *ceteris paribus*. Knowing that Term spread is a good proxy for business conditions, this positive relationship is consistent with our assumption and amongst others, Wheelock and Wohar (2009) and Viceira (2012) researches.

Insignificant parameters

Finally, some independent variables do not benefit from significant parameters for any country: the dummy variables D_GDP and D_EURIBOR-EONIA, CC, IP, MONPL, KEYR, TED and EXLIQU.

5.3.2. Model 2 regression results

Model 2 controls for the influence of financial stress periods by including a dummy variable reflecting the economic stance. As stated in the previous sub-section and based on model 1 regression results, the dummy variable D_V2X seems to be the most adequate candidate amongst the four dummies. Indeed, D_V2X is the only dummy variable that remains significant for all countries and the European benchmark across model 1 regressions.

$$\textbf{Model 2}: C_t = \alpha + \beta_1 C_{t-1} + \beta_2 X_t + \beta_3 D\_FINSTRESS_t + \varepsilon_t$$

This sub-section focuses on model 2 and interprets variables with a significant impact on the estimated stock-bond DCC. Tables presenting complete results per country are available in Appendix IX.

Model 2 regressions results suggest that the following independent variables have a significant impact on the stock-bond correlation for at least one of the covered countries and Europe: FINC (5 out of 7), CC (2 out of 7), UNEMP (1 out of 7), V2X (6 out of 7) and TERM (5 out of 6). Compared to regression model 1, consumer confidence variable becomes significant. Finally, the other variables (FINC, UNEMP and TERM) remain significant for at least one country with parameters values staying roughly the same.

Moreover, β_3 coefficients of the dummy variable D_V2X are significant in each regression. β_3 values are steady around -0.05 (with a minimum of -0.061 and a maximum of -0.031) meaning that stock-bond DCC becomes on average 0.05 lower during financial stress periods (as specified by D_V2X), *ceteris paribus*. Moreover, North countries exhibit on average lower coefficients than South-countries. β_3 coefficient values are not detailed and interpreted on a country-specific basis in this sub-section for readability reasons.

Business cycles

Similarly to model 1, FINC variable keeps a positive significant impact on the European benchmark (0.033, p-value = 0.017), Germany (0.033, p-value = 0.015), France (0.031, p-value = 0.006), Portugal (0.026, p-value = 0.007) and United Kingdom (0.041, p-value = 0.005).

Unemployment Rate

Based on model 2 regression outcomes, country-specific UNEMP variables become significant for Portugal stock-bond correlation while it is not significant anymore for the European benchmark. However, results reflect a positive relationship (0.064, p-value = 0.040) that is not consistent with our assumption and Ashgarian et al. (2014) or Skintzi (2017) researches. Nonetheless, we observe on the Portuguese unemployment rate evolution graph presented in Appendix VII - Figure A.7.5. that periods of higher unemployment correspond to the post-2008 period. This is also the period that Perego and Vermeulen (2013) highlighted with a clear decorrelation between South and North countries bonds.

Consumer Confidence

As for the UNEMP variable, Portugal and Italy results exhibit relation going against our assumption. Based on Ashgarian et al. (2014), Baele et al. (2014) and Skintzi (2017), consumer confidence is a good proxy for economic stance. Therefore, a positive link was expected between while regression results exhibit a significant negative impact: -0.006 (p-value =0.008) for Portugal and -0.006 (p-value = 0.049) for Italy.

Market Uncertainty

Knowing that the dummy variable D_V2X captures part of the volatility impact on the stock-bond correlation, coefficients that remain significant for model 2 exhibit lower values than for Model 1 regressions: -0.005 (p-value = 0.006) for the European benchmark, -0.005 (p-value = 0.006) for Germany, -0.004 (p-value = 0.007) for France, -0.003 (p-value = 0.078) for Italy, -0.002 (p-value = 0.061) for Portugal and -0.005 (p-value = 0.002) for United Kingdom. However, V2X variable is not significant anymore for Spain DCC.

Term Spread

TERM Spread variable keeps its significant positive impact on the same countries than for model 1: the European benchmark (0.115, p-value = 0.005), Germany (0.090, p-value = 0.001), France (0.093, p-value = 0.002) and Italy (0.082, p-value = 0.035). All values remain quite similar to model 1 regression outcomes.

Insignificant parameters

Finally, some independent variables do not benefit from significant parameters for any country: IP, MONPL, KEYR, TED and EXLIQU.

5.3.3. Model 3 regression results

Compared to model 1, model 3 controls for a change in the impact of the independent variable during financial stress periods by including an interactive dummy variable. As for model 2, D_V2X is the only dummy variable used for regressions.

Model 3: $C_t = \alpha + \beta_1 C_{t-1} + \beta_2 X_t + \beta_3 (X_t * D\_FINSTRESS_t) + \varepsilon_t$

This sub-section focuses on model 3 and interprets variables with a significant impact on the estimated stock-bond DCC. It means that both β_2 and β_3 succeed in statistical tests (at a 10% significance level). Tables presenting complete results per country are available in Appendix X.

Model 3 regression results suggest that the following independent variables have a significant impact on the stock-bond correlation for at least one of the countries covered by this thesis: IP (1 out of 7) and TED (2 out of 6).

Industrial production

Only the IP variable has a significant impact on the French DCC over the sample period. Based on regression outcomes, a 1 point improvement in the French Industrial Production

Index implies on average a 0.013 (p-value = 0.025) improvement of the correlation, *ceteris paribus*. Nonetheless, such rising is reduced to 0.004 (β_3 = -0.009, p-value = 0.056) during financial stress periods. These results are consistent with our assumption and Ashgarian et al. (2014) and Dimic et al. (2016) works.

TED spread

Italy and Portugal regressions are the only ones exhibiting significant parameters for the TED spread variable. Both countries show a positive β_2 (respectively 0.074, p-value = 0.039 and 0.055, p-value = 0.040) combined with a negative β_3 (respectively -0.062, p-value = 0.084 and -0.061, p-value = 0.023). Therefore, Portugal parameters imply a negative impact of -0.006 on the correlation during stress periods but Italian counterpart shows a positive impact of 0.008 for these periods. Such results are not totally consistent with Yang et al. (2009) and Baele et al. (2014) researches predicting a negative impact.

5.3.4. Model 4 regression results

Finally, model 4 goes one step further by including dummy variable D_V2X and an interactive dummy variable in the same regression.

Model 4: $C_t = \alpha + \beta_1 C_{t-1} + \beta_2 X_t + \beta_3 D\_FINSTRESS_t + \beta_4 (X_t * D\_FINSTRESS_t) + \varepsilon_t$

This sub-section focuses on model 4 and interprets variables with a significant impact on the estimated stock-bond DCC. More precisely, it details results for which both β_2 and β_4 are significant for, at least, a 10% significance level. Under these conditions, variables showing significant results are IP (1 out of 7) and TED (2 out of 6). Tables presenting complete results per country are available in Appendix XI.

Industrial production

Similarly to Model 3, IP variable is significant for French DCC. Even though the positive impact remains the same during non-crisis periods (β_2 = 0.013, p-value = 0.026), one can observe greater decrease during financial stress periods (β_4 = -0.010, p-value = 0.033).

TED spread

Finally, the TED variable becomes significant for European and German regressions. On the contrary, Italian and Portuguese results do not show reliable figures anymore. For the European benchmark, we observe a negative impact of the TED variable during periods without crisis (β_2 = -0.080, p-value = 0.056) that becomes positive during crisis periods (β_4 = 0.101, p-value = 0.025). We observe the same trend for German results (β_2 = -0.072, p-value = 0.074 and β_4 = 0.095, p-value = 0.032). Again, these results are not totally consistent with our assumption and literature (Yang et al. (2009) and Baele et al. (2014))

5.3.5. Tests carried out on regressions

As previously stated in section 4.2, explanatory variables have been constructed in order to ensure the stationarity over the sample period. In order to enhance the reliability of our observations, we also tested the regressions over the four models for the homoscedasticity of residuals, the absence of correlation between residuals and the absence of multicollinearity between explanatory variables.

First, homoscedasticity of residuals is primarily attested by graphical observations of squared residuals correlograms. Due to the integration of one lagged DCC in the models, none of the correlograms exhibit a presence of heteroscedasticity. Then regressions are also tested through Engle's ARCH test as presented in sub-section 3.3.2. As one can see across the test results available in Appendix XIII, p-values do not go below 5%.

Secondly, the absence of autocorrelation between residuals has been tested through correlograms observations and Durbin-Watson (DW) tests. DW statistics for all models are reported in Appendix XII. None of them bring statistical evidence of autocorrelation between residuals. Details of the DW test procedure are reported in sub-section 3.3.3.

Finally, the multicollinearity between explanatory variable has been tested through the Variance Inflation Factor (VIF) as explained in sub-section 3.3.5. None of these residuals exhibit extreme values which would imply multicollinearity problems.

5.3.6. Evaluation of the different models

As stated in sub-section 3.4.5, quality of the models were evaluated based on the adjusted R^2, the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC). Across the different country-specific results provided in Appendix XIV, one can observe that model 2 and model 4 systematically provide better indicators than model 1 and model 3. However, differences between Model 2 and Model 4 are weak and depend from one regression to another. Therefore, the selected model is the most parsimonious one: model 2.

Considering model 2 results, we saw that the lagged DCC (7 out of 7), D_V2X (7 out of 7), FINC (5 out of 7), UNEMP (1 out of 7), CC (2 out of 7), V2X (5 out of 7) and TERM (5 out of 6) variables presented significant impacts on the country-specific DCC estimates:

- The DCC lagged observation is the main driver with a strong positive impact. This is consistent with our assumption based on literature review (amongst other, Connolly et al. (2005) and Baele et al. (2010));
- The financial stress periods represented by our dummy variable D_V2X based on market uncertainty have a significant negative impact. The presence of flight to safety phenomenon is consistent with our assumption and past researches (Baele et al. (2012, 2014), Baur et al. (2006,2009), Ashgarian (2014));
- The FINC variable that represents the business cycle conditions has a strong positive impact in most of the countries. This positive relationship is consistent with our assumption based on Ilmanen (2003), Boyd et al. (2005) and Andersen et al. (2007) researches;
- UNEMP variable shows a positive relation between Portuguese unemployment rate and its DCC observations. Such a statement is not consistent with our assumption based on Ashgarian et al. (2014) and Skintzi (2017) findings;
- The consumer confidence variable CC exhibits negative coefficients for Italian and Portuguese regressions results. This observation is not consistent with our assumption and past literature (Ashgarian et al. (2014), Baele et al. (2014), Skintzi (2017));

- According to our results, market uncertainty is a significant driver of the stock-bond correlation. The V2X variable shows negative relations that are consistent with our assumption based on Baele et al. (2014), Connolly et al. (2004), Andersson et al. (2006) and Kim et al. (2005) findings.
- The TERM variable that represents the term spread shows positive impacts. Such statement is consistent with our assumption and past works of Wheelock and Wohar (2009) and Viceira (2012).

6. Conclusion

This master thesis aims to provide a comprehensive understanding of the highly unstable and dynamic relationship between stock and bond markets in the European Union. Indeed, the first goal is to describe the correlation evolution that we assume to be time-varying. Besides, the particular economic context of the European Union offers an interesting panel of economic conditions that vary through time. Therefore, we assume the existence of flight to safety phenomenon depending on the particular economic conditions of each country. More precisely, we expect temporary flights of the stock-bond correlation from positive to negative value in crisis periods. Finally, we assume that several macro-economic variables have a significant impact on the stock-bond correlation. Moreover, it exists a wide literature on the stock-bond relationship due to its large impact on finance and economy. Therefore, we benefited from a large number of insights both on the correlation and its drivers.

To compute the stock-bond correlation through last two decades, we use a multivariate DCC GARCH model that was first introduced by Engle (2001). We track the evolution of the stock-bond correlation in several European countries (Germany, France, United Kingdom, Spain, Italy and Portugal). The period under review includes 219 monthly observations starting on the 1st January 1999 and ending on the 28th April 2017. Afterward, based on four different models, we regress the macro-economic variables on the computed DCC to assess its influences.

Practically, we computed the different DCC-GARCH through the *Eviews* software and parameters conditions of the models were respected. The whole set of estimation is significant at the 99 % confidence interval. The computed correlation are varying through time which is consistent with Barsky (1989), Gulko (2002), Ilmanen (2003), Kim et al. (2005), Andersson et al. (2006) or Chiang and Li (2009). Therefore, we confirmed our first assumption due to a clear dynamic pattern of the stock-bond correlation in six countries and in Europe. Indeed, European DCC ranged from -0.73 to 0.19 with a standard deviation of 0.22. In the meantime, European countries experienced similar results with highly fluctuating DCC both on daily and monthly basis.

Secondly, we observed dramatic declines of the stock-bond correlation over the sample period. The existence of flight to safety is in line with our second assumption. Besides, observation of FTS episodes over the sample period is consistent with Baele et al. (2014), Hartman et al. (2001) and Ashgarian et al. (2014) researches. Besides, the second part of the assumption suggests that country specific stock-bond correlations are not affected in the same way by financial stress periods. Indeed, South (Italy, Spain and Portugal) and North (Germany, France and United Kingdom) countries do not follow the same pattern. On the one hand, North DCC estimations remain negative over the post-2008 period, reflecting the FTS phenomenon. On the other hand, South countries DCC estimations tend to be positive on the same period. These opposite results are consistent with Perego and Vermeulen (2013) explaining this opposition by the decorrelation between South- and North-bonds mainly implied by the European sovereign debt crisis.

Thirdly, our last assumption covers the influence of macro-economic variables on the dynamic conditional correlation of stock-bond returns. Results here are less straightforward and need a particular attention to the 4 models we developed. Indeed, with the model 1, we observed that the volatility index (D_V2X) is significant in every regression while other financial stress dummies were less convincing. Besides, the business cycle variable is significantly positive in each regression except Spain. This is consistent with Ilmanen (2003), Boyd et al. (2005) and Andersen et al. (2007) researches as well as with our assumption. Moreover, Unemployment driver shows significant negative influence in Europe in line with our assumption and Ashgarian et al. (2014) and Skintzi (2017) works. Furthermore, Market uncertainty driver has a significant negative impact except on Italy DCC. It is consistent with our assumption and Baele et al. (2014), Connolly et al. (2004), Andersson et al. (2006) and Kim et al. (2005) researches. Finally, the Term Spread variable presents significant positive impact in four out of seven cases consistently with our assumption and Wheelock and Wohar (2009) and Viceira (2012) papers.

Besides, model 2 provides slightly different results since it takes into account the influence of financial stress periods by including a dummy variable reflecting the economic stance. Compared to regression Model 1, market uncertainty variable is not significant anymore for any country. Other variables (FINC, UNEMP and TERM) remain significant for at least one country with parameters values staying roughly the same. On the contrary, consumer confidence variable becomes significant and negative. However, this result is not consistent with our assumption and Ashgarian et al. (2014), Baele et al. (2014) and Skintzi (2017) researches. Nonetheless, the impact is weak (-0.006 with a p-value =0.008).

Then, model 3 replaces the dummy variable by an interactive dummy variable in order to control for an impact change of the independent variable during financial stress periods. Only two variables exhibit significant results (IP and TED). On the one hand, the industrial production (IP) variable shows a significant positive impact on the French correlation evolution. However, this impact decreases during financial stress periods. Such result is consistent with our assumption and Ashgarian et al. (2014) and Dimic et al. (2016) works. On the other hand, TED spread variable exhibits positive or negative impact depending on the country. This result is not totally consistent with our assumption based on Yang et al. (2009) and Baele et al. (2014) findings.

Finally, model 4 integrates both the dummy variable and the interactive dummy variable. As for model 3, IP and TED are the only significant variable across our regression results and conserved the same relation signs.

Despite interesting insights from estimation results and regression models, there are some downsides we should highlight. Firstly, the fact that estimation were conducted on a monthly basis reduces the precision in case of extreme events occurring during the month. Indeed, working on a daily basis would avoid intra-month movements that could influence estimations. Besides, the selected sample period is widely influenced by different economic crisis. Even though the intuition was to focus on a highly troubled period, such a restraint window may obscure the view and provide results not reliable on a longer term basis.

To conclude, despite interesting and significant results we obtained, we think that it would be interesting to run similar analysis on a larger time-frame. Indeed, it would provide a better overview of the long-term evolution of the dynamic conditional correlation. Besides, it would be interesting to reduce the number of explanatory variables in order to get more precisions and understanding on the underlying reasons that lead some drivers to influence the stock-bond correlation.

