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On the dynamic behavior of the worldwide sovereign *Credit Default Swaps* markets

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Preface

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In order to address the thesis topic from different perspectives and to keep pace with the evolution of academic and professional research themes, this work is written in the form of an essays-based thesis. The five chapters constitute, thus, five essays, all of them are being submitted and under revision in academic journals with a scientific reading committee.

The structure of these chapters does not correspond to the production order of the essays, but rather to a coherent succession of ideas highlighted in the general introduction.

For both administrative and policy reasons, this thesis started on March 30, 2015.

Résumé

À propos du comportement dynamique des marchés des *Credit Default Swaps* souverains: Évidences internationales

Le phénomène de contagion, l'hypothèse d'efficience de marché et les transferts de chocs de volatilité sont parmi les théories économiques et financières les plus importantes, car elles fournissent une vision globale sur la stabilité financière. Or, elles restent les moins comprises depuis les récentes crises financières. Ainsi, cette thèse propose de fournir aux régulateurs économiques, aux investisseurs ainsi qu'aux divers acteurs des marchés financiers une vision actualisée du comportement dynamique des marchés mondiaux des Credit Default Swaps (CDS) : efficience informationnelle, interaction avec d'autres marchés financiers internationaux et exposition au risque systémique. La dynamique en constante mutation de ces marchés associée à l'évolution constante des politiques de réglementation suscite un enthousiasme mondial pour l'étude comportementale des marchés des CDS, auquel nous contribuons à travers cinq essais interconnectés.

Nous discutons, dans le premier essai, les faits stylisés des données des CDS souverains à travers l'estimation de 9 modèles de la famille GARCH. Ce chapitre compare les performances de plusieurs modèles prédictifs de volatilité linéaire et non linéaire en prenant en compte différentes caractéristiques financières des séries statistiques. L'application de ces modèles aux spreads de CDS de 38 pays révèle que le pouvoir prédictif de ces modèles dépend de leur capacité à capturer les faits stylisés des CDS souverains concernant l'estimation du processus de la variance. En effet, les modèles GARCH fractionnellement intégrés surpassent les modèles GARCH classiques à mémoire courte en termes de prévision, en raison de la flexibilité accordée au degré de persistance des chocs de variance. Ces résultats sont utilisés pour modéliser conjointement les rendements et les volatilités des spreads de CDS dans l'ensemble des prochains essais.

Le deuxième essai examine également les caractéristiques financières des marchés internationaux des CDS souverains, en donnant de nouvelles preuves sur leurs degrés d'efficience. En utilisant un nouveau cadre économétrique basé sur une estimation en trois étapes du modèle VECM-FIGARCH, nous montrons que les informations contenues dans les spreads de CDS et les rendements des obligations correspondantes ne sont pas toujours reflétées instantanément et correctement dans le niveau du risque souverain. Les résultats révèlent l'existence d'opportunités d'arbitrage avec un rejet partiel de l'hypothèse de marche aléatoire dans plusieurs des 37 pays étudiés, et donc de l'efficience de ces marchés.

Alors que le précédent essai utilise l'espérance conditionnelle des spreads de CDS pour étudier le comportement des marchés, les essais suivants se concentrent plutôt sur les propriétés de la variance et de la covariance des rendements logarithmiques des spreads de CDS. La prédictibilité de la volatilité des CDS souverains, basée sur l'information contenue dans certains facteurs macroéconomiques spécifiques à chaque pays, est étudiée dans le troisième chapitre. Étudiant un large échantillon de 38 pays producteurs et non producteurs de pétrole, ce chapitre s'intéresse particulièrement à l'impact des chocs pétroliers sur la détérioration des finances publiques. Les résultats du modèle à changement de régimes SETAR montrent que le pouvoir explicatif des variables étudiées varie en fonction des périodes de l'intensité des turbulences financières (faibles et fortes). En régime risqué, la volatilité de la plupart des CDS devient plus sensible au prix du pétrole, ce qui montre que la solvabilité des pays (producteurs ou non du pétrole) est corrélée avec les conditions du marché mondial de l'énergie.

Le quatrième essai examine les interactions dynamiques entre les marchés des CDS souverains et leurs marchés obligataires sous-jacents, en adaptant les faits stylisés détectés dans le premier essai à un cadre multivarié. L'hétéroscédasticité, l'effet de levier asymétrique ainsi que les caractéristiques de mémoire longue détectés dans les 33 séries temporelles étudiées sont simultanément pris en compte à travers le modèle FIEGARCH bivarié et le modèle bayésien VAR cointégré. Ce cadre économétrique permet de détecter les transferts de chocs de volatilité entre ces marchés de crédit, avec une accentuation de ce phénomène pendant les périodes de crise. Dans la plupart des cas, les transmissions de chocs financiers sont détectées du CDS vers le marché sous-jacent plutôt que dans la direction opposée. La divergence des statuts économiques et des positions géographiques des pays de notre échantillon montre que les marchés mondiaux présentent des niveaux de sensibilité différents et des réactions divergentes aux chocs financiers.

Le cinquième et dernier essai s'intéresse également au transfert de risque, non pas entre différents marchés, mais plutôt au sein du même marché mondial des CDS, en examinant le mouvement commun des spreads de CDS souverains à un niveau régional et mondial. L'application d'un modèle DCC-FIEGARCH aux spreads de CDS de 35 pays du monde entier montre que les marchés internationaux de CDS souverains sont sujets à des effets de contagion et qu'ils co-évoluent en particulier pendant les périodes de crise. Notre approche fournit la preuve que les marchés des CDS constituent un canal de transmission de crises entre les pays du monde entier, et ce indépendamment de leurs statuts économiques ou de leurs positions géographiques. Nos résultats montrent également que les marchés des CDS sont plus vulnérables pendant la crise de la dette souveraine européenne que pendant la crise financière globale.

Mots-clés: Credit Default Swaps, marchés souverains mondiaux, modèles économétrique fractionnellement intégrés , prédictibilité des volatilités, contagion, transfert de risques.

Abstract

On the dynamic behavior of the worldwide sovereign Credit Default Swaps market

Contagion phenomenon, efficiency hypothesis and spillover effects are amongst the most important economic theories as they provide an overall vision of the financial stability, yet the least understood in the aftermath of the recent crises. This thesis proposes to provide policy makers, investors and broadly market participants with an updated outlook of the dynamic behavior of the global sovereign Credit Default Swaps (CDS) markets: informational efficiency, interaction with other international financial markets and systemic-risk exposure. The steadily changing dynamics of these markets combined with the constantly evolving regulatory policies have led to a shared worldwide enthusiasm regarding the behavioral study of CDS markets, in which we contribute through five interconnected essays.

We first discuss, in the first essay, the statistical characteristics of the sovereign CDS data, through the estimation of 9 GARCH-class models. This chapter compares the predictability performances of several linear and non-linear volatility models taking into consideration different financial stylized facts. Application on CDS spreads of 38 countries reveals that the forecasting power of these models depends on their ability to capture sovereign CDS features while estimating the variance process. Yet, the fractionally-integrated models outperform the basic GARCH-class models due to the allowed flexibility regarding the persistence degree of the variance shocks. These results are used to jointly model returns and volatility of CDS spreads in the forthcoming essays.

The second essay also investigates the financial characteristics of the international sovereign CDS markets, by giving new evidences on their efficiency degrees. Using a new framework based on a 3-step estimation of a VECM-FIGARCH model, we show that information contained in CDS spreads and bond yields are not always instantaneously and properly reflected in the current sovereign risk level. Results reveal the existence of arbitrage opportunities with a partial rejection of the randomness hypothesis in some of the 37 studied countries.

While the previous essay used the conditional expectation of CDS spreads to study the market behavior, the next essays rather focus on the properties of the variance and covariance. The predictability of sovereign CDS volatility, based on the information contained in some country-specific and global macroeconomic factors, is investigated in the third chapter. Studying a large group of 38 oil-producing and oil-consuming countries, this chapter particularly emphasizes the impact of oil shocks on the deterioration of public finances. Results of the self-exciting regime switching (SETAR) model show that the explanatory power of the studied variables varies over periods of low and strong financial turmoils. During risky regime, most of CDS volatility become more sensitive to oil prices, indicating that countries' creditworthiness is correlated with the global energy market conditions whether the country is oil-related or not.

The fourth essay investigates the dynamic interactions between the sovereign CDS markets and their underlying government bonds markets, by adjusting the stylized facts detected in the first essay to a multivariate framework. Heteroscedasticity, asymmetric leverage effect and long-memory features detected in the 33 studied time series are simultaneously taken into account through a bivariate FIEGARCH model and a Bayesian cointegrated VAR model. This econometric framework detects volatility spillovers between these credit markets with an accentuation of this phenomenon during crisis periods. In most cases, financial shock transmissions are detected from the CDS to the underlying market rather than in the opposite

direction. The divergence in the economic status and geographical positions of the countries composing our sample show that global markets exhibit different sensitivity levels and reactions' divergences to financial shocks.

The fifth and last essay is also interested in risk transfer, not between different markets but rather within the global CDS market, by examining the common movement of sovereign CDS spreads on a regional and a worldwide levels. The application of a FIEGARCH-DCC model to CDS spreads of 35 worldwide countries shows that international sovereign CDS markets are prone to contagion effects and that they actually co-move especially during crisis periods. Our approach provides evidence that CDS markets constitute a channel of crisis transmission to countries across the world regardless their economic status or geographical positions. CDS markets are also found to be more vulnerable during the European Debt Crisis compared to the Global Financial Crisis.

Keywords: Credit Default Swaps, Worldwide Sovereign Markets, Fractionally-integrated models, Forecasting volatility, Contagion, risk spillover.

Contents

Introduction

1 Context

The increasingly frequent occurrence of financial crises in recent decades emphasizes the seriousness, the relevance and the usefulness of carrying out a sturdy and steady financial risk management strategy. Besides the liquidity and the market risks, hedge funders, arbitrageurs, speculators and financial market participants in general ought to constantly deal with the credit risk related to their respective activities. This credit-risk exposure arises from the real-world probability of the counterparties' failure to honor their commitments: a default in the reimbursement of all or a part of the required amount. Investors have several strategies to substantially manage, mitigate, transfer and redistribute the latent credit risk to financial transactions: Collaterization, Netting and Downgrade trigger. With the important development in the derivatives markets during the recent decades, new opportunities are being added to financial institutions, and in particular banks, which can henceforth use credit derivatives to continuously deal with the credit risk in their investment portfolios. During early 2000s, banks widely used these once-straightforward financial tools for both shifting loans risk to other parts of the financial system and diversifying the type of risk-exposure.

The most extensively traded credit derivative is the Credit Default Swap (CDS, hereafter). The CDS contract belongs to one of the most recent waves of innovations in the financial market. These derivative contracts are equivalent to bilateral insurance contracts[1] designed to manage the financial risk: The buyers of CDS contracts, which are mainly the banks, protect themselves from the credit risk of the loans they grant and thus transfer it to the protection sellers, which are mainly the insurance companies. In return for receiving of a periodic premium[2], the seller of the CDS makes a reimbursement of the defaulted debt in case of credit event. A credit event occurs when the reference entity, which is the company or the country on which the CDS bears, is not able to pay back its debts.

Besides the premium payment periodicity, the difference in the specifications of the CDS may concern, as well, the settlement of the credit event[3]: The default payment can either be made by a physical delivery of the underlying reference assets (the bonds) or by a cash settlement. In the first case, the CDS buyer has the right to sell the bonds issued by the

[1]The two key differences between an insurance contract and a CDS contract are: (i) An insurance contract protects its buyer from the losses related to the devaluation of an owned asset, while a CDS buyer is not necessarily obliged to physically held the underlying asset. And (ii) the underlying asset of an insurance contract cannot be a financial product (financial risks are not managed by insurance companies).

[2]Theoretically, the periodicity is fixed in advance in the contract terms and is usually one month, 4 months, 6 months or even 12 months. According to Hull (2011), in practice, payments are made in arrears on a quarterly basis. The default protection buyer has to make the payment until the end of the contract duration or the occurrence of a credit event.

[3]Obviously, when the reference entity does not fail to its commitments, no payoff is made.

defaulted reference entity and the CDS seller is obliged to buy them at their face value[1]. The delivered bonds should have the same seniority but not necessarily the same post-default market value. The CDS holder has the possibility to decide which bonds to deliver and should thus deliver the cheapest deliverable bonds (to maximize his payoff bond), whose characteristics are determined by the International Swaps and Derivatives Association (ISDA, hereafter) (See Ranciere (2002) for more details about the Cheapest-to-Deliver option). In the second case, which is the most frequent, the payoff consists of paying the difference between the notional principal and the market recovery value. In fact, a few days after the company's default, the ISDA proceeds to an auction in order to determine the recovery rate of the Cheapest-to-Deliver bond (Refer to the Credit Event Auction Primer published by Markit Ltd for more details about the Auction process.). The recovery rate is a percentage of the facial value and corresponds to the mid-market value of the defaulted bond. It depends on several factors, namely the seniority, the maturity and especially the annual market default rate. The more the average default rate is high, the less important the recovery rates are ("*A bad year for the default rate is usually doubly bad because it is accompanied by a low recovery rate*" (Hull, 2011)).

The CDS spread corresponds to the amount of the annual premium paid by the default protection buyer, which is none than a percentage of the bond's face value. It mainly depends on the solvency risk of the reference entity as well as on the maturity of the contract. As in the other financial markets, several market makers guarantee the CDS market liquidity by frequently and continuously offering bid and ask prices[2]. Usually, this protection is negotiated for a period of 5 years, which represents the most liquid market segment, but can also have longer or shorter maturities (1, 2, 3, 4, 7 and 10).

The credit event is one of the most important specifications of a CDS contract. Generally, the credit event is a change in the reference entity's ability to honor its repayment commitments. The International Swaps and Derivatives Association provides three widely used definitions of the credit event: (i) a failure to repay the principal notional or the interests when they are due, (ii) a bankruptcy of the entity on which the CDS has been negotiated and (iii) a debt restructuring[3]. A restructuring debt [4] is defined as a violation of the concluded contract terms. It includes a postponement of the payment date of the principal notional of the interests, a devaluation in the interest rate of the notional, a change in the repayment currency or a decrease in the debt quality (a change in the contact's subordination order, assigning it a lower priority level)(Berndt et al., 2007).

As mentioned before, the payoff mechanism of a CDS can either be a cash settlement or a physical delivery of the hedged debt. Particularly during after a restructuring event, the physical settlement can lead to some opportunistic behavior where the Cheapest-to-Deliver option allows for extra profits, even though there is no significant change in the quality of the bond. Several clauses can, thus, be added to consider for the reconstructing event in a CDS contract. Packer et al. (2005) report these different versions of the restructuring terms,

[1]The face value is none other than the notional principal that refers to the predetermined loan amount and on which the interests are calculated.

[2]For a market maker, who is usually a broker/dealer, the bid refers to the price at which he is willing to buy the protection contract and the ask (offer) is the price at which he is willing to sell.

[3]Other less common credit events are defined by the ISDA: obligation acceleration, repudiation/moratorium and obligation default (Berndt et al., 2007).

[4]Hull (2017) indicates that the North American CDS contracts do not recognize the restructuring of debt as a credit event, especially in case of high-yield bond.

depending on the maturities of the deliverable bonds[1]:

1. **Full restructuring (*FR*):** With the beginning of CDS trading in 1999, the ISDA agrees that any debt restructuring is considered as a credit loss event. A total reimbursement of the capital relief is recognized, in exchange of delivering any bond with maturity up to 30 years ($\hat{N} \leq 30$ years).

2. **Modified restructuring (*MR*):** A modified restructuring clause is published by the ISDA in 2001, limiting the deliverable bonds to have a maturity of 30 months (or less) beyond the expiration date of the CDS contract ($N \leq \hat{N} \leq N + 30$ months). This introduction of a new ISDA guideline is made to reduce the "take advantage of the system" possibilities by requesting payoff even though the reconstructing credit event does not prejudice the debt holders, as it was the case in 2000 after restructuring the debt of the Conseco Finance corporation.

3. **Modified-modified restructuring (*MM*):** The ISDA has relaxed, in 2003, the characteristics of the deliverable bond, deemed as too strict by investors, and has lengthened the maturity of the accepted restricted bonds up to 60 months ($N \leq \hat{N} \leq N + 60$ months). The maturity of the other deliverable bonds is still limited to 30 months or less.

4. **No restructuring (*XR*):** According to this clause, the restructuring events that do not result in real losses to debt holders, do not give rise to a settlement trigger. From 2002, the financial holding company JPMorgan excludes all restructuring event options from its hedging contracts . Similarly, the investment-grade and the high-yield versions of the North American CDS index are negotiated with the no restructuring clause.

CDS instruments are categorized in 2 types: (i) a single-name contract, in which the payoff depends on the creditworthiness of only one reference entity, and (ii) a multi-name contract, in which the reference entity is more than one company or country, such as basket CDS or CDS indices. A *basket credit default swap* is similar to the single-name CDS except that in this type of contract the payoff settlement depends on the default of several underlying-assets. When the payoff is provided following the failure of any one of the hedged reference entities, then it's called an *add-up basket CDS*, while when the contract is executed only when the k^{th} default occurs, it is called a *first-to-default CDS*. we are only interested in this thesis in the study of the single-name CDS written on sovereign debts.

Since its first introduction in 1997, this instrument has been characterized by a striking expansion in its notional outstanding amount, reaching its highest values by December 2007 and June 2008 with receptively \$58,243 and \$57,402 billion (BIS, 2017). In fact, the market notional amount of these contracts has increased steadily and briskly before and during the outset of the subprime crisis, making the CDS become the second most widely used type of swaps during the first half of 2008. The notional amount of outstanding CDS contracts has reached its highest value of \$58.24 billion at the end-June 2008, whilst the first largest (Interest rate) and the second largest (FX) swaps derivatives markets record respectively \$393,138.1 billion and \$56,23 billion of notional amount for the same period. Since then, a decease in the market value is observed, attaining \$9,644 billion at the end-June 2017. Nonetheless,

[1]Other modifications have followed in 2009 and 2012 ISDA definitions of the restructuring event.

compared to the amount recorded by 2001 ($1,170 billion of outstanding amount)[1], the size of the CDS market remains remarkably huge and more actively liquid than what it was during its emergence.

According to the Bank of International Settlement[2] semiannual OTC derivatives statistics (BIS, 2017), trading on single-name CDS ($5,042 billion of notional amount outstanding) is slightly greater than on multi-name CDS($4,602). The difference in these markets shares was more important in 2015, with 59% of transactions involve single-name instruments, while 41% are related to multi-name instruments. Index products (iTraxx index and CDX index) are considered as multi-name CDS and count for $4,229 billion at the end-June 2017. Yet, the market shares of the sovereign segment remain relatively steady with a percentage around 17%.

