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RETURN CO-MOVEMENTS AND VOLATILITY SPILLOVERS ACROSS UNITED STATES OF AMERICA AND EURO AREA STOCK MARKETS

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ABSTRACT

We strive to analyze the interaction between stock markets of United States of America (USA) and the major countries of the euro are, by implementing a dynamic conditional correlation model to capture return co-movements and a generalized vector autoregressive model to measure volatility spillovers where forecasted-variance decompositions are independent of sorting. Impacts of recent economic crises are considered, as we analyze data from January 2000 to January 2015. Countries involved are Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal and Spain – 10 of the first 12 countries to be part of the euro area – and USA. Greece and USA appear as the two markets with lowest return co-movements with other countries, whilst France and the Netherlands show themselves as the strongest ones. As both the dotcom and the subprime crises intensify, the spillover ratio enlarges to reflect the increasing interdependency of financial markets during times of depression. Also, the sovereign debt crisis and the recent Russian financial downfall coincide with the growth of the spillovers ratio. In general, empirical results indicate high return co-movements and volatility spillovers across markets. Additionally, we assess the connection between systemic risk and volatility spillovers.

JEL classification:

G10; C32

Keywords:

Stock return co-movements, Volatility spillovers, Generalized VAR, Systemic risk

RESUMO

O objetivo deste trabalho é analisar a interação entre os mercados de ações dos Estados Unidos da América (EUA) e dos principais países da zona euro, através da implementação de um modelo dinâmico de correlações condicionais com o intuito de capturar possíveis relações entre retornos e um modelo generalizado de um vetor autorregressivo para calcular repercussões na volatilidade em que a decomposição das variâncias previstas é independente da ordem como estão organizadas. Os impactes das recentes crises económicas são considerados, uma vez que analisamos dados entre janeiro de 2000 e janeiro de 2015. Os países considerados são Alemanha, Bélgica, Espanha, Finlândia, França, Grécia, Holanda, Irlanda, Itália e Portugal – 10 dos primeiros 12 países que adotaram o euro como moeda única – e os EUA. Grécia e EUA aparecem como os dois mercados com menores correlações com outros países, enquanto França e Países Baixos destacam-se pela sua forte ligação com os restantes índices. À medida que as crises da *dotcom* e do *subprime* se intensificam, o rácio da difusão da volatilidade vai aumentando, o que reflete a crescente interdependência dos mercados financeiros em tempos de crise. Além disso, a crise da dívida soberana e a recente queda financeira russa coincidem também com o crescimento deste rácio. De um modo geral, os resultados empíricos demonstram fortes relações entre retornos e altos níveis de dispersão da volatilidade entre mercados. Adicionalmente, avaliamos a relação entre risco sistémico e a difusão da volatilidade.

Classificação do JEL:

G10; C32

Palavras-chave:

Co-movimentos do retorno de ações, Repercussões de volatilidade, VAR generalizado, Risco sistémico

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ACRONYMS

BE – Belgium

EUR – Euro

CISS – Composite Indicator of Systemic Stress

CISSequity – Composite Indicator of Systemic Stress for equity

DCC – Dynamic Conditional Correlation

DE – Germany

D&Y – Diebold and Yilmaz

ESCS – European Coal and Steel Community

ES – Spain

FI – Finland

FR – France

GARCH – Generalized Autoregressive Conditional Heteroskedasticity

IGARCH – Integrated Generalized Autoregressive Conditional Heteroskedasticity

GR – Greece

IE – Ireland

IT – Italy

NL – Netherlands

PIIGS – Portugal, Ireland, Italy, Greece and Spain

PT – Portugal

FFSI – Fed Financial Stress Index

FRED – Federal Reserve Economic Data

SES – Systemic Expected Shortfall

US – United States

USA – United States of America

USD – United States dollar

VAR – Vector Autoregressive

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1. Introduction

Throughout history, economic and financial disasters have taken place. Since the beginning of the 19th century, dozens of crises like, for example, the numerous panic situations involving the US, the Wall Street crash of 1929, the Black Monday of 1987 and, more recently, the dot-com bubble, the global financial crisis and the European sovereign debt slump, all have shown the major catastrophes that these events can have on modern society. However, even when everything seems to crumble, one thing remains intact: the human's voracious ambition to attain wealth.

In order to enhance their economic growth, worldwide governments have resorted to economic integration to reach higher productivity. By being part of a large community, countries can achieve comparative advantages and economies of scale. While the latter refers to the benefits of expansion, comparative advantages are commonly used to express situations where a country can produce a given good or service at a lower cost. By having different relative costs, each country can specialize in the production of the good or service that is relatively cheaper and trade their excesses[1].

Politics is also one of the main reasons for economic integration. For example, after the World War II, the need to join European countries resulted in the creation of the European Coal and Steel Community (ECSC). In addition to the development of a common market for coal and steel, this organization also helped prevent future war situations.

Although economic integration brings numerous benefits, the strong dependency amongst the member's markets can also help propagate a given economic downturn, instead of containing it. Since it involves the coordination of fiscal and monetary policies, a stronger integration also means a lower ability for governments to adjust their own policies for their own benefit. However, the diffusion of an economic crises is not confined to a given country, community, or continent. As technologies evolve, information becomes easier to spread/diffuse. This means that even what happens in other parts of the globe – either good or bad – may have repercussions for us. The world

[1] For more information on comparative advantages we refer to "*On the Principles of Political Economy and Taxation*" from David Ricardo (1821).

has become a series of dots connected by technology and what happens in USA, does not stay in the USA.

"…I*nnovations in the U.S. stock market are rapidly transmitted to other markets in a clearly recognizable pattern, whereas no single foreign market can significantly explain U.S. market movements"*, Eun & Shim (1989, 243).

Even though this quote from 89 still applies, in part, to the present, recent events such as the subprime crisis, make a much stronger case to demonstrate the impact that the American economy can have on foreign countries. Despite being started in another continent, one can say that this crash helped expose the sovereign debt difficulties that Europe is facing. Therefore, it seems relevant to answer questions like: how big are these spillovers? Are they really important? Can we use them to shield us from sudden/unexpected changes in global markets? How the 2007 crisis affected these spillovers? And what about other major economic slumps?

Definitely, the answers to these questions can help us to have a deeper knowledge of how markets interact with each other, so that we can be more prepared to handle a future crisis.

Hence, this dissertation tries to add insight into return co-movements and, more importantly, volatility spillovers. The main goal is not to create a new method to measure these concepts, but to implement previous ones to different markets and/or timelines. We will analyze the results to perceive how these complex markets interact with each other, both empirically and theoretically.

Furthermore, this dissertation aims to evaluate the impact of major economic events that occurred since the beginning of the millennium on the volatility spillover index among the American stock market and some major euro area indexes.

Finally, we will cross our findings with two risk measures, namely, the Composite Indicator of Systemic Stress (CISS) provided by ECB and the Fed Financial Stress Index (FFSI) sourced from FRED, in order to detect any possible co-movements concerning these variables.

To address the return co-movements we will first test if there is a dynamic conditional correlation (DCC) using the framework developed by Tse (2000) and, in that case, use a DCC model to measure the relationship across markets. Engle (2002) argues that DCC models are suitable to explain different realities and offer sensitive empirical results.

Volatility spillovers require a more complex approach. By using the D&Y (2009, 2012) methodology that generates a spillover index, we will try to evaluate how markets interact in terms of volatility spillovers. We will attempt to explain the origin of each market's volatility and determine if a specific market is a net receiver or transmitter of volatility.

This thesis proceeds as follows. In section two we provide a literature review of the three main topics discussed, namely the volatility spillovers, return co-movements and systemic stress. Section three is intended to describe all of our data, while section four applies methodologies presented before. Empirical results are reported and interpreted in section five. Section six offers an overall sensitive analysis. We also aim to add some insight about systemic risk and volatility spillovers in section seven. Finally, section eight concludes.

2. Literature review

Since the Asian crisis during the late 90's, many questions have been answered about markets' interdependency. Nonetheless, many more are still waiting to be addressed. Economic incidents and major financial crises can expose some theoretical flaws, thus creating the opportunity and incentive for more knowledge concerning the interaction across sophisticated financial systems. For more details on market interdependence we refer to Forbes & Rigobon (2002).

After the 2007 subprime crisis that exhibited some of the main deficiencies of modern financial markets, the literature about return co-movements and especially volatility spillovers has grown significantly.

2.1. Volatility spillovers

There is not one single way to address volatility spillovers. As a matter of fact, multiple authors use different methodologies to measure these links [see for example, Kanas

(1998), Sola, Spagnolo, & Spagnolo (2002), Milunovich & Thorp (2006) or McMillan & Speight (2010)] and they all contributed to advertise volatility spillovers.

Although many articles have emerged, Diebold & Yilmaz (2009) stood apart from the others due to its simplicity and original way to measure volatility spillovers, where they confine all the information into one single index. An article that is then improved by the same authors in Diebold & Yilmaz (2012) using a different, yet similar, method to measure spillover effects.

While the paper from 2009 examines the return and volatility spillovers for stock markets all over the globe, the goal in D&Y (2012) is to evaluate the spillovers across the major finance markets in the United States of America – stocks, bonds, foreign exchange and commodity markets. Moreover, they utilize data from January 1999 to January 2010 to get a considerable number of observations, 2771 daily observations to be exact.

In their previous work, D&Y use a variance decomposition that is variable ordering dependent due to the Cholesky method. This means that the spillover index, which is the pillar of their whole work – and therefore the base of ours - can have different results based on how the variables are ordered. KlöBner & Wagner (2012) evaluate the 2009's spillover measures in terms of robustness and computation and conclude that the overall spillover index is fairly robust. However, the reordering of the variables has a major impact on the spillover table results. This study also suggests methods capable of producing empirical results that are more suitable than the 2009's spillover ratios.

To overcome the variable ordering problem, D&Y propose a generalized Vector Autoregressive (VAR), a model firstly developed by Koop, Pesaran & Potter (1996) and then by Pesaran & Shin (1998).

D&Y (2009) also ignore directional spillovers and focus only on its total value. Furthermore, the article does not analyze how different assets of different countries interact and/or how distinctive assets classes within the same country share volatility spillovers. Such limitations serve as basis for other subsequent articles.

After the publication of D&Y's index other authors resorted to this measure for their works. Yilmaz (2010) applies the D&Y (2009)'s methodology to address the degree of contagion across east Asian stock markets. The main findings reveal different fluctuations between return and volatility spillovers. Particularly, the volatility spillover index tends to rise sharply in times of economic turmoil.

In addition, Antonakakis (2012) aims to evaluate the impact of the introduction of the euro on the interaction of different exchange rates. Following the methodology applied in D&Y (2012), the author concludes that there is a significant share of volatility within these rates, but the link was stronger before the introduction of the euro. Furthermore, he advocates that significant US dollar appreciations are positively correlated with volatility spillovers. The euro (Deutsche mark) is the dominant net transmitter of volatility and the British pound is the net receiver of volatility before and after the introduction of the euro. Empirical data also shows that european markets have the highest spillover index value.

Conefrey & Cronin (2013) is also inspired by D&Y's framework as it measures the gross and net spillover effects across euro area sovereign bond markets. Like many other articles, this investigation also detects a considerable increase of the spillover index around 2008. The authors suggest that Greece has becoming a relatively detached country from other bond markets after its second bailout in March 2012. Furthermore, a great spike in net volatility spillovers from PIIGs to the principal countries is observed at the time of the first Greece bailout.