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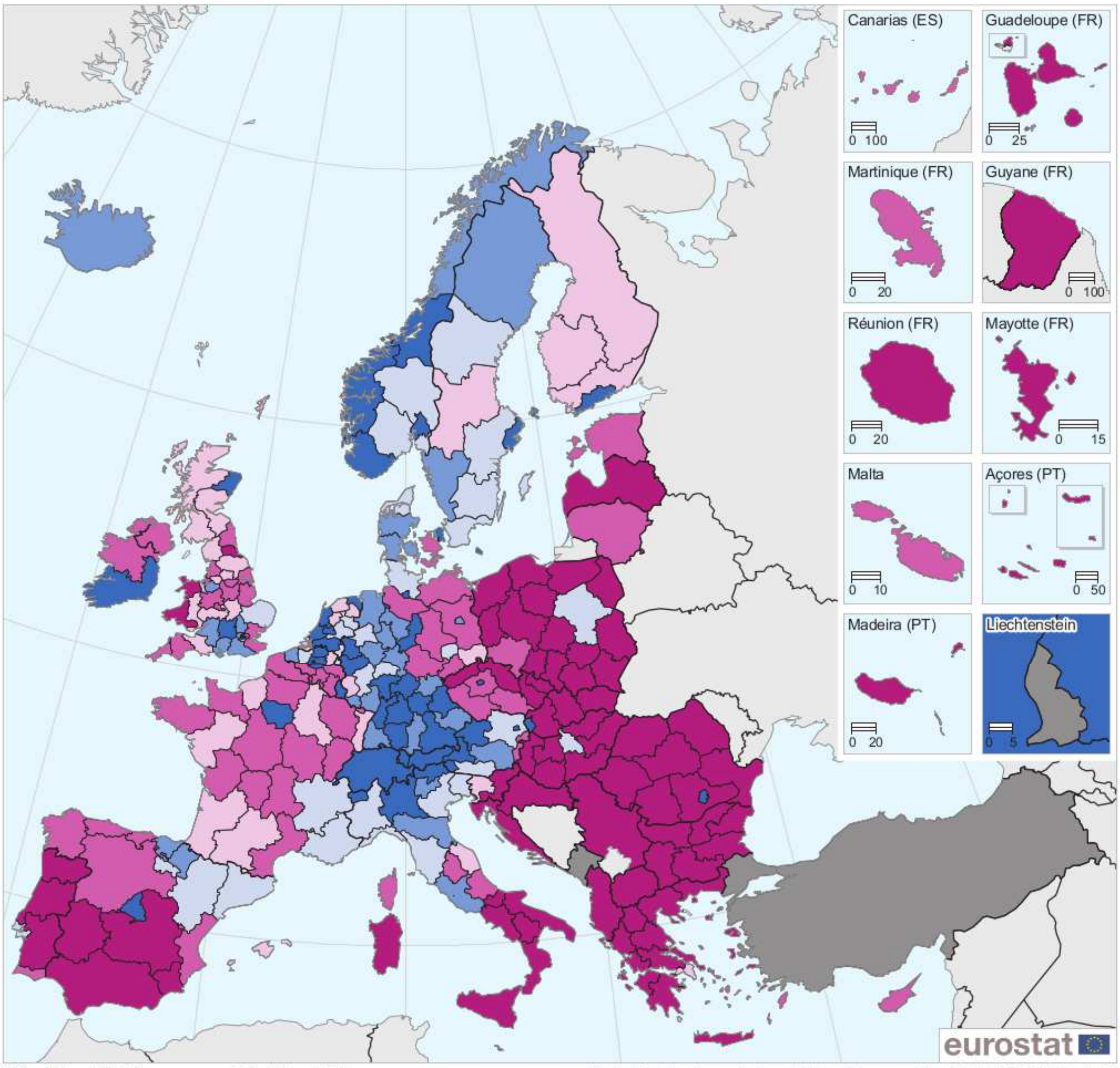
8.1. Appendix I: European regions divergences in GDP

Gross domestic product (GDP) per inhabitant in purchasing power standard (PPS) in relation to the EU-28 average, by NUTS 2 regions, 2014 (¹)

(% of the EU-28 average, EU-28 = 100)



(% of the EU-28 average, EU-28 = 100)

Administrative boundaries: © EuroGeographics © UN-FAO © Turkstat
Cartography: Eurostat - GISCO, 04/2016

EU-28 = 100

- < 75
- 75 – < 90
- 90 – < 100
- 100 – < 110
- 110 – < 125
- >= 125
- Data not available

0 200 400 600 800 km

(¹) Norway: 2013. Switzerland, Albania and Serbia: national data. Switzerland and Albania: provisional.
Source: Eurostat (online data codes: nama_10r_2gdp and nama_10_pc)

8.2. Appendix II: Augmented Dickey-Fuller (ADF) tests

Table A.2.1.: Augmented Dickey-Fuller (ADF) test results (C, FINC, INFL)

Variable		t-Statistic	Prob.*
DCC-correlation			
C (EU)	at level	-4.046	0.002
C (DE)	at level	-4.094	0.001
C (FR)	at level	-4.058	0.001
C (IT)	at level	-10.829	0.000
C (SP)	at level	-12.222	0.000
C (PT)	at level	-12.602	0.000
C (UK)	at level	-4.206	0.001
Business cycle			
FINC (EU)	at level	-3.640	0.006
	first difference	-10.334	0.000
FINC (UK)	at level	-2.683	0.079
	first difference	-10.864	0.000
Inflation rate			
INFL (EU)	at level	-2.371	0.151
	first difference	-12.354	0.000
INFL (FR)	at level	-2.847	0.054
	first difference	-6.918	0.000
INFL (DE)	at level	-2.646	0.085
	first difference	-17.689	0.000
INFL (IT)	at level	-2.018	0.279
	first difference	-14.311	0.000
INFL (SP)	at level	-2.513	0.114
	first difference	-11.535	0.000
INFL (PT)	at level	-1.949	0.309
	first difference	-13.185	0.000
INFL (UK)	at level	-2.087	0.250
	first difference	-12.576	0.000

* Mackinnon (1996) one-side p-values.

Table A.2.2.: Augmented Dickey-Fuller (ADF) test results (CC, IP)

Variable		t-Statistic	Prob.*
Consumer confidence			
CC (EU)	at level	-2.035	0.272
	first difference	-10.768	0.000
CC (FR)	at level	-2.576	0.100
	first difference	-14.957	0.000
CC (DE)	at level	-2.373	0.151
	first difference	-12.298	0.000
CC (IT)	at level	-2.310	0.170
	first difference	-16.079	0.000
CC (SP)	at level	-1.825	0.368
	first difference	-14.411	0.000
CC (PT)	at level	-1.423	0.571
	first difference	-13.340	0.000
CC (UK)	at level	-2.291	0.176
	first difference	-16.527	0.000
Industrial production			
IP (EU)	at level	-3.378	0.013
	first difference	-4.911	0.000
IP (FR)	at level	-1.106	0.714
	first difference	-21.038	0.000
IP (DE)	at level	-1.814	0.373
	first difference	-5.672	0.000
IP (IT)	at level	-1.144	0.699
	first difference	-6.257	0.000
IP (SP)	at level	-0.806	0.815
	first difference	-6.562	0.000
IP (PT)	at level	-1.168	0.689
	first difference	-17.186	0.000
IP (UK)	at level	-1.117	0.709
	first difference	-17.863	0.000

* Mackinnon (1996) one-side p-values.

Table A.2.3.: Augmented Dickey-Fuller (ADF) test results (UNEMP, V2X, MONPL, KEY, TERM, TED, EXLIQU)

Variable		t-Statistic	Prob.*
Unemployment rate			
UNEMP (EU)	at level	-1.661	0.450
	first difference	-4.131	0.001
UNEMP (FR)	at level	-2.306	0.171
	first difference	-5.506	0.000
UNEMP (DE)	at level	-0.484	0.891
	first difference	-4.396	0.000
UNEMP (IT)	at level	-1.104	0.714
	first difference	-4.992	0.000
UNEMP (SP)	at level	-1.263	0.647
	first difference	-3.785	0.004
UNEMP (PT)	at level	-1.265	0.646
	first difference	-5.969	0.000
UNEMP (UK)	at level	-1.194	0.677
	first difference	-4.115	0.001
Market uncertainty			
V2X	at level	-4.002	0.002
	first difference	-12.051	0.000
Monetary policy			
MONPL	at level	1.225	0.998
	first difference	-4.387	0.000
Interest rates			
KEYR (EU)	at level	-1.492	0.536
	first difference	-5.990	0.000
KEYR (UK)	at level	-1.040	0.739
	first difference	-7.774	0.000
Term spread			
TERM	at level	-2.449	0.130
	first difference	-11.513	0.000
Euro Ted spread			
TED	at level	-4.444	0.000
	first difference	-10.045	0.000
Liquidity			
EXLIQU	at level	1.293	0.999
	first difference	-4.165	0.001

* Mackinnon (1996) one-side p-values.

8.3. Appendix III: Overview of the financial stress periods highlighted by different dummy variables

Table A.3.1.: Financial stress periods highlighted by D_V2X

Periods when D_V2X = "1"
From 2/1999 to 5/1999
From 8/1999 to 8/1999
From 12/1999 to 5/2000
From 10/2000 to 12/2000
From 3/2001 to 4/2001
From 8/2001 to 2/2002
From 5/2002 to 10/2003
From 8/2007 to 8/2007
From 1/2008 to 3/2008
From 7/2008 to 7/2008
From 9/2008 to 11/2009
From 2/2010 to 2/2010
From 5/2010 to 8/2010
From 8/2011 to 1/2012
From 4/2012 to 6/2012
From 1/2015 to 1/2015
From 6/2015 to 6/2015
From 8/2015 to 9/2015
From 1/2016 to 2/2016
From 6/2016 to 6/2016

Table A.3.2.: Financial stress periods highlighted by D_EURIBOR-EONIA

Periods when D_EURIBOR-EONIA = "1"
From 2/1999 to 8/1999
From 3/2001 to 3/2001
From 6/2001 to 6/2001
From 8/2001 to 2/2002
From 12/2002 to 4/2003
From 6/2003 to 8/2003
From 10/2007 to 9/2010
From 11/2010 to 9/2012
From 6/2014 to 6/2014

Table A.3.3.: Financial stress periods highlighted by D_GDP per country

Country	Periods when D_GDP = "1"
European benchmark	From 4/2008 to 6/2009
	From 10/2011 to 3/2013
Germany	From 10/2002 to 3/2003
	From 10/2012 to 3/2013
France	From 4/2008 to 6/2009
Italy	From 4/2001 to 12/2001
	From 1/2003 to 6/2003
	From 7/2007 to 12/2007
	From 4/2008 to 6/2009
	From 7/2011 to 2/2013
Spain	From 7/2008 to 12/2009
	From 1/2011 to 9/2013
Portugal	From 4/2002 to 12/2002
	From 7/2004 to 12/2004
	From 4/2008 to 3/2009
	From 10/2010 to 12/2012
United Kingdom	From 4/2008 to 6/2009

8.4. Appendix IV: DCC-GARCH parameters estimates

Table A.4.1: DDC-GARCH(1,1) parameters estimates (EU)*

	Stock variance parameters			T-bond variance parameters			Correlation parameters	
	ω stock	α stock	β stock	ω bond	α bond	β bond	a	b
Coefficient	0.000***	0.085***	0.910***	0.000***	0.036***	0.958***	0.035***	0.954***
	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.4.2: DDC-GARCH(1,1) parameters estimates (DE)*

	Stock variance parameters			T-bond variance parameters			Correlation parameters	
	ω stock	α stock	β stock	ω bond	α bond	β bond	a	b
Coefficient	0.000***	0.085***	0.911***	0.000***	0.036***	0.958***	0.035***	0.953***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.4.3: DDC-GARCH(1,1) parameters estimates (FR)*

	Stock variance parameters			T-bond variance parameters			Correlation parameters	
	ω stock	α stock	β stock	ω bond	α bond	β bond	a	b
Coefficient	0.000***	0.086***	0.908***	0.000***	0.041***	0.949***	0.031***	0.958***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.4.4: DDC-GARCH(1,1) parameters estimates (IT)*

	Stock variance parameters			T-bond variance parameters			Correlation parameters	
	ω stock	α stock	β stock	ω bond	α bond	β bond	a	b
Coefficient	0.000***	0.083***	0.916***	0.000***	0.053***	0.939***	0.032***	0.964***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.4.5: DDC-GARCH(1,1) parameters estimates (SP)*

	Stock variance parameters			T-bond variance parameters			Correlation parameters	
	ω stock	**α stock**	**β stock**	**ω bond**	**α bond**	**β bond**	**a**	**b**
Coefficient	0.000***	0.083***	0.914***	0.000***	0.053***	0.940***	0.029***	0.967***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.4.6: DDC-GARCH(1,1) parameters estimates (PT)*

	Stock variance parameters			T-bond variance parameters			Correlation parameters	
	ω stock	**α stock**	**β stock**	**ω bond**	**α bond**	**β bond**	**a**	**b**
Coefficient	0.000***	0.117***	0.877***	0.000***	0.081***	0.906***	0.022***	0.974***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.4.7: DDC-GARCH(1,1) parameters estimates (UK)*

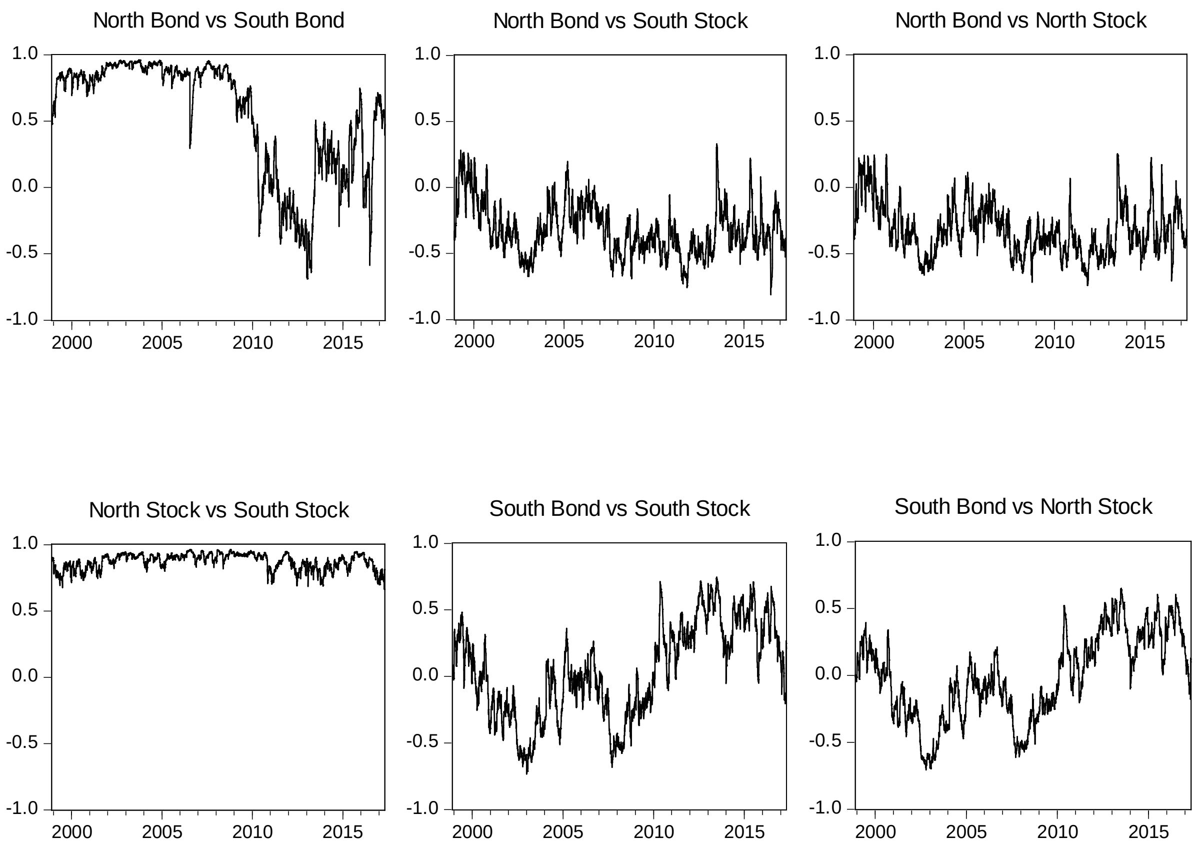
	Stock variance parameters			T-bond variance parameters			Correlation parameters	
	ω stock	**α stock**	**β stock**	**ω bond**	**α bond**	**β bond**	**a**	**b**
Coefficient	0.000***	0.106***	0.886***	0.000**	0.028***	0.969***	0.031***	0.949***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

8.5. Appendix V: North/South cross-assets DCC-GARCH estimations

Based on Perego and Vermeulen (2013) research, the following DCC-GARCH (1,1) estimations are computed based on North countries daily bond returns (DE, FR and UK weighted average based on annual government gross liabilities), North countries daily stock returns (DE, FR and UK weighted average based on stock market capitalization), South countries daily bond returns (IT, SP and PT weighted average based on annual government gross liabilities) and South countries daily stock returns (IT, SP and PT weighted average based on stock market capitalization).