The rapid expansion phenomenon of this derivative market segment can be explained by the widespread usage and the brisk integration of CDS instruments into financial markets, owed to the their basic structure, their relative mechanism simplicity, their easy implementation and their clear fundamental hedging purpose of corporate or sovereign credit instruments (bonds, loans...). Further, these derivatives seem really useful not only to reduce risk but also to take some. In fact, the exponential success of the CDS market is also due to the possibility of trading 'naked' contracts, with no underlying debts to hedge, for a pure speculation purpose and in a gain-making vision. An interesting fact about these credit derivatives is that the value of the CDS market is greater than the value of the underlying market (Loans and bonds). Transaction volume on CDS far exceeds reference contracts volume, indicating that speculation is becoming the widest function of these instruments. In this sense, Brandorf and Holmberg (2010) report that the CDS market is dominated by speculators placing their bets on the financial health and the credit quality of reference entities rather than by investors hedging their credit-risk exposures ("*Hedging is boring while speculation is exciting*"(Hull, 2017)). In this way, the CDS market neither eliminates nor mitigates credit risk, but it constitutes a broader source of financial shocks.

At first glance, CDS are the greatest financial innovation of the recent years. However the trading of these contracts remains subject to several controversies, especially regarding their contribution in triggering, intensifying and deepening the 2007 crisis[3]. According to their antagonists, the straightforward and useful nature of CDS actually hides several downsides: this credit market is neither regulated nor transparent, deteriorating economic welfare rather than mitigating risk.

In parallel with this rapid expansion of the CDS market, the legitimacy of using these instruments is becoming the most difficult financial challenge in both academic and non-academic areas. While some strands of the financial practitioners and researchers seem to be unanimous about their utility, other strands perpetually raise many criticisms, asking for the

[1]Even through the first CDS contract was introduced by JPMorgan in 1997, the first information about the market size was published 2 years after the 1999 International Swaps and Derivatives Association (ISDA) Agreement.

[2]The Bank of International Settlements (BIS, hereafter), is the secretariat of the Basel Committee on Banking Supervision Organization. As part of its missions (starting in 2004) the BIS collects data mainly on the notional amounts outstanding of derivative products (Forwards, Options and Swaps)

[3]Even though policy makers recognize CDS as an important risk management tools that contribute to the efficiency of credit markets (Tang and Yan, 2010*a*), the expansion usage of these contracts to speculation and trading-for-profit transactions makes them responsible for the intrinsically-unfounded volatility spikes recorded during the global financial crisis (See Stulz (2010) and Terzi and Ulucay (2011) for a debate on the role of CDS markets in the financial crisis).

ban of these contracts. This never-ending debate over the CDS market has contributed to awaken the interest of researchers in its dynamic mechanism. This thesis tries to contribute to the current CDS literature by examining its development, analyzing its reactions and studying its behavior towards some financial phenomena likely came out during recent years, with a particular emphasis on the sovereign segment, in which the underlying assets are government bonds.

Initially overlooked, sovereign CDS is definitely a hot topic in today's world economic and financial systems, and what is particularly interesting is that, despite the concerns and questions about the nonexistence of unambiguous execution guidelines for the contracts written on the Hellenic Republic's debts that have been raised following the Greece's bonds restructuring, CDS sovereign sector remains actively liquid with a notional amount outstanding of \$1,638 billion by the end of June 2017. Yet, despite their valuation's complexity, the potential of use of sovereign CDS contracts is still enormous, eventually as economic policy tools. In fact, sovereign CDS market constitutes a prominent bridge between the financial sphere and the real economy, particularly in the aftermath of the crisis. Being a measure of the credit risk level, CDS spreads provide an insight on the finance public conditions. Financial stability - reflected in CDS volatility - and economic welfare are thus closely related. In this sense, regulators assign a high priority to understand CDS spreads so they can reduce the extend of the country's vulnerability by putting in place the appropriate regulatory policies for macroeconomic-level supervision.

CDS trading also affects the activity of the financial world (financial institutions, fund managers and corporate treasurers). Instead of the measures of credit rating agencies, financial institutions use CDS spreads as an indicator of the default probabilities and the counterparty risk presented in their investment portfolios. Whether used for hedging or speculative purpose, changes in CDS spreads affect the market perception, influence the banks' investing decisions and impact the countries' borrowing costs. Thereby, understanding the dynamic evolution of the sovereign CDS market is very relevant, so portfolio managers can anticipate the market's reactions to turmoil periods, appropriately balance risk against profitability in investment mix, and take into account the limits of portfolio diversification. Yet, better control of the risks associated with the CDS market is crucial whether to avail of arbitrage opportunities, to realize some hedging operations or to speculate on the predictability of the borrowing cost.

2 Objectives

The dynamics of these markets are steadily changing: at first created to hedge, mitigate and diversify credit risk, CDS instruments have been gradually used for speculative purposes, resulting in a more liquid market where a risk-taking trading is done in much the same way as any other financial asset. Regulatory policies are also constantly evolving, leading to alter investors' perceptions, market reactions and prices' evolution. The recent two financial crises have played a main role in this market mutation, with the several restructuring events of banks and governments' debts.

In light of these observations and in order to keep pace with this changing nature of the CDS markets, one would clearly need to understand the mechanism and the characteristics of the global sovereign CDS sector and its interaction with the other financial markets, during both the recent crises, the Global Financial Crisis (2007-2009) and the European Sovereign debt crisis (2010-2012). This article-based thesis includes five complementary studies that provide a comprehensive view of the dynamic behavior of a large set of countries, by answering several inter-related research questions, treated in this topic:

- Are the sovereign CDS volatility forecastable?
- What is the repercussion of the predictability of forthcoming changes in the CDS market on the legitimacy of the efficiency hypothesis?
- What are the key drivers (country-specific and global-wide macroeconomic and financial factors) of the sovereign CDS volatility? And what is the role played by oil prices in determining the credit-risk level?
- Did the recent financial crises impact the volatility spillover mechanism between the sovereign CDS and its underlying market?
- Do the sovereign CDS market play a role in spreading systemic risk and deteriorating the financial system stability through contagion effects?

The first article-written chapter, ***Forecasting sovereign CDS volatility: A comparison of univariate GARCH-class models***, investigates the predictability of sovereign CDS volatility based on the forecasting performance of 9 linear and non-linear GARCH-class models. In this chapter, we are allowed to study and to take into account different statistical properties of the CDS spreads, not considered before in modeling the conditional mean and variance of these instruments. Results of this chapter are used to develop a new 3-step framework in the second chapter, ***On the Informational Market Efficiency of the Worldwide Sovereign Credit Default Swap***, allowing us to focus on the legitimacy of the Efficiency Hypothesis in the sovereign CDS market. Unlike the existing literature, this study is conducted in such a way that considers for the past information available in both CDS and the underlying bond prices and their reflection into current CDS spreads. The third chapter, ***Nonlinearities in the oil fluctuation effects on the sovereign credit risk: A Self-Exciting Threshold Autoregression approach***, gives an in-depth investigation on this predictability by explaining the sovereign CDS volatility by different country-specific and global macroeconomic and financial variables. A particular emphasis is given in this chapter to understanding the response of government public finances to oil price fluctuations.

We address the major issue of financial assets' comovements and investigates the interconnectedness and the risk spillover between sovereign global CDS markets and their underlying bond markets in the fourth chapter, ***International risk spillover in the sovereign credit markets: An empirical analysis***. Most of the previous studies generally focus on the spreads' first moment and suppose a non-informational volatility interaction. However, we believe that risk spillover is rather detected using conditional volatility rather than spread or log returns, and we use a similar framework as the second chapter to detect risk transfer between these markets. The fifth and last chapter, ***The Credit Default Swap market contagion during recent crises: International evidence***, also analyzes the risk transfer, but rather within the sovereign CDS market, by studying the vulnerability of this market during the Global Financial Crisis (2007-2099) and the European Sovereign Debt Crisis (2010-2012).

3 Methodology

This thesis contributes to answering the aforementioned uncertainties about the market functioning and its role in the stability of the economic sphere and the financial activity. The five interconnected studies composing the thesis extend the growing CDS studies in several ways: First, our investigations expand the field of study and go beyond the abundantly studied context: countries are chosen as to represent a benchmark of international CDS markets and thus provide international evidences from a global rather than a local or regional perspective as it has mainly been done in the literature. Yet, our data sample allows us to draw more robust conclusions, as it is composed of countries with different credit-risk exposures.

Second, the dataset ranges on a relatively long interval from January 2^{nd}, 2006 to March 31^{st}, 2017, As far as we are concerned, our database is the largest dataset ever used in studying sovereign CDS dynamics in terms of size and time-period. The studied time period covers thus the Global Financial Crisis as well as the Sovereign Crisis during which trading CDS contracts is altered by several ISDA regulatory amendments. It also allows us to examine the impact of crises magnitude and severity on the dynamic evolution of several CDS spreads.

Third, we mainly use sophisticated and accurate econometric methodologies (Bayesian VAR, FIGARCH, FIEGARCH, FIAPARCH and SETAR), which allows us to take into account more CDS market properties (such as long-memory range, information asymmetries...), to provide more robust estimates and to draw new conclusions. The first chapter uses a large set of of 9 linear and non-linear GARCH-class models (GARCH, IGARCH, EGARCH, GJR, APARCH, FIGARCH, FIEGARCH, FIAPARCH, HYGARCH) to forecast the volatility of the CDS spreads. The selection of the best fitted model in terms of predictability power is based on 7 heteroskedastic and no heteroskedastic-robust loss functions criteria (MSE, MAE, HMSE, HMAE, QLIKE, R^2LOG, MLAE). The stylized facts observed in the CDS spreads are taken into account in the methodological frameworks used in the remaining studies of this thesis. The efficient market hypothesis is investigated in the second chapter through a 3-step framework that combines a VECM and a FIGARCH models, allowing to take into account simultaneously the long-run properties (long-term equilibrium), the volatility clustering, the heteroscedasticity and the long-memory behavior. The third chapter uses a univariate FIAPARCH volatility model to estimate the CDS conditional volatility and a regime-switching nonlinear SETAR model to explain the impact of local and international variables on the CDS volatility. Through a bivariate FIEGARCH model and a Bayesian cointegrated VAR model, we investigate in the fourth chapter the interconnectedness and the volatility spillover between sovereign global CDS markets and their underlying bond markets. Finally, we determine whether the CDS market is prone to contagion effects by using a DCC-FIEGARCH framework.

4 Results

We start this thesis by showing that the global CDS market is characterized by the same stylized facts of the stock market: volatility clustering, nonlinearity, asymmetric leverage effects and long-memory behavior. Results support that allowing flexibility regarding the persistence degree of variance shocks significantly improves the model's suitability to sovereign CDS spreads. Furthermore, in the most of the studied countries, credit market volatility is found to be better predicted by the fractionally-integrated class of models.

We detect, in the second chapter, some degrees of inefficiency and reject in some extent the randomness of the sovereign CDS markets, conversely to the results of the literature. We provide worldwide evidence of CDS spreads predictability from both their own historical values and the past values of the underlying bond yields. The sub-periods (pre-crisis, crisis and post-crisis phases) analysis shows that crises negatively impact the randomness of CDS spreads with a significant increase in the number of forecastable prices, especially during the Sovereign Debt Crisis.

Results of the third chapter show that, after controlling for country-specific and macroeconomic-level factors, some divergences are detected in the explanatory power of oil prices and a regime-switching behavior is observed over time: During the low-volatility regime, limited evidence of a significant relationship between these two markets are found, whilst during the high-risk regime, credit volatility becomes more sensitive to oil market conditions for most of cases. The heterogeneity in the economic status and geographical positions of our studied sample allows us to argue that the decline in oil price worsens the public finances tenability whether the country is oil-related or not.

In the fourth chapter, our analysis shows that there is a risk transmission between these two markets and that this phenomenon is accentuated during turmoil phases. We also reveal that the studied countries exhibit different sensitivity levels and reactions' divergences to financial shocks.

These comovements are revealed as well within the CDS markets in the fifth and last chapter. Results show that this sovereign sector is prone to contagion effects, reinforced during turmoil episodes. This study also shows that the level of crisis exposure differs across global markets and regions and that crises spread to countries across the world regardless of their economic status or geographical positions, through the sovereign CDS markets (especially during the European Sovereign Debt Crisis).

5 Organization

The rest of this thesis is organized as follows: chapter 1 assesses the forecastability of CDS volatility through the implementation of 9 GARCH-class models, chapter 2 investigates the efficiency of the sovereign CDS spreads and the legitimacy of the random walk hypothesis, chapter 3 examines the determinants of government CDS volatility with a particular emphasis on the impact of oil prices on public finances, chapter 4 focuses the volatility spillover between the CDS and their underlying bond markets and chapter 5 studies the contagion effects on the sovereign CDS markets. We conclude this thesis with a reminder of the major contributions, the main implications of our results on regulatory policies and financial institutions decisions and some propositions for forthcoming studies.

Chapter 1

Forecasting sovereign CDS volatility: A comparison of univariate GARCH-class models

Initially overlooked by investors, the sovereign credit risk has been reassessed upwards since the 2000s which has contributed to awaken the interest of speculators in sovereign CDS.

The growing need of accurate forecasting models has led us to fill the gap in the literature by studying the predictability of sovereign CDS volatility, using both linear and non-linear GARCH-class models. This essay uses data from 38 worldwide countries, ranging from January 2006 to March 2017.

Results show that the CDS markets are subject to periods of volatility clustering, nonlinearity, asymmetric leverage effects and long-memory behavior. Using 7 heteroskedastic and no heteroskedastic-robust statistic criteria, results show that the fractionally-integrated models outperform the basic GARCH-class models in terms of forecasting ability and that allowing flexibility regarding the persistence degree of variance shocks significantly improves the model's suitability to data. Despite the divergence in the economic status and geographical positions of the countries composing our sample, the FIGARCH and FIEGARCH models are mainly found to be the most accurate models in predicting credit market volatility.

Keywords : CDS volatility, Predictability, Forecasting models, Loss functions criteria.

1.1 Introduction

Understanding the fluctuations' dynamic of financial assets has always been of a particular interest in the academic and non-academic spheres. The considerable number of studies focusing on the stock prices' mechanism point out several stylized facts characterizing the financial markets such as: the volatility clustering, the non-stationarity... (See for example Niu and Wang (2013) for a study of the statistical behaviors of the Shanghai Composite Index and Hang Seng Index). Besides the stock markets widely studied, analyzing the characteristics of the credit market, and particularly the sovereign CDS market, is likewise interesting especially when it comes to investigating the impact of financial properties on the suitability of the CDS volatility modeling and forecasting ability.

The curious increase in the empirical studies dealing with modeling CDS data during the last decade can be explained by several reasons: (i) the constantly evolving outstanding amount of the CDS contracts reaching its highest values during the crisis periods, (ii) the need of more clear understanding of the role played by this market in the spread of crises and (iii) and the requirement of identifying the main explaining factors of credit risk. Furthermore, the use of CDS contracts no more as hedging instruments but rather as diversification, trading and speculation instruments has legitimized the usefulness of CDS volatility forecasting to investors for both risk management and portfolio management.

Despite the relevance of the volatility forecasts particularly in the decision process and considering the grown interest in predicting credit spreads, the nonexistence of papers in the literature of CDS spreads dealing with the ability of GARCH models to accurately forecast the volatility of the CDS is completely outrageous[1]. The literature on CDS is mainly composed by studies that focus on the determinants of these credit spreads (Oliveira et al., 2012; Costantini et al., 2014; Fontana and Scheicher, 2016) or the Granger Causal relationship between CDS markets and related markets (Coudert et al., 2010; Longstaff et al., 2011; Coudert and Gex, 2013; Sabkha et al., 2018). The very few papers that investigate the forecasts of CDS spreads (Krishnan et al., 2010; Sharma and Thuraisamy, 2013; Avino and Nneji, 2014; Srivastava et al., 2016) only focus on the first moment order, while the predictability of the CDS volatility remains understudied. Yet, these studies try to forecast the CDS spreads based on the commonly known economic and financial determinants and not based on the predictive ability of the econometric models. Considering the foregoing gaps, this study aims to extent the literature by investigating the forecasting performance of 9 GARCH-class models in the sovereign CDS markets from January 2^{nd}, 2006 to March 31^{st}, 2017. Our study contributes to the existing literature in several ways: first, as far a we are concerned, none of the previous studies has focused on the predictability of CDS volatility, especially when it comes to the sovereign market. Second, our essay contributes as well to the literature by implementing a larger set of statistical loss function criteria -taking into account the nonzero mean and the heteroscedasticity of the forecast errors - to assess the out-of-sample predictive ability of the models in comparison with existing forecasting papers on financial assets. Third, the comparative study between linear and non-linear ARCH-class models provides a better and clearer comprehension of the in-sample and out-of-sample fit of the CDS data. Finally, our data set allows us to draw more robust and worldwide conclusions, as it is composed by CDS spreads for 38 countries from all over the world covering the recent two economic and financial crises when the volatility of asset prices have reached their highest unexpected levels.

Our empirical findings show that the sovereign CDS market is characterized by the same stylized facts as the stock market: volatility clustering, leverage effects and long memory behavior. The results of the diagnostic tests on the in-sample modeling generally show that no model outperforms all the others in terms of fitting. Based on the results the 7 loss functions, the predictive performance of the fractionally-integrated models seems to be more accurate, emphasizing the importance of taking into account the long-range memory and the nonlinear behavior of CDS spreads while forecasting volatility. Among the fractionally-integrated models, our results show that the FIGARCH and the FIEGARCH are the most accurate models, providing the best out-of-sample performances in most cases.

The rest of the chapter is organized as follows. A brief literature review of the previous

[1]The majority of papers dealing with the predictive power of GARCH models, only focus on the major stock indexes and exchange rates (Poon, 2005).

studies predicting financial assets is presented in section 1.2. section 1.3 presents the sample and data used to compare the predictive ability and displays the 9 volatility forecasting models under focus. Results of the in-sample and out-of-sample analysis are reported is section 1.4. section 1.5 concludes the essay.