More recently, Louzis (2013) aims to measure the interrelation of different financial markets in the euro area: money, stock, foreign exchange and bond markets in terms of return and volatility spillovers. The main findings of this paper suggest a high level of return and volatility spillovers amidst all markets. The volatility spillover index indicates that more than half of the forecast-error variance of the VAR model is explained by spillover effects. In particular, stock markets appear as the main contributors (transmitter) of these spillover effects and the bond market for the periphery countries[2] as the main receiver, in exception of the period 2011-2012 where they were net transmitters. The author also concludes that the money market has a

[2] Countries that were under financial support.

particular role on volatility transmission to other financial markets during crisis or periods of low liquidity.

In summary, there is an extensive and recent empirical research showing a significant level of volatility spillovers across multiple asset classes, particularly when highly developed markets are involved.

2.2. Return co-movements

Return co-movements has been a popular and interesting topic in finance as investors try to understand “what makes markets move?” or “how are they related with each other?”. Although nowadays it is common to witness high correlations among most developed markets, that was not always the case. Half a century ago, worldwide stock markets experienced very low return co-movements with USA. In fact, all countries, with the exception of Canada, manifested correlations with USA equal or lower than 0,3 (Grubel, 1968). In fact, during the 70’s, articles such as Agmon (1972), Lessard (1976), Panton, Lessig & Joy (1976) and Hilliard (1979) were published addressing covariances/correlations within markets, but despite using different methodologies, the results are similar. Erstwhile, co-movements between stock markets were unexpectedly low.

Such characteristics allowed for higher diversification benefits. With low correlations, investors can spread their capital through several countries in order to mitigate the risk for a given return. The goal is to balance negative and positive performances, so that the investor is not overly exposed to sudden bursts of volatility. On the other hand, if markets move as one, diversification becomes meaningless.

Nevertheless, the trend slowly started to shift. As economies evolve, linkages among worldwide economies begin to strengthen and it was just a matter of time until research started to capture these small, but important signs of growing interdependence [e.g. Schollhammer & Sand (1985), Eun & Shim (1989), Jeon & Von Furstenberg (1990) and Koch & Koch (1991)].

Being the attractive topic that it is, market co-movements never stopped as an important subject for several researches. Since then, numeric studies indicate that developed stock markets are widely related, but less-developed countries are more advanced, Friedman

& Shachmurove (1997). Moreover, Forbes & Rigobon (2002) conclude that correlations are conditional on market volatility. The authors acknowledge this bias and argue that, when adjusted, it eliminates contagion. All markets experience significant levels of co-movements throughout the data considered.

In particular, Bekaert, Hodrick & Zhang (2009) argues that European stocks are the only ones to display an increasing correlation. Beyond that, there is no proof that the stock returns' interdependence has increased over recent years.

So what are the main foundations for these changes? "…*as most advanced economies deregulated their capital markets, removed barriers to international investments, and improved the accessibility to information, investors in many countries have adopted a global view"* (Friedman & Shachmurove, 1997, 257). Quinn & Voth (2008) also point out capital openness as the main reason for the increasing levels of co-movements. As efforts to establish total free movement of capital continue to bring markets closer, diversification strategies are becoming less effective.

Return co-movements and volatility spillovers are closely tied together. In fact, one of the articles already mentioned in the previous sub-topic - Antonakakis (2012) - addresses both. The author argues that results show a high degree of return co-movements in some European exchange rates, but they are, on average, greater before the introduction of a single currency. Like what happens for the spillover index, US dollar appreciations appear to be related to return co-movements.

Up until the early 90's correlations were commonly measured using constant conditional correlation models that do not account for the true time-varying nature of these interactions. It has been showed that dynamic conditional correlation models (DCC) are more suitable to explain such events[3], since these models also consider time-varying variances and covariances present in each series. Antonakakis (2012) or Égert & Kočenda (2011), for example, use a DCC model proposed by Engle (2002) to measure exchange-rate returns co-movements.

However, in order to apply an appropriate model, one must know if the relationships are, indeed, dynamic. Accordingly, Tse (2000) proposes a test where the constant

[3] See Engle (2002) for more details on the performance of dynamic conditional correlation models.

correlations are considered in the null hypothesis, against an alternative where correlations are dynamic. In accordance with Forbes & Rigobon (2002), the main findings indicate a time-varying interdependence between stock markets, whereas spot-future prices and exchange rates have constant correlations.

2.3. Systemic stress/risk

Risk is a very broad concept. It can be associated with a wide variety of situations, which can go from a simple paper cut to a management of a sophisticated financial derivative. Risk management can be very useful for companies in general. It enables to identify and manage potential sources of danger, so that institutions can implement optimal strategies for each specific circumstance. As explained before, risk diversification can be one of many tools available to help in these cases, as investors try to apply their money in different assets and/or asset classes in order to mitigate their investment's risk for a given return. To do so, the investor has to consider two risk components: the specific and the systematic risks. Although the first portion represents the risk of an individual entity or asset and, thus, can be diminished through diversification, the latter cannot. Known as the overall risk of a financial market, the systematic risk is also famous for being undiversifiable. Investors must be always aware and able to identify both components and utilize the strategies that best fit each situation.

Although they share some similarities, the systematic and the systemic risks are different. While the first is associated with the whole market segment risk, the systemic risk is used to describe the threat of a possible crash of a whole industry or financial system due to a single event. The subprime crisis is a good example of what can happen if we do not consider this kind of risk.

Rochet & Tirole (1996, 733) is one the first steps towards analyzing systemic risk. The authors define it as "*the propagation of a bank's economic distress to other economic agents linked to that bank through financial transactions*".

The recent financial crisis demonstrated the gap between theory and reality. Since then, minds all around the world strive to fill that gap. The human mind is designed to find an explanation for everything, even for what is random and unpredictable. Hendry &

Grayham (2014) argue that the models that some central banks use to predict a financial crisis would also crash in that scenario. The authors emphasize questions like: how can we know with certainty that what happen in the past will happen in the future? The future is unknown, unpredictable and full of unexpected events. Forecasting models that central banks utilize are designed using past data. Thus, they take into consideration the averages and variations that occurred in the past to predict future fluctuations. Therefore, these models will remain valid as long as the financial structure stays the same. The problem is that a financial crisis is, at itself, a structural break. That is why most models fail to predict future crises.

Even though it is hard to forecast a crash, recent papers provide important insight on systemic risk. Haldane & May (2011) alert for the consequences of the introduction of new financial tools. These instruments were created to ensure optimal returns with minimal risks, but do not consider their impact on the stability of the banking system. The authors then suggest some policy lessons with the purpose of reducing systemic risk.

Acharya, Brownlees, Engle, Farazmand & Richardson (2011) show that the Systemic Expected Shortfall (SES) can be used to measure the directional contribution that a single institution can have on the systemic risk. It also introduces a single, non-complex model of systemic risk. The article shows the SES's capability to forecast some of the upcoming risks during the subprime crisis.

Bisias, Flood, Lo & Valavanis (2012) go for a more statistical approach, as it provides 31 different measures for systemic risk.

Hollo, Kremer & Lo Duca (2012) present the Composite Indicator of Systemic Stress (CISS), a new measure of contemporaneous stress in the financial system. It is a single measurement tool based on the structure of systemic risk. It contains a methodological novelty that allows to assign more weight to occasions, where financial stress prevails in the different markets simultaneously. This has the advantage of capturing how much the financial has diffused across the whole industry or financial system. The financial stress is more harmful in situations where the diffusion is greater. The more markets involved, the worst it is. Further in this thesis we will tackle how the volatility spillovers and the CISS move throughout time and witness their relationship.

3. Data description

In order to proceed with this study we collect data from January 2000 to January 2015, which will give almost 4000 daily prices to work with (3915 to be exact). The reason behind such period is to give us around seven years' worth of data before and after the bankruptcy of Lehman Brothers, which was a substantial mark of the subprime crisis. This timeline also covers other major economic events such as the dotcom bubble, the worldwide economic depression, the sovereign debt crisis and the recent Russian financial slump.

Due to different holidays and non-working days in each country, an interpolation method is used to avoid excluding more data. Depending on the number of days with missing data, we applied different versions of the same formula to fill those gaps.

As mentioned,

$$R_{i,t} = R_{i,0} + \frac{R_{i,T} - R_{i,0}}{T} \times t \qquad \text{(I)}$$

where $R_{i,t}$ represents the return of the stock market i at moment t. T is the number of observations until the next data available, with t being the number of days after the last missing data. Therefore, $t = 1, \ldots, T-1$.

This method has the advantage of avoiding any outliers. Throughout our data sample, there are cases where a stock market stays closed for one or more days (missing data), which may cause its price to jump instead of changing gradually. With this method we mitigate those jumps.

To replicate USA (US), Belgium (BE), Finland (FI), France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), the Netherlands (NL), Portugal (PT) and Spain (ES) stock markets we will use the daily prices of S&P 500, BEL 20, OMX Helsinki 25, CAC 40, DAX, Athens General, ISEQ Overall, FTSE MIB, AEX, PSI 20 and IBEX 35, respectively.

Note that we only want returns that come from variations in the price and not the exchange rate. If we use the same currency for all indexes (either all in USD or all in EUR) we will be exposed to exchange rate risk i.e., we will be including the returns (and volatilities) generated by changes in the exchange rate (and not only the price), specifically the EUR/USD rate. Thus, all euro area indexes will be priced in EUR and the S&P 500 in USD.

Weekly data will also be considered to analyze the volatility spillovers. In order to do so, we just have to focus our database on a Friday-to-Friday basis. This approach has the downfall of greatly reducing the number of observations, however it allows us to deal with daily noise that might come from using daily data.

All data mentioned before is sourced from Bloomberg.

Finally, to compare the systemic stress and the volatility spillovers we will use the CISS[4] for the equity market and the overall financial system, available in the European Central Bank's data warehouse and the FFSI, sourced from FRED. Both composites have a weekly frequency and will also contemplate the period considered for the volatility spillovers.

4. Methodology

To process the data we will use the regression analysis of time series (RATS) software that guarantees the best support for VAR models, which is the pillar of this work.

The software is also designed to deal with any data frequency, which is helpful because we will require daily and weekly data to address the two main topics of this thesis, return co-movements and volatility spillovers.

After obtaining the prices of each index we will use the natural logarithm to compute the daily returns, namely:

$$R_{i,t} = ln\left(P_{i,t}\right) - ln\left(P_{i,t-1}\right) = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \qquad \text{(II)}$$

$P_{i,t}$ is the price of the stock market i at moment t and $t = 1, 2, 3, \dots, T$.

[4] The euro area is used as a reference area to build this composite.

The returns will allow us to compute the weekly volatilities using a common realized volatility formula, such as:

$$\sigma_{i,x} = \sqrt{\frac{\sum_{t-4}^{t}[(R_{i,t-4} - \bar{R}_i)^2]}{5}} \quad \text{(III)}$$

where $\sigma_{i,x}$ is the weekly realized volatility of returns for the stock market i at week x, with $x = 1, 2, 3, \dots, X$ and $\bar{R}_i$ is the average of the last 5 (Monday-to-Friday) daily returns[5].

4.1. Return co-movements

A dynamic correlation analysis will be then implemented to clarify any co-movements amongst markets. Most common correlation equations assume that the variable's interrelation is constant through time. Nevertheless, it seems judicious to test if the interaction is, in fact, constant or if it is dynamic, i.e. if it changes as we advance in time. Tse (2000) solves this problem by proposing a test to assess if the conditional correlation is constant or dynamic:

H0: constant conditional correlation (CCC)
H1: dynamic conditional correlation (DCC)

If we do not reject the null, a constant correlation measure can be used to exhibit the overall magnitude of these relationships. Nonetheless, if the null is rejected, a DCC model needs to be implemented to better represent reality. Engle (2002) offers helpful insight into DCC models and alleges that they can adapt to different situations and provide sensible empirical results. For example, the model helps to deal with numerical problems that come from the usage of a large number of variables, in which the multivariate GARCH has to estimate several parameters at the same time. Additionally, it can generate covariances, correlations and variances that change throughout time.