Figure A.5.1.: North/South cross-assets DCC-GARCH estimations



8.6. Appendix VI: Monthly averaged DCC graphs

<u>Figure A.6.1.: Monthly averaged DCC graphs</u>

8.7. Appendix VII: Macroeconomic indicator evolution graphs

Figure A.7.1.:FINC (EU) indicator vs FINC (UK) indicator

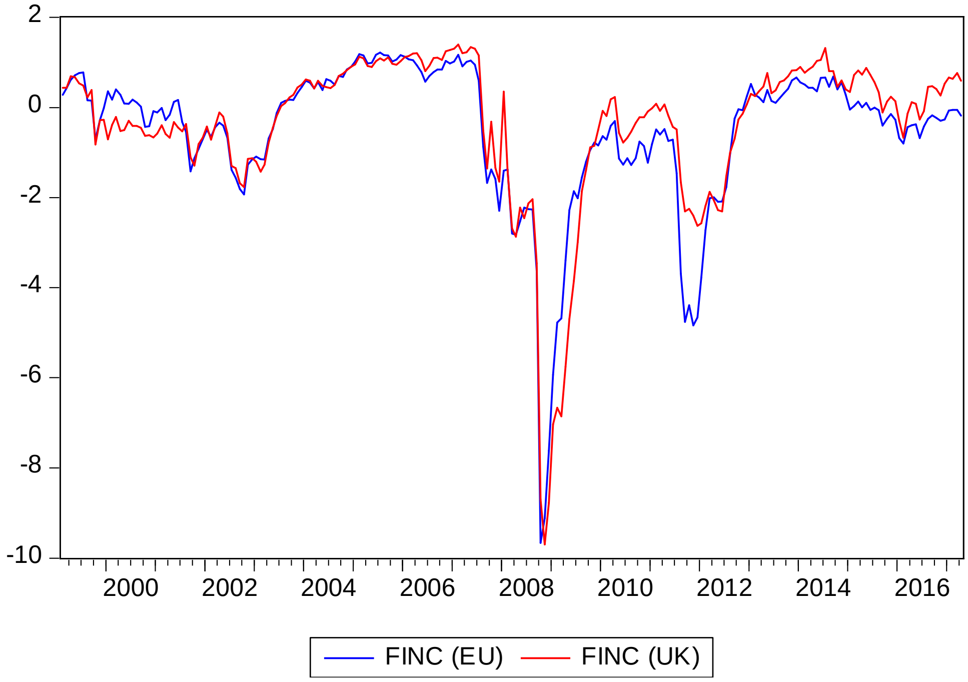


Figure A.7.2.: Country-specific INFL indicators vs European benchmark

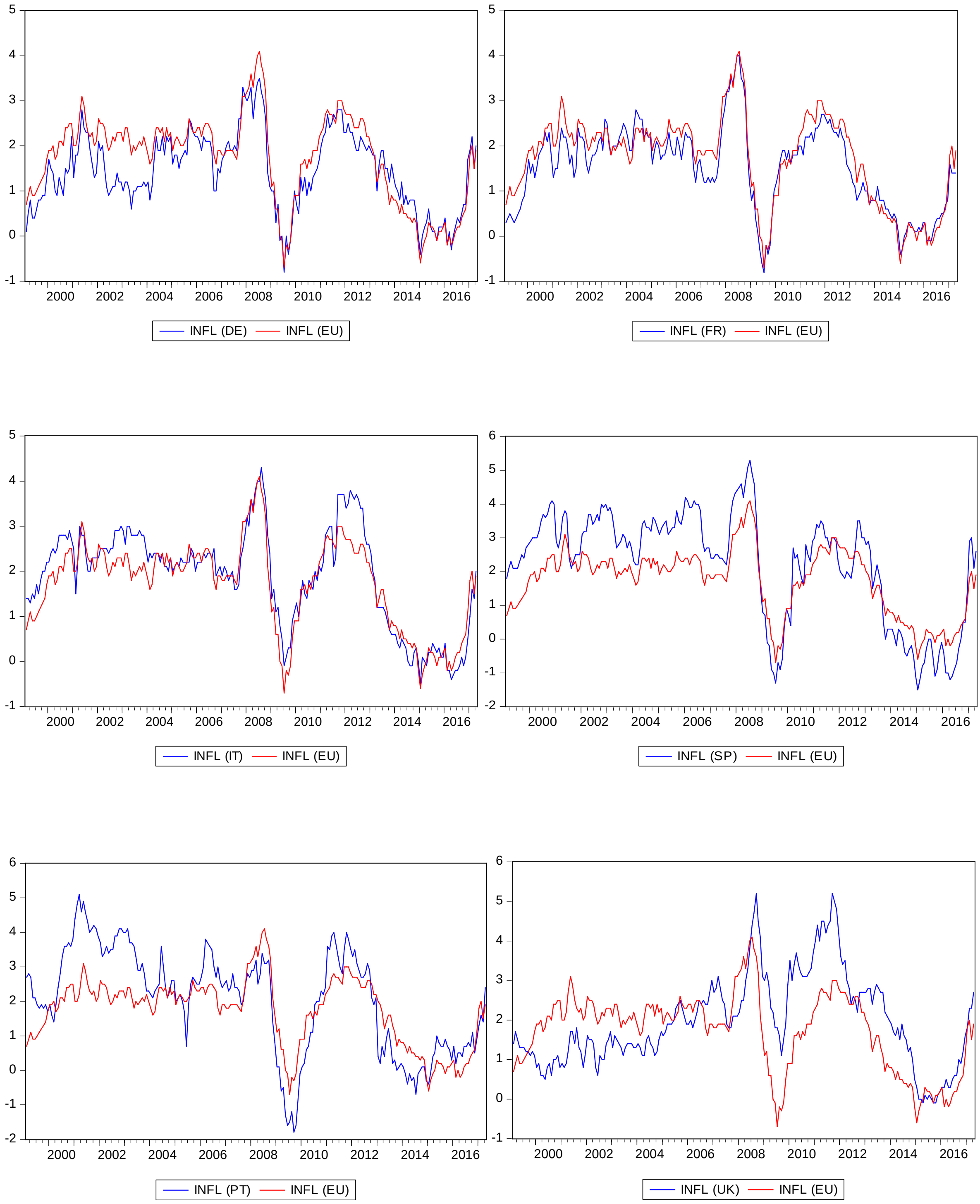
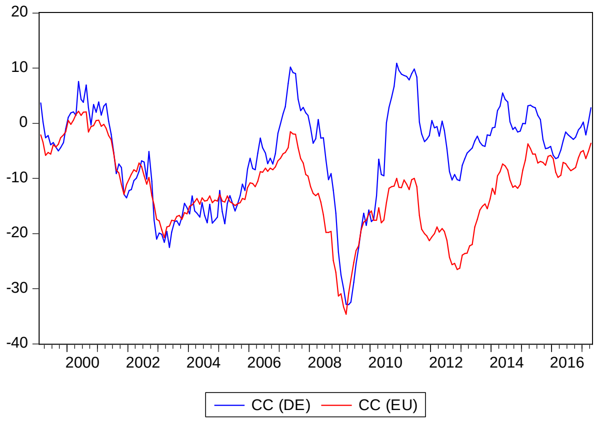
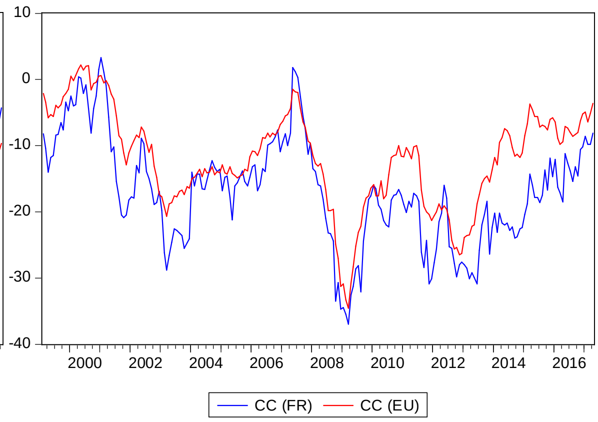
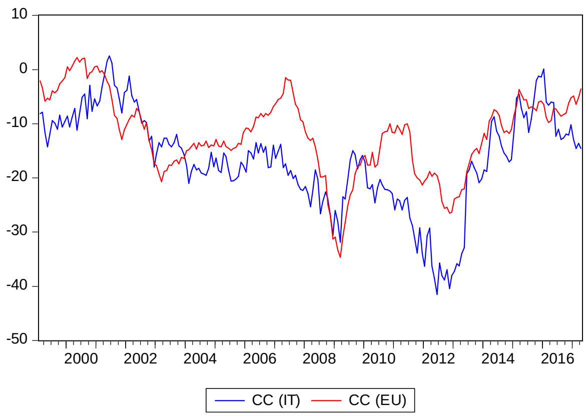
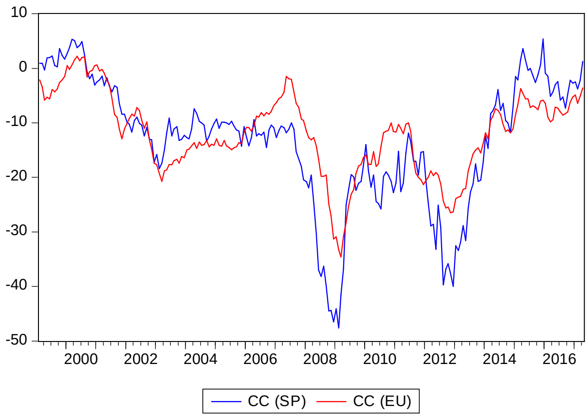


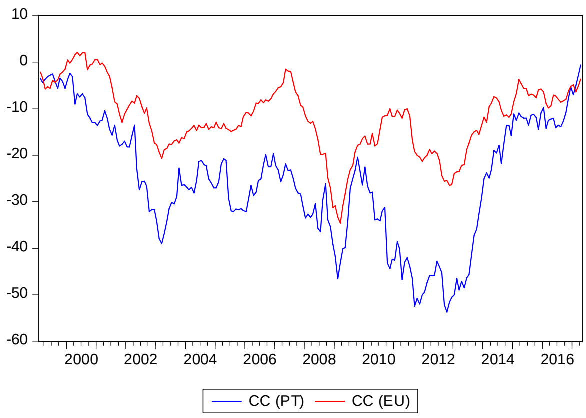
Figure A.7.3.: Country-specific CC indicators vs European benchmark