1.2 Literature review

Investigating the degree to which financial time series can be accurately forecast has always been in the limelight of researchers' issues. The empirical literature on the modeling and predicting volatility processes is extensive and takes into account more and more financial markets properties. Engle (1982) is the first researcher to model financial data through a time-varying stochastic process characterized by a nonconstant correlated variance so-called ARCH model. A generalization of this Autoregressive Conditional Heteroscedaticity model is then proposed by Bollerslev (1986) with more parsimonious and less overparametrization and biasedness in the estimates. Some extensions of this model are afterwards proposed, taking into account more stylized facts of the financial markets: leverage effects (Nelson, 1991; Glosten et al., 1993), stationarity issues (Engle and Bollerslev, 1986), long memory (Ding et al., 1993; Baillie et al., 1996; Bollerslev and Mikkelsen, 1996; Tse, 1998; Davidson, 2004)...[1]. These GARCH-class volatility models have been widely used to forecast various financial data, based on their predictive power. The great focus in these studies has been primarily given to stock returns (Keim and Stambaugh, 1986; Poon, 2005; Guidolin et al., 2009; Ferreira and Santa-Clara, 2011; Niu and Wang, 2013), in which recent past information is found to help forecast the future variance. Similar studies are conducted using commodity market data, especially oil data (Agnolucci, 2009; Wei et al., 2010; Chkili et al., 2014; Charles and Darné, 2017). Generally, these studies show that no model outperforms all the others in capturing the time series financial and statistical features, while the non-linear GARCH-class models are found to be more relevant in terms of forecasting accuracy[2]. Unlike stock markets, exchange rates and oil market data, not many studies have been conducted to assess the predictive performance of the volatility GARCH-type models using CDS data. Despite Krishnan et al. (2010), Sharma and Thuraisamy (2013), Avino and Nneji (2014) and Srivastava et al. (2016) whose aim is to predict the future changes in the CDS spreads based on some macroeconomic and market-wide variables, the literature on CDS spreads focuses generally on the key drivers and determinants of these credit spreads (Oliveira et al., 2012; Costantini et al., 2014; Fontana and Scheicher, 2016) or rather on the interaction and comovement between CDS markets and the other related financial markets (Coudert et al., 2010; Longstaff et al., 2011; Coudert and Gex, 2013; Sabkha et al., 2018). Among the first authors who are interested in the prediction of credit spreads, Krishnan et al. (2010) construct credit-spread curves, based on several macroeconomic and firm-specific variables, for 241 highly and lowly credit-risky firms from 1990 to 2005. Results show that only the information contained in the riskless yield curve significantly improve the out-of-sample forecasts. Focusing more precisely on the CDS as proxy for the credit risk level, Sharma and Thuraisamy (2013) investigates the forecastability of the CDS spreads of 8 Asian sovereign from 2005 to 2012. In-sample and out-of-sample evidences reveal that the oil price uncertainty provides valuable information for predicting the future fluctuations in the sovereign

[1]For an exhaustive survey of the proposed ARCH-class models, see Poon (2005).

[2]For a complete theoretical and empirical survey on the use of univariate ARCH processes in financial studies, see Bollerslev et al. (1992).

CDS spreads. Avino and Nneji (2014) use some economic and financial factors to investigate whether the iTraxx index spreads are forecastle. Based on the results of the predictive ability of some linear (Structural OLS model and AR(1)) and non-linear (Markov-switching) models, these authors show that the daily changes in the CDS index can be predictable from the yield curve, the equity returns and the changes in the VSTOXX volatility index. Using an error correction model before, during and after the subprime crisis, Srivastava et al. (2016) show that the VIX predicts the future changes in 98% of the studied sovereign CDS markets. These few studies on the forecastability of CDS spreads rely on the information contained in the theoretical determinants - widely used in the empirical literature - and its ability to predict future fluctuations in the CDS market. Yet, he accuracy of these CDS predictions is assessed through some loss function criteria that are subject to nonzero mean noise and serial correlation (such as RMSE, MAE...). Furthermore, the data studied so far only cover the period of the subprime crisis and end before or right after the outbreak of the Sovereign Debt Crisis, which is quite a weak point given that all the unexpected changes in the market behavior are not taken into account in their forecasting models. Finally, the most important shortcoming of the aforementioned studies, is that they focus on the first moment order and neglect the variance in forecasting the CDS spreads.

1.3 Data and methodology

This section introduces one of our essay contributions: the sample under study, composed by countries around the world, allowing us to provide international evidences and data time line covering both the recent two financial and economic crises. Volatility forecasting models are as well presented in this section.

1.3.1 Sample and data description

Our study focuses on a sample composed by 38 worldwide countries belonging to five different geographical areas: Eastern and Western Europe, North and South America and Asia. Besides the developed countries and the emerging countries, the sample under study in this essay includes some Newly Industrialized Countries (such as Brazil, Mexico, Philippines and Thailand...) and some low economic growth countries with the highest credit risk levels (such as Portugal, Ireland, Greece and Spain...). The sample details with the economic and geographical status of each country are given in Table 1.1. The dataset used is composed by daily 5-year sovereign CDS spreads, denominated in US dollars and collected from Thomson Reuters ®. The extracted series cover a period spanning from January 2006 to March 2017, during which the world financial and credit markets have been affected by two major crises, namely the Global Financial Crisis and the Sovereign Debt Crisis. Thus, modeling, forecasting the CDS volatility and comparing models performances are particularly interesting during this period, during which we observed some unexpected fluctuations on the credit market.

1.3.2 Marginal volatility processes: univariate ARCH-type models

The financial markets are generally characterized by periods of volatility clustering, during which the assets' second moment order remains high before regaining its normal levels. Engle (1982) proposes an Autoregressive Conditional Heteroscedasticity (ARCH) model able to capture such financial phenomenon. This volatility persistence is as well observed in the Credit

Table 1.1: Sample and countries classification into economic categories and geographical positions

Country	Geographical position	Country	Geographical position
Developed countries (20)		***Newly industrialized countries (7)***	
Austria	Western Europe	Brazil	South America
Belgium	Western Europe	China	Asia
Denmark	Western Europe	Mexico	North America
Finland	Western Europe	Philippines	Asia
France	Western Europe	Qatar	Asia
Germany	Western Europe	Thailand	Asia
Ireland	Western Europe		
Italy	Western Europe	***Emerging countries (11)***	
Japan	Asia	Bulgaria	Eastern Europe
Latvia	Eastern Europe	Croatia	Eastern Europe
Lithuania	Eastern Europe	Czech	Eastern Europe
Netherlands	Western Europe	Hungary	Western Europe
Norway	Western Europe	Greece	Western Europe
Portugal	Western Europe	Indonesia	Asia
Slovakia	Eastern Europe	Poland	Eastern Europe
Slovenia	Eastern Europe	Romania	Eastern Europe
Spain	Western Europe	Russia	Asia
Sweden	Western Europe	Ukraine	Eastern Europe
UK	Western Europe	Venezuela	South America
USA	North America		

The countries' economic classification is made according to the NU, the CIA World Factbook, the IMF and the World Bank criteria, in order to have a sample with a sufficient number of countries in each category.

Default Swap market and the use of ARCH-class models to model the variance of the CDS spreads is thus legitimate. As an extension of the ARCH model, Bollerslev (1986) proposes a generalized high-order ARCH process that is more parsimonious and allows for less over-parametrization and biasedness in the estimates. This GARCH model is given by:

$$\begin{aligned} x_t = \mu_t + a_t \quad / \quad a_t = \sigma_t \varepsilon_t, \quad \varepsilon_t | \mathcal{F}_{t-1} \rightsquigarrow \mathcal{D}(0,1), \\ \sigma_t^2 = V(x_t | \mathcal{F}_{t-1}) = \omega + \sum_{k=1}^{q} \alpha_k a_{t-1}^2 + \sum_{h=1}^{p} \beta_h \sigma_{t-1}^2. \end{aligned} \tag{1.1}$$

with x_t is a financial time series and μ_t and σ_t are respectively conditional mean and conditional volatility. To satisfy the positive-definite condition, some restrictions are imposed: $p \geq 0$, $q \geq 0$ and $\omega \geq 0$, $\alpha_k \geq 0$ for $k = 1, \ldots, q$, $\beta_h \geq 0$ for $h = 1, \ldots, p$. For sake of simplicity and suitability, only models with process orders (p and q) equal to 1 are estimated. In fact, the simplest GARCH(1,1) specification is the most useful and fitted for financial time series (Bollerslev, 1986; Wei et al., 2010). The GARCH(1,1) process, as proposed by Bollerslev

(1986), is given by the following formula:

$$\sigma_t^2 = \omega + \alpha a_{t-1}^2 + \beta \sigma_{t-1}^2. \tag{1.2}$$

Furthermore to the previous model restrictions, α and β parameters must satisfy the condition of $\alpha + \beta < 1$ to comply with the stationarity in the broad sense. A more restrictive version of the GARCH(1,1) is proposed by Engle and Bollerslev (1986) where the equivalent of the unit root in the mean is included in the variance so we can handle for the stationarity of the variance. The integrated GARCH(1,1) takes into account the persistence of conditional volatilities[1]. The main difference with the GARCH(1,1) is that the IGARCH requires the parameters α and β to respect the equality of $\alpha + \beta = 1$. Thus, the IGARCH(1,1)[2] can be written as follows:

$$\sigma_t^2 = \alpha a_{t-1}^2 + (1 - \alpha)\sigma_{t-1}^2. \tag{1.3}$$

Besides the aforementioned linear models, there exist some nonlinear GARCH-class of models taking into account the other financial market properties. The exponential GARCH, as proposed by Nelson (1991), is one of these models that accounts for the leverage effect and the asymmetry of the error distribution. While the nonnegativity of linear GARCH model is ensured by several parameters restrictions, the EGARCH model proposes another formulation allowing for a positive volatility without any restrictive constraints. The EGARCH(1,1) is expressed as follows:

$$\begin{aligned} ln(\sigma_t^2) &= \omega + \alpha ln(\sigma_{t-1}^2) + \beta g(\varepsilon_{t-1}), \\ \text{where} \quad g(\varepsilon_t) &= \theta\varepsilon_t + \gamma[\mid \varepsilon_t \mid - E(\mid \varepsilon_t \mid)]. \end{aligned} \tag{1.4}$$

The asymmetric relation between assets' fluctuation and volatility changes is depicted by the θ and γ representing respectively the sign and the magnitude of ε_t. Glosten et al. (1993) propose a model that allows the sign and the amplitude of the innovations (ε_t) to affect the conditional volatility separately. The asymmetric leverage effect[3] is represented in the following formulation of the GJR-GARCH(1,1)[4] model:

$$\sigma_t^2 = \omega + \alpha a_{t-1}^2 + \gamma I_{t-1} a_{t-1}^2 + \beta \sigma_{t-1}^2. \tag{1.5}$$

with I_t is a dummy variable equal to 0 when a_t is positive and 1 otherwise. The first model accounting for the long-range persistence of financial assets variance is developed by Ding et al. (1993). This asymmetric power ARCH model allows the volatility to be long-memory[5]. The APARCH(1,1) model is:

$$\sigma_t^2 = \omega + \alpha(\mid a_{t-1} \mid - \gamma a_{t-1})^{\delta} + \beta \sigma_{t-1}^{\delta}. \tag{1.6}$$

[1]Today's shocks on a financial asset (future contracts for example) have a significant impact on the conditional volatility several periods in the future.

[2]The IGARCH(1,1) is equivalent to the Exponentially Weighted Moving Average (EWMA) model developed by Morgan and Reuters (1996).

[3]Positive and negative financial shocks revamp asymmetrically the variance. Furthermore, bad news (shocks) generate greater volatility than good news.

[4]The volatility's different reactions to signs and sizes of past innovations are also suggested in the Threshold Heteroskedastic model (TGARCH) of Zakoian (1994). The major difference is that in the TGARCH model the conditional standard deviation (σ_t) is considered rather than the conditional variance (σ_t^2).

[5]The autocorrelation function of time series returns decreases gradually.

where δ depicts the Box-Cox power transformation of the conditional volatility (σ_t) and satisfies the condition of $\delta \geq 0$. A more flexible class of GARCH models is proposed by Baillie et al. (1996) who introduce a new feature of the unit root for the variance. In fact, the fractionally integrated GARCH model (FIGARCH) highlights the fact that - unlike stationary processes where the persistence of volatility shocks is finite - in unit root processes, the impact of lagged errors occurs at a slow hyperbolic rate of decay. The FIGARCH model allows, thus, to capture the long memory in financial volatility with a complete flexibility regarding the persistence degree. In fact, the FIGARCH(1,d,1) formulation depends on fractional integration parameter (d) as follows:

$$\sigma_t^2 = \omega + [1 - (1 - \beta(L))^{-1}(1 - \phi(L))(1 - L)^d]a_t^2 + \beta\sigma_{t-1}^2. \tag{1.7}$$

with $0 < d < 1$. When d=1, the FIGARCH(1,d,1) is equivalent to an IGARCH(1,1) where the persistence of conditional variance is supposed to be complete, while when d=0, it is rather equivalent to a GARCH(1,1) and no volatility persistence is taken into consideration. L is the lag operator and $(1 - L)^d$ is the financial fractional differencing operator. Other ARCH formulations are extended to the fractionally integrated GARCH, including asymmetric leverage effect presented in the EGARCH model. Bollerslev and Mikkelsen (1996) propose a new class of model combining characteristics of the FIGARCH and the EGARCH models, so-called FIEGARCH(p,d,q). Financial assets' volatility is, thus, better explained and depicted by a mean-reverting fractionally integrated process. The FIEGARCH(1,d,1) model is written as follows:

$$ln(\sigma_t^2) = \omega + \phi(L)^{-1}(1 - L)^{-d}[1 + \psi(L)]g(\varepsilon_{t-1}). \tag{1.8}$$

where $\phi(L)$ and $\psi(L)$ are lag polynomials, and - as in the EGARCH(1,1)[1] - $g(\varepsilon_t)$ is a quantization function of information flows such as:

$$g(\varepsilon_t) = \theta_i\varepsilon_t + \gamma_i[\mid \varepsilon_t \mid - E(\mid \varepsilon_t \mid)].$$

An extension of the conventional fractionally integrated GARCH model is proposed by Tse (1998) so-called FIAPARCH(1,d,1). The new approach combines the long-range dependencies feature and the asymmetric impact of lagged positive and negative shocks on future volatility in one fractionally integrated model. The FIAPARCH(1,d,1) is written as follows:

$$\sigma_t^\delta = \omega(1 - \beta)^{-1} + [1 - (1 - \beta(L))^{-1}\phi(L)(1 - L)^d](\mid a_t \mid - \gamma a_t)^\delta. \tag{1.9}$$

More recently, another linear GARCH model, called hyperbolic GARCH (HYGARCH) is proposed by Davidson (2004) who argues that the impact of lagged errors on the conditional variance discloses near-epoch dependence feature. The main contribution of this model is that the fractional integration parameter is negative (-d) instead of positive and that d increases rather when it approaches zero[2].The statistical properties included in the HYGARCH make it the most successful and used approach by financial practitioners in modeling time series volatility. The HYGARCH(1,d,1) is defined under the following formulation:

$$\sigma_t^2 = \omega + [1 - (1 - \beta(L))^{-1}(1 - \phi(L))[1 + \alpha((1 - L)^d - 1)]]a_t^2. \tag{1.10}$$

[1]When the memory parameter, d=0, the FIEGARCH formulation is equivalent to the conventional EGARCH(1,1) (FIEGARCH(1,0,1)$\simeq$ EGARCH(1,1)).

[2]When d of the HYGARCH is positive, it is considered as a unit root process.

The volatility estimation of the CDS log returns of the 38 countries is computed for 9 GARCH-class models taking into account, each time, different financial stylized facts such as long-run properties in the conditional mean and volatility clustering and long-memory behavior in the conditional variance. The BFGS-BOUNDS method (Broyden, 1970) is used to optimize the likelihood function rather than the conventional numerical optimization, in order to respect the parameters constraints, notably the stationary and the nonnegativity constraints. In addition to the widely used Box-Pierce tests and the LM ARCH effects test, several other diagnostic tests are conducted here, namely the Nyblom test, the adjusted Pearson goodness-of-fit test and the Residual-Based Diagnostic (as suggested by Fantazzini (2011)). The Joint Nyblom (Nyblom, 1989) is a stability test under the null hypothesis of parameters joint constancy over time against the alternative of parameters shift at an undefined breakpoint. According to Palm and Vlaar (1997), the adjusted Pearson goodness-of-fit test verifies whether the residuals' empirical distribution matches or not the theoretical distribution (namely Gauss, Student or Generalized Error Distribution (G.E.D) depending on the country). The Residuals-Based Diagnostic test (Tse, 2002) checks for conditional Heteroscedasticity, by complementing and filling the gaps of the Box-Pierce Q statistics. All these univariate models are estimated through the most widely used approach: the Maximum Likelihood (ML) approach approximated under one of four assumed distributions about the residuals ε_t (Gauss, Student, Generalized Error Distribution and Skewed-Student). Among the several existing techniques to optimize the non-linear (log-)likelihood functions, we use in this essay the limited Broyden, Fletcher, Goldfarb and Shanno (BFGS-bounds) algorithm (Nocedal and Wright, 1999). The BFGS-bounds allows the estimated parameters (Ω) to only range between selected lower and upper boundaries, so we can impose the stationarity and the positivity of the models. A detailed discussion on the Maximum Likelihood estimation method and the numerical optimization algorithm used in this essay is presented in section 1.7.

1.3.3 Loss function criteria

Following Wei et al. (2010), the forecasting process of the CDS volatility is implemented as follows: the 38 CDS times series timeline is divided into two subperiods: the in-sample volatility estimation is conducted from January 2^{nd}, 2006 to March 31^{st}, 2014 (2152 observations), and the out-of-sample model forecasts concern the last three years, i.e. from April 1^{st}, 2014 to March 31^{st}, 2017 (783 observations). The twenty-day out-of-sample forecasting are used to assess and compare the predictive performance of the 9 studied models. The comparison of the volatility models' forecasting ability is not straightforward. Several measures of the predictive ability are suggested in the literature based on some loss functions. According to Poon (2005), Wei et al. (2010) and Pilbeam and Langeland (2015), we cannot conclude with certainty the superiority of one model over another in terms of forecasting performance, based solely on the result of a single error statistic since each criterion may be more and less relevant from one case to another[1]. That's why the conclusions made in this study are based on the results of a rich set of statistics composed by the 7 most popular and relevant ones, including:

- The Mean Square Error (MSE):

$$MSE = \frac{1}{N}\sum_{t=1}^{N}(\hat{\sigma}_t - \sigma_t)^2, \tag{1.11}$$

[1]Diebold and Mariano (2002) argue that allowing for forecast errors to be non-Gaussian, nonzero mean and autocorrelated produces better tests' results.