This model estimates in two steps. First, each conditional variance is estimated through a univariate GARCH model. Then, the standardized residuals that we got from the previous procedure are used to obtain the conditional correlation matrix.

[5] D&Y's methodology applies a daily standard deviation using the high-low prices of stock markets.

The DCC model has the following specification:

$$r_t = \mu_t(\theta) + \epsilon_t, \text{ and } \epsilon_t \sim N(0, C_t) \tag{IV}$$

$$\epsilon_t = C_t^{1/2} v_t, \text{ and } v_t \sim N(0, I) \tag{V}$$

$$C_t = D_t M_t D_t \tag{VI}$$

$r_t = (r_{i,t}, \dots, r_{N,t})'$ is a 11x1 vector of stock returns, representing all markets from Belgium to USA. $\mu_t(\theta) = (\mu_{i,t}, \dots, \mu_{N,t})'$ is the conditional mean vector for the returns. C_t is the conditional covariance matrix. $D_t = diag(c_{ii,t}^{1/2}, \dots, c_{NN,t}^{1/2})'$ is a diagonal matrix with the conditional standard deviations and $c_{ii,t}^{1/2}$ can be explained by each univariate GARCH model. M_t is the $tx(\frac{N(N-1)}{2})$ matrix for all the time-varying conditional correlations:

$$M_t = diag(s_{ii,t}^{-1/2}, \dots, s_{NN,t}^{-1/2}) S_t diag(s_{ii,t}^{-1/2}, \dots, s_{NN,t}^{-1/2})$$

$$\text{or } \rho_{ji,t} = \rho_{ij,t} = \frac{s_{ji,t}}{\sqrt{s_{jj,t} \times s_{ii,t}}} \tag{VII}$$

and $S_t = (s_{ij,t})$ is a NxN symmetric positive definite matrix:

$$S_t = (1 - \alpha - \beta)\bar{S} + \alpha v_{t-1} v'_{t-1} + \beta S_{t-1} \tag{VIII}$$

and $\bar{S}$ is the NxN unconditional variance matrix of v_t. $v_t = (v_{1,t}, \dots, v_{N,t})'$ is the Nx1 vector of standardized residuals. The sum α and β must be lower than 1. Both parameters are equal or greater than zero (nonnegative condition).

α and β are non-negative scalar parameters that capture the effects of previous shocks and previous dynamic conditional correlations on the current on the current dynamic conditional correlation and should satisfy the condition $\alpha + \beta < 1$. As S_t is conditional on the vector of standardized residuals, (VIII) is a conditional convariance matrix and $\bar{S}$ is the unconditional covariance matrix of η_t. When $\alpha = \beta = 0$, $\bar{S}$ in (VIII) is equivalent to the covariance matrix of the CCC model proposed by Bollerslev (1990).

4.2. Volatility spillovers

D&Y (2009) changed the way we measure volatility spillovers by introducing, in their first work, a methodology based on a VAR framework that uses forecasted-error variance decompositions to determine the spillover index. However, it had some flaws that restricted its application. The original VAR uses a Cholesky decomposition which makes the results - variance decompositions - variable ordering dependent. This means that we need to know in advance which variables are theoretically more important (if there are any) and introduce them first. It would be better to let the data "speak by itself" and tell us which variables are more relevant.

The initial VAR framework only addressed the total spillover index and not the net directional spillovers. This can be viewed as a limitation since it does not allow to see which markets are, on average, receivers or transmitters of volatility. A directional spillover index would allow us to understand part of the market's volatility source.

D&Y (2012) implement a generalized vector autoregressive framework that is based on the research from Koop, Pesaran & Potter (1996) and Pesaran & Shin (1998). This approach creates variance decompositions that are independent of variable ordering. D&Y (2012) also introduce a directional spillover to overcome some of the limitations of their previous work. In the remainder of this section we will try to summarize and explain the D&Y's methodology.

Consider a N-variable VAR(p) that is covariance stationary:

$$y_t = \sum_{i=1}^{p} \theta_i y_{t-i} + \varepsilon_t \quad \text{(IX)}$$

where ε_t is a vector of independent and identically distributed disturbances $\varepsilon \sim (0, \Sigma)$.

Given that it is covariance stationary, the moving average form of (IX) is given by:

$$y_t = \sum_{i=1}^{\infty} A_i \varepsilon_{t-i} \quad \text{(X)}$$

where $A_i = \theta_1 A_{i-1} + \theta_2 A_{i-2} + \theta_3 A_{i-3} + \cdots + \theta_p A_{i-p}$ and A_0 is an $N \times N$ indentity matrix and $A_i = 0$ for $i < 0$.

Based on this, the variance decompositions allow us to determine a spillover index using H-step-ahead forecasted error variance, due to shocks from other markets or variables, i.e. shocks from j to i whenever $i \neq j$. If we consider the H-step-ahead forecasted-error variance decompositions as $\vartheta_{ij}^{g}(H)$ for $h = 1, 2, 3, \ldots$ we have:

$$\vartheta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \qquad \text{(XI)}$$

Σ is the variance-covariance matrix for the error vector ε, σ_{jj} is the standard deviation of the error for the jth equation and e_i is the selection vector with one as the ith element and zeros in the rest.

By construction, the sum of each variance decomposition is not equal to one, a requirement needed to build the spillover ratio. Therefore, each variance decomposition is normalized by its row (by the sum of the cells in each column of that particular row).

$$\tilde{\vartheta}_{ij}^{g}(H) = \frac{\vartheta_{ij}^{g}(H)}{\sum_{j=1}^{N} \vartheta_{ij}^{g}(H)} \qquad \text{(XII)}$$

This help us get what we need, $\sum_{j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H) = N$.

If we look to the diagonal elements of the matrix as the variance that the variable "generates" for itself, the other elements of the same column can be interpreted as the variance that comes from other variables, i.e. spillovers.

Thus, the total spillover is just the sum of each off-diagonal element of the matrix divided by the sum of each element of the matrix. We multiply each spillover ratio to gives a percentage.

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 \qquad \text{(XIII)}$$

As we can see the numerator does not consider cells that belong in matrix diagonal ($i \neq j$).

Now that we have all the variance decompositions that we need, we can use them to create any type of spillover that we want. By considering only the elements of one given column j we can determine how much of i's volatility comes from other variables. We just have to sum each element of that particular column (**excluding** the one in the matrix diagonal) and divided that by the sum each element of that particular column (**including** the one in the matrix diagonal). Accordingly, the directional volatility spillover can be written as a receiver or a transmitter denoted by $S_{i.}^{g}(H)$ and $S_{.i}^{g}(H)$, respectively.

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 \tag{XIV}$$

$$S_{.i}^{g}(H) = \frac{\sum_{\substack{i=1 \\ i \neq j}}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 \tag{XV}$$

A receiver represents the volatility that a market i receives from all other markets j, whereas a transmitter indicates the volatility that a market i transmits to all other markets j.

The difference between these two measures will tell us if the market is predominantly a receiver or a transmitter, depending on which directional spillover is greater.

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{i.}^{g}(H) \tag{XVI}$$

Note that we use a VAR with two lags (p = 2)[6] and a 10-step-ahead forecasted-error, thus H = 10[7].

5. Empirical results

5.1. Descriptive statistics

To analyze the statistics for each return series we have to examine table I (see next page).

[6] VAR(2).
[7] Other similar studies such as Antonakakis (2012) or D&Y (2012) also use a 10 forecast horizon.

Table I: Descriptive statistics of stock returns

Country	BE	FI	FR	DE	GR	IE	IT	NL	PT	ES	US	Stoxx
Mean	0	0	0,0001	0,0001	-0,0005	0	-0,0002	-0,0001	-0,0002	0	0,0001	-0,0001
Median	0,0004	0,0005	0,0003	0,0008	0,0001	0,0007	0,0007	0,0005	0,0001	0,0007	0,0005	0,0001
Maximum	0,0933	0,0929	0,1059	0,108	0,1343	0,0973	0,1087	0,1003	0,102	0,1348	0,1096	0,1044
Minimum	-0,0832	-0,0891	-0,0947	-0,0887	-0,1367	-0,1396	-0,086	-0,0959	-0,1038	-0,0959	-0,0947	-0,0821
Std. Dev.	0,0127	0,0153	0,0148	0,0152	0,0176	0,0139	0,0151	0,0146	0,0118	0,0149	0,0124	0,015
Skewness	0,0312	-0,1043	0,0127	-0,0303	-0,1563	-0,5993	-0,0776	-0,0951	-0,2008	0,0868	-0,1539	0,0031
Kurtosis	9,3515	6,4135	8,0382	7,6188	7,6998	11,1286	7,6922	9,6677	9,8653	8,2226	11,682	7,5742
Jarque-Bera	6578	1907	4139	3479	3617	11007	3594	7254	7711	4452	12305	3411
Probability	0	0	0	0	0	0	0	0	0	0	0	0
ADF*	-58,67**	-60,33**	-30,96**	-63,35**	-56,74**	-59,31**	-29,43**	-30,07**	-57,81**	-62,22**	-48,55**	-30,64**
KPSS[a)]	0,123**	0,265**	0,118**	0,211**	0,142**	0,160**	0,069**	0,179**	0,122**	0,095**	0,280**	0,128**

* Augmented Dickey-Fuller test with no intercept nor trend was implemented to verify the existence of a unit root. Critical value at 1% is – 2,58.
** 1% significant.
a) Kwiatkowski-Phillips-Schmidt-Shin test with intercept and no trend was also implemented to verify the existence of a unit root. Critical value at 1% is 0,739.

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Considering all 3914 observations, DE (along with US) and GR markets have the largest and lowest average returns, respectively. The latter reflects the consequences that GR faced due to both the sub-prime and the sovereign debt crises. As a whole, the euro area (Euro Stoxx) and the US have symmetric average returns of -0,0001 and 0,0001, respectively.

Following the same thought, GR also has the largest standard deviation. A difference of, at least, 0,2 percentage points in comparison to other markets. Curiously, Portuguese stock appears as the “safest” asset.

Since the kurtosis values are, for all series, far greater than zero, it is presumable that all series are not normal distributed. As expected, that premise is confirmed as the null for all Jarque-Bera tests is rejected.

The same happens in the Augmented Dickey-Fuller (ADF) tests as the hypothesis for the existence of a unit root is rejected in each return series considered. Each series stationarity is also supported by the KPSS unit root test. Unlike the previous test (ADF) the KPSS’s null hypothesis represents the stationarity of a given series and the results displayed are consistent with the ones gotten from the ADF test, i.e., the null is never rejected.

In order to get an overall view for the major shifts since the change of millennium, we take a small glance into the American (USD) and the euro area (EUR) indexes in levels.