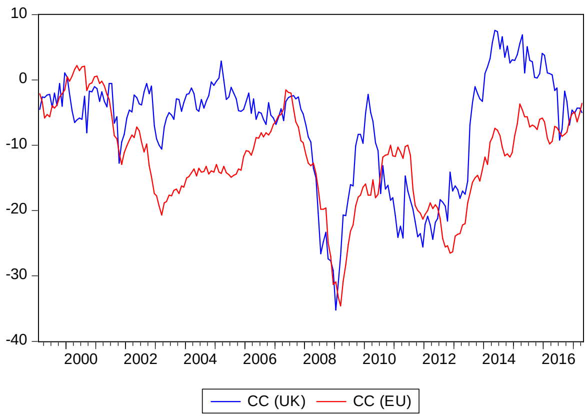


Figure A.7.4.: Country-specific IP indicators vs European benchmark

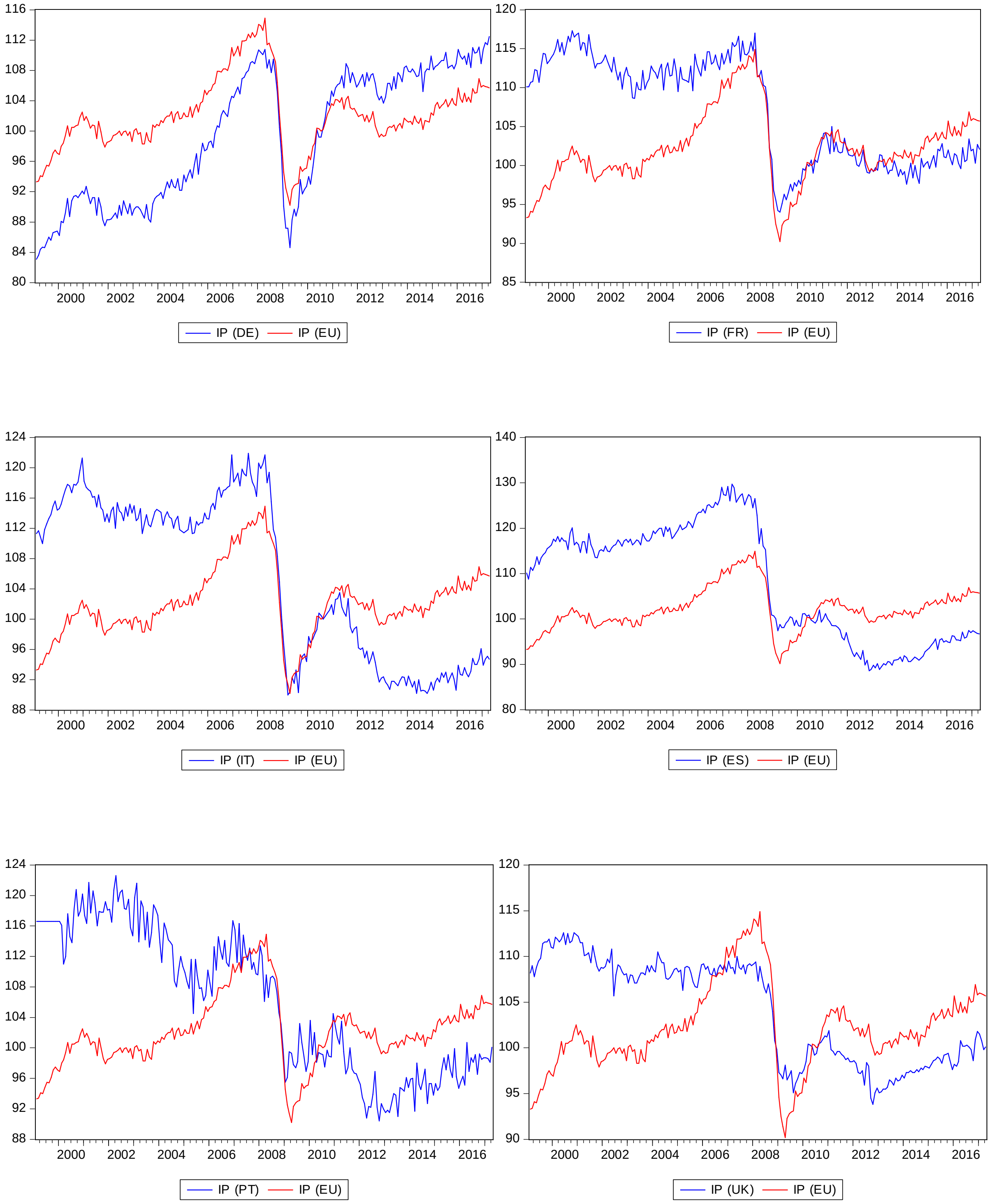


Figure A.7.5.: Country-specific UNEMP indicators vs European benchmark

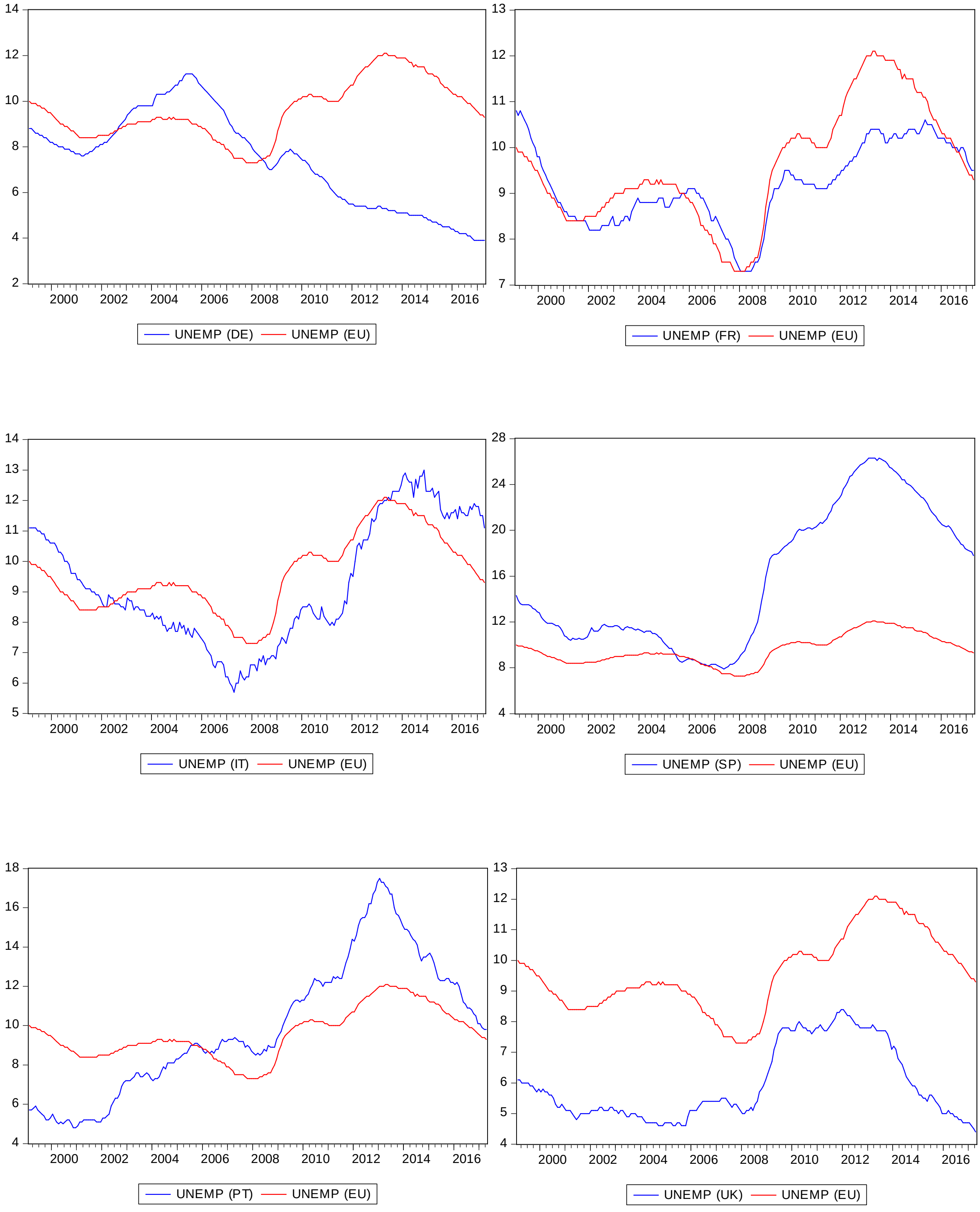


Figure A.7.6.: V2X indicator evolution over the sample period

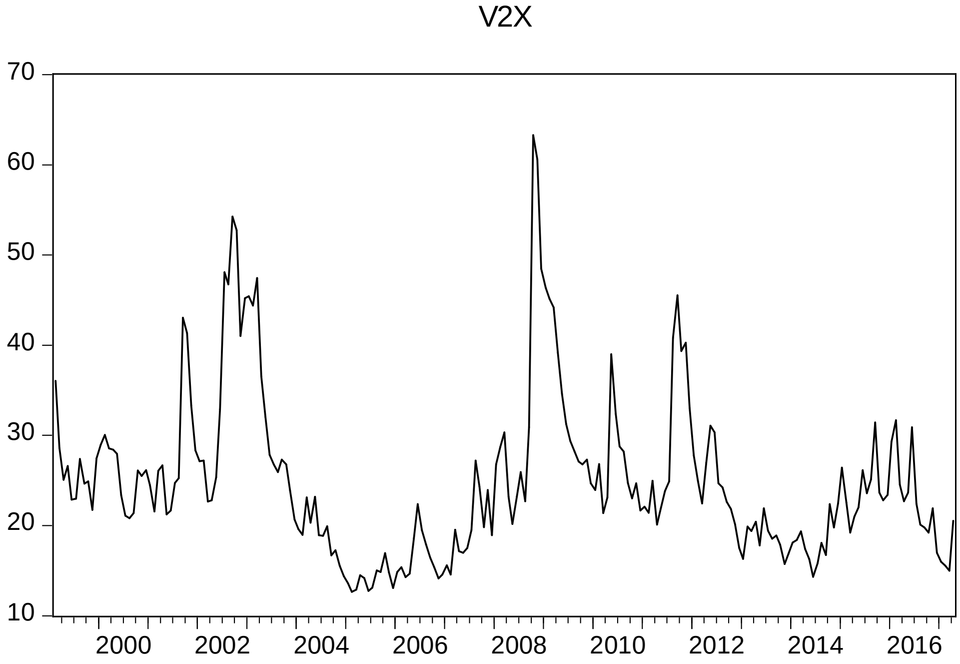


Figure A.7.7.: MONPL indicator evolution over the sample period

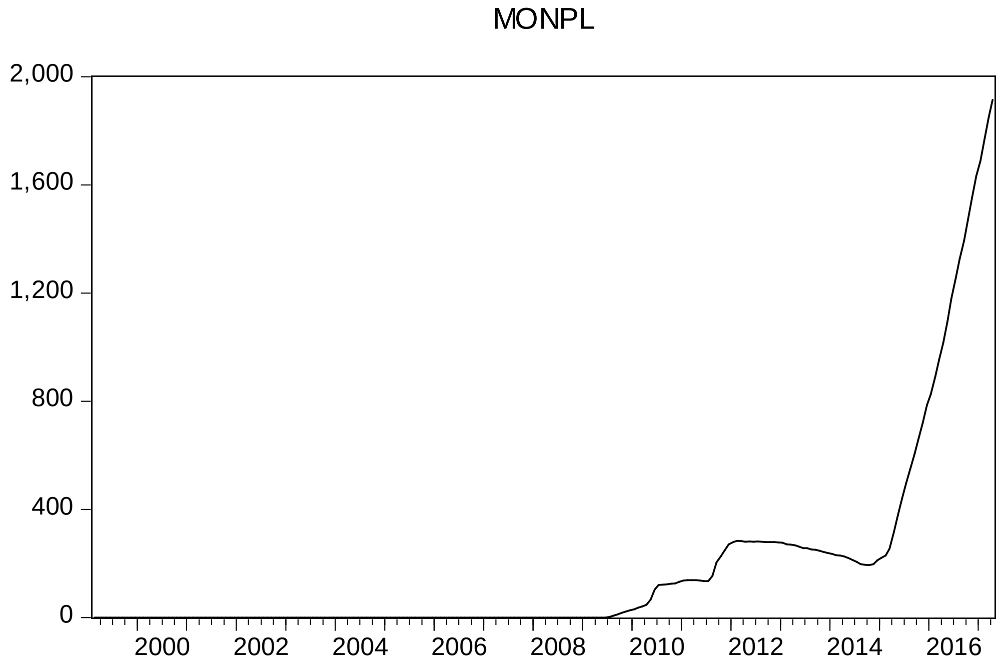


Figure A.7.8.: KEYR (EU) indicator vs KEYR (UK) indicator over the sample period

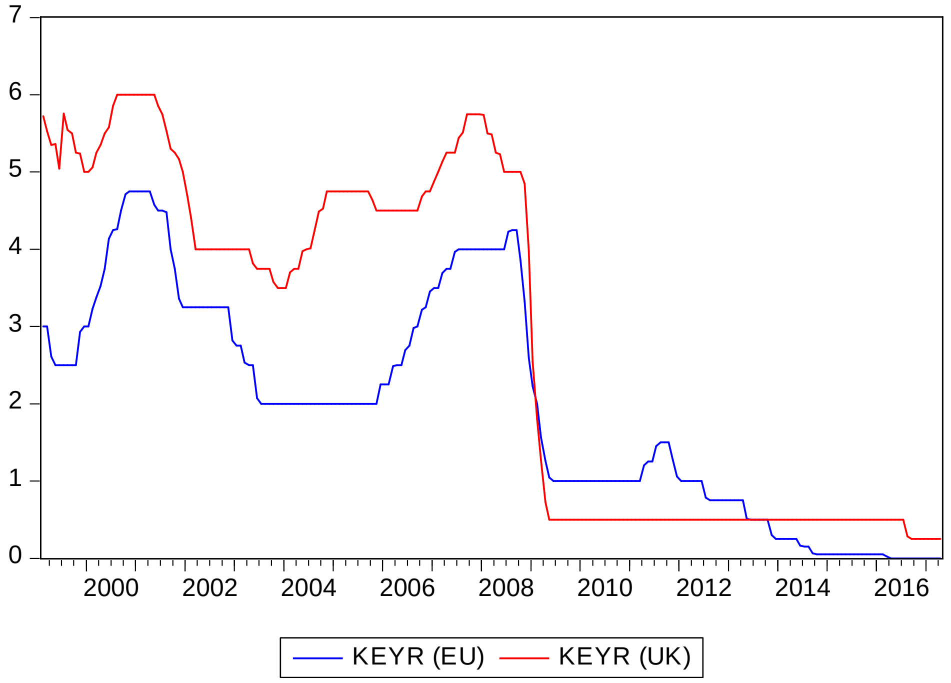


Figure A.7.9.: TERM indicator evolution over the sample period

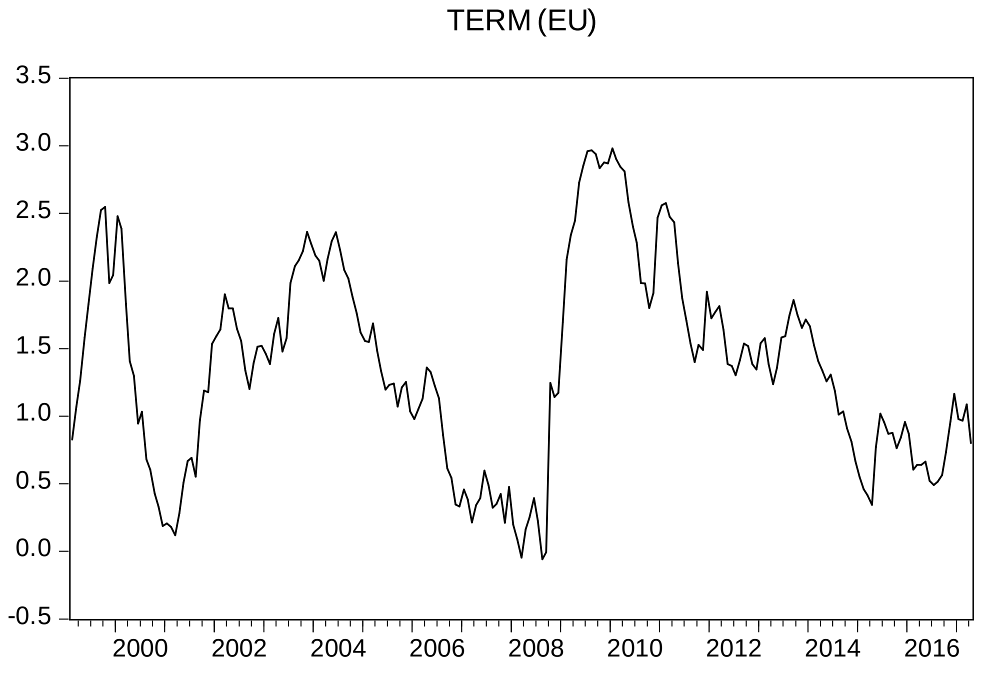


Figure A.7.10.: TED indicator evolution over the sample period

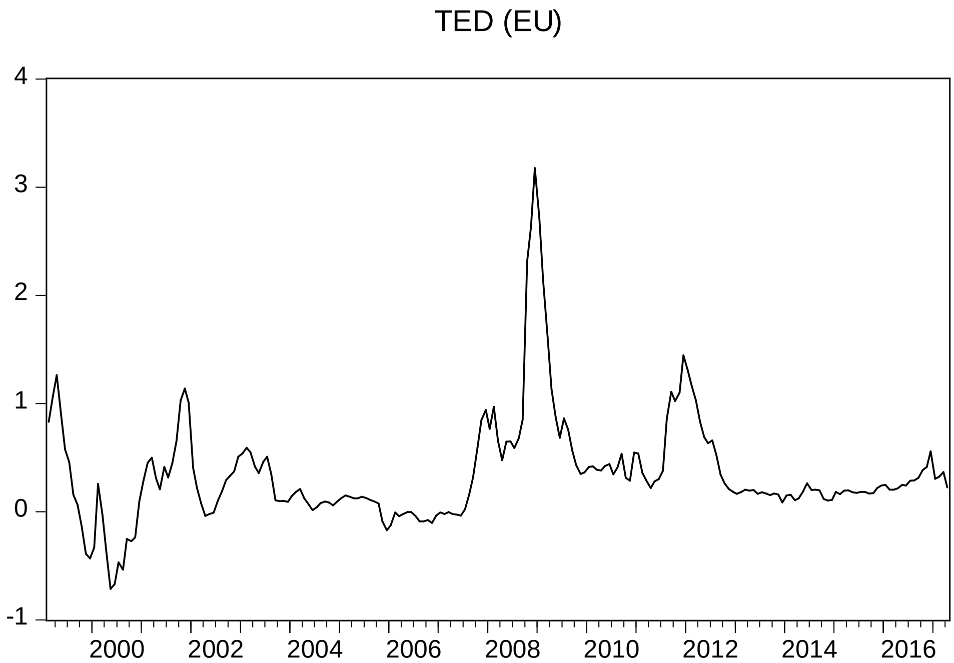
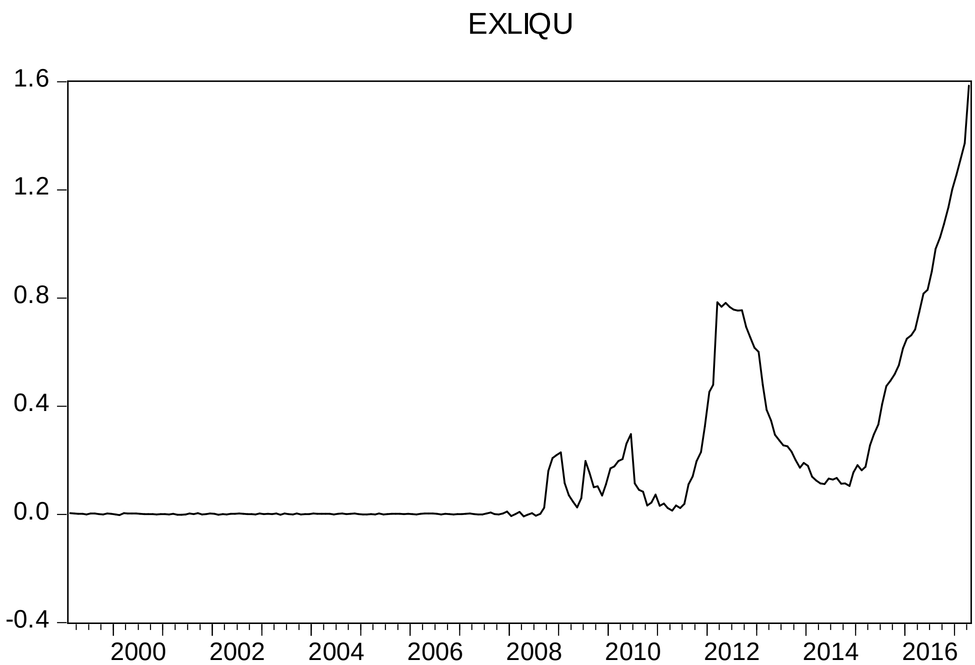


Figure A.7.11.: EXLIQU indicator evolution over the sample period



8.8. Appendix VIII: Model 1 regression results

Table A.8.1: Regression outputs of Model 1 (EU)*

Variable	Parameters			Adj. R^2
	α	β1	β2	
D_GDP (EU)	-0.061***	0.809***	-0.029	0.690
	(0.000)	(0.000)	(0.246)	
D_V2X	-0.047***	0.801***	-0.057***	0.703
	(0.002)	(0.000)	(0.001)	
D_EURIBOR-EONIA	-0.058***	0.801***	-0.026	0.691
	(0.000)	(0.000)	(0.159)	
D_CRISIS (EU)	-0.043***	0.769***	-0.067***	0.708
	(0.005)	(0.000)	(0.000)	
FINCOND (EU)	-0.060***	0.828***	0.037***	0.697
	(0.000)	(0.000)	(0.009)	
INFL (EU)	-0.061***	0.824***	0.038	0.690
	(0.000)	(0.000)	(0.238)	
CC (EU)	-0.062***	0.820***	0.006	0.689
	(0.000)	(0.000)	(0.310)	
IP (EU)	-0.060***	0.825***	0.000	0.688
	(0.000)	(0.000)	(0.979)	
UNEMP (EU)	-0.072***	0.792***	-0.195**	0.693
	(0.000)	(0.000)	(0.044)	
V2X	-0.058***	0.835***	-0.006***	0.704
	(0.000)	(0.000)	(0.001)	
MONPL	-0.060***	0.826***	0.000	0.688
	(0.000)	(0.000)	(0.969)	
KEYR (EU)	-0.061***	0.823***	0.012	0.688
	(0.000)	(0.000)	(0.848)	
TERM (EU)	-0.061***	0.825***	0.102**	0.696
	(0.000)	(0.000)	(0.014)	
TED (EU)	-0.059***	0.811***	-0.018	0.689
	(0.000)	(0.000)	(0.310)	
EXLIQU (EU)	-0.060***	0.825***	-0.075	0.688
	(0.000)	(0.000)	(0.701)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.8.2: Regression outputs of Model 1 (DE)*

Variable	Parameters			Adj. R^2
	α	β1	β2	
D_GDP (DE)	-0.056***	0.814***	-0.029	0.686
	(0.000)	(0.000)	(0.281)	
D_V2X	-0.042***	0.802***	-0.055***	0.699
	(0.004)	(0.000)	(0.001)	
D_EURIBOR-EONIA	-0.053***	0.805***	-0.024	0.686
	(0.000)	(0.000)	(0.195)	
D_CRISIS (DE)	-0.038**	0.772***	-0.064***	0.704
	(0.011)	(0.000)	(0.000)	
FINCOND (EU)	-0.054***	0.828***	0.036***	0.694
	(0.000)	(0.000)	(0.008)	
INFL (DE)	-0.055***	0.826***	0.005	0.684
	(0.000)	(0.000)	(0.823)	
CC (DE)	-0.055***	0.826***	0.001	0.684
	(0.000)	(0.000)	(0.650)	
IP (DE)	-0.055***	0.826***	0.000	0.684
	(0.000)	(0.000)	(0.966)	
UNEMP (DE)	-0.055***	0.826***	0.006	0.684
	(0.000)	(0.000)	(0.947)	
V2X	-0.053***	0.835***	-0.006***	0.700
	(0.000)	(0.000)	(0.001)	
MONPL	-0.055***	0.826***	0.000	0.684
	(0.000)	(0.000)	(0.973)	
KEYR (EU)	-0.056***	0.823***	0.020	0.684
	(0.000)	(0.000)	(0.751)	
TERM (EU)	-0.056***	0.825***	0.077*	0.689
	(0.000)	(0.000)	(0.058)	
TED (EU)	-0.054***	0.814***	-0.016	0.685
	(0.000)	(0.000)	(0.365)	
EXLIQU (EU)	-0.055***	0.826***	-0.071	0.684
	(0.000)	(0.000)	(0.709)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.8.3: Regression outputs of Model 1 (FR)*

Variable	Parameters			Adj. R^2
	α	**β1**	**β2**	
D_GDP (FR)	-0.039***	0.825***	-0.020	0.692
	(0.001)	(0.000)	(0.516)	
D_V2X	-0.027**	0.806***	-0.046***	0.704
	(0.020)	(0.000)	(0.004)	
D_EURIBOR-EONIA	-0.038***	0.826***	-0.007	0.692
	(0.002)	(0.000)	(0.679)	
D_CRISIS (FR)	-0.024**	0.799***	-0.043***	0.702
	(0.049)	(0.000)	(0.005)	
FINCOND (EU)	-0.040***	0.828***	0.034***	0.702
	(0.001)	(0.000)	(0.007)	
INFL (FR)	-0.039***	0.831***	0.017	0.692
	(0.001)	(0.000)	(0.539)	
CC (FR)	-0.040***	0.825***	0.002	0.693
	(0.001)	(0.000)	(0.357)	
IP (FR)	-0.039***	0.828***	0.007	0.694
	(0.001)	(0.000)	(0.162)	
UNEMP (FR)	-0.039***	0.831***	-0.001	0.692
	(0.001)	(0.000)	(0.986)	
V2X	-0.038***	0.839***	-0.005***	0.706
	(0.001)	(0.000)	(0.001)	
MONPL	-0.044***	0.823***	0.000	0.693
	(0.000)	(0.000)	(0.265)	
KEYR (EU)	-0.039***	0.831***	-0.002	0.692
	(0.001)	(0.000)	(0.974)	
TERM (EU)	-0.039***	0.833***	0.084**	0.699
	(0.001)	(0.000)	(0.026)	
TED (EU)	-0.039***	0.832***	0.001	0.692
	(0.001)	(0.000)	(0.937)	
EXLIQU (EU)	-0.042***	0.825***	0.264	0.695
	(0.000)	(0.000)	(0.136)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.8.4: Regression outputs of Model 1 (IT)*

Variable	Parameters			Adj. R^2
	α	β1	β2	
D_GDP (IT)	-0.001	0.941***	0.009	0.883
	(0.950)	(0.000)	(0.602)	
D_V2X	0.018*	0.925***	-0.043***	0.886
	(0.067)	(0.000)	(0.010)	
D_EURIBOR-EONIA	-0.009	0.946***	0.029	0.884
	(0.346)	(0.000)	(0.071)	
D_CRISIS (IT)	0.009	0.937***	-0.013	0.883
	(0.443)	(0.000)	(0.420)	
FINCOND (EU)	0.002	0.939***	0.024*	0.884
	(0.803)	(0.000)	(0.075)	
INFL (IT)	0.002	0.939***	-0.028	0.883
	(0.798)	(0.000)	(0.287)	
CC (IT)	0.002	0.942***	-0.005	0.884
	(0.833)	(0.000)	(0.104)	
IP (IT)	0.002	0.941***	-0.002	0.883
	(0.827)	(0.000)	(0.705)	
UNEMP (IT)	0.002	0.938***	0.048	0.884
	(0.801)	(0.000)	(0.211)	
V2X	0.002	0.941***	-0.004**	0.885
	(0.842)	(0.000)	(0.024)	
MONPL	0.001	0.939***	0.000	0.883
	(0.874)	(0.000)	(0.851)	
KEYR (EU)	0.002	0.941***	-0.016	0.883
	(0.835)	(0.000)	(0.779)	
TERM (EU)	0.002	0.944***	0.076*	0.885
	(0.827)	(0.000)	(0.055)	
TED (EU)	-0.005	0.942***	0.019	0.883
	(0.626)	(0.000)	(0.236)	
EXLIQU (EU)	0.000	0.938***	0.216	0.883
	(0.959)	(0.000)	(0.241)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.8.5: Regression outputs of Model 1 (SP)*