- The Mean Absolute Error (MAE):

$$MAE = \frac{1}{N} \mid \hat{\sigma_t} - \sigma_t \mid, \tag{1.12}$$

- The Heteroscedatiscity-adjusted Mean Square Error (HMSE). As suggested by Bollerslev and Ghysels (1996), the HMSE is calculated as follows:

$$HMSE = \frac{1}{N} \sum_{t=1}^{N} \left(\frac{\sigma_t}{\hat{\sigma_t}} - 1 \right)^2, \tag{1.13}$$

- The Heteroscedatiscity-adjusted Mean Absolute Error (HMAE). Andersen et al. (1999) proposes a loss function that better accommodates the heteroskedasticity in the forecast bias . The HMAE is calculated as follows:

$$HMAE = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{\sigma_t}{\hat{\sigma_t}} - 1 \right|, \tag{1.14}$$

- The QLIKE loss function (QLIKE). This is a test of forecast bias implied by a Gaussian likelihood (see Wei et al. (2010) for a further details.)

$$QLIKE = \frac{1}{N} \sum_{t=1}^{N} \left(ln(\hat{\sigma_t}) + \frac{\sigma_t}{\hat{\sigma_t}} \right), \tag{1.15}$$

- The R^{2}LOG loss function (R^{2}LOG): This loss function assesses the goodness-of-fit of the out-of-sample forecasts, based on the regressions of Mincer and Zarnowitz (1969)

$$R^2LOG = \frac{1}{N} \sum_{t=1}^{N} \left(ln(\frac{\sigma_t}{\hat{\sigma_t}}) \right)^2, \tag{1.16}$$

- The Mean Logarithm of Absolute Errors (MLAE): As proposed Pagan and Schwert (1990), the MLAE criterion is written as follows:

$$MLAE = \frac{1}{N} \sum_{t=1}^{N} ln \mid \hat{\sigma_t} - \sigma_t \mid . \tag{1.17}$$

With N is the number of predicted data and $\hat{\sigma_t}$ is the volatility forecasts. The latent daily CDS spreads volatility σ_t is not observed and is thus proxied by the squared daily logarithmic returns[1]. Previous studies (Lopez, 2001; Poon, 2005) report that the use of such a proxy produces unbiased estimates, even though it remains questionable (noisy estimator because of its asymmetric distribution).

[1]More methods exist in the literature to proxy the volatility of financial assets, such as the high-low measure and the realized volatility estimate. For a complete survey of these methods, see Poon (2005).

Table 1.2: Descriptive statistics and ARCH effect tests for the CDS time series

	CDS spreads						CDS log returns			
	Obs.	Min	Mean	Max	Std. Dev	*ADF statistics*	*ARCH-LM (2)*	*ARCH-LM (5)*	*ARCH-LM (10)*	*GPH*
Austria	2936	1.40	36.13	132.77	24.96	-2.45	249.75 ***	127.05 ***	72.58 ***	0.29 ***
Belgium	2936	2.05	72.39	398.78	74.62	-1.67	508.94 ***	237.99 ***	120.84 ***	0.18 ***
Brazil	2936	61.50	178.55	606.31	94.86	-2.46	25.01 ***	43.70 ***	37.71 ***	0.11 ***
Bulgaria	2936	13.22	180.37	692.65	121.88	-2.25	12.71 ***	10.36 ***	6.72 ***	0.08 ***
China	2936	10.00	82.44	276.30	43.56	-2.82 *	120.85 ***	63.09 ***	39.00 ***	0.22 ***
Croatia	2936	24.88	244.20	592.50	128.47	-2.15	137.90 ***	58.87 ***	47.62 ***	0.26 ***
Czech	2936	3.41	66.89	350.00	49.54	-2.62 *	62.52 ***	46.01 ***	29.50 ***	0.14 ***
Denmark	2936	11.25	36.65	157.46	32.94	-2.17	87.27 ***	41.66 ***	24.36 ***	0.21 ***
Finland	2936	2.69	26.85	94.00	19.24	-2.33	13.79 ***	7.98 ***	4.43 ***	0.05 ***
France	2936	1.50	54.30	245.27	50.56	-1.71	276.95 ***	120.56 ***	62.86 ***	0.20 ***
Germany	2936	1.40	28.77	118.38	24.50	-2.05	252.46 ***	128.31 ***	73.27 ***	0.29 ***
Greece	2936	5.20	9508.85	37081.41	15351.1	-1.46	5.E-04	4.E-04	6.E-04	-4.E-04
Hungary	2936	17.34	225.98	729.89	153.05	-2.18	14.48 ***	15.20 ***	8.67 ***	0.10 ***
Indonesia	2936	118.09	219.29	1240.00	116.83	-2.63 *	139.82 ***	105.31 ***	61.49 ***	0.23 ***
Ireland	2936	1.75	188.89	1249.30	234.02	-1.36	218.63 ***	103.01 ***	63.33 ***	0.18 ***
Italy	2936	5.575	151.75	586.7	127.38	-1.79	127.35 ***	60.46 ***	35.18 ***	0.19 ***
Japan	2936	2.13	49.26	152.64	33.28	-1.94	71.53 ***	31.30 ***	21.68 ***	0.13 ***
Latvia	2936	5.50	210.89	1176.30	216.13	-1.62	152.57 ***	68.47 ***	35.36 ***	0.26 ***
Lithuania	2936	6.00	169.21	850.00	154.01	-1.90	56.75 ***	26.91 ***	13.56 ***	0.15 ***
Mexico	2936	64.17	141.89	613.11	59.36	-3.03 *	356.35 ***	160.17 ***	127.50 ***	0.39 ***
Netherlands	2936	7.67	37.13	133.84	29.50	-2.00	10.79 ***	4.33 ***	5.59 ***	0.05 ***
Norway	2936	10.59	30.95	62.00	17.82	-1.68	3.22 ***	2.46 ***	2.06 ***	0.05 **
Philippines	2936	78.30	188.72	840.00	101.70	-1.77	154.83 ***	127.66 ***	90.03 ***	0.23 ***
Poland	2936	7.67	101.35	421.00	73.12	-2.32	311.98 **	135.64 **	75.78 **	0.21 ***
Portugal	2936	4.02	289.89	1600.98	323.68	-1.60	53.57 ***	42.23 ***	22.61 ***	0.17 ***
Qatar	2936	7.8	83.13	390.00	53.89	-2.12	37.65 ***	17.33 ***	9.55 ***	0.09 ***
Romania	2936	17.00	204.20	767.70	144.17	-2.09	57.88 ***	33.74 ***	17.50 ***	0.17 ***
Russia	2936	36.88	209.09	1106.01	147.84	-2.95 *	258.09 ***	117.58 ***	65.50 ***	0.29 ***
Slovakia	2936	5.33	77.52	306.01	66.71	-2.03	25.14 ***	24.62 ***	19.31 ***	0.11 ***
Slovenia	2936	4.25	131.24	488.58	114.88	-1.65	13.23 ***	9.82 ***	34.88 ***	0.11 ***
Spain	2936	2.55	144.63	634.35	135.01	-1.56	195.02 ***	78.80 ***	39.98 ***	0.19 **
Sweden	2936	1.63	27.17	159.00	25.70	-2.64 *	69.49 ***	30.82 ***	20.72 ***	0.16 ***
Thailand	2936	51.01	120.94	500.00	41.89	-3.64 *	81.52 ***	120.36 ***	96.33 ***	0.17 ***
Turkey	2936	109.82	217.65	835.01	72.41	-3.72 *	69.04 ***	86.65 ***	46.84 ***	0.21 ***
UK	2936	16.50	42.89	165.00	28.11	-2.07	27.33 ***	21.12 ***	23.19 ***	0.11 ***
Ukraine	2936	1.00	2173.76	15028.76	3969.27	-2.15	60.42 ***	32.53 ***	17.13 ***	0.11 ***

Table 1.2: Descriptive statistics and ARCH effect tests for the CDS time series (*Continued*)

	CDS spreads						**CDS log returns**			
	Obs.	Min	Mean	Max	Std. Dev	*ADF statistics*	*ARCH-LM (2)*	*ARCH-LM (5)*	*ARCH-LM (10)*	*GPH*
USA	2936	10.02	24.01	90.00	11.11	-3.58 *	94.96 ***	46.67 ***	24.57 ***	0.18 ***
Venezuela	2936	124.62	1771.08	10995.67	1869.79	-2.00	36.17 ***	38.56 ***	22.73 ***	0.11 ***

The table reports descriptive statistics for the daily sovereign CDS spreads of 38 countries. Min., Max. and Std. Dev. denote respectively the minimum, the maximum and the standard deviation. The Augmented-Dickey Fuller (Individual intercept included in the test equation) is a unit root test that informs about the stationary of time-series with a null hypothesis of the presence of a unit root in the process. The Engle's ARCH-LM test with 2, 5 and 10 lag orders informs about the presence of ARCH effects in the series under the null hypothesis of no autocorrecations in the squared residuals. GPH is the log periodogram test of Geweke and Porter-Hudak (1983) with d-parameter (m=1467). This test is applied to the squared logarithmic returns (as proxy for unconditional volatility) to detect any long-range dependence volatility process. *, ** and *** refer to the statistical significance at respectively 10%, 5% and 1% levels.

1.4 Empirical results

This section presents the summary statistics for the 38 studied time series. The modeling, estimation and testing of the forecasting ability of the 9 GARCH-class models are presented, as well, in this section.

1.4.1 Descriptive statistics

Descriptive statistics, displayed in Table 1.2, show that the studied countries present dissimilar credit risk levels with CDS spreads ranging from 1 bp to 37081.41 bp. The average daily spreads highlights, as well, this divergence in sovereign financing conditions with the largest value recorded, as expected, in Greece (9508.85 bp) and the smallest value recorded in the USA (24.01 bp). The high levels of standard deviations reveal, on the other side, that the worldwide financial and economic troubles impacted the public finances of the countries under study, doubtlessly with different magnitudes. The least volatile CDS market is Germany (24.50). According to the Augmented Dickey-Fuller test (Dickey and Fuller, 1981), all the time series present a unit root, implying that the CDS spreads of the 38 countries are non-stationary at 5% statistical level at least.

Focusing on the evolution of the CDS log returns (computed as $x_t = log(\frac{S_t}{S_{t-1}})$) over the studied period, as presented in Figure 1.1, some volatility clustering periods are detected. Results of the ARCH-LM test in Table 1.2 confirm that the data used clearly exhibit heteroscedastic properties and support the appropriate use of GARCH-class processes to model the conditional volatility. The GPH test (Geweke and Porter-Hudak, 1983) conducted on the squared CDS log returns rejects the null hypothesis of no long-memory behavior in the series' volatility process, suggesting the use of the fractionally-integrated models[1]. Figure 1.2 reports the density estimation and show that the series, composing our international sample, exhibit dissimilar statistical behaviors as to their empirical distributions. The majority of the data returns' distributions does not clearly overlay the Gaussian reference, which indicates that the residuals should be allowed to follow a Gaussian, a student and a Generalized Error Distribution (G.E.D)[2].

1.4.2 Models estimation and diagnostic tests

Results of the 9 GARCH-class model estimates are not reported here but are available upon request. Even though some models are difficult to optimize, no miss-convergences are recorded for any time series. However, at first sight, the major conclusion that could be drawn regarding the models estimation process is that, taking into account several financial markets' stylized facts (long memory characteristic, shock persistence and asymmetric leverage effects...) does not necessarily improve the models in-sample performances since the more the model is over-parametrized, the more its computation and its convergence are complicated. In fact, different inconsistency and inaccuracy of the estimator parameters in some countries and for some model can result from the complexity of the model's statistical specifications. At the opposite, the models that great perform as to strong numerical convergence and computing-time delay are

[1] Another commonly used long-range test is the Gaussian semi-parametric (GSP) (Robinson, 1995). Results of the GSP are not reported here but they are similar to those of the GPH.

[2] Other statistical distributions should, as well, be taken into account in further studies, such as the Skewed t-student...

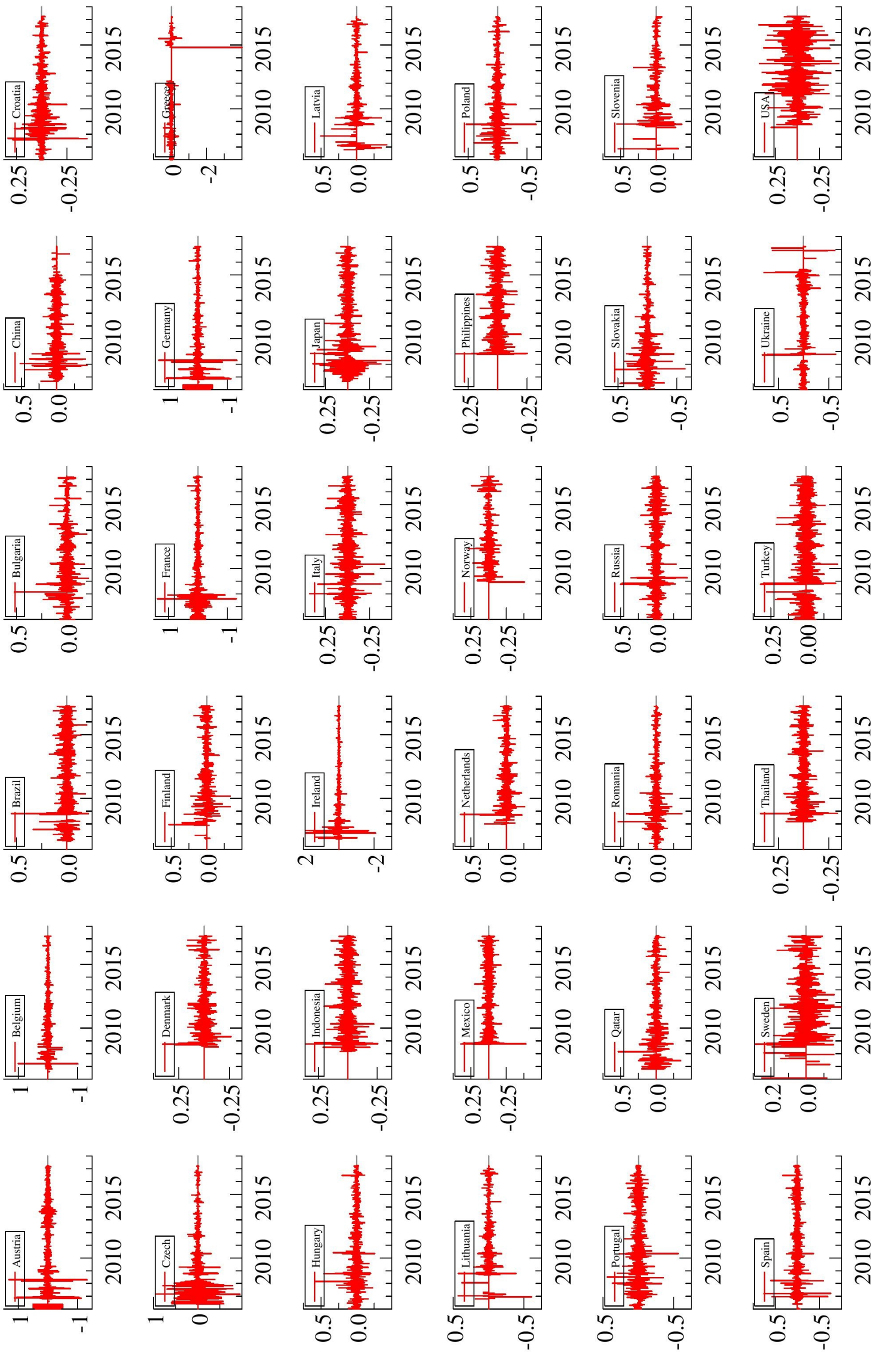

Figure 1.1: Daily CDS log returns of some chosen worldwide countries

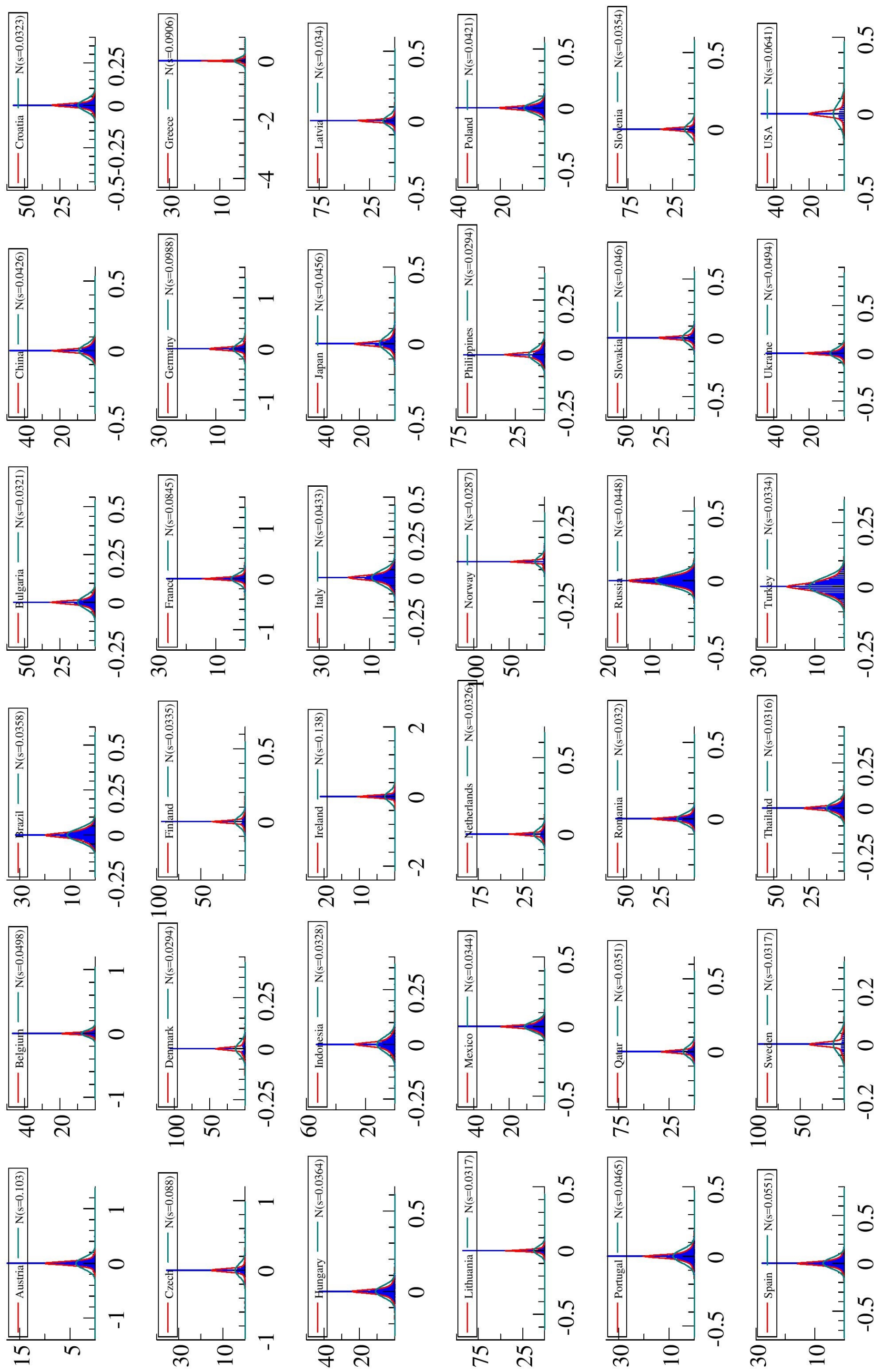

Figure 1.2: Density estimation of some chosen worldwide countries

the GARCH, the IGARCH, FIGARCH and FIEGARCH.