Fig. I: American and euro area indexes in levels

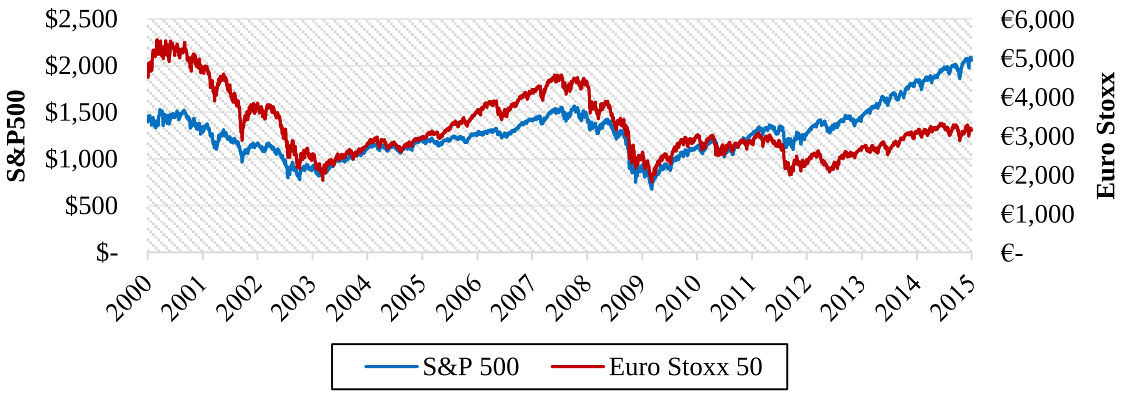


Figure I shows the evolution of the Standard and Poor's 500 index (S&P 500) and the Euro Stoxx 50 index from 2000 until 2015 in levels. Both indexes are world widely accepted to characterize the American and the euro area stock markets, respectively. During that period, the American market has a steadier curve, whereas the euro area is much more volatile. Nonetheless, the two indexes seem to move in the same direction. For example, both variables manifest crashes after 2000 and 2007/08 as a result of the dotcom and the sub-prime crises, respectively. Moreover, since the beginning of 2012 that both markets have an upward slope consistent with the overall economic recovery. Note that, despite experiencing a positive relationship, variations are lower in the American market which is in accordance with the fact that the S&P 500 has a steadier curve.

If we compare figures IA and IB (below), we can interpret that in the second period (IB) the lines change closely together than the ones from the previous period. This could suggest an increase in market co-movements. In fact, the orthodox unconditional correlations given in table X reflect just that, as the interdependence strengthens after the subprime crisis – from 0,52 to 0,63. Furthermore, Sandoval & Franca (2012) and Dalkir (2009) show that in situations of high volatility, like, for instance, recession periods, correlations across markets rise. In addition, Dalkir concludes that the higher levels of co-movements remain even after the turbulence dissipates. Given that investors are risk averse, a jump in uncertainty will result in a significant number of dropouts – less demand/more supply – leading to a decrease of value. Negative returns will then originate more skepticism, keeping the circle "alive". The same mechanism can happen for positive returns, which can help create a bubble, however, studies on financial behavior argue that investors are much more affected by losses than profits. The evolution of technologies and information flows also help investors keeping track of the worldwide economy and financial assets.

Fig. I.A: American and euro area indexes in levels **before** the subprime crisis, 2084 obs

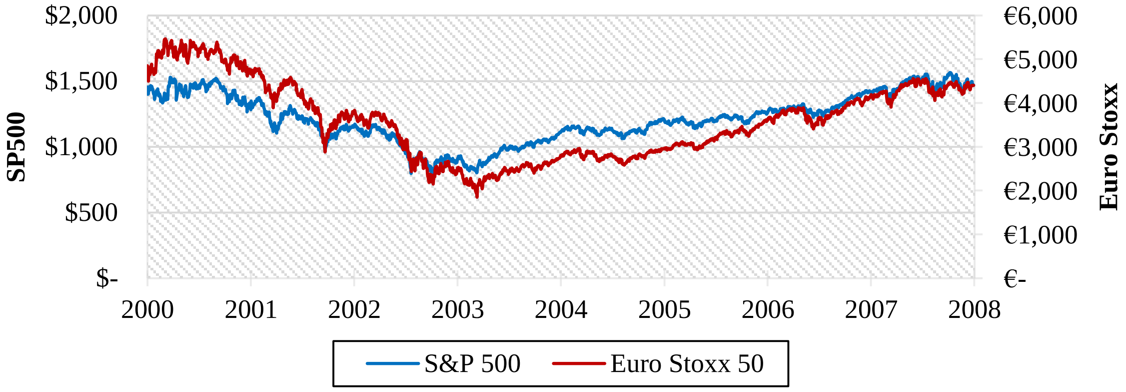
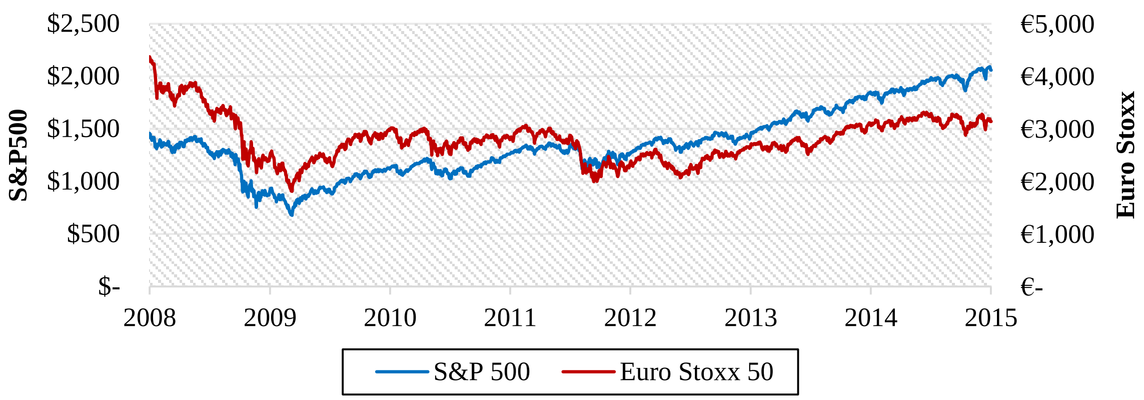


Fig. I.B: American and euro area indexes in levels **after** the subprime crisis, 1829 obs



In Table VIII (see annexes) are presented unconditional correlations amidst all stock indices to give us an idea of the each relationship's strength.

$$corr_{ij} = \rho_{ij} = \frac{\sigma_{ij}}{\sigma_i \sigma_j} \quad \text{(XVII)}$$

In majority, correlations are greater than 0,6 which shows that markets experience a considerable positive interrelationship. However, there are two special cases: GR and US. In the first situation, all correlations are lower than 50%. Despite sharing the same currency (euro) these results are somewhat of expected since GR was one of the most affected countries by the sub-prime crisis and, more recently, the sovereign debt crisis. Such events raised the level of uncertainty around this country and investors became much more skeptic. In the case of US, almost half of the correlations are also lower than 0,5.

5.2. Stock return co-movements

Here we will discuss the results obtained from applying the co-movement methodology of Engle (2002) to the US with the euro area stock markets' returns. First, we have to test if the correlations are constant or dynamic, i.e. if the correlations are time-varying or not. Accordingly, we perform the test proposed by Tse (2000). As we can see from table II, the null hypothesis for a constant conditional correlation is rejected at the 1% significance level. This would suggest that a DCC model is more accurate to represent the reality of our data. Thus, the methodology of Engle (2002) is applied to describe such interactions.

Table II: Tse test for CC

Chi-Sq (55)	Sig. Level
112,81	0

According to results from the Tse test displayed in table II, we can conclude that conditional correlations are dynamic since the null is rejected at the 1% level. Thus, a DCC model is the more advisable approach to represent the proper features of this sample.

The simplest case is the GARCH (1,1), $h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$, that has become the most popular application in modeling the time-varying conditional volatility (see, e.g., Baillie & Bollerslev, 1992 or Hansen & Lunde, 2005).

As we can see from table III (see next page) all the estimates for the coefficients α (ARCH) and β (GARCH) are statistically significant at a 1% level, i.e. the associated terms (lagged error and conditional variance) are all statistically relevant to explain changes in the dependent variable. Further, the ARCH estimates tend to be small (less than 0,2) and the GARCH estimates are generally high. As a result, the degree of long run persistence, $\alpha + \beta$, is close to one, which supports long memory processes.

Peculiarly, GR emerges as the index with the greatest long run persistence, whereas the Belgian and the Portuguese stock markets show the highest short run persistence.

Table III: GARCH estimates

Panel A: Step one - GARCH estimates

Country	BE	FI	FR	DE	GR	IE	IT	NL	PT	ES	US
Constant	0,023	0,016	0,023	0,018	0,015	0,023	0,017	0,021	0,014	0,023	0,017
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
$\boldsymbol{\alpha}$	0,108	0,062	0,077	0,077	0,089	0,100	0,075	0,087	0,108	0,086	0,096
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
$\boldsymbol{\beta}$	0,876	0,930	0,911	0,913	0,912	0,889	0,919	0,900	0,887	0,905	0,893
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

* Values between ( ) represent the probability values associated with the t-student statistic.

Panel B: DCC estimates

$\boldsymbol{\alpha}$	0,012
	(0)
$\boldsymbol{\beta}$	0,981
	(0)

Truthfully, if we scrutinize the results, we detect that, for the Greek market, the sum of the estimates for α and β is higher than one. Consequently, it is plausible that there is a unit root in the GARCH process. This feature alters how a time series develops in the long run, thus affecting our interpretation of the results. In the presence of a non-stationary process, i.e. when $\sum_{i=1}^{p} \beta_i + \sum_{i=1}^{q} \alpha_i = 1$, an IGARCH must be deployed. By construction, this particular version of the classic GARCH modifies how we compute the symmetric positive definite matrix[8] in the DCC model:

$$S_t = \alpha v_{t-1} v'_{t-1} + \beta S_{t-1} \qquad \text{(XVIII)}$$

Nevertheless, first we need to test if the sum of α and β is, indeed, one. The Wald test is a parametric statistical procedure that enables us to verify the accurate value of a given coefficient based on an estimate. Hence, the two hypotheses can be expressed as:

H0: $\alpha_i + \beta_i = 1$
H1: $\alpha_i + \beta_i \neq 1$

After a brief group of tests, we realized that, in general, the null hypothesis is not rejected. As a result, and consistent with a study from Engle & Bollerslev (1986), an IGARCH model is more desirable to address the existence of a unit root. Subsequently, the same authors published another article[9] to support the importance of IGARCH models to manage the existence of an estimated unit root, which is common on series that utilize high frequency data.

[8] See equation (VIII).
[9] Bollerslev & Engle (1993)

Table IV: Step one – IGARCH estimates

Panel A: IGARCH estimates

Country	**BE**	**FI**	**FR**	**DE**	**GR**	**IE**	**IT**	**NL**	**PT**	**ES**	**US**
Constant	0,019	0,013	0,017	0,013	0,018	0,023	0,015	0,016	0,013	0,020	0,015
	(0)	(0)	(0)	(0)	(0,0001)	(0)	(0)	(0)	(0)	(0)	(0)
$\boldsymbol{\alpha}$	0,117	0,069	0,086	0,084	0,089	0,113	0,081	0,097	0,112	0,095	0,107
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
$\boldsymbol{\beta}$	0,883	0,931	0,914	0,916	0,911	0,887	0,919	0,903	0,888	0,905	0,893
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

* Values between ( ) represent the probability values associated with the t-student statistic.

Panel B: DCC estimates

$\boldsymbol{\alpha}$	0,013
	(0)
$\boldsymbol{\beta}$	0,982
	(0)

Panel A of table IV plots the coefficient estimates for the IGARCH process. Again, the ARCH and GARCH estimates are all statistical significant at the 1% level. Consequently, empirical evidence shows that the market's one lagged day shock (α) and one day lagged volatility (β) are relevant to explain its own volatility. By construction, the sum of each market's α and β is, now, equal to one.