Variable	Parameters			Adj. R^2
	α	β1	β2	
D_GDP (SP)	-0.005	0.928***	0.022	0.877
	(0.544)	(0.000)	(0.241)	
D_V2X	0.017*	0.918***	-0.045***	0.880
	(0.086)	(0.000)	(0.006)	
D_EURIBOR-EONIA	-0.008	0.941***	0.020	0.877
	(0.413)	(0.000)	(0.208)	
D_CRISIS (SP)	0.006	0.935***	-0.011	0.876
	(0.624)	(0.000)	(0.492)	
FINCOND (EU)	0.000	0.935***	0.018	0.877
	(0.968)	(0.000)	(0.176)	
INFL (SP)	0.000	0.936***	0.008	0.876
	(0.962)	(0.000)	(0.656)	
CC (SP)	0.000	0.936***	-0.001	0.876
	(0.965)	(0.000)	(0.611)	
IP (SP)	0.000	0.935***	0.000	0.876
	(0.969)	(0.000)	(0.962)	
UNEMP (SP)	0.000	0.935***	-0.003	0.876
	(0.972)	(0.000)	(0.925)	
V2X	-0.001	0.937***	-0.003**	0.878
	(0.935)	(0.000)	(0.038)	
MONPL	-0.002	0.932***	0.000	0.876
	(0.827)	(0.000)	(0.630)	
KEYR (EU)	0.000	0.934***	0.020	0.876
	(0.997)	(0.000)	(0.737)	
TERM (EU)	0.000	0.939***	0.061	0.877
	(0.957)	(0.000)	(0.123)	
TED (EU)	-0.003	0.937***	0.008	0.876
	(0.749)	(0.000)	(0.621)	
EXLIQU (EU)	-0.002	0.934***	0.175	0.877
	(0.842)	(0.000)	(0.338)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.8.6: Regression outputs of Model 1 (PT)*

Variable	Parameters			Adj. R^2
	α	β1	β2	
D_GDP (PT)	0.005	0.940***	-0.006	0.886
	(0.485)	(0.000)	(0.671)	
D_V2X	0.018**	0.922***	-0.035***	0.890
	(0.023)	(0.000)	(0.005)	
D_EURIBOR-EONIA	-0.002	0.946***	0.012	0.886
	(0.835)	(0.000)	(0.321)	
D_CRISIS (PT)	0.011	0.934***	-0.013	0.886
	(0.234)	(0.000)	(0.281)	
FINCOND (EU)	0.003	0.943***	0.029***	0.890
	(0.585)	(0.000)	(0.004)	
INFL (PT)	0.003	0.942***	-0.006	0.886
	(0.581)	(0.000)	(0.674)	
CC (PT)	0.003	0.948***	-0.005**	0.889
	(0.620)	(0.000)	(0.013)	
IP (PT)	0.003	0.941***	0.000	0.886
	(0.578)	(0.000)	(0.934)	
UNEMP (PT)	0.002	0.948***	0.043	0.887
	(0.744)	(0.000)	(0.169)	
V2X	0.003	0.943***	-0.003**	0.889
	(0.617)	(0.000)	(0.015)	
MONPL	0.003	0.941***	0.000	0.886
	(0.595)	(0.000)	(0.974)	
KEYR (EU)	0.004	0.938***	0.027	0.886
	(0.517)	(0.000)	(0.540)	
TERM (EU)	0.003	0.942***	0.015	0.886
	(0.590)	(0.000)	(0.618)	
TED (EU)	0.003	0.941***	0.000	0.886
	(0.661)	(0.000)	(0.987)	
EXLIQU (EU)	0.004	0.941***	-0.030	0.886
	(0.558)	(0.000)	(0.828)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.8.7: Regression outputs of Model 1 (UK)*

Variable	Parameters			Adj. R^2
	α	β1	β2	
D_GDP (UK)	-0.070***	0.749***	-0.009	0.561
	(0.000)	(0.000)	(0.740)	
D_V2X	-0.061***	0.724***	-0.045***	0.580
	(0.000)	(0.000)	(0.002)	
D_EURIBOR-EONIA	-0.069***	0.729***	-0.021	0.565
	(0.000)	(0.000)	(0.168)	
D_CRISIS (UK)	-0.059***	0.713***	-0.043***	0.578
	(0.000)	(0.000)	(0.003)	
FINCOND (UK)	-0.071***	0.748***	0.032***	0.575
	(0.000)	(0.000)	(0.009)	
INFL (UK)	-0.071***	0.750***	0.030	0.564
	(0.000)	(0.000)	(0.225)	
CC (UK)	-0.072***	0.747***	0.002	0.562
	(0.000)	(0.000)	(0.391)	
IP (UK)	-0.071***	0.747***	0.009	0.564
	(0.000)	(0.000)	(0.224)	
UNEMP (UK)	-0.071***	0.750***	-0.074	0.563
	(0.000)	(0.000)	(0.276)	
V2X	-0.068***	0.762***	-0.005***	0.587
	(0.000)	(0.000)	(0.000)	
MONPL	-0.070***	0.751***	0.000	0.561
	(0.000)	(0.000)	(0.920)	
KEYR (UK)	-0.070***	0.756***	-0.049	0.564
	(0.000)	(0.000)	(0.236)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

8.9. Appendix IX: Model 2 regression results

Table A.9.1: Regression outputs of Model 2 (EU)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (EU)	-0.047***	0.805***	0.033**	-0.054***	0.710
	(0.002)	(0.000)	(0.017)	(0.002)	
INFL (EU)	-0.048***	0.801***	0.025	-0.056***	0.703
	(0.002)	(0.000)	(0.426)	(0.001)	
CC (EU)	-0.048***	0.798***	0.003	-0.056***	0.703
	(0.002)	(0.000)	(0.550)	(0.001)	
IP (EU)	-0.046***	0.803***	-0.003	-0.058***	0.702
	(0.003)	(0.000)	(0.700)	(0.001)	
UNEMP (EU)	-0.056***	0.781***	-0.131	-0.052***	0.705
	(0.001)	(0.000)	(0.178)	(0.003)	
V2X	-0.047***	0.813***	-0.005***	-0.047***	0.713
	(0.002)	(0.000)	(0.006)	(0.006)	
MONPL	-0.046***	0.801***	0.000	-0.058***	0.702
	(0.003)	(0.000)	(0.875)	(0.001)	
KEYR (EU)	-0.044***	0.807***	-0.047	-0.061***	0.703
	(0.005)	(0.000)	(0.469)	(0.001)	
TERM (EU)	-0.046***	0.798***	0.115***	-0.062***	0.713
	(0.002)	(0.000)	(0.005)	(0.000)	
TED (EU)	-0.047***	0.804***	0.004	-0.059***	0.702
	(0.002)	(0.000)	(0.831)	(0.001)	
EXLIQU (EU)	-0.046***	0.801***	-0.080	-0.058***	0.702
	(0.003)	(0.000)	(0.673)	(0.001)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.9.2: Regression outputs of Model 2 (DE)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (EU)	-0.042***	0.806***	0.033**	-0.052***	0.706
	(0.004)	(0.000)	(0.015)	(0.002)	
INFL (DE)	-0.042***	0.802***	-0.005	-0.056***	0.698
	(0.005)	(0.000)	(0.834)	(0.001)	
CC (DE)	-0.042***	0.802***	0.000	-0.055***	0.698
	(0.004)	(0.000)	(0.931)	(0.001)	
IP (DE)	-0.040***	0.803***	-0.003	-0.057***	0.698
	(0.006)	(0.000)	(0.544)	(0.001)	
UNEMP (DE)	-0.039***	0.804***	0.057	-0.057***	0.698
	(0.010)	(0.000)	(0.541)	(0.001)	
V2X	-0.042***	0.814***	-0.005***	-0.045***	0.708
	(0.003)	(0.000)	(0.006)	(0.008)	
MONPL	-0.042***	0.802***	0.000	-0.055***	0.698
	(0.006)	(0.000)	(0.945)	(0.001)	
KEYR (EU)	-0.040***	0.806***	-0.037	-0.058***	0.698
	(0.008)	(0.000)	(0.555)	(0.001)	
TERM (EU)	-0.042***	0.799***	0.090**	-0.059***	0.705
	(0.004)	(0.000)	(0.024)	(0.001)	
TED (EU)	-0.042***	0.806***	0.006	-0.058***	0.698
	(0.004)	(0.000)	(0.749)	(0.002)	
EXLIQU (EU)	-0.041***	0.802***	-0.074	-0.055***	0.698
	(0.005)	(0.000)	(0.691)	(0.001)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.9.3: Regression outputs of Model 2 (FR)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (EU)	-0.029**	0.805***	0.031**	-0.043***	0.711
	(0.014)	(0.000)	(0.012)	(0.006)	
INFL (FR)	-0.028**	0.806***	0.010	-0.045***	0.702
	(0.020)	(0.000)	(0.699)	(0.004)	
CC (FR)	-0.029**	0.801***	0.002	-0.046***	0.703
	(0.016)	(0.000)	(0.385)	(0.004)	
IP (FR)	-0.028**	0.804***	0.006	-0.045***	0.704
	(0.017)	(0.000)	(0.217)	(0.005)	
UNEMP (FR)	-0.027**	0.808***	0.026	-0.046***	0.702
	(0.028)	(0.000)	(0.753)	(0.003)	
V2X	-0.029**	0.817***	-0.004***	-0.036**	0.712
	(0.014)	(0.000)	(0.007)	(0.021)	
MONPL	-0.033**	0.797***	0.000	-0.046***	0.704
	(0.010)	(0.000)	(0.258)	(0.004)	
KEYR (EU)	-0.026**	0.811***	-0.049	-0.050***	0.703
	(0.034)	(0.000)	(0.400)	(0.002)	
TERM (EU)	-0.026**	0.805***	0.093**	-0.049***	0.711
	(0.024)	(0.000)	(0.012)	(0.002)	
TED (EU)	-0.030**	0.816***	0.020	-0.054***	0.704
	(0.014)	(0.000)	(0.214)	(0.002)	
EXLIQU (EU)	-0.031**	0.799***	0.273	-0.046***	0.706
	(0.010)	(0.000)	(0.117)	(0.003)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.9.4: Regression outputs of Model 2 (IT)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (EU)	0.018*	0.925***	0.021	-0.041**	0.887
	(0.078)	(0.000)	(0.108)	(0.014)	
INFL (IT)	0.019*	0.924***	-0.030	-0.043***	0.886
	(0.062)	(0.000)	(0.246)	(0.009)	
CC (IT)	0.020	0.926***	-0.006**	-0.046***	0.888
	(0.051)	(0.000)	(0.049)	(0.005)	
IP (IT)	0.018*	0.926***	-0.002	-0.043***	0.886
	(0.070)	(0.000)	(0.644)	(0.010)	
UNEMP (IT)	0.018*	0.923***	0.046	-0.042**	0.887
	(0.068)	(0.000)	(0.224)	(0.011)	
V2X	0.016	0.928***	-0.003*	-0.036**	0.887
	(0.121)	(0.000)	(0.078)	(0.030)	
MONPL	0.018*	0.923***	0.000	-0.043***	0.886
	(0.092)	(0.000)	(0.772)	(0.010)	
KEYR (EU)	0.019*	0.926***	-0.065	-0.048***	0.886
	(0.054)	(0.000)	(0.284)	(0.006)	
TERM (EU)	0.019*	0.929***	0.082**	-0.045***	0.888
	(0.056)	(0.000)	(0.035)	(0.006)	
TED (EU)	0.011	0.924***	0.041	-0.060***	0.889
	(0.311)	(0.000)	(0.235)	(0.001)	
EXLIQU (EU)	0.017*	0.922***	0.223	-0.043***	0.887
	(0.093)	(0.000)	(0.221)	(0.009)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.9.5: Regression outputs of Model 2 (SP)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (EU)	0.016*	0.918***	0.015	-0.044***	0.880
	(0.098)	(0.000)	(0.253)	(0.008)	
INFL (SP)	0.017*	0.918***	0.001	-0.045***	0.880
	(0.089)	(0.000)	(0.950)	(0.007)	
CC (SP)	0.017	0.919***	-0.002	-0.046***	0.880
	(0.085)	(0.000)	(0.552)	(0.006)	
IP (SP)	0.017*	0.918***	0.000	-0.045***	0.880
	(0.087)	(0.000)	(0.944)	(0.006)	
UNEMP (SP)	0.017*	0.920***	0.015	-0.047***	0.880
	(0.081)	(0.000)	(0.640)	(0.005)	
V2X	0.015	0.921***	-0.003	-0.040**	0.881
	(0.142)	(0.000)	(0.122)	(0.017)	
MONPL	0.015	0.913***	0.000	-0.046***	0.880
	(0.138)	(0.000)	(0.541)	(0.006)	
KEYR (EU)	0.017*	0.919***	-0.026	-0.048***	0.880
	(0.081)	(0.000)	(0.659)	(0.006)	
TERM (EU)	0.018*	0.921***	0.067*	-0.047***	0.881
	(0.075)	(0.000)	(0.082)	(0.004)	
TED (EU)	0.011	0.919***	0.028*	-0.057***	0.881
	(0.274)	(0.000)	(0.088)	(0.001)	
EXLIQU (EU)	0.016	0.916***	0.180	-0.046***	0.880
	(0.114)	(0.000)	(0.317)	(0.006)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.9.6: Regression outputs of Model 2 (PT)*

Variable	α	β1	β2	β3	Adj. R^2
	Parameters				
FINCOND (EU)	0.017**	0.926***	0.026***	-0.032***	0.893
	(0.034)	(0.000)	(0.007)	(0.009)	
INFL (PT)	0.018**	0.923***	-0.010	-0.036***	0.890
	(0.021)	(0.000)	(0.485)	(0.004)	
CC (PT)	0.018**	0.929***	-0.006***	-0.037***	0.893
	(0.020)	(0.000)	(0.008)	(0.003)	
IP (PT)	0.018**	0.922***	0.000	-0.035***	0.889
	(0.023)	(0.000)	(0.832)	(0.005)	
UNEMP (PT)	0.018**	0.931***	0.064**	-0.041***	0.892
	(0.021)	(0.000)	(0.040)	(0.001)	
V2X	0.016*	0.926***	-0.002*	-0.030**	0.891
	(0.051)	(0.000)	(0.061)	(0.017)	
MONPL	0.018**	0.919***	0.000	-0.036***	0.889
	(0.028)	(0.000)	(0.764)	(0.005)	
KEYR (EU)	0.018**	0.922***	-0.006	-0.036***	0.889
	(0.023)	(0.000)	(0.890)	(0.006)	
TERM (EU)	0.018**	0.924***	0.019	-0.036***	0.890
	(0.023)	(0.000)	(0.520)	(0.004)	
TED (EU)	0.015*	0.925***	0.014	-0.041***	0.890
	(0.077)	(0.000)	(0.254)	(0.002)	
EXLIQU (EU)	0.018**	0.922***	-0.025	-0.035***	0.889
	(0.023)	(0.000)	(0.855)	(0.005)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.9.7: Regression outputs of Model 2 (UK)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (UK)	-0.063***	0.724***	0.028**	-0.041***	0.588
	(0.000)	(0.000)	(0.020)	(0.005)	
INFL (UK)	-0.062***	0.725***	0.015	-0.043***	0.579
	(0.000)	(0.000)	(0.550)	(0.004)	
CC (UK)	-0.062***	0.719***	0.003	-0.045***	0.580
	(0.000)	(0.000)	(0.316)	(0.002)	
IP (UK)	-0.062***	0.721***	0.007	-0.044***	0.580
	(0.000)	(0.000)	(0.290)	(0.002)	
UNEMP (UK)	-0.061***	0.725***	-0.026	-0.044***	0.578
	(0.000)	(0.000)	(0.710)	(0.004)	
V2X	-0.061***	0.739***	-0.005***	-0.035**	0.596
	(0.000)	(0.000)	(0.002)	(0.015)	
MONPL	-0.061***	0.724***	0.000	-0.045***	0.578
	(0.000)	(0.000)	(0.972)	(0.002)	
KEYR (UK)	-0.059***	0.729***	-0.088	-0.053***	0.587
	(0.000)	(0.000)	(0.125)	(0.000)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

8.10. Appendix X: Model 3 regression results

Table A.10.1: Regression outputs of Model 3 (EU)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (EU)	-0.059***	0.829***	0.048	-0.013	0.696
	(0.000)	(0.000)	(0.238)	(0.768)	
INFL (EU)	-0.061***	0.825***	0.044	-0.012	0.688
	(0.000)	(0.000)	(0.322)	(0.850)	
CC (EU)	-0.061***	0.820***	0.002	0.007	0.688
	(0.000)	(0.000)	(0.836)	(0.545)	
IP (EU)	-0.061***	0.827***	0.011	-0.020	0.689
	(0.000)	(0.000)	(0.344)	(0.208)	
UNEMP (EU)	-0.073***	0.795***	-0.292**	0.193	0.694
	(0.000)	(0.000)	(0.030)	(0.296)	
V2X	-0.056***	0.832***	-0.001	-0.006	0.705
	(0.000)	(0.000)	(0.707)	(0.173)	
MONPL	-0.060***	0.820***	0.001	-0.002***	0.697
	(0.000)	(0.000)	(0.226)	(0.006)	
KEYR (EU)	-0.061***	0.823***	0.018	-0.007	0.686
	(0.000)	(0.000)	(0.885)	(0.959)	
TERM (EU)	-0.061***	0.825***	0.099	0.004	0.695
	(0.000)	(0.000)	(0.127)	(0.965)	
TED (EU)	-0.060***	0.827***	0.055	-0.064	0.687
	(0.000)	(0.000)	(0.612)	(0.585)	
EXLIQU (EU)	-0.061***	0.822***	0.130	-0.561	0.689
	(0.000)	(0.000)	(0.592)	(0.160)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.10.2: Regression outputs of Model 3 (DE)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (EU)	-0.054***	0.830***	0.053	-0.019	0.693
	(0.000)	(0.000)	(0.184)	(0.661)	
INFL (DE)	-0.055***	0.826***	0.007	-0.003	0.682
	(0.000)	(0.000)	(0.828)	(0.945)	
CC (DE)	-0.055***	0.826***	0.002	-0.001	0.683
	(0.000)	(0.000)	(0.703)	(0.914)	
IP (DE)	-0.056***	0.827***	0.003	-0.006	0.683
	(0.000)	(0.000)	(0.706)	(0.584)	
UNEMP (DE)	-0.055***	0.831***	-0.067	0.186	0.684
	(0.000)	(0.000)	(0.575)	(0.329)	
V2X	-0.051***	0.832***	-0.002	-0.005	0.701
	(0.000)	(0.000)	(0.665)	(0.201)	
MONPL	-0.055***	0.820***	0.001	-0.002***	0.695
	(0.000)	(0.000)	(0.178)	(0.004)	
KEYR (EU)	-0.057***	0.822***	0.051	-0.043	0.683
	(0.000)	(0.000)	(0.668)	(0.757)	
TERM (EU)	-0.056***	0.824***	0.057	0.033	0.688
	(0.000)	(0.000)	(0.371)	(0.688)	
TED (EU)	-0.055***	0.828***	0.046	-0.054	0.683
	(0.000)	(0.000)	(0.666)	(0.642)	
EXLIQU (EU)	-0.056***	0.822***	0.147	-0.596	0.686
	(0.000)	(0.000)	(0.539)	(0.129)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.10.3: Regression outputs of Model 3 (FR)*