Results of the univariate misspecification tests applied on the standardized residuals are presented in Table 1.5 (section 1.6). The Q portmanteau empirical statistics with 20 lags, applied on both standardized residuals in levels and squared, show that the null hypothesis of no serial correlation is accepted in most cases, for all the studied models. The LM-ARCH test up to 10 lag orders shows, as well, that there is no heteroscdasticity in the conditional variance equations of most of time series. The GARCH, IGARCH and FIGARCH models pass this test in 100% of cases, whilst the least performant model, in terms of serial correlation, is the FIAPARCH with the presence of ARCH effects detected in 6 countries. Moreover, testing for conditional heteroscadticity through the Residual-Based Diagnostic (RDB) (Tse, 2002) gives better results, with absolutely no serial correlation detected in all series for the APARCH, IGARCH and FIGARCH. Based on the Nyblom test, proposed by Nyblom (1989), no possible shifts are detected and the parameters coefficients of the 9 models are found to be constant over time for all countries. One of the recommended steps in modeling financial data process is to evaluate the goodness of fit (D'Agostino, 2017). The fitting of our models are thus assessed, in this essay, through the adjusted Pearson goodness-of-fit test. Statistics indicate that mostly there is no difference between the empirical distributions of the residuals and the theoretical ones. Interestingly, the basic GARCH model seems to have the highest number (12 over the 38 studied series) of unconformity and discrepancy of the data from the hypothesized probability distributions.

In addition to the diagnostic tests, Table 1.5 (section 1.6) displays the Akaike information criterion (AIC) for each model and each country. Results do not allow us to unanimously select only one most appropriate model. AIC results of the studied models are mitigated across the 38 countries of the sample. By minimizing the AIC, the APARCH turns out to be the best fitted model for the CDS data of 34% of the sample, while HYGARCH, IGARCH and FIAPARCH provide the best in-sample fit for respectively 26%, 18% and 11% of the studied countries. However, these results are not in line with the preliminary analysis where all the studied CDS log returns are found to be subject to long-memory feature in the variance. By only focusing in the fractionally integrated subset of models, the HYGARCH is found to majority outperform in 53% of cases, followed by the FIAPARCH in 40% of cases. These results divergence points out the limits of using the "minimizing loss of information" technique in comparing models appropriateness. Thus, this approach seems to be, in this case, not totally consistent and should only be used tentatively, at least if it is not associated with any other approaches. Hence, it is better to rather rely on the forecasting ability to select the best performant volatility model.

Table 1.3: Results of the loss function criteria for the twenty-day out-of-sample volatility predictions

	MSE								
	GARCH	*EGARCH*	*GJR*	*APARCH*	*IGARCH*	*FIGARCH*	*FIEGARCH*	*FIAPARCH*	*HYGARCH*
Austria	0.0168	0.2640	0.0181	0.0483	0.0189	0.0189	0.1318	0.0189	0.0194
Belgium	0.0051	0.1971	0.0050	0.0073	0.0050	0.0050	0.6694	0.0058	0.0095
Brazil	0.0012	0.1120	0.0014	0.0020	0.0010	0.0010	0.9925	0.0010	0.0027
Bulgaria	0.0009	0.1813	0.0009	0.0010	0.0008	0.0008	0.1759	0.0008	0.0022
China	0.0042	0.3349	0.0047	0.0050	0.0055	0.0044	0.0003	0.0044	0.0046
Croatia	0.0025	0.0046	0.0023	0.0461	0.0008	0.0007	0.0004	0.0008	0.5356
Czech	0.0082	0.9185	0.0089	0.0092	0.0081	0.0082	0.9067	0.0077	0.0010
Denmark	0.0070	0.2619	0.0053	0.0076	0.0052	0.0052	0.3797	0.0046	0.0051
Finland	0.0067	0.7343	0.0065	0.0051	0.0059	0.0065	0.0165	0.0060	0.0064
France	0.0104	0.0237	0.0114	0.0378	0.0057	0.0055	0.0237	0.0048	0.0290

Germany	0.0182	0.0165	0.0170	0.0197	0.0171	0.0183	0.1753	0.0205	0.0194
Greece	0.4862	0.6709	0.4788	0.4704	0.4758	0.4814	0.2765	0.4754	0.4775
Hungary	0.0032	0.0055	0.0031	0.0012	0.0011	0.0010	0.0049	0.0015	0.0008
Indonesia	0.4590	0.4590	0.4588	0.4585	0.4587	0.4585	0.6687	0.4586	0.4588
Ireland	0.0228	0.0889	0.0206	0.0375	0.0197	0.0189	0.7325	0.0175	0.0919
Italy	0.0043	0.0046	0.0038	0.0015	0.0046	0.0013	0.0012	0.0013	0.0013
Japan	0.0026	0.6015	0.0023	0.0033	0.0022	0.0022	0.5609	0.0022	0.0044
Latvia	0.0052	0.1550	0.0051	0.0098	0.0042	0.0044	0.3013	0.0043	0.0046
Lithuania	0.0073	0.4946	0.0076	0.0074	0.0067	0.0063	0.4168	0.0079	0.0075
Mexico	0.0024	0.0034	0.0026	0.0026	0.0028	0.0023	0.2575	0.0028	0.0031
Netherlands	0.0199	0.0184	0.0179	0.0182	0.0177	0.0178	0.1028	0.0181	0.0184
Norway	0.0675	0.2614	0.0668	0.0693	0.3232	0.0673	0.3232	0.0677	0.0675
Philippines	0.0008	0.0032	0.0008	0.0007	0.0009	0.0006	0.2773	0.0010	0.0012
Poland	0.0029	0.0048	0.0029	0.0043	0.0012	0.0012	0.0088	0.0011	0.0010
Portugal	0.0035	0.0068	0.0038	0.0059	0.0015	0.0015	0.0113	0.0023	0.0015
Qatar	0.0042	0.0066	0.0043	0.0062	0.0604	0.0043	0.0042	0.0045	0.0044
Romania	0.0016	0.0198	0.0009	0.0009	0.0008	0.0007	0.7783	0.0011	0.0026
Russia	0.0012	0.0021	0.0012	0.0012	0.0012	0.0012	0.0021	0.0011	0.0012
Slovakia	0.0024	0.0339	0.0025	0.0264	0.0018	0.0018	0.6179	0.0019	0.0067
Slovenia	0.0034	0.0405	0.0034	0.0033	0.0034	0.0034	0.2103	0.0049	0.0044
Spain	0.0028	0.0279	0.0027	0.0031	0.0025	0.0024	0.0279	0.0023	0.0061
Sweden	0.0055	0.1411	0.0060	0.0059	0.0056	0.0058	0.2944	0.0060	0.0058
Thailand	0.0013	0.2656	0.0014	0.0015	0.0013	0.0013	0.4255	0.0013	0.0016
Turkey	0.0008	0.0117	0.0009	0.0010	0.0007	0.0007	0.4182	0.0006	0.0013
UK	0.0015	0.0028	0.0017	0.0016	0.0016	0.0014	0.4541	0.0015	0.0019
Ukraine	0.0042	0.1403	0.0049	0.0052	0.0043	0.0046	0.1388	0.0045	0.0067
USA	0.0151	0.0177	0.0151	0.0151	0.0148	0.0146	0.0177	0.0147	0.0163
Venezuela	0.0009	0.0025	0.0009	0.0008	0.0007	0.0007	0.0662	0.0007	0.0018

					MAE				
	GARCH	*EGARCH*	*GJR*	*APARCH*	*IGARCH*	*FIGARCH*	*FIEGARCH*	*FIAPARCH*	*HYGARCH*
Austria	0.0597	0.1335	0.0603	0.1620	0.0643	0.0643	0.1249	0.0527	0.0636
Belgium	0.0313	0.2422	0.0323	0.0450	0.0324	0.0325	0.2595	0.0332	0.0577
Brazil	0.0249	0.1668	0.0276	0.0326	0.0222	0.0219	0.5846	0.0216	0.0381
Bulgaria	0.0174	0.1050	0.0174	0.0206	0.0105	0.0159	0.0159	0.0156	0.0277
China	0.0322	0.3501	0.0342	0.0375	0.0410	0.0346	0.0270	0.0361	0.0342
Croatia	0.0304	0.0418	0.0291	0.1430	0.0161	0.0160	0.0409	0.0166	0.1537
Czech	0.0380	0.6732	0.0372	0.0504	0.0455	0.0369	0.2705	0.0441	0.0404
Denmark	0.0456	0.1950	0.0481	0.0621	0.0487	0.0476	0.1142	0.0578	0.0471
Finland	0.0396	0.4611	0.0408	0.0368	0.0390	0.0400	0.0913	0.0410	0.0402
France	0.0483	0.0654	0.0504	0.1088	0.0371	0.0370	0.0654	0.0358	0.0828
Germany	0.0552	0.0603	0.0548	0.0597	0.1203	0.0554	0.0548	0.0585	0.0666
Greece	0.1550	0.2466	0.1490	0.1483	0.1643	0.1511	0.9744	0.1472	0.1496
Hungary	0.0367	0.0301	0.0361	0.0200	0.0203	0.0190	0.0306	0.0259	0.0173
Indonesia	0.1924	0.1925	0.1926	0.1928	0.1925	0.1926	0.1539	0.1925	0.1930
Ireland	0.0487	0.0625	0.0477	0.0637	0.0477	0.0439	0.5391	0.0439	0.1077
Italy	0.0496	0.0476	0.0463	0.0286	0.0239	0.0256	0.0476	0.0263	0.0254
Japan	0.0290	0.8366	0.0290	0.0374	0.0284	0.0284	0.1798	0.0283	0.0448
Latvia	0.0319	0.2975	0.0330	0.0471	0.0316	0.0314	0.1861	0.0327	0.0316
Lithuania	0.0389	0.3211	0.0401	0.0405	0.0398	0.0381	0.1271	0.0401	0.0396
Mexico	0.0397	0.0384	0.0367	0.0381	0.0398	0.0365	0.2979	0.0395	0.0409
Netherlands	0.0743	0.0758	0.0739	0.0754	0.0732	0.0731	0.0000	0.0747	0.0765
Norway	0.1514	0.2985	0.1484	0.1575	0.1050	0.1480	0.1050	0.1488	0.1489
Philippines	0.0226	0.0209	0.0206	0.0199	0.0231	0.0185	0.9723	0.0221	0.0236
Poland	0.0325	0.0471	0.0321	0.0401	0.0202	0.0201	0.0612	0.0197	0.0176
Portugal	0.0405	0.0545	0.0422	0.0557	0.0263	0.0260	0.0743	0.0334	0.0247
Qatar	0.0349	0.0421	0.0353	0.0444	0.0350	0.0346	0.0835	0.0362	0.0357
Romania	0.0172	0.1187	0.0183	0.0184	0.0156	0.0154	0.1630	0.0188	0.0292
Russia	0.0239	0.0259	0.0238	0.0237	0.0243	0.0243	0.0259	0.0235	0.0239
Slovakia	0.0252	0.0633	0.0265	0.0752	0.0218	0.0218	0.2373	0.0220	0.0420
Slovenia	0.0302	0.0426	0.0300	0.0297	0.0299	0.0298	0.8524	0.0312	0.0296
Spain	0.0317	0.0827	0.0320	0.0351	0.0295	0.0285	0.0827	0.0282	0.0477
Sweden	0.0475	0.5913	0.0481	0.0481	0.0485	0.0464	0.4491	0.0473	0.0465
Thailand	0.0252	0.2061	0.0261	0.0271	0.0256	0.0252	0.3849	0.0259	0.0299

Turkey	0.0198	0.0583	0.0207	0.0221	0.0186	0.0185	0.0773	0.0185	0.0270
UK	0.0298	0.0296	0.0303	0.0292	0.0312	0.0284	0.3958	0.0281	0.0330
Ukraine	0.0274	0.1164	0.0249	0.0290	0.0258	0.0250	0.4394	0.0244	0.0304
USA	0.0949	0.0965	0.0949	0.0950	0.0929	0.0907	0.0965	0.0916	0.0990
Venezuela	0.0209	0.0239	0.0207	0.0201	0.0188	0.0187	0.0454	0.0176	0.0310

	HMSE								
	GARCH	*EGARCH*	*GJR*	*APARCH*	*IGARCH*	*FIGARCH*	*FIEGARCH*	*FIAPARCH*	*HYGARCH*
Austria	0.1054	0.8545	0.1717	0.8324	0.8449	0.8449	0.5361	0.2306	0.1342
Belgium	0.2503	0.7892	0.1511	0.6688	0.1655	0.2009	0.5731	0.4235	0.0048
Brazil	0.1497	0.5024	0.3147	0.1508	0.3319	0.8107	0.1001	0.1605	0.1141
Bulgaria	0.2314	0.0789	0.2566	0.1750	0.9986	0.2960	0.7895	0.1858	0.3913
China	0.4782	0.2142	0.4046	0.3621	0.5312	0.3100	0.9334	0.3090	0.1973
Croatia	0.7409	0.6537	0.7541	0.8237	0.1212	0.9844	0.6604	0.9817	0.9754
Czech	0.1454	0.8973	0.3804	0.1615	0.1679	0.7687	0.3568	0.1866	0.1210
Denmark	0.5989	0.5122	0.7105	0.9270	0.5294	0.7015	0.4449	0.1866	0.1334
Finland	0.6953	0.3033	0.1419	0.7411	0.1322	0.1299	0.1036	0.1107	0.2654
France	0.1332	0.9806	0.3916	0.3300	0.1807	0.1572	0.9806	0.1188	0.9758
Germany	0.6588	0.5757	0.2565	0.4401	0.5318	0.8237	0.8339	0.4818	0.5216
Greece	0.1278	0.2750	0.5632	0.1728	0.3808	0.1166	0.1101	0.1085	0.3914
Hungary	0.3472	0.8314	0.3482	0.2020	0.1544	0.1241	0.8405	0.1136	0.1327
Indonesia	0.1921	0.2052	0.6001	0.1478	0.1356	0.9473	0.2363	0.6628	0.4736
Ireland	0.2413	0.7882	0.2727	0.5478	0.2666	0.8881	0.1456	0.2613	0.4427
Italy	0.5366	0.5444	0.5332	0.5444	0.8795	0.6657	0.1005	0.7044	0.6773
Japan	0.6194	0.6122	0.1605	0.2312	0.2424	0.1800	0.1526	0.2020	0.7090
Latvia	0.3333	0.1770	0.1466	0.4932	0.2723	0.2850	0.3223	0.4290	0.1014
Lithuania	0.3953	0.0091	0.6748	0.9203	0.7588	0.8314	0.7358	0.0203	0.1169
Mexico	0.2895	0.7833	0.2091	0.4638	0.3383	0.1779	0.4335	0.3150	0.1786
Netherlands	0.3460	0.3922	0.0019	0.6496	0.3412	0.2072	0.0637	0.0000	0.0000
Norway	0.1775	0.3831	0.8095	0.3640	0.1293	0.1105	0.1105	0.5344	0.9276
Philippines	0.3565	0.1793	0.1944	0.4249	0.4094	0.5997	0.1045	0.2713	0.1959
Poland	0.1300	0.6250	0.1288	0.2891	0.5712	0.1017	0.6582	0.1118	0.1405
Portugal	0.1268	0.6310	0.1711	0.4652	0.9779	0.9757	0.8876	0.9183	0.1444
Qatar	0.1153	0.3138	0.1555	0.2364	0.5162	0.6170	0.4738	0.1086	0.1277
Romania	0.2258	0.8050	0.2356	0.2481	0.4849	0.1579	0.2475	0.2162	0.7391
Russia	0.5568	0.5423	0.5564	0.5567	0.5493	0.5487	0.5422	0.5583	0.5558
Slovakia	0.1452	0.9206	0.1461	0.3172	0.1572	0.1572	0.2691	0.2237	0.1246
Slovenia	0.1053	0.1037	0.1043	0.1004	0.9656	0.5711	0.3511	0.5791	0.2105
Spain	0.1217	0.8926	0.1756	0.3023	0.1479	0.1879	0.8925	0.1131	0.1946
Sweden	0.6479	0.4459	0.2442	0.6636	0.1900	0.4728	0.7608	0.9317	0.1547
Thailand	0.3675	0.4288	0.1456	0.2096	0.4946	0.1019	0.2233	0.6441	0.4063
Turkey	0.1419	0.5795	0.3787	0.3207	0.3749	0.1958	0.2613	0.6156	0.2767
UK	0.5338	0.9596	0.2678	0.3819	0.3119	0.1041	0.4351	0.8048	0.1135
Ukraine	0.1530	0.9590	0.1479	0.1547	0.1262	0.4541	0.1003	0.3017	0.3461
USA	0.5902	0.5131	0.5874	0.5831	0.5456	0.5450	0.5131	0.5807	0.7764
Venezuela	0.6137	0.5943	0.6039	0.6044	0.6700	0.6665	0.2341	0.1708	0.1064

	HMAE								
	GARCH	*EGARCH*	*GJR*	*APARCH*	*IGARCH*	*FIGARCH*	*FIEGARCH*	*FIAPARCH*	*HYGARCH*
Austria	0.4810	0.9513	0.1400	0.1135	0.1160	0.1160	0.1014	0.1504	0.3334
Belgium	0.3403	0.3789	0.2287	0.1332	0.9186	0.1058	0.1382	0.6533	0.5977
Brazil	0.1071	0.1247	0.4636	0.1299	0.1570	0.8090	0.8774	0.1018	0.9637
Bulgaria	0.3834	0.8154	0.4077	0.1066	0.2605	0.1725	0.0815	0.3563	0.3590
China	0.1656	0.4026	0.4940	0.1455	0.4296	0.1343	0.1503	0.1302	0.3417
Croatia	0.7310	0.7544	0.7297	0.8821	0.7854	0.7447	0.7559	0.7434	0.9875
Czech	0.8474	0.9255	0.1102	0.8713	0.8982	0.1697	0.2686	0.9185	0.3290
Denmark	0.4203	0.3393	0.4420	0.2553	0.5189	0.4186	0.9326	0.1785	0.5613
Finland	0.5708	0.5239	0.1105	0.4776	0.3471	0.1356	0.2766	0.0150	0.4860
France	0.2958	0.7225	0.4459	0.7253	0.7944	0.7757	0.7225	0.1098	0.7805
Germany	0.1277	0.9793	0.7806	0.7225	0.7484	0.1438	0.1015	0.6760	0.2014
Greece	0.1711	0.2910	0.4335	0.8196	0.4155	0.1881	0.1490	0.1759	0.3499
Hungary	0.7520	0.7063	0.7510	0.7681	0.7416	0.7162	0.7102	0.7423	0.7524