Further, the DCC estimates (α and β) displayed on panel B are, once again, statistically relevant to explain fluctuations on the dependent variable, i.e., the impact of past shocks on current conditional correlations (α) and the impact of previous dynamic conditional correlations (β) are statistically significant. This suggests that the conditional correlations are time-varying and sustains that, in this case, the DCC specification is more appropriate to address the true nature of these series. Additionally, note that the estimate α is almost null, whilst β is practically one, which indicates that, according to equation (XVIII), the matrix S_t is almost totally explained by its one day lagged self (S_{t-1}).

Table V: Step two - correlation estimates from the standardized residuals

DCC covariance/correlation matrix

	BE	**FI**	**FR**	**DE**	**GR**	**IE**	**IT**	**NL**	**PT**	**ES**	**US**
BE	1,00										
FI	0,69	1,00									
FR	0,81	0,79	1,00								
DE	0,77	0,75	0,90	1,00							
GR	0,44	0,43	0,43	0,42	1,00						
IE	0,61	0,61	0,65	0,61	0,40	1,00					
IT	0,75	0,72	0,87	0,83	0,42	0,59	1,00				
NL	0,81	0,78	0,91	0,87	0,44	0,65	0,82	1,00			
PT	0,59	0,61	0,64	0,60	0,40	0,50	0,62	0,62	1,00		
ES	0,74	0,72	0,86	0,81	0,43	0,59	0,84	0,80	0,66	1,00	
US	0,50	0,45	0,56	0,59	0,23	0,38	0,53	0,54	0,37	0,51	1,00

In step two we estimate the conditional correlations. Unlike the ones given in table VIII, these are dynamic, thus they are more suitable to represent the time-varying component. Nevertheless the results are similar. GR stands out as the country with, on average, the lowest co-movements with other markets. US also has some of the weakest interconnections in comparison to other markets. With respect to the US, the use of a different currency unit and the independent economic policies can justify these differences.

On the other hand, stock markets from FR and the NL have, on average, a strong correlation with other countries. In section 5.3.2. we will also realize that these two countries are net transmitters of volatility spillovers.

5.3. Volatility spillovers

In this section we show and interpret the results got from applying the methodology of D&Y (2012). Realized weekly volatilities with a Friday-to-Friday approach were used as input. D&Y (2009) propose a formula following previous literature originated in Parkinson (1980) to compute daily standard deviations using the high and low values of each stock's price, however this approach does not allow to deal with any daily noise that might come from using day-to-day data. In accordance, Black (1986) argues that noise is everywhere and it is what makes trading in stock markets possible. Traders see these fluctuations in prices as random changes (or noise) and try to profit from them by the use of algorithms. These strategies can be implemented without any use of fundamental information.

After a more wide analysis, a rolling sample will be implemented to observe the behavior of all variables throughout the period considered since it seems unlikely that any single fixed-parameter model would apply over the entire sample. In this vein, we estimate the D&Y spillover measure on a moving window basis as it allows us to construct time-varying spillover indices that reflect the economic and financial evolution.

Finally, results for net directional spillovers are displayed to conclude about which markets are net transmitters/receivers.

Table VI: Volatility spillovers of returns

	From (j)											
To (i)	**BE**	**FI**	**FR**	**DE**	**GR**	**IE**	**IT**	**NL**	**PT**	**ES**	**US**	From Others
BE	17,5	6,2	12	8,9	2,8	7,8	8,7	13,3	6,2	9,5	7,1	83
FI	8	20	10,8	8,2	3,3	5,8	8,7	9,4	7,1	9,9	8,8	80
FR	10,9	7,5	14,8	10,9	2,4	5,3	9,7	13,7	5,9	11,2	7,5	85
DE	10,5	7,2	13,6	16,2	2	4,4	9,3	14,4	4,7	9,9	7,9	84
GR	6,3	7,1	6,6	4,2	37,8	5,3	8,1	5,3	9,3	7,2	2,9	62
IE	11,9	7,4	8,2	4,6	3,2	25,2	6	8,9	7,9	8,1	8,5	75
IT	9,9	7,4	12	9,6	3,6	4,7	16	10,4	8,1	11,7	6,7	84
NL	12,3	6,4	13,5	10,9	1,9	6,3	8	18,1	4,9	9,9	7,8	82
PT	9,3	7,9	9,3	6	5	6,6	9,4	7,6	23	10,7	5,1	77
ES	9,6	7,4	12,4	8,8	3,6	5,2	10,6	10,9	8,2	16,7	6,6	83
US	10	7,6	9,8	6,6	1,7	9,2	6,8	10,9	5,7	8,1	23,5	76
Contrib. to others	99	72	108	79	29	61	85	105	68	96	69	871
Contrib. incl. own	116	92	123	95	67	86	101	123	91	113	92	**79,20%**
Net Spillover	16	-8	23	-5	-33	-14	1	23	-9	13	-7	

Table VI shows the overall spillover index and the directional spillovers for this sample. Is important to explain how it should be interpreted to avoid any problems.

Each column represents the volatility spillover that the country *j* transmits to each one of the remaining markets. Therefore, the sum of all the cells, excluding the main diagonal, in a given column represents the contribution that a given country is transmitting to others. If we include the main diagonal, we are looking to the contribution including the market itself.

Following the same rationale, each row represents the volatility spillover that a given country *i* receives from each one of the remaining markets and its sum, excluding the main diagonal, will tells us how much spillovers a given market is receiving from all the other indexes.

The sum of all contributions to others and the sum of all from others is the same and, when divided by the sum of all contribution including the market itself, results in the overall spillover index: 79,2%.

The net spillovers are just the difference between the contribution to other and the contribution from others.

Now that we covered the interpretation of table VI, we will evaluate the obtained results. First and foremost, it is possible to see that the overall spillover index is quite high – almost 80%. This indicates that the spillovers from the market itself can only explain a small part of the share of volatility. Such a high spillover index reflects the great interdependency in today's developed markets. This value if boosted due to the fact that almost all of our sample is composed by euro area countries: 10 out of 11. The use of a single currency helps union markets. The countries' inability to freely adapt their economic and fiscal policies and the use of a common monetary policy make euro area countries closely linked. A shock in euro has an impact on all of them. In comparison to the D&Y (2009) results for worldwide stock markets, our spillover index is twice as big, 79,2% against 39,5%, pointing to the greater interdependency of euro area markets. This can also be explained by the fact that the sample period and, of course, the countries analyzed are different than the ones used by D&Y (2009).

In addition, GR stands out as the major receiver of spillover volatility. Since the recent crises and the struggle to produce economic growth, the fragilities of the Greek economy were exposed. Thus, any sudden changes in euro area markets would greatly impact Greek markets. The same argument can, in some degree, be made for the fact that IE and PT are also receivers of spillover volatility, as both countries faced their own harsh times.

In contrast, FR and the NL appear as the main transmitters of spillover volatility.

Although our findings appear to be quite good, they are not new in Europe. Some of the articles already mentioned here and others such as Alter & Beyer (2014), Antonakakis & Vergos (2013) and Sosvilla-Rivero & Morales-Zumaquero (2012) also show significant volatility spillovers for different financial markets in the eurozone.

5.3.1. Rolling sample

In general, table VI offers insightful information regarding overall and directional spillovers across markets. However, it does not allow to witness the fluctuations over time. In fact, it seems reckless to think that any single fixed-parameter model would apply through the entire sample. To circumvent this, a moving window basis of the overall D&Y's spillover measure is implemented in order to construct a time-varying spillover index. Along these lines, we use a 100-week rolling sample to produce a rolling spillover ratio.

Fig. II: Spillover index with a 100 weekly rolling sample

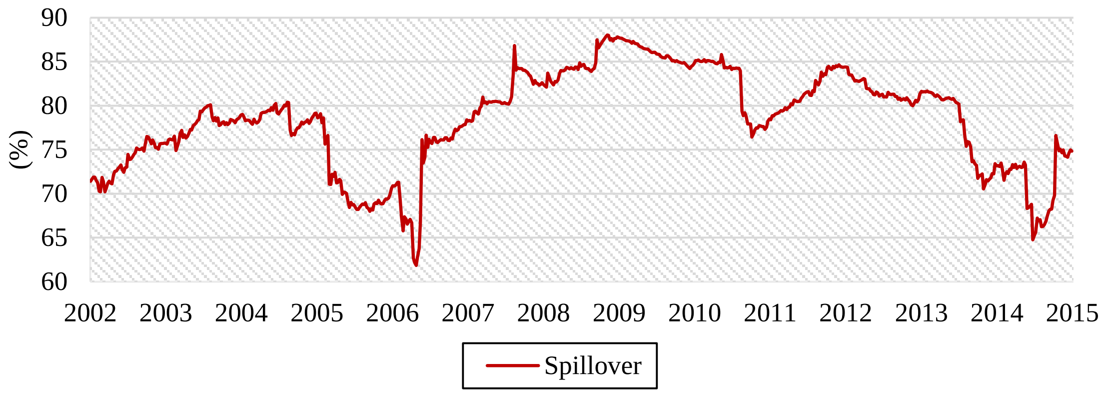


Fig. II illustrates the evolution of the spillover index using a roll-over approach with 100 observations. This allows us to witness how diffusion patterns evolve throughout time.

It is relatively easy to notice different trends. For example, from 2002 until 2005 the spillover index increases coinciding with the post dot-com crisis, but since then until midst 2006 it starts to fall. Then, after achieving its lowest level, the index erupts until 2008/09, where it flattens until 2010, reflecting the first symptoms and developments of the subprime crisis. Notice that, during the end of that decade which was a period also marked by the Irish banking crisis, the spillover index reaches its highest level. Curiously, after that point the measure starts falling, in exception for 2011 with the emergence of European sovereign debt crisis. It is only after 2014 that the spillovers begin again to rise, at the same time that a financial slump begins to develop in Russia

(RU). Although RU is not part of our database, the overall distrust can spread out to the euro zone and possibly increases the spillover ratio.

To examine the rolling windows' robustness, we re-computed the rolling spillover index using different magnitudes for the associated parameters. This will allow us to access if this procedure is robust to changes in: (i) the length of the rolling windows, (ii) the number of steps ahead utilized to generate the variance decomposition and (iii) the number of lags in the VAR. Formerly, we computed the rolling windows using a two lagged VAR with a 10-step-ahead forecasted-error variances and a 100 weekly rolling sample. Alternatively, we provide two different situations to infer about the overall robustness of this procedure:

A. VAR (3), 15 ahead forecast and 150 weekly rolling sample
B. VAR (4), 20 ahead forecast and 200 weekly rolling sample

As we can perceive below by figures IIA and IIB, the two alternative scenarios produce similar evolutions when compared to our benchmark spillover index, thus suggesting an overall robustness of our rolling windows.

It is also possible to notice that, even though the trends and fluctuations appear to match in all scenarios, the variations are, in general, lower for the alternative settings.