Variable	Parameters α	β1	β2	β3	Adj. R^2
FINCOND (EU)	-0.040***	0.827***	0.057	-0.026	0.701
	(0.000)	(0.000)	(0.117)	(0.498)	
INFL (FR)	-0.039***	0.831***	0.002	0.028	0.691
	(0.001)	(0.000)	(0.962)	(0.616)	
CC (FR)	-0.040***	0.826***	0.003	-0.001	0.691
	(0.001)	(0.000)	(0.424)	(0.877)	
IP (FR)	-0.040***	0.832***	0.013**	-0.009*	0.698
	(0.001)	(0.000)	(0.025)	(0.056)	
UNEMP (FR)	-0.039***	0.835***	-0.085	0.168	0.692
	(0.001)	(0.000)	(0.476)	(0.322)	
V2X	-0.036***	0.838***	-0.002	-0.004	0.706
	(0.002)	(0.000)	(0.485)	(0.357)	
MONPL	-0.044***	0.820***	0.001	-0.001**	0.698
	(0.000)	(0.000)	(0.159)	(0.045)	
KEYR (EU)	-0.039***	0.831***	-0.004	0.003	0.690
	(0.001)	(0.000)	(0.968)	(0.978)	
TERM (EU)	-0.038***	0.832***	0.116*	-0.054	0.698
	(0.001)	(0.000)	(0.051)	(0.485)	
TED (EU)	-0.041***	0.832***	0.018	-0.019	0.691
	(0.001)	(0.000)	(0.602)	(0.586)	
EXLIQU (EU)	-0.044***	0.820***	0.513**	-0.675	0.698
	(0.000)	(0.000)	(0.020)	(0.111)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.10.4: Regression outputs of Model 3 (IT)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (EU)	0.002	0.939***	0.021	0.003	0.884
	(0.798)	(0.000)	(0.592)	(0.938)	
INFL (IT)	0.002	0.939***	-0.013	-0.030	0.883
	(0.809)	(0.000)	(0.716)	(0.570)	
CC (IT)	0.001	0.941***	-0.003	-0.004	0.884
	(0.899)	(0.000)	(0.525)	(0.462)	
IP (IT)	0.002	0.938***	0.003	-0.009	0.883
	(0.837)	(0.000)	(0.682)	(0.383)	
UNEMP (IT)	0.003	0.934***	-0.001	0.191**	0.886
	(0.718)	(0.000)	(0.976)	(0.028)	
V2X	0.000	0.941***	-0.007*	0.004	0.885
	(0.951)	(0.000)	(0.052)	(0.306)	
MONPL	0.002	0.940***	0.000	0.000	0.882
	(0.842)	(0.000)	(0.701)	(0.595)	
KEYR (EU)	0.000	0.944***	0.064	-0.114	0.883
	(0.982)	(0.000)	(0.571)	(0.405)	
TERM (EU)	0.002	0.944***	0.110*	-0.059	0.884
	(0.779)	(0.000)	(0.075)	(0.465)	
TED (EU)	-0.010	0.936***	0.074**	-0.062*	0.885
	(0.326)	(0.000)	(0.039)	(0.084)	
EXLIQU (EU)	0.000	0.938***	0.201	0.043	0.883
	(0.958)	(0.000)	(0.383)	(0.910)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.10.5: Regression outputs of Model 3 (SP)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (EU)	0.000	0.936***	0.014	0.004	0.876
	(0.978)	(0.000)	(0.713)	(0.919)	
INFL (SP)	0.001	0.935***	-0.002	0.033	0.876
	(0.943)	(0.000)	(0.934)	(0.408)	
CC (SP)	0.000	0.936***	-0.001	-0.001	0.876
	(0.959)	(0.000)	(0.801)	(0.829)	
IP (SP)	0.000	0.936***	0.000	0.002	0.875
	(0.976)	(0.000)	(0.950)	(0.881)	
UNEMP (SP)	-0.001	0.936***	-0.025	0.035	0.876
	(0.879)	(0.000)	(0.629)	(0.592)	
V2X	-0.002	0.937***	-0.006*	0.003	0.878
	(0.776)	(0.000)	(0.090)	(0.407)	
MONPL	-0.002	0.931***	0.000	0.000	0.876
	(0.821)	(0.000)	(0.690)	(0.915)	
KEYR (EU)	-0.001	0.936***	0.052	-0.046	0.876
	(0.926)	(0.000)	(0.643)	(0.735)	
TERM (EU)	0.000	0.938***	0.090	-0.050	0.877
	(1.000)	(0.000)	(0.144)	(0.534)	
TED (EU)	-0.007	0.931***	0.054	-0.052	0.877
	(0.461)	(0.000)	(0.131)	(0.150)	
EXLIQU (EU)	-0.002	0.934***	0.173	0.008	0.876
	(0.842)	(0.000)	(0.451)	(0.984)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.10.6: Regression outputs of Model 3 (PT)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (EU)	0.002	0.940***	0.067**	-0.044	0.891
	(0.677)	(0.000)	(0.018)	(0.144)	
INFL (PT)	0.003	0.945***	0.001	-0.023	0.886
	(0.671)	(0.000)	(0.957)	(0.479)	
CC (PT)	0.003	0.948***	-0.005	0.000	0.888
	(0.625)	(0.000)	(0.068)	(0.952)	
IP (PT)	0.003	0.941***	0.001	-0.003	0.885
	(0.605)	(0.000)	(0.791)	(0.582)	
UNEMP (PT)	0.003	0.950***	0.061	-0.055	0.887
	(0.603)	(0.000)	(0.109)	(0.401)	
V2X	0.002	0.943***	-0.004	0.001	0.888
	(0.692)	(0.000)	(0.141)	(0.692)	
MONPL	0.003	0.940***	0.000	0.000	0.885
	(0.600)	(0.000)	(1.000)	(0.933)	
KEYR (EU)	0.003	0.941***	0.060	-0.047	0.886
	(0.633)	(0.000)	(0.477)	(0.647)	
TERM (EU)	0.004	0.941***	0.039	-0.040	0.886
	(0.544)	(0.000)	(0.406)	(0.505)	
TED (EU)	-0.001	0.929***	0.055**	-0.061**	0.888
	(0.922)	(0.000)	(0.040)	(0.023)	
EXLIQU (EU)	0.004	0.941***	0.013	-0.118	0.885
	(0.558)	(0.000)	(0.938)	(0.675)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.10.7: Regression outputs of Model 3 (UK)*

Variable	Parameters				Adj. R^2
	α	β1	β2	β3	
FINCOND (UK)	-0.071***	0.749***	0.038	-0.007	0.573
	(0.000)	(0.000)	(0.235)	(0.846)	
INFL (UK)	-0.071***	0.755***	0.066*	-0.074	0.566
	(0.000)	(0.000)	(0.056)	(0.137)	
CC (UK)	-0.070***	0.750***	0.004	-0.005	0.562
	(0.000)	(0.000)	(0.212)	(0.358)	
IP (UK)	-0.071***	0.746***	0.008	0.001	0.562
	(0.000)	(0.000)	(0.424)	(0.924)	
UNEMP (UK)	-0.071***	0.750***	-0.058	-0.034	0.561
	(0.000)	(0.000)	(0.551)	(0.808)	
V2X	-0.067***	0.760***	-0.004	-0.002	0.586
	(0.000)	(0.000)	(0.233)	(0.568)	
MONPL	-0.072***	0.741***	0.000	-0.002**	0.571
	(0.000)	(0.000)	(0.227)	(0.013)	
KEYR (UK)	-0.068***	0.758***	-0.143*	0.128	0.565
	(0.000)	(0.000)	(0.078)	(0.178)	

* The values between brackets ( ) indicate the p-vales of the respective estimates.
The marks */**/*** indicate that the estimate is significant at the 10%/5%/1%
significance level, respectively.

8.11. Appendix XI Model 4 regression results

Table A.11.1: Regression outputs of Model 4 (EU)*

Variable	Parameters					Adj. R^2
	α	β1	β2	β3	β4	
FINCOND (EU)	-0.047***	0.805***	0.033	-0.054***	0.000	0.709
	(0.002)	(0.000)	(0.406)	(0.002)	(0.991)	
INFL (EU)	-0.048***	0.801***	0.032	-0.056***	-0.015	0.702
	(0.002)	(0.000)	(0.458)	(0.001)	(0.816)	
CC (EU)	-0.048***	0.799***	0.000	-0.056***	0.006	0.702
	(0.002)	(0.000)	(0.999)	(0.001)	(0.602)	
IP (EU)	-0.047***	0.805***	0.007	-0.058***	-0.019	0.703
	(0.003)	(0.000)	(0.542)	(0.001)	(0.238)	
UNEMP (EU)	-0.057***	0.784***	-0.232*	-0.053***	0.202	0.705
	(0.001)	(0.000)	(0.081)	(0.003)	(0.264)	
V2X	0.002	0.783***	-0.003	-0.061	0.001	0.703
	(0.977)	(0.000)	(0.359)	(0.437)	(0.719)	
MONPL	-0.049***	0.803***	0.000	-0.046**	-0.001*	0.705
	(0.002)	(0.000)	(0.505)	(0.013)	(0.097)	
KEYR (EU)	-0.044***	0.808***	0.001	-0.050***	-0.007*	0.715
	(0.003)	(0.000)	(0.831)	(0.004)	(0.088)	
TERM (EU)	-0.046***	0.798***	0.110*	-0.062***	0.008	0.712
	(0.002)	(0.000)	(0.083)	(0.000)	(0.924)	
TED (EU)	-0.037**	0.782***	-0.080*	-0.087***	0.101**	0.708
	(0.019)	(0.000)	(0.056)	(0.000)	(0.025)	
EXLIQU (EU)	-0.048***	0.800***	0.053	-0.055***	-0.364	0.702
	(0.002)	(0.000)	(0.825)	(0.002)	(0.357)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.11.2: Regression outputs of Model 4 (DE)*

Variable	Parameters					Adj. R^2
	α	β1	β2	β3	β4	
FINCOND (EU)	-0.042***	0.806***	0.039	-0.052***	-0.007	0.705
	(0.004)	(0.000)	(0.319)	(0.002)	(0.863)	
INFL (DE)	-0.042***	0.802***	-0.001	-0.056***	-0.009	0.697
	(0.005)	(0.000)	(0.962)	(0.001)	(0.849)	
CC (DE)	-0.042***	0.802***	0.001	-0.055***	-0.001	0.697
	(0.004)	(0.000)	(0.875)	(0.001)	(0.894)	
IP (DE)	-0.041***	0.804***	-0.001	-0.057***	-0.004	0.697
	(0.006)	(0.000)	(0.869)	(0.001)	(0.744)	
UNEMP (DE)	-0.040***	0.809***	0.001	-0.048***	-0.007	0.711
	(0.006)	(0.000)	(0.884)	(0.004)	(0.106)	
V2X	0.004	0.786***	-0.003	-0.066	0.001	0.698
	(0.939)	(0.000)	(0.382)	(0.389)	(0.679)	
MONPL	-0.045***	0.803***	0.000	-0.043**	-0.002*	0.701
	(0.003)	(0.000)	(0.405)	(0.018)	(0.065)	
KEYR (EU)	-0.042***	0.804***	0.016	-0.059***	-0.074	0.697
	(0.007)	(0.000)	(0.893)	(0.001)	(0.589)	
TERM (EU)	-0.042***	0.798***	0.068	-0.059***	0.037	0.704
	(0.004)	(0.000)	(0.276)	(0.001)	(0.649)	
TED (EU)	-0.032**	0.788***	-0.072*	-0.084***	0.095**	0.703
	(0.036)	(0.000)	(0.074)	(0.000)	(0.032)	
EXLIQU (EU)	-0.043***	0.800***	0.076	-0.053***	-0.409	0.698
	(0.004)	(0.000)	(0.747)	(0.002)	(0.292)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.11.3: Regression outputs of Model 4 (FR)*

Variable	Parameters					Adj. R^2
	α	β1	β2	β3	β4	
FINCOND (EU)	-0.030**	0.804***	0.049	-0.042***	-0.020	0.710
	(0.012)	(0.000)	(0.173)	(0.007)	(0.598)	
INFL (FR)	-0.027**	0.806***	-0.005	-0.045***	0.028	0.701
	(0.022)	(0.000)	(0.904)	(0.004)	(0.602)	
CC (FR)	-0.026**	0.815***	-0.001	-0.038**	-0.005	0.713
	(0.027)	(0.000)	(0.828)	(0.016)	(0.237)	
IP (FR)	-0.028**	0.807***	0.013**	-0.047***	-0.010**	0.709
	(0.018)	(0.000)	(0.026)	(0.003)	(0.033)	
UNEMP (FR)	-0.027**	0.812***	-0.046	-0.046***	0.144	0.702
	(0.026)	(0.000)	(0.698)	(0.004)	(0.388)	
V2X	0.012	0.785***	-0.002	-0.027	0.000	0.704
	(0.829)	(0.000)	(0.417)	(0.710)	(0.929)	
MONPL	-0.034***	0.800***	0.001	-0.040**	-0.001	0.704
	(0.008)	(0.000)	(0.146)	(0.020)	(0.331)	
KEYR (EU)	-0.026**	0.811***	-0.038	-0.050***	-0.015	0.702
	(0.034)	(0.000)	(0.719)	(0.003)	(0.905)	
TERM (EU)	-0.026**	0.805***	0.125**	-0.049***	-0.053	0.710
	(0.026)	(0.000)	(0.032)	(0.002)	(0.483)	
TED (EU)	-0.021	0.810***	-0.029	-0.071***	0.060	0.706
	(0.109)	(0.000)	(0.432)	(0.001)	(0.133)	
EXLIQU (EU)	-0.033***	0.797***	0.466**	-0.043***	-0.526	0.707
	(0.007)	(0.000)	(0.033)	(0.007)	(0.142)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.11.4: Regression outputs of Model 4 (IT)*

Variable	Parameters					Adj. R^2
	α	β1	β2	β3	β4	
FINCOND (EU)	0.018*	0.925***	0.016	-0.041**	0.006	0.887
	(0.078)	(0.000)	(0.674)	(0.014)	(0.891)	
INFL (IT)	0.019*	0.924***	-0.016	-0.043***	-0.028	0.886
	(0.065)	(0.000)	(0.654)	(0.009)	(0.586)	
CC (IT)	0.019	0.924***	-0.003	-0.047***	-0.005	0.888
	(0.056)	(0.000)	(0.452)	(0.004)	(0.347)	
IP (IT)	0.019*	0.922***	0.004	-0.044***	-0.012	0.886
	(0.062)	(0.000)	(0.587)	(0.008)	(0.262)	
UNEMP (IT)	0.019*	0.920***	-0.002	-0.042**	0.188**	0.889
	(0.057)	(0.000)	(0.955)	(0.011)	(0.029)	
V2X	0.014	0.929***	-0.006	-0.035**	0.003	0.887
	(0.195)	(0.000)	(0.125)	(0.039)	(0.417)	
MONPL	0.019*	0.919***	0.000	-0.048***	0.001	0.885
	(0.075)	(0.000)	(0.999)	(0.009)	(0.528)	
KEYR (EU)	0.018*	0.929***	0.020	-0.048***	-0.120	0.886
	(0.088)	(0.000)	(0.861)	(0.005)	(0.374)	
TERM (EU)	0.020*	0.928***	0.118*	-0.045***	-0.059	0.888
	(0.051)	(0.000)	(0.055)	(0.007)	(0.455)	
TED (EU)	0.011	0.924***	0.038	-0.061***	0.004	0.888
	(0.365)	(0.000)	(0.309)	(0.004)	(0.932)	
EXLIQU (EU)	0.018*	0.922***	0.143	-0.045***	0.221	0.886
	(0.083)	(0.000)	(0.531)	(0.008)	(0.558)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.11.5: Regression outputs of Model 4 (SP)*

Variable	Parameters					Adj. R^2
	α	β1	β2	β3	β4	
FINCOND (EU)	0.017*	0.919***	0.009	-0.044***	0.007	0.880
	(0.096)	(0.000)	(0.822)	(0.008)	(0.859)	
INFL (SP)	0.017*	0.918***	-0.006	-0.044***	0.024	0.879
	(0.084)	(0.000)	(0.781)	(0.008)	(0.540)	
CC (SP)	0.017	0.918***	-0.001	-0.046***	-0.002	0.879
	(0.086)	(0.000)	(0.814)	(0.006)	(0.729)	
IP (SP)	0.017*	0.918***	0.000	-0.046***	-0.001	0.879
	(0.087)	(0.000)	(0.996)	(0.006)	(0.930)	
UNEMP (SP)	0.016	0.920***	-0.012	-0.047***	0.043	0.880
	(0.104)	(0.000)	(0.814)	(0.005)	(0.505)	
V2X	0.013	0.921***	-0.005	-0.039**	0.002	0.881
	(0.205)	(0.000)	(0.213)	(0.021)	(0.550)	
MONPL	0.018*	0.903***	0.000	-0.057***	0.001	0.881
	(0.080)	(0.000)	(0.955)	(0.002)	(0.143)	
KEYR (EU)	0.017	0.920***	0.009	-0.048***	-0.050	0.879
	(0.102)	(0.000)	(0.937)	(0.006)	(0.707)	
TERM (EU)	0.018*	0.920***	0.098	-0.047***	-0.052	0.881
	(0.069)	(0.000)	(0.107)	(0.004)	(0.511)	
TED (EU)	0.013	0.920***	0.018	-0.061***	0.014	0.881
	(0.271)	(0.000)	(0.636)	(0.004)	(0.746)	
EXLIQU (EU)	0.016	0.915***	0.109	-0.047***	0.196	0.880
	(0.103)	(0.000)	(0.630)	(0.005)	(0.601)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.11.6: Regression outputs of Model 4 (PT)*