Indonesia	0.4057	0.1180	0.1912	0.1402	0.9120	0.1323	0.1130	0.8306	0.2002
Ireland	0.1308	0.1289	0.1344	0.1949	0.3797	0.2469	0.9929	0.1316	0.1094
Italy	0.6671	0.6652	0.6584	0.7089	0.6766	0.6411	0.6652	0.6588	0.6456
Japan	0.1814	0.2176	0.9274	0.1048	0.1202	0.9272	0.2593	0.8864	0.7186
Latvia	0.1678	0.3185	0.4106	0.6083	0.1436	0.5743	0.1662	0.5234	0.3183
Lithuania	0.2231	0.3007	0.9843	0.9596	0.3581	0.9213	0.2896	0.1487	0.3957
Mexico	0.2657	0.4865	0.7087	0.3329	0.1242	0.5829	0.2816	0.2391	0.2095
Netherlands	0.3186	0.8029	0.0619	0.3484	0.7852	0.6322	0.0961	0.0000	0.0000
Norway	0.9625	0.1405	0.4785	0.9825	0.1400	0.1836	0.1005	0.7092	0.1546
Philippines	0.2934	0.7178	0.2247	0.1017	0.1411	0.1141	0.4089	0.3749	0.7089
Poland	0.8264	0.7200	0.8248	0.1145	0.8328	0.7086	0.7477	0.7300	0.7939
Portugal	0.9365	0.6933	0.9749	0.7071	0.7109	0.7116	0.7557	0.5761	0.7929
Qatar	0.1042	0.1068	0.1197	0.2883	0.1930	0.7598	0.5004	0.3111	0.3036
Romania	0.1133	0.8750	0.7715	0.7773	0.7664	0.7499	0.7592	0.8042	0.1228
Russia	0.6024	0.5999	0.6010	0.6019	0.6011	0.6008	0.5999	0.6019	0.6018
Slovakia	0.2604	0.7703	0.2627	0.1362	0.2946	0.2946	0.2534	0.3357	0.6022
Slovenia	0.1349	0.1303	0.1343	0.1317	0.1338	0.1214	0.5795	0.1575	0.1595
Spain	0.5370	0.7852	0.1700	0.2662	0.6153	0.7971	0.7852	0.1443	0.8480
Sweden	0.2643	0.7898	0.6910	0.1042	0.8460	0.4014	0.8354	0.9885	0.1769
Thailand	0.8256	0.9634	0.1751	0.2007	0.1378	0.1017	0.1734	0.3048	0.2604
Turkey	0.1840	0.2208	0.9913	0.2780	0.9056	0.7166	0.8171	0.6053	0.3471
UK	0.1085	0.1513	0.2461	0.9242	0.4022	0.1572	0.8956	0.4215	0.1596
Ukraine	0.9458	0.9780	0.1663	0.1696	0.2055	0.9862	0.9370	0.1562	0.8165
USA	0.4248	0.3882	0.4241	0.4244	0.4127	0.4116	0.3882	0.4194	0.7035
Venezuela	0.6130	0.6045	0.6066	0.6017	0.6276	0.6244	0.1536	0.1447	0.2678

					QLIKE				
	GARCH	*EGARCH*	*GJR*	*APARCH*	*IGARCH*	*FIGARCH*	*FIEGARCH*	*FIAPARCH*	*HYGARCH*
Austria	0.3750	0.1801	0.3647	0.1122	0.0853	0.0853	0.2368	0.4388	0.2264
Belgium	0.3249	0.2503	0.2132	0.1330	0.9026	0.9056	0.1228	0.4992	0.4427
Brazil	0.9257	0.2236	0.4483	0.1299	0.1426	0.6683	0.7384	0.1017	0.8118
Bulgaria	0.3663	0.9138	0.3905	0.1048	0.2435	0.1555	0.9137	0.3393	0.1829
China	0.1481	0.2386	0.4922	0.1437	0.4296	0.1168	0.0789	0.1285	0.3236
Croatia	0.1083	0.1065	0.1081	0.8651	0.9786	0.1022	0.1065	0.1028	0.0301
Czech	0.6735	0.4635	0.9242	0.7804	0.7404	0.1523	0.9019	0.7355	0.1502
Denmark	0.2878	0.3238	0.4243	0.2553	0.5189	0.4019	0.9147	0.1785	0.5447
Finland	0.5708	0.3954	0.1089	0.3253	0.3324	0.1202	0.1426	0.4608	0.4697
France	0.1680	0.5936	0.3170	0.9615	0.4206	0.4408	0.5936	0.4926	0.6442
Germany	0.1148	0.2539	0.6543	0.7091	0.7356	0.1309	0.3156	0.6746	0.1885
Greece	0.1711	0.2741	0.4335	0.6542	0.2582	0.1862	0.1472	0.1756	0.3319
Hungary	0.8936	0.8885	0.8926	0.8866	0.8261	0.8524	0.7965	0.8634	0.8103
Indonesia	0.1115	0.1167	0.1895	0.1385	0.8979	0.1307	0.4041	0.8149	0.2002
Ireland	0.1150	0.1970	0.1187	0.1932	0.3638	0.2309	0.8289	0.1300	0.4509
Italy	0.7739	0.7709	0.7740	0.6496	0.7049	0.6434	0.7709	0.6969	0.6980
Japan	0.1677	0.8736	0.9131	0.1186	0.1065	0.9130	0.1034	0.8725	0.5747
Latvia	0.1488	0.2997	0.3894	0.6083	0.1251	0.0393	0.0413	0.5231	0.3183
Lithuania	0.2044	0.2832	0.8059	0.9593	0.1943	0.7515	0.2709	0.1485	0.3763
Mexico	0.2510	0.3569	0.7069	0.3311	0.2391	0.5811	0.2799	0.1242	0.2095
Netherlands	0.3186	0.7874	0.0602	0.3482	0.7697	0.6164	0.0943	0.0000	0.0000
Norway	0.9625	0.9873	0.4605	0.9822	0.1382	0.1817	0.1382	0.7092	0.1546
Philippines	0.2764	0.5689	0.4073	0.9985	0.1411	0.9867	0.2082	0.3731	0.7089
Poland	0.7821	0.9163	0.7809	0.5306	0.7129	0.8302	0.9038	0.8112	0.7167
Portugal	0.4618	0.7363	0.4295	0.6806	0.6288	0.6279	0.4300	0.6775	0.5410
Qatar	0.8931	0.9255	0.1047	0.2883	0.1782	0.6127	0.3549	0.2950	0.2885
Romania	0.9652	0.7679	0.8900	0.1095	0.5996	0.8822	0.9351	0.8511	0.1053
Russia	0.7350	0.7483	0.7483	0.7356	0.7394	0.7396	0.7342	0.7346	0.7355
Slovakia	0.8763	0.8667	0.8932	0.1168	0.1221	0.1220	0.7453	0.1612	0.4213
Slovenia	0.3175	0.3700	0.3231	0.3431	0.3232	0.4420	0.3842	0.1575	0.1376
Spain	0.4066	0.6002	0.1569	0.2526	0.4860	0.6670	0.6002	0.1314	0.7091
Sweden	0.2641	0.6405	0.6727	0.1040	0.8460	0.4014	0.1769	0.9883	0.1595
Thailand	0.8093	0.8193	0.1599	0.1990	0.8699	0.1228	0.1717	0.2893	0.2446
Turkey	0.1695	0.2053	0.8470	0.2632	0.7646	0.5755	0.6912	0.7542	0.3322
UK	0.1066	0.1342	0.2441	0.9221	0.4022	0.1400	0.8769	0.4213	0.1576
Ukraine	0.9283	0.0917	0.1489	0.1544	0.4717	0.8153	0.4308	0.1525	0.8165

USA	0.3082	0.2732	0.3076	0.3077	0.2962	0.2956	0.2732	0.3036	0.5831
Venezuela	0.8257	0.8405	0.8291	0.8315	0.7997	0.7998	0.0123	0.0011	0.1111

	R²LOG								
	GARCH	*EGARCH*	*GJR*	*APARCH*	*IGARCH*	*FIGARCH*	*FIEGARCH*	*FIAPARCH*	*HYGARCH*
Austria	0.4459	0.7794	0.3746	0.1370	0.4488	0.4488	0.7341	0.4363	0.4395
Belgium	0.1054	0.2292	0.1098	0.2206	0.1329	0.1001	0.1417	0.9336	0.1345
Brazil	0.7850	0.1215	0.1084	0.2500	0.8061	0.0688	0.9786	0.2601	0.9204
Bulgaria	0.8627	0.1904	0.0860	0.0089	0.8123	0.0809	0.1905	0.8050	0.1035
China	0.9805	0.1314	0.1498	0.1259	0.5610	0.1031	0.8734	0.1774	0.1013
Croatia	0.1315	0.1591	0.1290	0.2399	0.9687	0.1007	0.1578	0.1020	0.6233
Czech	0.7963	0.3167	0.8417	0.1125	0.1092	0.8436	0.6036	0.1074	0.7744
Denmark	0.1056	0.1821	0.1860	8.9493	0.1191	0.1809	0.3673	0.9240	0.1931
Finland	0.2240	0.9955	0.1902	0.8405	0.1390	0.1120	0.1508	0.1576	0.1479
France	0.8680	0.1060	0.8859	0.1270	0.7548	0.7518	0.1060	0.7389	0.1080
Germany	0.7950	0.8545	0.7606	0.9179	0.8703	0.8189	0.1209	0.1020	0.9904
Greece	0.9231	0.2916	0.3044	0.1760	0.2234	0.1340	0.1506	0.1627	0.1451
Hungary	0.1249	0.1124	0.1238	0.9855	0.1046	0.9688	0.1137	0.1132	0.9037
Indonesia	0.1362	0.3234	0.2156	0.2222	0.1270	0.2141	0.1169	0.1719	0.1636
Ireland	0.1118	0.9596	0.1110	0.1807	0.1237	0.1165	0.1204	0.1527	0.1330
Italy	0.8880	0.8694	0.8575	0.6427	0.5658	0.6196	0.8694	0.6496	0.6142
Japan	0.8854	0.2290	0.1141	0.1226	0.8269	0.1080	0.1235	0.1013	0.9994
Latvia	0.1304	0.1525	0.1490	0.5939	0.1431	0.1339	0.2170	0.2523	0.1506
Lithuania	0.1440	0.1894	0.1353	0.3666	0.1400	0.1467	0.2463	0.2881	0.1599
Mexico	0.1281	0.6893	0.3228	0.2731	0.1787	0.2829	0.4145	0.1144	0.2030
Netherlands	0.1709	0.1953	0.1873	0.4355	0.1955	0.1852	0.2312	0.0005	0.0205
Norway	0.1780	0.3609	0.2067	0.6787	0.4132	0.2810	0.4132	0.1752	0.6818
Philippines	0.1427	0.8120	0.1290	0.2031	0.1566	0.9553	0.1075	0.1789	0.2175
Poland	0.9412	0.1378	0.9352	0.8913	0.7587	0.8056	0.1298	0.7800	0.7594
Portugal	0.9387	0.1244	0.9564	0.1147	0.7570	0.7513	0.1116	0.9194	0.6986
Qatar	0.1012	0.1193	0.1063	0.5715	0.1140	0.9339	0.1519	0.1160	0.1245
Romania	0.8422	0.2420	0.8845	0.1900	0.7781	0.8136	0.1131	0.8882	0.1068
Russia	0.4808	0.5077	0.4789	0.4786	0.4858	0.4856	0.5077	0.4764	0.4806
Slovakia	0.8999	0.1717	0.9302	0.1374	0.8099	0.8099	0.7402	0.7805	0.1089
Slovenia	0.2210	0.2280	0.2209	0.2202	0.2200	0.2192	0.1958	0.4102	0.1607
Spain	0.7214	0.1041	0.7774	0.8834	0.6883	0.7057	0.1041	0.7092	0.9179
Sweden	0.3345	0.1262	0.1958	0.3440	0.1552	0.1162	0.3369	0.4645	0.1294
Thailand	0.1665	0.9046	0.1089	0.2126	0.9387	0.1019	0.3224	0.1245	0.1270
Turkey	0.0647	0.9940	0.6162	0.7366	0.5595	0.5477	0.7946	0.4184	0.7218
UK	0.2285	0.1329	0.2740	0.3564	0.1378	0.1115	0.3719	0.4688	0.2560
Ukraine	0.1233	0.5386	0.8248	0.1418	0.7089	0.7697	0.3086	0.7997	0.1493
USA	0.1617	0.1628	0.1621	0.1624	0.1574	0.1545	0.1628	0.1573	0.1809
Venezuela	0.4877	0.5290	0.4847	0.4770	0.4530	0.4516	0.7244	0.4906	0.0751

	MLAE								
	GARCH	*EGARCH*	*GJR*	*APARCH*	*IGARCH*	*FIGARCH*	*FIEGARCH*	*FIAPARCH*	*HYGARCH*
Austria	0.1624	0.1566	0.1630	0.9488	0.1566	0.1067	0.1110	0.1589	0.1588
Belgium	0.1863	0.1824	0.1836	0.1651	0.1833	0.1339	0.1484	0.1817	0.1469
Brazil	0.1796	0.1865	0.1750	0.1672	0.1860	0.1052	0.1930	0.1893	0.1591
Bulgaria	0.2087	0.1254	0.2091	0.1990	0.2131	0.2136	0.1253	0.2135	0.1873
China	0.1991	0.1922	0.2230	0.2163	0.2025	0.1741	0.1936	0.1756	0.2061
Croatia	0.1767	0.1567	0.1789	0.1092	0.2061	0.2034	0.1568	0.2014	0.0012
Czech	0.2128	0.6195	0.2197	0.1678	0.1717	0.2149	0.2106	0.1719	0.1999
Denmark	0.1664	0.1641	0.1784	0.1610	0.1652	0.1723	0.1604	0.1587	0.1707
Finland	0.1771	0.1743	0.1839	0.1809	0.1765	0.1840	0.1251	0.1777	0.1783
France	0.1662	0.1409	0.1643	0.1266	0.1754	0.1749	0.1409	0.1757	0.1426
Germany	0.1838	0.1603	0.1796	0.1759	0.1804	0.1832	0.1229	0.1821	0.1599
Greece	0.2184	0.1930	0.2217	0.1652	0.1427	0.2053	0.1288	0.2246	0.1799
Hungary	0.1651	0.1798	0.1659	0.1942	0.1904	0.1941	0.1789	0.1788	0.1987
Indonesia	0.1719	0.1723	0.1672	0.1601	0.1665	0.1633	0.1671	0.1641	0.1639
Ireland	0.1812	0.1743	0.1814	0.1641	0.1804	0.1860	0.1927	0.1813	0.1378
Italy	0.1445	0.1467	0.1481	0.1737	0.1841	0.1767	0.1467	0.1735	0.1773

Japan	0.1799	0.6318	0.1818	0.1678	0.1818	0.1826	0.1264	0.1852	0.1569
Latvia	0.2083	0.2026	0.2191	0.2075	0.2019	0.2029	0.1468	0.2280	0.2022
Lithuania	0.2013	0.1874	0.1961	0.2050	0.2178	0.1868	0.1892	0.1843	0.2069
Mexico	0.1763	0.1759	0.1708	0.1667	0.1653	0.1671	0.1679	0.1614	0.1675
Netherlands	0.1654	0.1684	0.1700	0.1744	0.1659	0.1615	0.1623	0.1727	0.1670
Norway	0.1437	0.1651	0.1523	0.1538	0.1503	0.1381	0.1503	0.1739	0.1646
Philippines	0.1795	0.1935	0.1903	0.1895	0.1784	0.1917	0.1560	0.1876	0.1968
Poland	0.1784	0.1484	0.1797	0.1742	0.1980	0.1951	0.1391	0.1965	0.2008
Portugal	0.1622	0.1432	0.1597	0.1456	0.1789	0.1790	0.1329	0.1632	0.1841
Qatar	0.1862	0.1694	0.1848	0.1849	0.1841	0.1904	0.1386	0.1877	0.1859
Romania	0.2064	0.9735	0.1975	0.1904	0.2119	0.2063	0.1761	0.1986	0.1834
Russia	0.1800	0.1776	0.1804	0.1799	0.1792	0.1794	0.1776	0.1805	0.1801
Slovakia	0.2046	0.2085	0.2005	0.1745	0.2107	0.2107	0.1445	0.2113	0.1864
Slovenia	0.1792	0.2325	0.1793	0.1805	0.1802	0.1810	0.1997	0.1744	0.2168
Spain	0.1740	0.1237	0.1731	0.1682	0.1774	0.1806	0.1237	0.1804	0.1557
Sweden	0.1690	0.1603	0.1873	0.1824	0.1660	0.1791	0.0519	0.1810	0.1814
Thailand	0.1873	0.1890	0.1884	0.1864	0.1849	0.1848	0.1811	0.1816	0.1763
Turkey	0.1901	0.1437	0.1887	0.1847	0.1927	0.1933	0.1416	0.1886	0.1728
UK	0.1728	0.1788	0.1775	0.1804	0.1811	0.1772	0.1809	0.1692	0.1701
Ukraine	0.1969	0.5542	0.2127	0.2020	0.2016	0.2059	0.0591	0.2100	0.2195
USA	0.1222	0.1218	0.1222	0.1221	0.1243	0.1268	0.1218	0.1265	0.1189
Venezuela	0.1926	0.1912	0.1943	0.1965	0.1980	0.1992	0.1737	0.1986	0.1716

1.4.3 Forecasting performance

Results of the twenty-day out-of-sample volatility forecasts are reported in Table 1.3 and Table 1.4. As mentioned before, the forecasting robustness and reliability of the 9 models is studied through 7 error statistics, namely the MSE, MAE, HMSE, HMAE, QLIKE, R^2LOG and MLAE. Even though there is no unanimous dominant model in terms of forecasting ability according to all the comparison measure, it is clearly seen that the fractionally-integrated class of model outperforms the basic GARCH models - not taking into account long-memory in volatility process. Ranked in the last position by 5 out of the 7 criteria, the least forecasting performant model for CDS volatility is the EGARCH with the largest recorded errors. The lowest values of MSE, MAE and R^2LOG are recorded for the FIGARCH, whilst the lowest values of HMSE, QLIKE and MLAE are reported for the FIEGARCH, making them preferable, in terms of accurate forecasting abilities, to the other studied models. At the opposite, and according to the results of the MSE, MAE, HMAE, R^2LOG and MLAE criteria, the HYGARCH produce the highest errors, probably due to its computational complexity. These findings empirically reveal the nonlinear predictability pattern of CDS volatility. In general, our results are in line with the findings of other financial markets: the non-linear GARCH-class models, that allows for leverage effects, unsymmetrical dependencies and long-range memory in the volatility model provide a more accurate in-sample performance and a more reliable out-of-sample forecasting ability. The improvement of the forecasting power of the studied models depends, thus, on their ability to capture a maximum of financial stylized facts while estimating the CDS volatility of future days.