Fig. IIA: Spillover index with a VAR (3), 15 ahead forecast and 150 weekly rolling sample

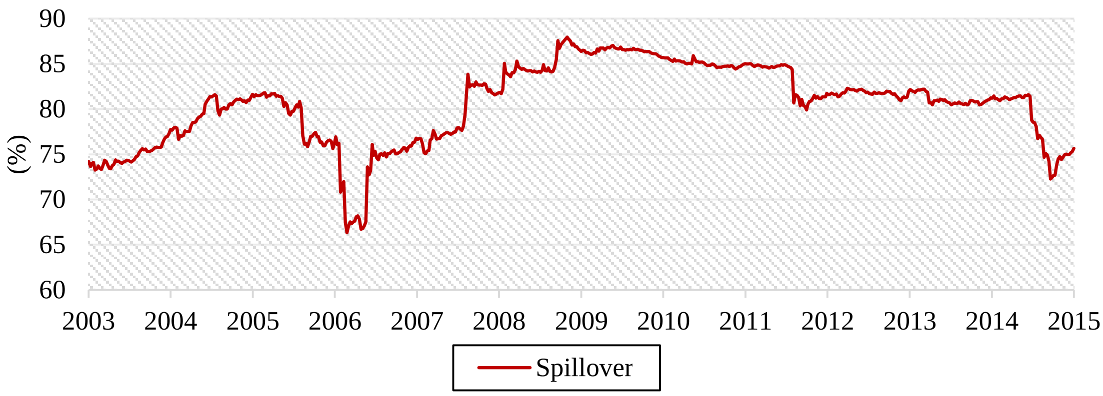
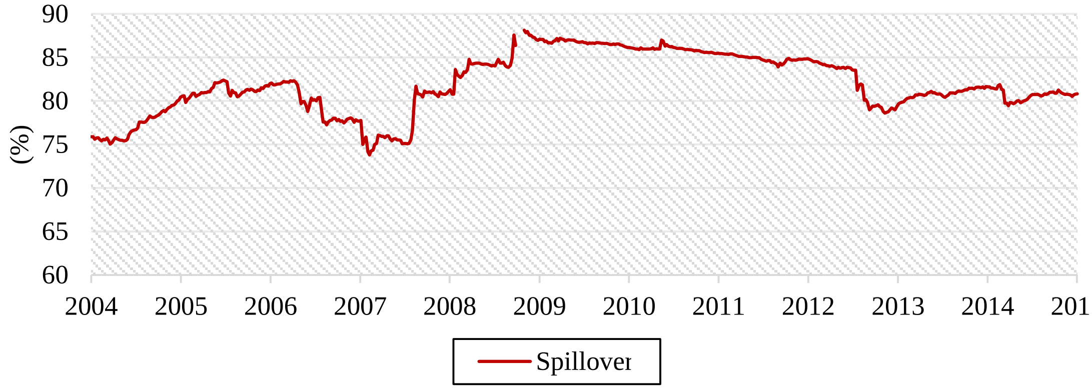


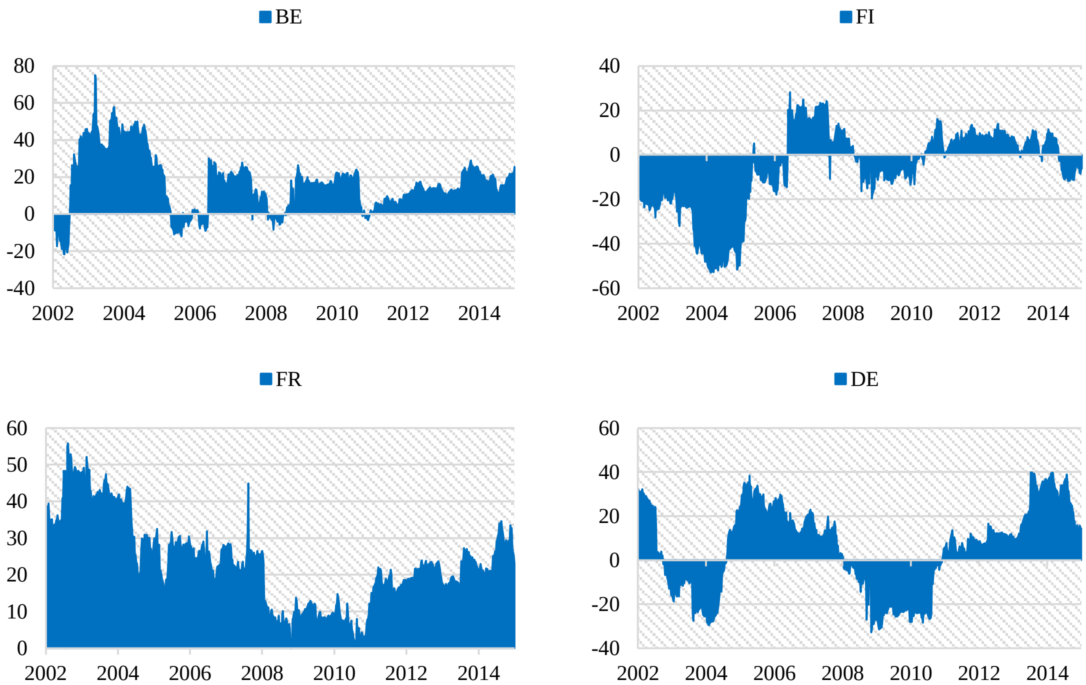
Fig. IIB: Spillover index with a VAR (4), 20 ahead forecast and 200 weekly rolling sample

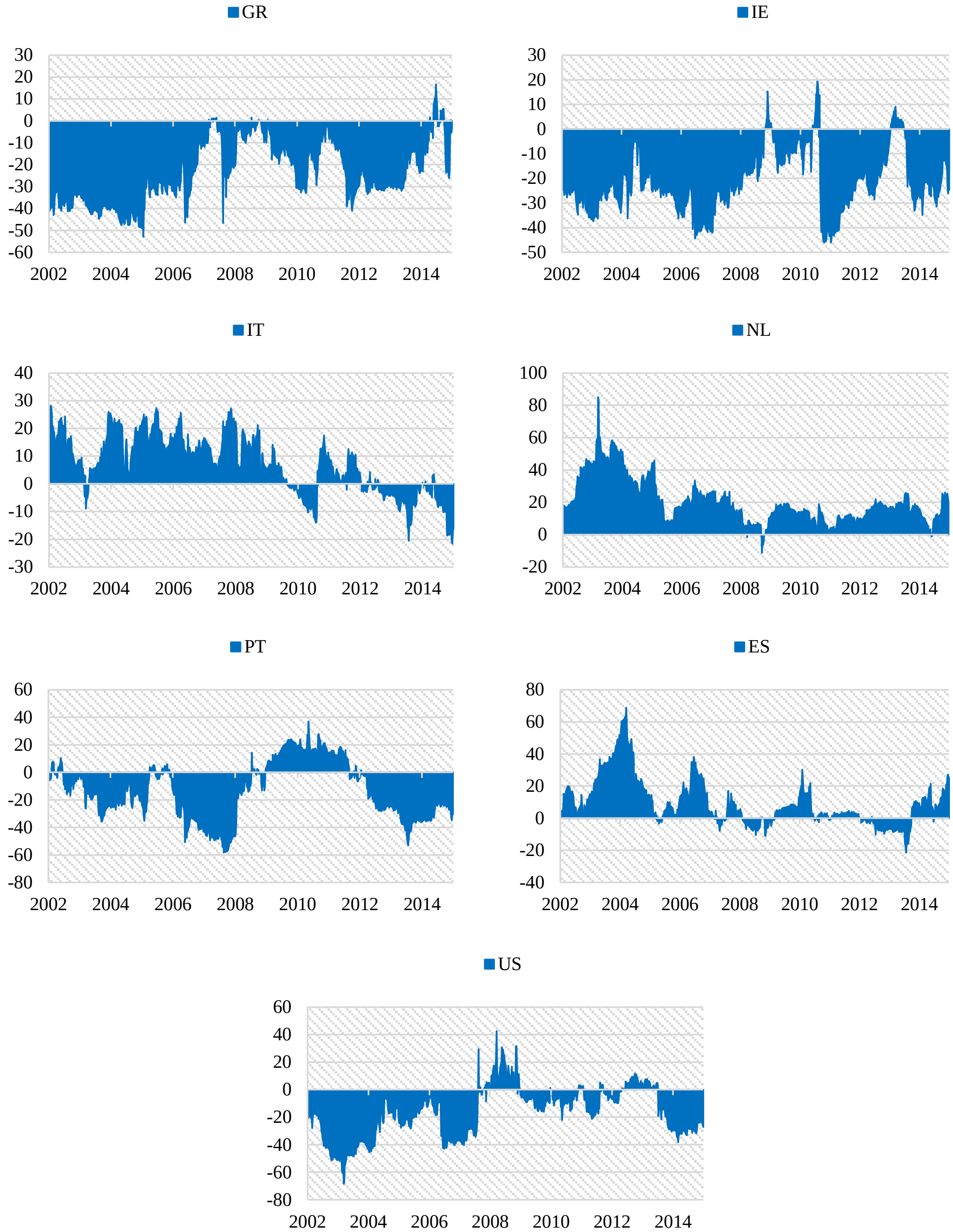


5.3.2. Net directional spillovers

The net directional spillovers are computed using equation (XIV). By construction, it provides us the difference between the spillovers that a given market transmits to others and the spillovers it receives from all others. Therefore, a country with positive net directional spillovers indicates that it transmits more than it receives, i.e., it is a net transmitter. The opposite case is considered a net receiver.

Fig. III: Net spillovers using a 100 weekly rolling sample





On average, BE, FR, IT, NL and ES are net transmitters of spillovers. Particularly, FR has never been, during this sample, a net receiver of volatility, which suggests that others countries are susceptible to sudden changes in the French stock market. NL presents a similar case, since there is only a short period (around 2008) where the country is a net receiver.

Oppositely, GR, IE, PT and US are, on average, receivers of volatility spillovers. The first two are the opposite case of FR and the NL, because both are almost always net receivers of volatility spillovers. This indicates that these countries are somewhat dependent of bursts in other nations. A curious case can be made about US, given that it was expected that this particular market would express an overall strong net transmission of volatility spillovers, but evidence shows quite the opposite.

The general large values for all the net volatility spillovers are consistent with the high level of spillover index established in table VI.

6. Sensitive analysis

In this thesis, the spillover index (or output) is computed using realized weekly standard deviations (or inputs). Therefore, our results are directly linked to how we estimate these volatilities, but what happens if we change our inputs? Or, in this case, what happens when we change the way we estimate these volatilities?

There are many ways to do a sensitive analysis which allow us, among other considerations, to test the robustness of our results and evaluate the level of uncertainty of the output. D&Y (2012) use a simple formula to compute daily standard deviations using only the high and low daily prices.

$$\tilde{\sigma}_{i,t} = \sqrt{0{,}361[\ln\left(P_{i,t}^{max}\right) - \ln\left(P_{i,t}^{min}\right)]^2} \tag{XIX}$$

In this section, we will witness the impacts in the spillover index and the rolling-sample analysis if we use this formula to estimate our inputs.

Due to missing data regarding the high/low prices of the Italian index (FTSE MIB), we will only use daily prices from late June, 2003 until January 2015. This still accounts for over 3000 observations, which gives us roughly less 1000 (-25%) daily prices. However, since we used weekly standard deviations to compute the previous volatility spillovers, the actual amount of inputs is, now, four times higher.

Even though we are aware that these changes on our database can mislead us, we feel that we need to at least comprehend what happens when we use different inputs or methodologies, but always keeping in mind that any major differences or similarities may be exclusively a consequence of this.

6.1. Spillover Index

To have a clearer view of the changes across volatility spillovers using the different methods, next we provide a comparison over the net spillovers of stock indexes.

Table VII: Regular volatility spillovers versus sensitive analysis

	Net Spillover											Total
	BE	**FI**	**FR**	**DE**	**GR**	**IE**	**IT**	**NL**	**PT**	**ES**	**US**	**Index**
Spillover	16	-8	23	-5	-33	-14	1	23	-9	13	-7	**79,2%**
Sensitive Analysis	5	0	18	-1	-33	-14	8	6	-4	-1	15	**80,0%**

According to Table VII, it is possible to verify that, aside from ES and the US, the results displayed are quite similar (in terms of being a net transmitter or receiver of volatility). Actually, GR and IE maintain the exact levels of net spillovers with -33 and -14, respectively. On the contrary, the US shows the biggest variation, going from -7 to 15. Moreover, despite the magnitude of each net spillover has decreased, in overall terms, the total spillover index does not change much, staying near the 80% mark.