Variable	Parameters					Adj. R^2
	α	β1	β2	β3	β4	
FINCOND (EU)	0.016**	0.923***	0.063**	-0.031**	-0.041	0.894
	(0.046)	(0.000)	(0.026)	(0.011)	(0.166)	
INFL (PT)	0.018**	0.926***	-0.002	-0.036***	-0.025	0.889
	(0.028)	(0.000)	(0.890)	(0.004)	(0.436)	
CC (PT)	0.018**	0.929***	-0.005	-0.037***	-0.001	0.893
	(0.021)	(0.000)	(0.059)	(0.003)	(0.880)	
IP (PT)	0.018**	0.923***	0.001	-0.036***	-0.003	0.889
	(0.024)	(0.000)	(0.796)	(0.004)	(0.475)	
UNEMP (PT)	0.018**	0.930***	0.061	-0.041***	0.010	0.891
	(0.021)	(0.000)	(0.104)	(0.002)	(0.888)	
V2X	0.015*	0.926***	-0.003	-0.030**	0.001	0.891
	(0.063)	(0.000)	(0.300)	(0.019)	(0.853)	
MONPL	0.021**	0.908***	0.000	-0.044***	0.001	0.890
	(0.012)	(0.000)	(0.789)	(0.001)	(0.136)	
KEYR (EU)	0.017**	0.925***	0.027	-0.036***	-0.047	0.889
	(0.036)	(0.000)	(0.750)	(0.006)	(0.640)	
TERM (EU)	0.019**	0.922***	0.045	-0.036***	-0.044	0.889
	(0.020)	(0.000)	(0.329)	(0.004)	(0.463)	
TED (EU)	0.011	0.923***	0.034	-0.034**	-0.025	0.890
	(0.234)	(0.000)	(0.226)	(0.030)	(0.433)	
EXLIQU (EU)	0.018**	0.922***	-0.030	-0.035***	0.014	0.889
	(0.023)	(0.000)	(0.861)	(0.005)	(0.961)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

Table A.11.7: Regression outputs of Model 4 (UK)*

Variable	Parameters					Adj. R^2
	α	β1	β2	β3	β4	
FINCOND (UK)	-0.063***	0.723***	0.025	-0.041***	0.004	0.587
	(0.000)	(0.000)	(0.441)	(0.005)	(0.900)	
INFL (UK)	-0.062***	0.730***	0.053	-0.044***	-0.078	0.582
	(0.000)	(0.000)	(0.124)	(0.003)	(0.112)	
CC (UK)	-0.061***	0.722***	0.005	-0.045***	-0.004	0.579
	(0.000)	(0.000)	(0.189)	(0.002)	(0.394)	
IP (UK)	-0.062***	0.721***	0.008	-0.044***	0.000	0.578
	(0.000)	(0.000)	(0.442)	(0.003)	(0.986)	
UNEMP (UK)	-0.061***	0.725***	-0.008	-0.044***	-0.035	0.576
	(0.000)	(0.000)	(0.931)	(0.004)	(0.798)	
V2X	-0.060***	0.736***	-0.002	-0.037**	-0.003	0.596
	(0.000)	(0.000)	(0.499)	(0.012)	(0.388)	
MONPL	-0.064***	0.723***	0.000	-0.036**	-0.001	0.580
	(0.000)	(0.000)	(0.495)	(0.019)	(0.142)	
KEYR (UK)	-0.058***	0.731***	-0.154*	-0.051***	0.091	0.587
	(0.000)	(0.000)	(0.052)	(0.001)	(0.328)	

* The values between brackets ( ) indicate the p-vales of the respective estimates. The marks */**/*** indicate that the estimate is significant at the 10%/5%/1% significance level, respectively.

8.12. Appendix XII: Durbin-Watson (DW) tests on Model 1,2,3,4 regressions

Table A.12.1: Durbin-Watson (DW) test for the three models (EU)

Variable	Durbin-Watson stat			
	Model 1	**Model 2**	**Model 3**	**Model 4**
D_GDP (EU)	1.780	/		/
D_V2X	1.783	/		/
D_EURIBOR-EONIA	1.788	/		/
D_CRISIS (EU)	1.803	/		/
FINCOND (EU)	1.823	1.817	1.821	1.817
INFL (EU)	1.793	1.780	1.792	1.779
CC (EU)	1.816	1.794	1.811	1.792
IP (EU)	1.796	1.790	1.795	1.789
UNEMP (EU)	1.771	1.758	1.777	1.765
V2X	1.861	1.857	1.857	1.757
MONPL	1.797	1.784	1.843	1.822
KEYR (EU)	1.793	1.803	1.792	1.851
TERM (EU)	1.823	1.837	1.823	1.836
TED (EU)	1.782	1.787	1.799	1.782
EXLIQU (EU)	1.797	1.783	1.783	1.786

Table A.12.2: Durbin-Watson (DW) test for the three models (DE)

Variable	Durbin-Watson stat			
	Model 1	**Model 2**	**Model 3**	**Model 4**
D_GDP (DE)	1.771	/		/
D_V2X	1.774	/		/
D_EURIBOR-EONIA	1.774	/		/
D_CRISIS (DE)	1.787	/		/
FINCOND (EU)	1.805	1.804	1.801	1.803
INFL (DE)	1.784	1.773	1.784	1.773
CC (DE)	1.786	1.775	1.786	1.774
IP (DE)	1.783	1.780	1.787	1.783
UNEMP (DE)	1.783	1.777	1.775	1.835
V2X	1.838	1.839	1.835	1.747
MONPL	1.782	1.775	1.839	1.820
KEYR (EU)	1.776	1.791	1.775	1.791
TERM (EU)	1.814	1.830	1.812	1.829
TED (EU)	1.769	1.781	1.783	1.777
EXLIQU (EU)	1.781	1.771	1.771	1.776

Table A.12.3: Durbin-Watson (DW) test for the three models (FR)

Variable	Durbin-Watson stat			
	Model 1	**Model 2**	**Model 3**	**Model 4**
D_GDP (FR)	1.727	/		/
D_V2X	1.721	/		/
D_EURIBOR-EONIA	1.730	/		/
D_CRISIS (FR)	1.733	/		/
FINCOND (EU)	1.762	1.758	1.758	1.754
INFL (FR)	1.735	1.721	1.731	1.717
CC (FR)	1.739	1.725	1.740	1.785
IP (FR)	1.722	1.707	1.719	1.709
UNEMP (FR)	1.733	1.722	1.747	1.738
V2X	1.787	1.784	1.789	1.691
MONPL	1.723	1.711	1.745	1.727
KEYR (EU)	1.734	1.744	1.734	1.744
TERM (EU)	1.761	1.769	1.760	1.766
TED (EU)	1.735	1.747	1.736	1.743
EXLIQU (EU)	1.750	1.745	1.745	1.749

Table A.12.4: Durbin-Watson (DW) test for the three models (IT)

Variable	Durbin-Watson stat			
	Model 1	**Model 2**	**Model 3**	**Model 4**
D_GDP (IT)	1.766	/		/
D_V2X	1.723	/		/
D_EURIBOR-EONIA	1.795	/		/
D_CRISIS (IT)	1.748	/		/
FINCOND (EU)	1.764	1.732	1.763	1.731
INFL (IT)	1.767	1.729	1.770	1.733
CC (IT)	1.766	1.726	1.781	1.745
IP (IT)	1.766	1.731	1.766	1.731
UNEMP (IT)	1.771	1.738	1.772	1.747
V2X	1.766	1.741	1.762	1.738
MONPL	1.758	1.718	1.752	1.721
KEYR (EU)	1.766	1.746	1.766	1.748
TERM (EU)	1.779	1.751	1.774	1.745
TED (EU)	1.777	1.759	1.763	1.759
EXLIQU (EU)	1.762	1.728	1.728	1.736

Table A.12.5: Durbin-Watson (DW) test for the three models (SP)

Variable	Durbin-Watson stat			
	Model 1	Model 2	Model 3	Model 4
D_GDP (SP)	1.774	/		/
D_V2X	1.753	/		/
D_EURIBOR-EONIA	1.794	/		/
D_CRISIS (SP)	1.764	/		/
FINCOND (EU)	1.785	1.769	1.786	1.769
INFL (SP)	1.770	1.753	1.777	1.757
CC (SP)	1.771	1.752	1.774	1.756
IP (SP)	1.772	1.754	1.771	1.755
UNEMP (SP)	1.771	1.759	1.762	1.746
V2X	1.782	1.771	1.768	1.761
MONPL	1.764	1.743	1.765	1.747
KEYR (EU)	1.767	1.762	1.765	1.761
TERM (EU)	1.775	1.764	1.773	1.761
TED (EU)	1.776	1.772	1.776	1.770
EXLIQU (EU)	1.773	1.757	1.757	1.761

Table A.12.6: Durbin-Watson (DW) test for the three models (PT)

Variable	Durbin-Watson stat			
	Model 1	Model 2	Model 3	Model 4
D_GDP (PT)	1.732	/		/
D_V2X	1.730	/		/
D_EURIBOR-EONIA	1.755	/		/
D_CRISIS (PT)	1.709	/		/
FINCOND (EU)	1.775	1.777	1.776	1.777
INFL (PT)	1.741	1.740	1.744	1.744
CC (PT)	1.706	1.700	1.706	1.700
IP (PT)	1.735	1.730	1.733	1.730
UNEMP (PT)	1.748	1.759	1.761	1.757
V2X	1.749	1.752	1.743	1.749
MONPL	1.735	1.725	1.736	1.742
KEYR (EU)	1.720	1.735	1.716	1.731
TERM (EU)	1.742	1.743	1.734	1.732
TED (EU)	1.735	1.751	1.750	1.757
EXLIQU (EU)	1.734	1.729	1.729	1.729

Table A.12.7: Durbin-Watson (DW) test for the three models (UK)

Variable	Durbin-Watson stat			
	Model 1	Model 2	Model 3	Model 4
D_GDP (UK)	1.914	/		/
D_V2X	1.905	/		/
D_EURIBOR-EONIA	1.905	/		/
D_CRISIS (UK)	1.920	/		/
FINCOND (UK)	1.963	1.953	1.963	1.954
INFL (UK)	1.913	1.903	1.913	1.909
CC (UK)	1.937	1.924	1.935	1.920
IP (UK)	1.923	1.907	1.922	1.907
UNEMP (UK)	1.910	1.901	1.908	1.898
V2X	2.023	2.017	2.019	2.010
MONPL	1.917	1.905	1.978	1.951
KEYR (UK)	1.929	1.937	1.924	1.937

8.13. Appendix XIII: ARCH tests on Model 1,2,3,4 regressions

Table A.13.1: ARCH test for the three models (EU)*

Variable	Model 1		Model 2		Model 3		Model 4	
	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.
D_GDP (EU)	5.881	0.015	/	/	/	/	/	/
D_V2X	1.828	0.176	/	/	/	/	/	/
D_EURIBOR-EONIA	5.041	0.025	/	/	/	/	/	/
D_CRISIS (EU)	0.936	0.333	/	/	/	/	/	/
FINCOND (EU)	6.216	0.013	1.91	0.17	1.91	0.17	1.95	0.16
INFL (EU)	6.434	0.011	1.83	0.18	1.83	0.18	1.82	0.18
CC (EU)	6.185	0.013	1.82	0.18	1.82	0.18	1.85	0.17
IP (EU)	6.473	0.011	1.88	0.17	1.74	0.19	1.74	0.19
UNEMP (EU)	6.522	0.011	2.13	0.14	2.09	0.15	2.09	0.15
V2X	2.940	0.086	1.94	0.16	1.99	0.16	1.99	0.16
MONPL	5.851	0.016	1.85	0.17	1.85	0.17	0.65	0.42
KEYR (EU)	6.447	0.011	1.70	0.19	1.70	0.19	1.61	0.21
TERM (EU)	6.383	0.012	1.71	0.19	1.84	0.18	1.84	0.18
TED (EU)	6.473	0.011	1.82	0.18	1.32	0.25	1.32	0.25
EXLIQU (EU)	5.578	0.018	1.91	0.17	1.45	0.23	1.45	0.23

* The included number of observations is 218 after adjustments. ARCH tests are performed with one lagged squared residuals variable and a constant.

Table A.13.2: ARCH test for the three models (DE)*

Variable	Model 1		Model 2		Model 3		Model 4	
	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.
D_GDP (DE)	5.881	0.015	/	/	/	/	/	/
D_V2X	1.828	0.176	/	/	/	/	/	/
D_EURIBOR-EONIA	5.041	0.025	/	/	/	/	/	/
D_CRISIS (DE)	0.936	0.333	/	/	/	/	/	/
FINCOND (EU)	6.216	0.013	1.91	0.17	1.91	0.17	1.95	0.16
INFL (DE)	6.434	0.011	1.83	0.18	1.83	0.18	1.82	0.18
CC (DE)	6.185	0.013	1.82	0.18	1.82	0.18	1.85	0.17
IP (DE)	6.473	0.011	1.88	0.17	1.74	0.19	1.74	0.19
UNEMP (DE)	6.522	0.011	2.13	0.14	2.09	0.15	2.09	0.15
V2X	2.940	0.086	1.94	0.16	1.99	0.16	1.99	0.16
MONPL	5.851	0.016	1.85	0.17	1.85	0.17	0.65	0.42
KEYR (EU)	6.447	0.011	1.70	0.19	1.70	0.19	1.61	0.21
TERM (EU)	6.383	0.012	1.71	0.19	1.84	0.18	1.84	0.18
TED (EU)	6.473	0.011	1.82	0.18	1.32	0.25	1.32	0.25
EXLIQU (EU)	5.578	0.018	1.91	0.17	1.45	0.23	1.45	0.23

* The included number of observations is 218 after adjustments. ARCH tests are performed with one lagged squared residuals variable and a constant.

Table A.13.3: ARCH test for the three models (FR)*

Variable	Model 1		Model 2		Model 3		Model 4	
	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.
D_GDP (FR)	3.056	0.080	/	/	/	/	/	/
D_V2X	1.808	0.179	/	/	/	/	/	/
D_EURIBOR-EONIA	3.078	0.079	/	/	/	/	/	/
D_CRISIS (FR)	1.504	0.220	/	/	/	/	/	/
FINCOND (EU)	3.050	0.081	1.72	0.19	3.02	0.08	1.73	0.19
INFL (FR)	3.007	0.083	1.73	0.19	3.18	0.08	1.83	0.18
CC (FR)	3.459	0.063	2.05	0.15	3.40	0.07	1.98	0.16
IP (FR)	3.424	0.064	1.94	0.16	3.77	0.05	2.13	0.15
UNEMP (FR)	3.184	0.074	1.78	0.18	2.79	0.10	1.50	0.22
V2X	2.137	0.144	1.93	0.17	3.04	0.08	1.93	0.17
MONPL	2.583	0.108	1.89	0.17	1.43	0.23	1.30	0.26
KEYR (EU)	3.493	0.062	1.50	0.22	3.18	0.08	1.49	0.22
TERM (EU)	3.180	0.075	2.34	0.13	3.97	0.05	2.28	0.13
TED (EU)	4.133	0.042	1.66	0.20	3.12	0.08	1.46	0.23
EXLIQU (EU)	3.210	0.073	1.85	0.17	2.82	0.09	1.65	0.20

* The included number of observations is 218 after adjustments. ARCH tests are performed with one lagged squared residuals variable and a constant.

Table A.13.4: ARCH test for the three models (IT)*

Variable	Model 1		Model 2		Model 3		Model 4	
	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.
D_GDP (IT)	0.634	0.426	/	/	/	/	/	/
D_V2X	2.004	0.157	/	/	/	/	/	/
D_EURIBOR-EONIA	1.176	0.278	/	/	/	/	/	/
D_CRISIS (IT)	0.881	0.348	/	/	/	/	/	/
FINCOND (EU)	1.433	0.233	2.47	0.12	1.45	0.23	2.50	0.11
INFL (IT)	0.802	0.370	2.09	0.15	0.71	0.40	1.97	0.16
CC (IT)	0.599	0.439	1.75	0.19	0.27	0.60	1.08	0.30
IP (IT)	0.815	0.367	2.03	0.16	1.10	0.29	2.44	0.12
UNEMP (IT)	0.308	0.579	1.27	0.26	0.72	0.40	1.47	0.23
V2X	1.119	0.290	2.17	0.14	0.71	0.40	2.11	0.15
MONPL	0.744	0.388	1.89	0.17	0.95	0.33	1.68	0.20
KEYR (EU)	0.682	0.409	2.12	0.15	0.87	0.35	2.30	0.13
TERM (EU)	0.763	0.382	2.19	0.14	0.70	0.40	2.06	0.15
TED (EU)	0.896	0.344	2.59	0.11	1.27	0.26	2.59	0.11
EXLIQU (EU)	0.777	0.378	1.64	0.20	0.39	0.53	1.48	0.22

* The included number of observations is 218 after adjustments. ARCH tests are performed with one lagged squared residuals variable and a constant.

Table A.13.5: ARCH test for the three models (ES)*

Variable	Model 1		Model 2		Model 3		Model 4	
	Obs * R²	**Chi² prob.**	**Obs * R²**	**Chi² prob.**	**Obs * R²**	**Chi² prob.**	**Obs * R²**	**Chi² prob.**
D_GDP (ES)	0.273	0.601	/	/	/	/	/	/
D_V2X	0.159	0.690	/	/	/	/	/	/
D_EURIBOR-EONIA	0.400	0.527	/	/	/	/	/	/
D_CRISIS (ES)	0.223	0.636	/	/	/	/	/	/
FINCOND (EU)	0.315	0.577	0.18	0.67	0.32	0.57	0.18	0.67
INFL (ES)	0.263	0.608	0.16	0.69	0.27	0.61	0.15	0.70
CC (ES)	0.258	0.612	0.19	0.67	0.25	0.62	0.18	0.67
IP (ES)	0.258	0.612	0.16	0.69	0.25	0.62	0.16	0.69
UNEMP (ES)	0.267	0.606	0.13	0.72	0.30	0.58	0.15	0.70
V2X	0.215	0.643	0.17	0.68	0.44	0.51	0.14	0.71
MONPL	0.254	0.614	0.20	0.66	0.27	0.61	0.19	0.67
KEYR (EU)	0.275	0.600	0.16	0.69	0.29	0.59	0.19	0.67
TERM (EU)	0.252	0.616	0.22	0.64	0.45	0.50	0.28	0.60
TED (EU)	0.404	0.525	0.19	0.67	0.36	0.55	0.18	0.67
EXLIQU (EU)	0.280	0.597	0.21	0.65	0.30	0.58	0.19	0.67

* The included number of observations is 218 after adjustments. ARCH tests are performed with one lagged squared residuals variable and a constant.