Table 1.4: Summary of the number of selected models according to each criterion

	MSE	**MAE**	**HMSE**	**HMAE**	**QLIKE**	**R^2LOG**	**MLAE**
GARCH	5	4	3	4	6	5	2
EGARCH	1	0	3	3	2	2	3
GJR	2	1	2	2	2	2	0
APARCH	2	0	2	4	3	1	3

IGARCH	7	3	2	3	3	3	0
FIGARCH	16	14	4	6	4	9	6
FIEGARCH	5	6	10	7	10	6	18
FIAPARCH	13	11	7	11	7	8	5
HYGARCH	3	4	9	1	5	5	4

1.5 Conclusion

This chapter aimed to assess the performances of 9 linear and non-linear volatility models. Using daily sovereign CDS data, GARCH, IGARCH, EGARCH, GJR, APARCH, FIGARCH, FIEGARCH, FIAPARCH and HYGARCH are estimated, allowing to take into account different financial markets properties such as the leverage effect, the asymmetric reaction to good and bad news and long-range persistence. The performance comparison being made upon several loss function criteria and several multivariate diagnostic tests, a certain number of conclusions can be drawn.

First, the in-sample estimation shows that all the models almost always pass all diagnostic tests for the most cases, and that the smallest Akaike criterion does not allow us to choose only one best fitted model. Second, none of the volatility models studied in this chapter is found to be more relevant than all the others in all situations, in terms of forecasting ability. The chosen model varies from one country to another and from one loss function criterion to another. Third, in most cases and according to the majority of the errors statistics criteria, the non-linear GARCH-class models, that capture the long-memory behavior, the leverage effects and the asymmetric dependencies in the volatility process are more relevant in terms of out-of-sample forecasting ability than the others. Fourth, the FIGARCH and FIEGARCH models are found to be the most relevant and robust forecasting models.

Since comparing predictive performance of volatility models is of a paramount in assessing diversifiable risk, in dynamic asset pricing theory and in optimization of portfolio allocation, the economic implication of our findings concerns particularly policymakers, financial practitioners and financial market participants generally. The in-sample performances show that no model clearly outperforms all the others, and since the results are mitigated and differ from one country to another, no volatility model should be selected in an arbitrary way. The model selection should rather be based on the particular features of the data used and the country studied. When it comes to the forecasting performances, some models are preferable and seem to predict accurately and robustly the future volatility of the CDS market. Thus, after taking into account the transaction costs, investors can eventually take advantage of the market's relative inefficiency and generate extra-profits by putting in place a simple trading strategy exploiting the predictability of sovereign CDS volatility. Finally, our study shows that improving the volatility forecasts needs including the maximum of CDS market's stylized facts. However, in practice, the implementation of complex models generates additional costs that are not necessarily reflected in our comparison method, which may controvert the usefulness of using better volatility predictive models.

Our research line can be pursued in several ways. First, a further investigation on the performances of the volatility models can be done by carrying out a comparative study based on the superior predictive ability test rather than on the diagnostic tests and loss function criteria as in our case. We can also use informations ratios based on a trading strategy (Sharpe ratio) as an alternative to these statistic criteria. Second, it would be interesting to reevaluate the forecasting performance of these different models when the estimation of the models' parameters is carried out on a sliding window. Third, our study can be applied to the corporate CDS market, in order to assess whether the nature of the reference entity impacts the performances of the studied models. Fourth, since there is a dynamic segmentation in financial markets, it can be interesting to check the robustness of our findings using a different sample from other regions and/or a CDS term structure with different maturities.

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Appendices

1.6 Appendix: Post-estimation diagnostic tests

Table 1.5: Results of the diagnostic tests for the 38 worldwide countries

Countries		GARCH	ERGARCH	GJR	APARCH	IGARCH	FIGARCH	FIEGARCH	FIAPARCH	HYGARCH
		Models								
Austria	I. Criteria	-3.347	-3.415	-0.548	-3.851	-3.364	-3.362	-3.407	-3.352	-3.355
	Q(20)	29.0760 *	5.0765	4.8651	5.7814	15.8231 *	15.8233 *	23.1804	37.6455 ***	53.4004 ***
	$Q^2(20)$	0.2384	0.0271	0.1230	0.0140	0.3135	0.3135	0.7559	4.8655	29.6438 **
	ARCH(10)	0.0117	0.0043	0.0124	0.0014	0.0309	0.0309	0.0058	0.0173	0.1805
	J. Nyblom		59.82	41.55	181.32	8.83	18.05	38.20	39.73	26.14
	A.P G.o.f	2082.67 ***	3088.26 ***	3348.04 ***	1773.18 ***	3206.35 ***	3206.35 ***	2131.51 ***	-	3427.08 ***
	RDB (10)	0.5595	0.3902	0.0044	0.0012	0.3850	0.3775	0.3927	-	2.2517
Belgium	I. Criteria	-4.798	-5.087	-5.134	-5.339	-5.177	-4.978	-4.977	-4.776	-5.258
	Q(20)	0.0826	590.777 ***	0.0271	0.0252	0.0494	0.1992	0.0958	386.283 ***	0.1010
	$Q^2(20)$	0.0134	456.839 ***	0.0104	0.0099	0.0214	0.0214	0.0127	266.753 ***	0.0331
	ARCH(10)	0.0007	68.8840 ***	0.0005	0.0005	0.0011	0.0011	0.0006	32.6210 ***	0.0016
	J. Nyblom	210.80	651.05	274.01	299.26	202.39	185.82	241.35	306.75	242.27
	A.P G.o.f	7363.14 ***	4087.95 ***	4140.51 ***	2471.35 ***	3226.50 ***	2173.43 ***	6964.53 ***	2467.60 ***	6685.60 ***
	RDB (10)	3.68E-09	66.3374	6.82E-10	3.23E-15	5.49E-12	6.26E-08	1.02E-06	-	8.98E-06
Brazil	I. Criteria	-4.841	-4.721	-5.045	-9.427	-4.970	-4.932	-1.601	-5.891	-5.087
	Q(20)	0.0657	1.1139	0.0115	0.0069	0.0429	0.3063	0.0918	0.0197	0.0471
	$Q^2(20)$	0.0286	0.0241	0.0269	0.0069	0.0288	0.0196	0.0140	0.0288	0.0289
	ARCH(10)	0.0014	0.0013	0.0013	-	0.0014	0.0010	0.0007	0.0014	0.0014
	J. Nyblom	350.53	336.89	303.95	344.13	263.17	236.35	353.85	284.42	289.61
	A.P G.o.f	1362.83 ***	-	1129.91 ***	-	965.11 ***	709.56 ***	12945.72 ***	1341.09 ***	1219.48 ***
	RDB (10)	1.06E-07	-	3.13E-10	-	4.00E-08	1.42E-06	1.86E-10	-	1.46E-07
Bulgaria	I. Criteria	-5.436	-5.345	-5.438	-5.539	-5.380	-5.380	-5.342	-5.384	-5.508
	Q(20)	0.0069	25.0836	0.0069	0.0069	69.5080	0.0069	25.0304	0.0069	0.0078
	$Q^2(20)$	0.0069	0.0627	0.0069	0.0069	0.0069	0.0069	0.0627	0.0069	0.0069
	ARCH(10)	0.0003	0.0028	0.0003	0.0003	0.0003	0.0003	0.0028	0.0003	0.0003
	J. Nyblom	73.69	77.44	76.87	39.92	30.81	31.87	81.79	20.12	66.07
	A.P G.o.f	4499.06 ***	3906.25 ***	3546.85 ***	4318.73 ***	2960.60 ***	2971.07 ***	3886.62 ***	2889.18 ***	4352.37 ***
	RDB (10)	5.34E-16	1.4874	4.20E-16	7.48E-18	2.87E-15	3.43E-14	1.4868	-	2.41E-10
China	I. Criteria	-5.448	-5.204	-6.390	-6.121	-6.964	-5.536	-5.333	-5.353	-6.230
	Q(20)	0.5744	2.8891	37.8428 ***	4.2686	0.0069	0.4017	0.0058	0.0085	3.8754
	$Q^2(20)$	0.0443	0.0950	2.6997	0.0409	0.0069	0.0450	0.0069	0.0069	0.0485
	ARCH(10)	0.0023	0.0048	0.0021	0.0019	-	0.0023	0.0003	0.0003	0.0025
	J. Nyblom	147.78	298.22	298.22	233.25	263.50	86.17	202.05	204.24	297.64
	A.P G.o.f	3162.01 ***	-	-	7042.35 ***	7718.56 ***	1104.85	10697.77 ***	11407.99	3817.47
	RDB (10)	6.71E-07	-	-	1.74E-09	1.55E-05	7.83E-07	2.33E-10	3.59E-10	1.08E-07
Croatia	I. Criteria	-5.529	-5.530	-5.529	-5.609	-5.464	-	-5.533	-5.493	-5.554
	Q(20)	58.8880 ***	70.9629 ***	60.3308 ***	103.421 ***	67.1915 ***	55.7512 ***	68.6914 ***	60.3614 ***	54.0052 ***
	$Q^2(20)$	19.8615	11.2012	20.1640	17.5633	16.7475	11.4109	9.6043	11.4741	12.9607
	ARCH(10)	1.1293	0.4670	1.0589	0.7049	0.8960	0.5925	0.3932	0.3538	0.8576
	J. Nyblom	21.17	51.15	22.15	7.30	11.50	12.58	49.41	13.46	8.44
	A.P G.o.f	1624.25 ***	1729.94	1651.28	-	1870.74 ***	2016.27 ***	1707.68 ***	2004.17	1550.56 ***

Table 1.5: Results of the diagnostic tests for the 38 worlwide countries (*Continued*)

Countries		Models								
		GARCH	**ERGARCH**	**GJR**	**APARCH**	**IGARCH**	**FIGARCH**	**FIEGARCH**	**FIAPARCH**	**HYGARCH**
	RDB (10)	44.9519 ***	783.3480 ***	38.4528 ***	-	1.5691	10.2708	539.2280 ***	18.7316 **	-
	I. Criteria	-5.460	-5.707	-5.529	-4.029	-3.832	-5.833	-4.076	-4.118	-5.660
	Q(20)	1.1361	178.713 ***	1.1746	19.3863	16.2848	1.0567	28.1956 *	14.9785	5.6146
	$Q^2(20)$	0.3438	142.618 ***	0.0491	29.8426 **	5.5208	0.1636	95.3242 ***	34.6246 **	0.2789
Czech	ARCH(10)	0.0186	7.4291 ***	0.0024	2.9599 ***	0.5229	0.0083	9.9514 ***	3.3487 ***	0.0195
	J. Nyblom	304.86	75.39	251.86	2.48	2.30	101.94	213.66	2.84	251.01
	A.P G.o.f	5073.43 ***	11394.00 ***	2065.11	19300.08 ***	14895.55 ***	8931.95	8526.67 ***	15533.45 ***	2707.45 ***
	RDB (10)	0.0013	51.2730 ***	0.0040	2.6905	7.4466	0.0015	6.0092	5.5932	0.1864
	I. Criteria	-5.001	-6.320	-7.209	-51.583	-24.427	-6.632	-4.523	-60.873	-7.299
	Q(20)	22.9743	8.2895	11.1878	0.0012	0.0069	10.2966	2.4864	0.0069	3.8123
	$Q^2(20)$	1.1090	0.0250	0.9706	0.0084	0.0069	0.4900	0.0352	0.0069	0.1021
Denmark	ARCH(10)	0.0486	0.0013	0.0737	-	-	0.0178	0.0019	-	-
	J. Nyblom	4.68	602.91	604.19	542.38	614.94	585.49	401.82	560.41	708.00
	A.P G.o.f	34939.38 ***	11332.87 ***	14714.60 ***	-	30376.46 ***	10407.58 ***	6117.50	30616.72 ***	14265.76 ***
	RDB (10)	0.4752	3.84E-05	0.5105	-	4.05E-15	5.38E-04	1.78E-05	-	6.25E-06
	I. Criteria	-11.208	-5.788	-6.466	-4.432	-6.434	-	-6.278	-6.604	-6.718
	Q(20)	0.0186	2.5689	0.0950	45.8500 ***	0.4296	15.1393	4.0708	846.760 ***	2.1983
	$Q^2(20)$	0.0110	0.0486	0.0683	116.692 ***	0.0707	1.9299	0.0296	730.361 ***	0.0363
Finland	ARCH(10)	-	0.0025	0.0034	0.1088	0.0036	0.0287	0.0006	93.3870 ***	0.0016
	J. Nyblom	460.24	367.73	669.51	2.03	440.48	503.83	330.64	461.05	567.30
	A.P G.o.f	32006.70 ***	30265.32 ***	13822.82 ***	37705.84 ***	30719.51	31432.73 ***	16195.14	13648.38 ***	29730.18
	RDB (10)	1.02E-08	0.0004	5.01E-08	1.0815	5.41E-07	0.0055	0.0054	-	8.63E-06
	I. Criteria	-4.100	-4.134	-	-	-4.038	-4.041	-4.133	-4.032	-4.134
	Q(20)	0.9096	23.7291	0.3972	0.0504	18.7233	17.1288	23.4623	18.2128	0.8961
	$Q^2(20)$	0.0068	23.7291	0.0068	0.0069	5.7989	4.2451	23.7292	2.3464	0.0070
France	ARCH(10)	0.0004	0.7788	0.0003	0.0003	0.3162	0.2667	0.7788	0.1837	0.0004
	J. Nyblom	96.07	58.46	101.48	73.40	10.14	12.07	68.83	16.22	90.94
	A.P G.o.f	6384.03 ***	7012.25	6842.79 ***	5469.24	4847.63 ***	4735.22	7012.25	4221.79	5802.09
	RDB (10)	4.07E-08	21.4607 **	5.20E-09	1.25E-10	1.8916	1.7622	21.5068	2.3503	5.52E-09
	I. Criteria	-4.457	-3.264	-4.461	-4.588	-4.580	-4.528	-4.463	-4.560	-
	Q(20)	122.807 ***	64.5231 ***	18.4334	0.1859	0.0518	38.5063 ***	10.3676	0.0030	0.0535
	$Q^2(20)$	150.00 ***	5.3478	0.8178	0.0102	0.0100	38.5063 ***	0.3631	0.0077	0.0097
Germany	ARCH(10)	0.0115	0.1604	0.0144	0.0005	0.0005	5.7621	0.0243	0.0004	0.0005
	J. Nyblom	245.11	3.33	245.61	277.64	38.10	60.97	37.88	78.34	156.04
	A.P G.o.f	5271.93	3475.68	6702.13	7682.50	16685.33 ***	14.82 ***	16535.60	8513.85	8510.04
	RDB (10)	4.52E-04	2.7357	0.0125	1.71E-06	9.61E-08	4.35E-04	1.8196	7.18E-12	8.24E-08
	I. Criteria	-78.634	-4.280	-7.890	-5.485	-6.595	-5.701	-5.535	-6.633	-5.188
	Q(20)	0.0018	0.0459	0.0161	11.3689	11.4352	0.0053	0.2391	0.0048	0.0207
	$Q^2(20)$	0.0091	0.0069	0.0074	0.0120	0.0133	0.0070	0.0068	0.0070	0.0072
Greece	ARCH(10)	890.1470	0.0003	0.0004	0.0006	0.0007	0.0003	0.0003	0.0003	0.0004
	J. Nyblom		437.98	153.05	535.30	900.98	446.12	210.99	364.23	285.71

Table 1.5: Results of the diagnostic tests for the 38 worlwide countries (*Continued*)