6.2. Rolling Sample

Just like we did previously, here we apply a rolling sample to the "new" data available. To ensure that the method is based on the same information, we consider 500 daily observations in order to simulate two years' worth of data. This allows us to match the 100 weekly observations used previously (also around two years).

Fig. IV: Sensitive spillover index versus regular spillover index using a two year rolling sample.

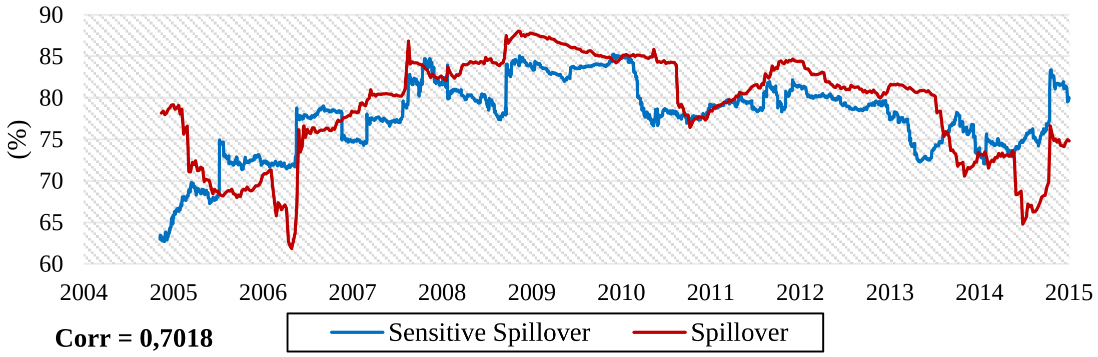


Figure IV - and the considerable high correlation - demonstrates that the two spillover measures have a similar behavior throughout time. Both variables experience greater values from 2007 to 2013, but start to softly decrease after that. It was just recently that the overall spillover indices began to rise once again. These fluctuations are in accordance with all the economic disturbances that affected this period. The spillover measure appears a little more volatile than the sensitive one, since its increases and decreases are, in general, greater. One explanation for this particularity is the fact that spillover roll-over measure relies on weekly observations, exposing it to sudden changes within that given week. Conversely, the sensitive measure’s roll-over method is associated with daily standard deviations, allowing it to reflect the current market conditions. However, the daily standard deviations are computed using only daily high and low prices.

In summary, it is clear that the results gotten from both approaches are in tune and consistent with the financial and economic environments experienced during this sample, which may point to an overall robustness of our data. Nonetheless, as we mentioned before, the data changes may, or may not, be misleading our comparison of both results.

7. Systemic stress and volatility spillovers

As a way to add insight surrounding the spillovers and how we can relate them to other financial areas, we will first compare the CISS presented in Hollo, Kremer & Lo Duca (2012) against the rolling over of the spillover index for only the euro area markets and see if we can identify any similarities. Since the CISS considers only the euro area markets it would not be wise to include the S&P 500 in this first analysis, so we exclude it. To complement our research we will also analyze the Fed Financial Stress Index (FFSI) alongside the spillover’s index.

In this section we will do the comparison using the overall CISS for the euro area and the CISS-equity for equity markets.

7.1. Overall and equity CISS vs spillover index

Fig. V: Overall CISS and spillover index with a 100 weekly rolling sample

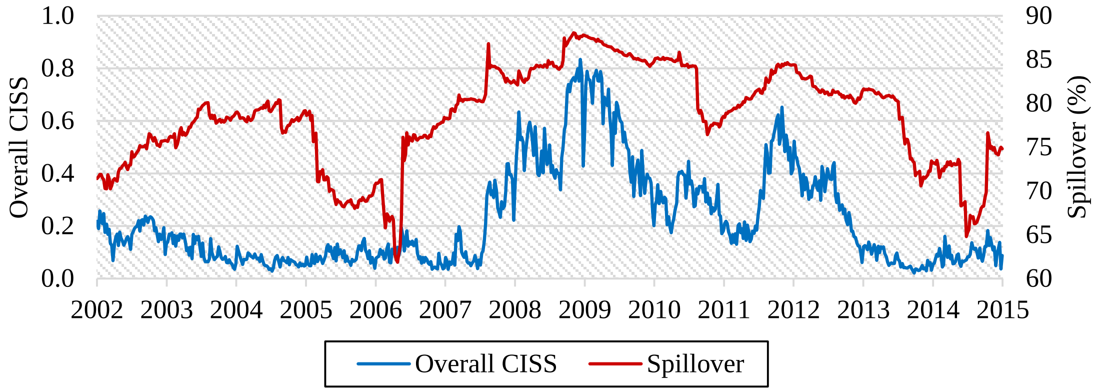
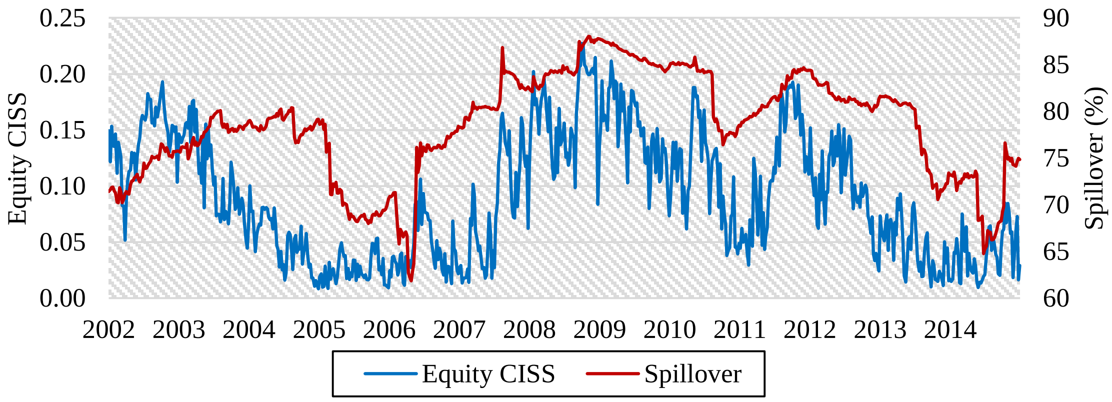


Fig. VI: Equity CISS and spillover index with a 100 weekly rolling sample



In compliance with both figures V and VI, the spillover ratio seems to manifest a positive relationship with the overall and equity CISS, respectively. All variables exhibit a peak in 2009 and another high level in 2012, which is consistent with the subprime crash along with the sovereign debt crisis in Europe. The fact that all variables achieve their peaks during that period confirms the severity of that situation. Since the end of 2012 is showed a downward tendency across variables. Also, both CISS measures appear to be more volatile than the spillover roll-over index.

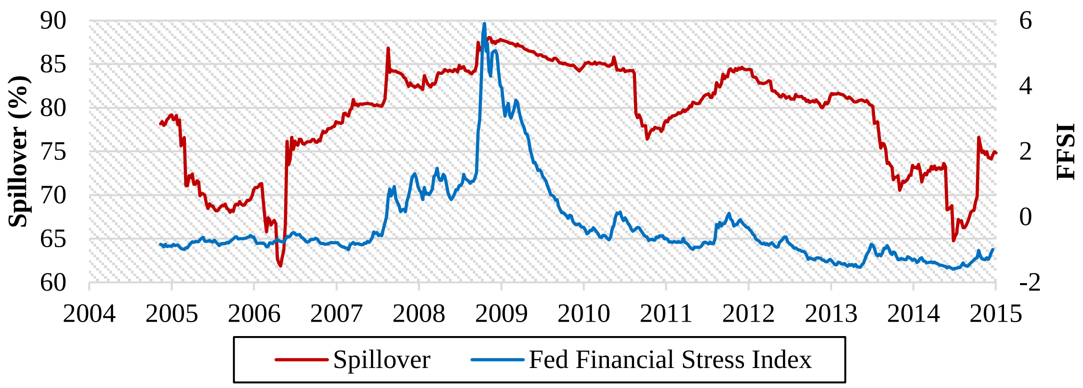
Additionally, on average, the trends of the spillover index and the CISS appear to be correlated. In fact, the larger the spillovers are, the greater the interdependency of markets is expected to be. When the spillovers remain at a high level, a sudden burst in a given market's volatility can have a major impact on remaining markets, especially during a crisis, thus increasing the possibility of a systemic crash. According to this thought, the greater the spillover index, the greater should be the CISS, which represents a higher probability of a systemic default.

7.2. Fed Financial Stress Index vs spillover index

The FFSI is given by the Federal Reserve Economic Data (FRED) and measures the level of financial stress across markets. This index summarizes data gathered from 18 weekly series: seven interest rates, six yields spreads and five other indicators and should embody the economic landscape.

Unlike the previous composite, the FFSI may display negative values. Any value below zero is considered to be below-average and indicates that the financial distress is under its typical standards. On the contrary, positive values suggest that the financial distress is above-average. Thus, zero accounts for the average of the index[10].

Fig. VII: FFSI and spillover index with a 100 weekly rolling sample



According to figure VII, the FFSI is only positive during the subprime turmoil, suggesting a financial distress beyond its usual standard. Subsequently, the index drops below zero indicating under-average financial hazard. This is not consistent with the fluctuations of the spillover index. Despite reaching their respective spikes around the same period, the spillover index remains high for most of its series, whilst the FFSI decreases shortly after.

[10] The index starts in late 1993

8. Conclusions

In this thesis we analyze return co-movements and volatility spillovers amidst 10 euro zone and an American stock markets since 2000 until 2015. In order to do so, a dynamic conditional correlation and a generalized VAR are implemented to address both topics, respectively. A comparison between the systemic stress and the volatility spillover index in then considered.

These methodologies allowed us to gather some of the following results. Focusing first in the return co-movements, time-varying correlations are fitter to represent reality. Thus, Greece and United States stand out as the two most independent countries of our sample, whilst France and the Netherlands are the most correlated ones. Regarding the volatility spillovers, the methodology from Diebold and Yilmaz (2012) overcomes the problem regarding the ordering of variables and provides a spillover index that appears to coincide with major economic events/crisis, namely the dotcom, the subprime, the sovereign debt and the Russian financial crises. In the 11 stock markets considered, the level of volatility spillovers is substantially high (79,2%), emphasizing the importance of economic integration of euro area countries in the transmission of volatility. Furthermore, much like in the return co-movements, France and the Netherlands are, on average, transmitters of volatility, as both countries registered the highest levels of net spillovers. On the contrary, Greece stands out as the main receiver of volatility, followed by Ireland and Portugal. In fact, these countries are amongst the most affected economies by recent crises. Although we did not utilize the exact same database to compute both the daily and the weekly standard deviations, the overall findings point that both approaches are in tune and in consistency with financial and economic environments. In addition, this dissertation has the particularity of analyzing the connection among two measures of systemic stress and the volatility spillover index. A positive correlation concerning the CISS and the volatility spillover index is illustrated, transpiring signs of co-movement. However, the same does not apply over the spillover ratio and the FFSI.

These results can have important implications for risk management and portfolio management, due to the fact that a major part of the volatility of each stock market is coming from other sources. Also, they can alert institutions to be aware of volatility spillovers in their decision making for important economic policies.