Table A.13.6: ARCH test for the three models (PT)*

Variable	Model 1		Model 2		Model 3		Model 4	
	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.
D_GDP (PT)	0.035	0.851	/	/	/	/	/	/
D_V2X	0.004	0.949	/	/	/	/	/	/
D_EURIBOR-EONIA	0.020	0.887	/	/	/	/	/	/
D_CRISIS (PT)	0.065	0.799	/	/	/	/	/	/
FINCOND (EU)	0.036	0.850	0.00	1.00	0.12	0.73	0.01	0.91
INFL (PT)	0.098	0.755	0.00	0.97	0.05	0.82	0.00	0.99
CC (PT)	0.130	0.718	0.00	0.96	0.13	0.72	0.00	0.96
IP (PT)	0.069	0.793	0.00	0.96	0.09	0.76	0.00	0.99
UNEMP (PT)	0.130	0.719	0.00	0.95	0.05	0.83	0.00	0.97
V2X	0.004	0.947	0.00	0.95	0.04	0.84	0.05	0.82
MONPL	0.234	0.628	0.01	0.91	0.07	0.80	0.06	0.80
KEYR (EU)	0.063	0.802	0.01	0.95	0.07	0.80	0.01	0.94
TERM (EU)	0.077	0.781	0.01	0.94	0.10	0.75	0.00	0.97
TED (EU)	0.049	0.825	0.02	0.88	0.03	0.86	0.01	0.91
EXLIQU (EU)	0.065	0.799	0.00	0.96	0.06	0.80	0.00	0.96

* The included number of observations is 218 after adjustments. ARCH tests are performed with one lagged squared residuals variable and a constant.

Table A.13.7: ARCH test for the three models (UK)*

Variable	Model 1		Model 2		Model 3		Model 4	
	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.	Obs * R^2	Chi^2 prob.
D_GDP (UK)	1.118	0.290	/	/	/	/	/	/
D_V2X	0.039	0.843	/	/	/	/	/	/
D_EURIBOR-EONIA	0.772	0.380	/	/	/	/	/	/
D_CRISIS (UK)	0.002	0.966	/	/	/	/	/	/
FINCOND (UK)	1.297	0.257	0.12	0.73	1.38	0.24	0.11	0.74
INFL (UK)	1.040	0.308	0.05	0.83	1.21	0.27	0.08	0.78
CC (UK)	0.909	0.341	0.00	0.95	0.49	0.48	0.01	0.92
IP (UK)	1.100	0.294	0.04	0.85	1.09	0.30	0.04	0.85
UNEMP (UK)	0.745	0.388	0.03	0.87	0.75	0.39	0.03	0.87
V2X	0.113	0.737	0.03	0.86	1.23	0.27	0.03	0.86
MONPL	1.186	0.276	0.04	0.84	0.74	0.39	0.08	0.78
KEYR (UK)	1.169	0.280	0.03	0.85	1.30	0.25	0.03	0.86

* The included number of observations is 218 after adjustments. ARCH tests are performed with one lagged squared residuals variable and a constant.

8.14. Appendix XIV: Goodness of fit (Adj. R², AIC and SC on Model 1,2,3,4 regressions)

Table A.14.1: Quality tests (Adj. R², AIC, SC) for the three models (EU)

Variable	Adj. R²				AIC				SC			
	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4
D_GDP (EU)	0.690	/	/	/	-1.362	/	/	/	-1.316	/	/	/
D_V2X	0.703	/	/	/	-1.408	/	/	/	-1.361	/	/	/
D_EURIBOR-EONIA	0.691	/	/	/	-1.365	/	/	/	-1.319	/	/	/
D_CRISIS (EU)	0.708	/	/	/	-1.425	/	/	/	-1.378	/	/	/
FINCOND (EU)	0.697	0.710	0.696	0.709	-1.388	-1.425	-1.379	-1.416	-1.341	-1.363	-1.317	-1.339
INFL (EU)	0.690	0.703	0.688	0.702	-1.362	-1.402	-1.353	-1.393	-1.316	-1.340	-1.291	-1.315
CC (EU)	0.689	0.703	0.688	0.702	-1.361	-1.400	-1.353	-1.393	-1.314	-1.338	-1.291	-1.315
IP (EU)	0.688	0.702	0.689	0.703	-1.356	-1.399	-1.354	-1.397	-1.309	-1.338	-1.292	-1.319
UNEMP (EU)	0.693	0.705	0.694	0.705	-1.375	-1.407	-1.371	-1.404	-1.328	-1.345	-1.309	-1.327
V2X	0.704	0.713	0.705	0.703	-1.409	-1.435	-1.409	-1.398	-1.363	-1.373	-1.347	-1.320
MONPL	0.688	0.702	0.697	0.705	-1.356	-1.399	-1.383	-1.403	-1.309	-1.337	-1.321	-1.325
KEYR (EU)	0.688	0.703	0.686	0.715	-1.356	-1.401	-1.347	-1.439	-1.310	-1.339	-1.285	-1.362
TERM (EU)	0.696	0.713	0.695	0.712	-1.384	-1.436	-1.375	-1.427	-1.337	-1.374	-1.313	-1.349
TED (EU)	0.689	0.702	0.687	0.708	-1.361	-1.399	-1.348	-1.413	-1.314	-1.337	-1.286	-1.336
EXLIQU (EU)	0.688	0.702	0.689	0.702	-1.357	-1.400	-1.357	-1.394	-1.310	-1.338	-1.295	-1.317

Table A.14.2: Quality tests (Adj. R², AIC, SC) for the three models (DE)

Variable	Adj. R²				AIC				SC			
	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4
D_GDP (DE)	0.686	/	/	/	-1.399	/	/	/	-1.353	/	/	/
D_V2X	0.699	/	/	/	-1.444	/	/	/	-1.397	/	/	/
D_EURIBOR-EONIA	0.686	/	/	/	-1.401	/	/	/	-1.355	/	/	/
D_CRISIS (DE)	0.704	/	/	/	-1.459	/	/	/	-1.412	/	/	/
FINCOND (EU)	0.694	0.706	0.693	0.705	-1.426	-1.462	-1.418	-1.453	-1.380	-1.400	-1.356	-1.376
INFL (DE)	0.684	0.698	0.682	0.697	-1.394	-1.435	-1.385	-1.426	-1.347	-1.373	-1.323	-1.349
CC (DE)	0.684	0.698	0.683	0.697	-1.395	-1.435	-1.385	-1.426	-1.348	-1.373	-1.324	-1.348
IP (DE)	0.684	0.698	0.683	0.697	-1.394	-1.436	-1.386	-1.428	-1.347	-1.375	-1.324	-1.350
UNEMP (DE)	0.684	0.698	0.684	0.711	-1.394	-1.436	-1.389	-1.473	-1.347	-1.375	-1.327	-1.396
V2X	0.700	0.708	0.701	0.698	-1.446	-1.470	-1.444	-1.432	-1.399	-1.408	-1.382	-1.354
MONPL	0.684	0.698	0.695	0.701	-1.394	-1.435	-1.424	-1.442	-1.347	-1.373	-1.362	-1.364
KEYR (EU)	0.684	0.698	0.683	0.697	-1.394	-1.436	-1.385	-1.429	-1.348	-1.374	-1.323	-1.351
TERM (EU)	0.689	0.705	0.688	0.704	-1.410	-1.458	-1.402	-1.450	-1.364	-1.397	-1.340	-1.373
TED (EU)	0.685	0.698	0.683	0.703	-1.397	-1.435	-1.385	-1.448	-1.351	-1.373	-1.324	-1.370
EXLIQU (EU)	0.684	0.698	0.686	0.698	-1.394	-1.435	-1.396	-1.432	-1.348	-1.374	-1.334	-1.354

Table A.14.3: Quality tests (Adj. R², AIC, SC) for the three models (FR)

Variable	Adj. R^2				AIC				SC			
	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4
D_GDP (FR)	0.692	/	/	/	-1.553	/	/	/	-1.507	/	/	/
D_V2X	0.704	/	/	/	-1.591	/	/	/	-1.545	/	/	/
D_EURIBOR-EONIA	0.692	/	/	/	-1.552	/	/	/	-1.506	/	/	/
D_CRISIS (FR)	0.702	/	/	/	-1.587	/	/	/	-1.541	/	/	/
FINCOND (EU)	0.702	0.711	0.701	0.710	-1.585	-1.611	-1.578	-1.603	-1.538	-1.549	-1.516	-1.526
INFL (FR)	0.692	0.702	0.691	0.701	-1.553	-1.583	-1.545	-1.575	-1.507	-1.521	-1.483	-1.497
CC (FR)	0.693	0.703	0.691	0.713	-1.555	-1.585	-1.546	-1.613	-1.509	-1.524	-1.485	-1.536
IP (FR)	0.694	0.704	0.698	0.709	-1.561	-1.589	-1.568	-1.601	-1.514	-1.527	-1.507	-1.524
UNEMP (FR)	0.692	0.702	0.692	0.702	-1.552	-1.582	-1.547	-1.577	-1.505	-1.521	-1.485	-1.499
V2X	0.706	0.712	0.706	0.704	-1.600	-1.616	-1.595	-1.584	-1.554	-1.554	-1.533	-1.506
MONPL	0.693	0.704	0.698	0.704	-1.557	-1.588	-1.567	-1.583	-1.511	-1.526	-1.505	-1.506
KEYR (EU)	0.692	0.703	0.690	0.702	-1.552	-1.585	-1.542	-1.576	-1.505	-1.523	-1.480	-1.499
TERM (EU)	0.699	0.711	0.698	0.710	-1.574	-1.612	-1.568	-1.605	-1.528	-1.550	-1.506	-1.527
TED (EU)	0.692	0.704	0.691	0.706	-1.552	-1.589	-1.544	-1.591	-1.505	-1.527	-1.482	-1.513
EXLIQU (EU)	0.695	0.706	0.698	0.707	-1.562	-1.593	-1.569	-1.594	-1.515	-1.532	-1.507	-1.517

Table A.14.4: Quality tests (Adj. R², AIC, SC) for the three models (IT)

Variable	Adj. R^2				AIC				SC			
	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4
D_GDP (IT)	0.883	/	/	/	-1.469	/	/	/	-1.422	/	/	/
D_V2X	0.886	/	/	/	-1.498	/	/	/	-1.452	/	/	/
D_EURIBOR-EONIA	0.884	/	/	/	-1.483	/	/	/	-1.436	/	/	/
D_CRISIS (IT)	0.883	/	/	/	-1.471	/	/	/	-1.424	/	/	/
FINCOND (EU)	0.884	0.887	0.884	0.887	-1.482	-1.501	-1.473	-1.492	-1.436	-1.439	-1.411	-1.415
INFL (IT)	0.883	0.886	0.883	0.886	-1.473	-1.496	-1.465	-1.488	-1.426	-1.434	-1.403	-1.410
CC (IT)	0.884	0.888	0.884	0.888	-1.480	-1.507	-1.473	-1.502	-1.433	-1.445	-1.411	-1.425
IP (IT)	0.883	0.886	0.883	0.886	-1.468	-1.490	-1.463	-1.487	-1.422	-1.428	-1.401	-1.410
UNEMP (IT)	0.884	0.887	0.886	0.889	-1.475	-1.496	-1.488	-1.509	-1.428	-1.434	-1.426	-1.432
V2X	0.885	0.887	0.885	0.887	-1.491	-1.504	-1.487	-1.498	-1.445	-1.442	-1.425	-1.420
MONPL	0.883	0.886	0.882	0.885	-1.468	-1.490	-1.460	-1.482	-1.421	-1.428	-1.398	-1.405
KEYR (EU)	0.883	0.886	0.883	0.886	-1.468	-1.495	-1.462	-1.489	-1.422	-1.433	-1.400	-1.412
TERM (EU)	0.885	0.888	0.884	0.888	-1.485	-1.510	-1.478	-1.504	-1.438	-1.448	-1.416	-1.426
TED (EU)	0.883	0.889	0.885	0.888	-1.474	-1.517	-1.479	-1.508	-1.428	-1.455	-1.417	-1.431
EXLIQU (EU)	0.883	0.887	0.883	0.886	-1.474	-1.496	-1.465	-1.489	-1.428	-1.434	-1.403	-1.411

Table A.14.5: Quality tests (Adj. R^2, AIC, SC) for the three models (SP)

Variable	Adj. R^2				AIC				SC			
	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4
D_GDP (SP)	0.877	/	/	/	-1.486	/	/	/	-1.439	/	/	/
D_V2X	0.880	/	/	/	-1.514	/	/	/	-1.468	/	/	/
D_EURIBOR-EONIA	0.877	/	/	/	-1.487	/	/	/	-1.440	/	/	/
D_CRISIS (SP)	0.876	/	/	/	-1.481	/	/	/	-1.435	/	/	/
FINCOND (EU)	0.877	0.880	0.876	0.880	-1.488	-1.511	-1.479	-1.502	-1.441	-1.450	-1.417	-1.425
INFL (SP)	0.876	0.880	0.876	0.879	-1.480	-1.505	-1.474	-1.498	-1.434	-1.443	-1.412	-1.421
CC (SP)	0.876	0.880	0.876	0.879	-1.480	-1.507	-1.471	-1.498	-1.434	-1.445	-1.410	-1.421
IP (SP)	0.876	0.880	0.875	0.879	-1.479	-1.505	-1.470	-1.496	-1.433	-1.443	-1.408	-1.419
UNEMP (SP)	0.876	0.880	0.876	0.880	-1.479	-1.506	-1.471	-1.499	-1.433	-1.444	-1.410	-1.422
V2X	0.878	0.881	0.878	0.881	-1.499	-1.516	-1.493	-1.509	-1.453	-1.455	-1.431	-1.432
MONPL	0.876	0.880	0.876	0.881	-1.480	-1.507	-1.471	-1.508	-1.434	-1.445	-1.409	-1.431
KEYR (EU)	0.876	0.880	0.876	0.879	-1.480	-1.506	-1.471	-1.498	-1.433	-1.444	-1.409	-1.420
TERM (EU)	0.877	0.881	0.877	0.881	-1.490	-1.519	-1.483	-1.512	-1.444	-1.457	-1.421	-1.435
TED (EU)	0.876	0.881	0.877	0.881	-1.480	-1.519	-1.481	-1.510	-1.434	-1.457	-1.419	-1.433
EXLIQU (EU)	0.877	0.880	0.876	0.880	-1.483	-1.510	-1.474	-1.502	-1.437	-1.448	-1.412	-1.425

Table A.14.6: Quality tests (Adj. R^2, AIC, SC) for the three models (PT)

Variable	Adj. R^2				AIC				SC			
	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4
D_GDP (PT)	0.886	/	/	/	-2.055	/	/	/	-2.008	/	/	/
D_V2X	0.890	/	/	/	-2.091	/	/	/	-2.045	/	/	/
D_EURIBOR-EONIA	0.886	/	/	/	-2.058	/	/	/	-2.012	/	/	/
D_CRISIS (PT)	0.886	/	/	/	-2.059	/	/	/	-2.013	/	/	/
FINCOND (EU)	0.890	0.893	0.891	0.894	-2.093	-2.115	-2.094	-2.115	-2.046	-2.053	-2.032	-2.038
INFL (PT)	0.886	0.890	0.886	0.889	-2.055	-2.084	-2.048	-2.078	-2.008	-2.022	-1.986	-2.000
CC (PT)	0.889	0.893	0.888	0.893	-2.083	-2.115	-2.074	-2.106	-2.036	-2.053	-2.012	-2.028
IP (PT)	0.886	0.889	0.885	0.889	-2.054	-2.082	-2.046	-2.075	-2.007	-2.020	-1.984	-1.998
UNEMP (PT)	0.887	0.892	0.887	0.891	-2.062	-2.101	-2.057	-2.092	-2.016	-2.039	-1.995	-2.015
V2X	0.889	0.891	0.888	0.891	-2.081	-2.098	-2.073	-2.089	-2.035	-2.036	-2.011	-2.012
MONPL	0.886	0.889	0.885	0.890	-2.054	-2.082	-2.045	-2.084	-2.007	-2.020	-1.983	-2.006
KEYR (EU)	0.886	0.889	0.886	0.889	-2.055	-2.082	-2.047	-2.074	-2.009	-2.020	-1.985	-1.996
TERM (EU)	0.886	0.890	0.886	0.889	-2.055	-2.084	-2.048	-2.077	-2.008	-2.022	-1.986	-2.000
TED (EU)	0.886	0.890	0.888	0.890	-2.054	-2.088	-2.069	-2.082	-2.007	-2.026	-2.007	-2.004
EXLIQU (EU)	0.886	0.889	0.885	0.889	-2.054	-2.082	-2.046	-2.073	-2.007	-2.020	-1.984	-1.995

Table A.14.7: Quality tests (Adj. R², AIC, SC) for the three models (UK)

Variable	Adj. R^2				AIC				SC			
	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4	M 1	M 2	M 3	M 4
D_GDP (UK)	0.561	/	/	/	-1.697	/	/	/	-1.650	/	/	/
D_V2X	0.580	/	/	/	-1.741	/	/	/	-1.694	/	/	/
D_EURIBOR-EONIA	0.565	/	/	/	-1.705	/	/	/	-1.659	/	/	/
D_CRISIS (UK)	0.578	/	/	/	-1.737	/	/	/	-1.691	/	/	/
FINCOND (UK)	0.575	0.588	0.573	0.587	-1.728	-1.757	-1.719	-1.748	-1.682	-1.695	-1.658	-1.671
INFL (UK)	0.564	0.579	0.566	0.582	-1.703	-1.733	-1.704	-1.736	-1.657	-1.671	-1.642	-1.659
CC (UK)	0.562	0.580	0.562	0.579	-1.700	-1.736	-1.695	-1.731	-1.653	-1.675	-1.633	-1.653
IP (UK)	0.564	0.580	0.562	0.578	-1.703	-1.737	-1.694	-1.728	-1.657	-1.675	-1.632	-1.650
UNEMP (UK)	0.563	0.578	0.561	0.576	-1.702	-1.732	-1.693	-1.724	-1.655	-1.670	-1.631	-1.646
V2X	0.587	0.596	0.586	0.596	-1.758	-1.776	-1.750	-1.771	-1.711	-1.714	-1.688	-1.693
MONPL	0.561	0.578	0.571	0.580	-1.696	-1.732	-1.716	-1.733	-1.650	-1.670	-1.654	-1.655
KEYR (UK)	0.564	0.587	0.565	0.587	-1.703	-1.753	-1.702	-1.748	-1.656	-1.691	-1.640	-1.671

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