The reduced number of countries to be part on this thesis can be seen as a limitation. Although being one of the main goals of this work, the fact that we only analyze euro area stock markets (plus US) can be interpreted as a limitation, because our results, namely the spillover index, may be overvalued due to the fact that almost all of our sample shares the same currency (EUR). Another possible restraint can be associated with the use of weekly standard deviations to compute our spillover index, since it does not allow to detect the day-by-day fluctuations of markets.

Even though this thesis takes a small glimpse into systemic stress, it would be interesting, for future research, to have a deeper understanding of its correlation to volatility spillovers, or even other possible linkages regarding economic crashes and this measure. Additionally, it would be relevant to include and investigate other stock markets with different economic realities and compare them against other assets, such as bonds, exchange rates, money market rates, options and/or other derivatives. Finally, one could also research how structural breaks can affect the spillover index.

9. Bibliography

Acharya, V. V., Brownlees, C., Engle, R., Farazmand, F., & Richardson, M. 2011. Measuring Systemic Risk. ***Regulating Wall Street: The Dodd-Frank Act and the New Architecture of Global Finance***: 85–119. John Wiley and Sons.

Agmon, T. 1972. The Relations Among Equity Markets: A Study of Share Price Co-Movements in the United States, United Kingdom, Germany and Japan. ***The Journal of Finance***, 27(4): 839–855.

Alter, A., & Beyer, A. 2014. The dynamics of spillover effects during the European sovereign debt turmoil. ***Journal of Banking and Finance***, 42(1): 134–153.

Antonakakis, N. 2012. Exchange return co-movements and volatility spillovers before and after the introduction of euro. ***Journal of International Financial Markets, Institutions and Money***, 22(5): 1091–1109.

Antonakakis, N., & Vergos, K. 2013. Sovereign bond yield spillovers in the Euro zone during the financial and debt crisis. ***Journal of International Financial Markets, Institutions and Money***, 26(1): 258–272.

Baillie, R. T., & Bollerslev, T. 1992. Prediction in dynamic models with time-dependent conditional variances. ***Journal of Econometrics***.

Bekaert, G., Hodrick, R. J., & Zhang, X. 2009. International stock return comovements. ***Journal of Finance***, 64(6): 2591–2626.

Bisias, D., Flood, M., Lo, A. W., & Valavanis, S. 2012. A Survey of Systemic Risk Analytics. ***Annual Review of Financial Economics***.

Black, F. 1986. Noise. ***The Journal of Finance***, 41(3): 529–543. http://www.jstor.org/stable/2328481.

Bollerslev, T. 1990. Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. ***Review of Economics and Statistics***, 72(3): 498–505.

Bollerslev, T., & Engle, R. F. 1993. Common Persistence in Conditional Variances. ***Econometrica***, 61(1): 167. http://www.jstor.org/stable/2951782?origin=crossref.

Conefrey, T., & Cronin, D. 2013. Spillover in Euro Area Sovereign Bond Markets. ***Central Bank of Ireland***.

Dalkir, M. 2009. Revisiting stock market index correlations. ***Finance Research Letters***, 6(1): 23–33.

Diebold, F. X., & Yilmaz, K. 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. ***Economic Journal***, 119(534): 158–171.

Diebold, F. X., & Yilmaz, K. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. ***International Journal of Forecasting***, 28(1): 57–66.

Égert, B., & Kočenda, E. 2011. Time-varying synchronization of European stock markets. ***Empirical Economics***, 40(2): 393–407.

Engle, R. 2002. Dynamic Conditional Correlation. ***Journal of Business & Economic Statistics***.

Engle, R., & Bollerslev, T. 1986. Modelling the Persistence of Conditional Variances. ***Econometric Reviews***. http://www.informaworld.com/openurl?genre=article&doi=10.1080/07474938608800095&magic=crossref.

Eun, C. S., & Shim, S. 1989. International Transmittion of Stock Market Movements. ***Journal of Financial and Quantitative Analysis***, 24(2).

Forbes, K. J., & Rigobon, R. 2002. No Contagion, Only Interdependence: Measuring Stock Market Comovements. ***The Journal of Finance***, 57(5): 2223–2261.

Friedman, J., & Shachmurove, Y. 1997. Co-Movements of Major European Community Stock Markets: a Vector Autoregression Analysis. ***Global Finance Journal***, 8(2): 257–277.

Grubel, H. G. 1968. Internationally Diversified Portfolios: Welfare Gains and Capital Flows. ***The American Economic Review***, 58: 1299–1314.

Haldane, A. G., & May, R. M. 2011. Systemic risk in banking ecosystems. ***Nature***, 469(7330): 351–355.

Hansen, P. R., & Lunde, A. 2005. A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? ***Journal of Applied Econometrics***, 20(7): 873–889.

Hendry, D., & Grayham, M. 2014. Why DSGEs crash during crises. ***Why DSGEs crash during crises***. http://www.voxeu.org/article/why-standard-macro-models-fail-crises.

Hilliard, J. E. 1979. The Relationships Between Equity Indices on World Exchanges. ***The Journal of Finance***, 34(1): 103–114.

Hollo, D., Kremer, M., & Lo Duca, M. 2012. CISS - A Composite Indicator of Systemic Stress in the Financial System. ***European Central Bank***. http://papers.ssrn.com/abstract=2018792.

Jeon, B., & Von Furstenberg, G. M. 1990. Growing international co-movement in stock price indexes. ***The Quarterly Review of Economics and Business***, 30(3): 15–30.

Kanas, A. 1998. Volatility spillovers across equity markets: European evidence. ***Applied Financial Economics***.

KlöBner, S., & Wagner, S. 2012. ***Robustness and Computation of Spillover Measures for Financial Asset Returns and Volatilities***. http://www.oekonometrie.uni-saarland.de/papers/SKSW.pdf.

Koch, P. D., & Koch, T. W. 1991. Evolution in dynamic linkages across daily national stock indexes. ***Journal of International Money and Finance***, 10(2): 231–251.

Koop, G., Pesaran, M. H., & Potter, S. M. 1996. Impulse response analysis in nonlinear multivariate models. ***Journal of Econometrics***, 74(1): 119–147.

Lessard, D. R. 1976. World, Country and Industry Relationships in Equity Returns. ***Financial Analysts Journal***, 32(1): 32–38.

Louzis, D. 2013. Measuring return and volatility spillovers in euro area financial markets. ***Bank of Greece***, 1–38.

McMillan, D. G., & Speight, A. E. H. 2010. Return and volatility spillovers in three euro exchange rates. ***Journal of Economics and Business***, 62(2): 79–93.

Milunovich, G., & Thorp, S. 2006. Valuing volatility spillovers. ***Global Finance Journal***, 17(1): 1–22.

Panton, D. B., Lessig, V. P., & Joy, O. M. 1976. Comovement of International Equity Markets: A Taxonomic Approach. ***The Journal of Financial and Quantitative Analysis***, 11(3): 415–432.

Parkinson, M. 1980. The Extreme Value Method for Estimating the Variance of the Rate of Return. ***The Journal of Business***.

Pesaran, M. H., & Shin, Y. 1998. Generalized Impulse Response Analysis in Linear Multivariate Models. ***Economics Letters***, 58(1): 17–29.

Quinn, D. P., & Voth, H. J. 2008. A century of global equity market correlations. ***American Economic Review***: 535–540.

Ricardo, D. 1821. ***On the Principles of Political Economy and Taxation***. ***The Works and Correspondence of David Ricardo***: 566.

Rochet, J., & Tirole, J. 1996. Interbank lending and systemic risk. ***Journal of Money, credit and Banking***, 28(4): 733–762. http://www.jstor.org/stable/2077918.

Sandoval, L., & Franca, I. D. P. 2012. Correlation of financial markets in times of crisis. ***Physica A: Statistical Mechanics and its Applications***, 391(1-2): 187–208.

Schollhammer, H., & Sand, O. 1985. The interdependence among the stock markets of major European countries and the United States: An empirical investigation of interrelationships among national stock prices movements. ***Management International Review***, 25(1): 17.

Sola, M., Spagnolo, F., & Spagnolo, N. 2002. A test for volatility spillovers. ***Economics Letters***, 76(1): 77–84.

Sosvilla-Rivero, S., & Morales-Zumaquero, A. 2012. Volatility in EMU sovereign bond yields: permanent and transitory components. ***Applied Financial Economics***.

Tse, Y. . 2000. A test for constant correlations in a multivariate GARCH model. ***Journal of Econometrics***.

Yilmaz, K. 2010. Return and volatility spillovers among the East Asian equity markets. ***Journal of Asian Economics***, 21(3): 304–313.

10. Annexes

10.1. **Table VIII**: Unconditional correlations amidst the returns of stock markets.

	BE	FI	FR	DE	GR	IE	IT	NL	PT	ES	US
BE	1										
FI	0,69	1									
FR	0,84	0,80	1								
DE	0,76	0,73	0,89	1							
GR	0,44	0,43	0,44	0,42	1						
IE	0,66	0,63	0,67	0,59	0,42	1					
IT	0,78	0,74	0,89	0,82	0,45	0,62	1				
NL	0,85	0,76	0,93	0,86	0,44	0,66	0,83	1			
PT	0,63	0,66	0,69	0,62	0,45	0,56	0,70	0,64	1		
ES	0,77	0,74	0,87	0,79	0,44	0,62	0,87	0,82	0,72	1	
US	0,53	0,48	0,56	0,61	0,26	0,42	0,53	0,55	0,40	0,52	1

10.2. **Table IX**: Volatility spillovers of the sensitive analysis

	From *(j)*											
To (i)	**BE**	**FI**	**FR**	**DE**	**GR**	**IE**	**IT**	**NL**	**PT**	**ES**	**US**	From Others
BE	15,2	9	11,5	9	2,5	7,1	9	10,8	7,3	8,4	10,2	85
FI	9,5	19,8	9,9	8,6	2,8	8,4	8,6	9,4	6	7,4	9,7	80
FR	10,1	8,3	14,2	10,7	2,2	5,2	10,1	11,4	6,3	9,2	12,2	86
DE	9,7	8,7	12,6	15,6	2,2	4,6	8,9	11,5	5,6	7,9	12,6	84
GR	5,6	5,9	6,1	4,3	37,3	5,7	6,7	5	10,5	6,2	6,8	63
IE	8,7	10,5	7,6	5,9	3,7	30	6,1	7,7	6,5	5,6	7,7	70
IT	8,7	7,4	11,1	8,5	3,4	4,4	18,3	8,4	8,3	10,8	10,7	82
NL	10,7	8,9	12,6	11	2,4	6,2	8,3	14,9	5,8	7,8	11,4	85
PT	8,7	6,2	9	6,1	4,9	5,4	10,2	7,1	24	9,3	9	76
ES	9	7,1	11	7,9	3	4,5	12,4	8,5	8,7	16,9	11	83
US	9,5	8,3	12,8	11,2	2,5	5	10	10,8	6,6	9,6	13,8	86
Contrib. to others	90	80	104	83	30	56	90	91	72	82	101	880
Contrib. Inc. own	105	100	118	99	67	86	109	106	96	99	115	**80,00%**
Net Spillovers	5	0	18	-1	-33	-14	8	6	-4	-1	15	

10.3. **Table X**: Unconditional correlations before and after the subprime crisis between the returns of S&P 500 and Euro Stoxx 50.

Before the Subprime				After the Subprime		
Stock Index	**SP500**	**Stoxx**		**Stock Index**	**SP500**	**Stoxx**
SP500	1	0,52		**SP500**	1	0,63
Stoxx	0,52	1		**Stoxx**	0,63	1

Note: The unconditional correlations are computed using, $corr_{ij} = \rho_{ij} = \frac{\sigma_{ij}}{\sigma_i \sigma_j}$.