		Models								
Countries		**GARCH**	**ERGARCH**	**GJR**	**APARCH**	**IGARCH**	**FIGARCH**	**FIEGARCH**	**FIAPARCH**	**HYGARCH**
	A.P G.o.f	78466.31	10746.67	14825.81	19611.06	15941.53	88899.88	11070.29	6694.36***	9807.51***
	RDB (10)	0.0004	2.17E-07	0.0233	0.0002	0.0001	1.07E-11	1.60E-05	4.43E-15	7.34E-09
Hungary	I. Criteria	-4.926	-4.240	-4.925	-5.167	-5.138	-5.089	-4.204	-5.224	-5.113
	Q(20)	1.6930	28.2994	1.7769	26.2051	29.9851*	52.1714***	28.4870*	76.7774***	59.3085***
	$Q^2(20)$	0.0152	5.6046	0.0154	0.1162	0.1537	0.4651	2.5608	12.1500	1.6252
	ARCH(10)	0.0008	0.4845	0.0008	0.0071	0.0081	0.0277	0.0687	0.9990	0.1113
	J. Nyblom	12.88	19.17	13.14	141.07	181.27	79.67	68.48	145.79	104.79
	A.P G.o.f	1586.45	1846.23***	1597.37	2751.07	1532.29	1681.68***	1766.78	1781.95***	3150.59
	RDB (10)	0.0006	106.9260	0.0006	0.0057	0.0325	0.0755	0.7631	15.9512	1.9650
Indonesia	I. Criteria	-5.546	-5.236	-6.511	-6.658	-5.699	-	-3.225	-6.467	-6.910
	Q(20)	113.132***	23.6731	2.6780	1.8670	26.7126	1.4812	3.9180	11.7813	172.627***
	$Q^2(20)$	18.8160	40.8243***	0.0119	0.0074	6.2195	0.0064	0.0182	0.0349	104.791***
	ARCH(10)	1.6382	1.4670	0.0005	0.0003	0.3782	0.0003	0.0009	0.0029	5.7026***
	J. Nyblom	514.46	513.97	533.16	566.07	593.40	541.72	429.26	506.17	529.39
	A.P G.o.f	5146.61***	7204.41	5776.80	5125.68	7546.30	1828.68	10287.98***	9721.04***	9136.52
	RDB (10)	45.5986	6.1253	0.0009	0.0002	9.9746	0.0002	9.47E-05	0.0369	62.3447***
Ireland	I. Criteria	-5.056	-4.659	-4.938	-5.257	-5.006	-	-1.922	-	-4.844
	Q(20)	26.5312	27.3471	23.5468	2.3312	3.1835	20.6532	74.7792	0.6608	16.8009
	$Q^2(20)$	0.5981	0.2699	0.2775	0.0161	0.0076	0.2668	74.0952	0.0066	0.0645
	ARCH(10)	0.0012	0.0163	0.0015	0.0008	0.0003	0.0006	0.0121	0.0003	0.0025
	J. Nyblom	242.19	194.38	317.43	304.89	161.35	193.01	308.56	270.22	231.19
	A.P G.o.f	3194.19	3262.90	2191.53	1618.81	2538.36	2631.58	11417.77	1324.35	2390.37
	RDB (10)	0.0059	0.1951	0.0132	0.0031	0.0001	0.0003	0.0039	2.11E-06	0.0395
Italy	I. Criteria	-4.117	-4.128	-4.117	-4.292	-4.301	-4.104	-4.128	-4.232	-3.814
	Q(20)	18.3550	20.7661	18.5368	48.8710	37.9334	19.8358	20.7663	44.4320	19.4447
	$Q^2(20)$	16.1005	10.6894	15.2346	84.9849***	19.7886	7.8508	10.6893	95.9543***	8.8074
	ARCH(10)	1.0983	0.7044	1.0255	7.6263***	1.4640	0.4515	0.7044	7.6864***	0.4818
	J. Nyblom	6.42	20.93	7.09	173.33	215.87	4.36	32.59	146.59	3.09
	A.P G.o.f	706.76***	701.34	706.18	2803.25	2121.04	742.72***	701.34	1124.49***	1547.15
	RDB (10)	79.1957	78.4549	102.6090	0.3320	34.0994	4.9326	4.8578	56.7892	4.8663
Japan	I. Criteria	-4.820	-4.838	-5.035	-5.140	-4.840	-4.991	-4.586	-5.018	-5.016
	Q(20)	0.2421	4.0528	0.0229	0.0240	0.7752	0.0129	15.8544	0.0379	11.9659
	$Q^2(20)$	0.0265	0.0111	0.0243	0.0099	0.0399	0.0159	0.1658	0.0070	0.8543
	ARCH(10)	0.0013	0.0004	0.0012	0.0005	0.0021	0.0008	0.0008	0.0003	0.0065
	J. Nyblom	289.80	202.05	202.05	268.30	165.41	154.24	214.76	142.79	255.87
	A.P G.o.f	2900.87	9224.14	4412.83	3341.43	2958.77	3052.91	7362.93***	5069.07***	2500.80
	RDB (10)	4.49E-07	0.0007	8.08E-10	5.69E-10	5.14E-06	1.56E-09	0.0048	5.32E-09	7.60E-05
Latvia	I. Criteria	-6.762	-6.422	-6.783	-8.153	-6.823	-6.591	-6.318	-7.147	-6.050
	Q(20)	0.8951	0.1819	135.984***	3.9882	0.1178	25.6995	7.8609	0.0216	0.0276
	$Q^2(20)$	0.0684	0.0192	112.715***	0.0953	0.0213	2.5939	0.0934	0.0184	0.0273
	ARCH(10)	0.0035	0.0009	601.7120	-	0.0011	0.0594	0.0059	0.0009	0.0014

Table 1.5: Results of the diagnostic tests for the 38 worlwide countries (*Continued*)

		Models								
Countries		**GARCH**	**ERGARCH**	**GJR**	**APARCH**	**IGARCH**	**FIGARCH**	**FIEGARCH**	**FIAPARCH**	**HYGARCH**
	J. Nyblom	518.40	317.56	601.71	467.21	385.26	318.69	308.06	491.50	241.98
	A.P G.o.f	5582.53	7264.60	10645.24	-	6067.43	8478.85	11365.35	8126.94	3930.96
	RDB (10)	9.34E-05	5.75E-06	175.0040 ***	-	1.21E-06	0.7795	0.0696	2.93E-09	6.78E-16
	I. Criteria	-6.986	-6.493	-6.728	-7.589	-47.880	-7.446	-4.365	-7.763	-6.983
	Q(20)	22.9839	0.0127	29.4856	0.0209	35.5081 **	2.2311	0.3887	0.0364	17.4218
	$Q^2(20)$	0.5948	0.0243	1.2122	0.0224	0.2251	0.0548	0.0381	0.0342	0.2280
Lithuania	ARCH(10)	0.0027	0.0012	0.0062	0.0011	0.0040	0.0026	0.0019	0.0017	0.0023
	J. Nyblom	626.88	361.43	48.72	338.70	267.36	526.61	425.87	548.06	736.56
	A.P G.o.f	8019.14	6720.50	12154.68	21762.97	79526.05	10417.77	6323.87	6935.73	19071.59
	RDB (10)	0.0016	1.41E-07	0.0331	9.09E-15	-	4.21E-04	3.41E-06	3.52E-07	0.0046
	I. Criteria	-5.775	-5.141	-7.185	-7.063	-29.261	-6.052	-3.288	-66.974	-11.191
	Q(20)	42.1415 ***	55.9448 ***	0.0186	0.0659	0.0069	0.0376	0.0350	0.0069	0.5601
	$Q^2(20)$	0.0255	35.3469 ***	0.0069	0.0069	0.0069	0.0069	0.0073	-	0.1274
Mexico	ARCH(10)	0.0018	0.9119	0.0003	0.0003	-	0.0003	0.0004	-	-
	J. Nyblom	628.12	575.62	631.92	652.20	681.00	761.49	618.85	536.51	606.15
	A.P G.o.f	7472.34	-	8368.05	7895.86	8752.33	8112.90	10814.81	9598.41	10556.06
	RDB (10)	0.2978	-	1.24E-08	1.02E-07	-	4.41E-08	8.58E-09	-	2.13E-06
	I. Criteria	-25.100	-6.332	-6.404	-6.659	-6.395	-6.489	-3.994	-6.320	-6.124
	Q(20)	0.0069	0.9895	35.8215 **	50.5043 ***	1.0616	36.7613 ***	0.8355	19.9480	15.7230
	$Q^2(20)$	0.0069	0.0092	4.6167	4.9283	0.0208	2.9217	0.0135	0.1904	0.3814
Netherlands	ARCH(10)	-	0.0005	0.0067	0.0023	0.0011	0.0032	0.0007	0.0005	0.0031
	J. Nyblom	553.51	466.90	652.35	564.21	596.30	497.92	493.78	759.38	599.37
	A.P G.o.f	23743.78	25026.02	20888.56	9962.05	22535.77	7366.89	6810.24	7247.08	4646.54
	RDB (10)	-	2.43E-06	0.0059	-	2.37E-06	0.0004	4.44E-05	1.48E-07	0.0050
	I. Criteria	-30.204	-6.029	-6.799	-8.543	-30.400	-6.879	-5.595	-10.666	-8.168
	Q(20)	0.0069	0.4984	28.7313	46.8995 ***	0.0069	1.1235	0.0444	0.0069	0.0410
	$Q^2(20)$	0.0069	0.0160	1.4934	1.2125	0.0069	0.0122	0.0087	0.0069	0.0075
Norway	ARCH(10)	-	0.0008	0.0104	0.0006	-	0.0006	-	-	0.0004
	J. Nyblom	646.42	411.98	731.24	664.89	658.59	695.05	526.34	821.47	818.18
	A.P G.o.f	35160.34	13618.65	18536.04	14001.38	34622.64 ***	5532.87	4376.50	16500.80	17491.46
	RDB (10)	-	4.54E-07	0.0198	0.0001	-	2.59E-07	2.99E-08	7.33E-24	1.06E-13
	I. Criteria	-6.564	-5.646	-6.554	-7.543	-28.595	-6.607	-4.025	-6.269	-6.188
	Q(20)	3.8317	92.5266 ***	0.7813	0.0180	0.0069	8.9322	0.0173	1.0833	24.8994
	$Q^2(20)$	0.0178	0.9462	0.0114	0.0080	0.0069	0.0516	0.0079	0.0254	5.5387
Philippines	ARCH(10)	0.0008	0.0919	0.0006	0.0004	-	0.0024	0.0004	0.0013	-
	J. Nyblom	713.13	696.82	632.62	622.12	686.30	590.67	526.10	462.53	632.05
	A.P G.o.f	13233.96	8147.63	9185.87	9278.99	13230.25	7501.75	8707.55	14578.78	14900.23
	RDB (10)	0.0013	1.1129	4.83E-06	-	-	0.0183	2.88E-10	-	6.1970
	I. Criteria	-4.848	-4.132	-4.848	-4.888	-4.763	-4.782	-4.828	-4.794	-5.035
	Q(20)	2.0980	27.7586	2.1334	12.3081	12.3977	26.1377	17.4744	22.8794	36.1529 **
	$Q^2(20)$	0.0978	7.8754	0.0969	0.0534	0.2211	9.2676	0.9354	7.0298	8.9171
Poland										

Table 1.5: Results of the diagnostic tests for the 38 worlwide countries (*Continued*)

		Models								
Countries		**GARCH**	**ERGARCH**	**GJR**	**APARCH**	**IGARCH**	**FIGARCH**	**FIEGARCH**	**FIAPARCH**	**HYGARCH**
	ARCH(10)	0.0052	0.4914	0.0051	0.0036	0.0074	0.4373	0.0514	0.3230	0.5005
	J. Nyblom	20.42	11.27	21.12	36.52	18.45	27.14	4.53	29.56	492.06
	A.P G.o.f	2999.61	234.00	2920.70	1212.52	2828.57	2379.12	-	2354.31	4551.14
	RDB (10)	2.74E-04	3.48E+01	2.77E-04	6.05E-02	2.23E-02	2.82E+00		8.05E+00	13.8160
	I. Criteria	-4.213	-4.210	-4.213	-4.303	-4.153	-4.154	-4.394	-4.672	-4.559
	Q(20)	8.1460	18.2045	5.7994	1.2002	15.9522	16.0789	58.8919 ***	29.5043 *	36.9416 ***
	$Q^2(20)$	0.0211	55.8087 ***	0.0140	0.0072	70.8632 ***	74.7565 ***	69.6413 ***	73.0205 ***	49.9189 ***
Portugal	ARCH(10)	0.0007	0.5970	0.0005	0.0004	0.5714	0.6954	6.2972 ***	4.6828 ***	1.0429
	J. Nyblom	58.26	68.31	58.89	87.59	5.59	6.07	152.73	385.28	367.01
	A.P G.o.f	2148.92	-	2148.55	2317.98	2230.79	2257.34	1115.63	2650.32	3579.22
	RDB (10)	0.0032	-	0.0012	8.48E-06	0.5644	1.4703	116.2830 ***	10.4886	26.7028
	I. Criteria	-5.730	-5.497	-5.420	-27.306	-5.719	-5.621	-5.508	-5.857	-5.922
	Q(20)	0.4905	0.0709	0.8484	0.0069	0.0357	4.6512	1.1313	0.0717	0.0250
	$Q^2(20)$	0.0187	0.0099	0.0182	0.0069	0.0120	0.0953	0.0154	0.0137	0.0118
Qatar	ARCH(10)	0.0009	0.0005	0.0009	-	0.0006	0.0049	0.0007	0.0007	0.0006
	J. Nyblom	390.72	265.54	374.56	309.20	334.22	132.74	245.86	240.42	362.05
	A.P G.o.f	6144.22	17904.04	2428.71	-	9521.18	7661.36	12152.78	9689.31	7443.30
	RDB (10)	7.14E-06	4.73E-07	4.36E-06	-	7.45E-08	0.0005	0.0018	3.12E-07	1.52E-08
	I. Criteria	-5.494	-4.804	-5.554	-5.000	-4.975	-5.439	-5.430	-5.803	-5.892
	Q(20)	0.0063	414.353 ***	14.2707	16.9822	12.2667	0.0069	32.9755 **	6.1051	29.2195
	$Q^2(20)$	0.0069	86.8006 ***	0.0307	0.0377	0.0297	0.0069	0.2570	0.0244	0.1838
Romania	ARCH(10)	0.0003	9.1538 ***	0.0017	0.0022	0.0016	0.0003	0.0172	0.0013	0.0029
	J. Nyblom	65.55	710.67	710.67	58.57	130.78	130.78	14.80	140.42	181.41
	A.P G.o.f	2596.78	2766.51	5143.54	1352.79	1223.21	2853.53	2809.52	4615.76	1969.51
	RDB (10)	1.38E-13	8.2466	0.0003	0.0006	0.0009	1.27E-12	0.0062	0.0020	0.0223
	I. Criteria	-3.999	-3.991	-4.003	-4.005	-4.000	-3.999	-3.991	-4.004	-3.998
	Q(20)	11.5329	11.9272	11.5791	10.8970	11.6009	11.7362	11.9273	11.3651	11.6701
	$Q^2(20)$	20.5284	17.1360	21.3905	21.0426	20.8452	20.1840	17.1361	19.6115	19.7961
Russia	ARCH(10)	0.8859	0.5738	0.8695	0.8779	0.9494	0.9201	0.5739	0.7418	0.8525
	J. Nyblom	1.61	5.15	1.95	1.89	1.53	3.56	5.53	2.78	3.71
	A.P G.o.f	115.86	123.06	98.86	117.02	115.63	112.15	121.93	113.72	118.90
	RDB (10)	126.4820	3.4639	54.5139	2.0299	14.5312	16.1394	3.4049	6.4765	16.3329
	I. Criteria	-5.927	-4.916	-5.927	-5.965	-5.862	-5.861	-4.342	-5.872	-5.991
	Q(20)	1.2437	16.3954	1.3406	20.9647	2.1215	2.1236	34.7287 **	1.3533	0.3934
	$Q^2(20)$	0.1159	0.8987	0.1297	0.3732	0.1761	0.1763	16.5740	0.1081	0.1137
Slovakia	ARCH(10)	0.0068	0.0517	0.0077	0.0193	0.0111	0.0111	0.5374	0.0063	0.0060
	J. Nyblom	185.57	35.08	186.41	205.68	9.87	13.15	184.26	14.90	155.07
	A.P G.o.f	11600.19	9232.98	11357.85	4500.97	13642.82	13694.25	7317.98	12610.89	7839.59
	RDB (10)	1.21E-05	2.2528	1.36E-05	0.0757	7.72E-05	7.74E-05	12.2474	4.94E-05	6.23E-07
	I. Criteria	-4.772	-4.269	-4.773	-4.780	-4.756	-4.768	-5.822	-5.361	-6.688
	Q(20)	24.7842	25.6910	24.3340	23.5669	32.4648 **	29.1249	4.3473	1.0354	23.3301
Slovenia										

Table 1.5: Results of the diagnostic tests for the 38 worlwide countries (*Continued*)

		Models								
Countries		**GARCH**	**ERGARCH**	**GJR**	**APARCH**	**IGARCH**	**FIGARCH**	**FIEGARCH**	**FIAPARCH**	**HYGARCH**
	$Q^2(20)$	8.2290	0.7816	8.6544	8.4562	9.0434	8.5046	0.0554	0.0343	2.1289
	ARCH(10)	0.1474	0.0436	0.1186	0.1056	0.2165	0.2446	0.0032	0.0017	0.0592
	J. Nyblom	2.11	53.05	2.61	3.57	1.52	2.30	392.92	334.97	659.86
	A.P G.o.f	38119.51	9279.12	19844.39	35336.01	38756.52	38813.78	7540.61	4494.23	6649.50
	RDB (10)	1.5993	0.6477	1.4358	1.2934	2.3373	2.7887	-	4.29E-05	1.3382
	I. Criteria	-4.205	-4.105	-4.208	-4.159	-4.168	-4.154	-4.104	-4.199	-4.316
	Q(20)	0.1149	11.8580	0.0265	0.0269	0.1050	0.0387	11.8577	0.0090	0.0381
	$Q^2(20)$	0.0072	0.5806	0.0069	0.0070	0.0072	0.0080	0.5806	0.0069	0.0114
Spain	ARCH(10)	0.0004	0.0377	0.0003	0.0003	0.0004	0.0004	0.0377	0.0003	0.0006
	J. Nyblom	123.66	42.62	118.58	224.62	74.75	91.95	93.64	74.36	133.45
	A.P G.o.f	1230.66	1542.01	3360.48	1658.02	1250.66	1098.28	1541.60	1331.34	1042.58
	RDB (10)	3.90E-07	20.6711	5.96E-10	3.87E-08	3.20E-07	1.32E-07	16.4878	-	2.02E-07
	I. Criteria	-6.431	-5.793	-0.658	-6.486	-9.591	-6.114	-6.059	-7.378	-6.300
	Q(20)	0.0011	2.6122	133.390 ***	14.1611	0.0069	0.0080	153.937 ***	0.0750	8.5002
	$Q^2(20)$	0.0739	0.0910	176.560 ***	0.7800	0.0069	0.0069	74.9719 ***	0.0882	0.6284
Sweden	ARCH(10)	0.0037	0.0044	17.2900 ***	0.0111	-	0.0003	5.8773 ***	0.0044	0.0327
	J. Nyblom	513.78	374.98	542.42	533.81	434.039	149.21	332.10	608.11	409.05
	A.P G.o.f	10848.62	7896.91	10075.54	8622.64	22159.64	18914.88	8389.55	22405.91	3540.58
	RDB (10)	1.86E-13	0.0005	292.3860	-	1.14E-07	5.82E-11	49.8163	2.16E-06	0.1756
	I. Criteria	-6.065	-5.546	-5.524	-6.332	-5.906	-5.952	-3.326	-5.882	-6.258
	Q(20)	1.7565	30.9012 **	24.6423	0.3637	32.5837 **	18.9330	0.0428	212.707 ***	2.3372
	$Q^2(20)$	0.0071	0.4201	0.9679	0.0078	1.5782	0.1015	0.0076	15.9829	0.0084
Thailand	ARCH(10)	0.0003	0.0175	0.0885	0.0004	0.1525	0.0091	0.0004	1.6022	0.0004
	J. Nyblom	581.98	459.32	548.26	553.98	570.66	552.50	455.17	545.84	596.53
	A.P G.o.f	4923.16	5299.30	5771.18	6412.52	5646.48	1333.21	10646.13	2692.58	8097.17
	RDB (10)	0.0003	0.2655	7.8470	4.65E-05	1.6670	0.1011	1.48E-08	0.4598	0.0015
	I. Criteria	-4.727	-4.514	-4.739	-4.787	-4.688	-4.639	-4.420	-4.208	-4.721
	Q(20)	0.0167	0.0978	0.0249	0.0064	0.0366	0.085201	1.3771	17.3861	0.0078
	$Q^2(20)$	0.0138	0.0135	0.0269	0.0064	0.0074	0.0192	0.0120	3.8679	0.0069
Turkey	ARCH(10)	0.0007	0.0007	0.0013	0.0013	0.0004	0.0010	0.0007	0.1367	0.0003
	J. Nyblom	92.81	98.71	98.85	151.98	68.56	89.0917	410.32	1.90	89.71
	A.P G.o.f	289.45	806.84	254.14	569.65	273.77	238.4297	981.06	869.68	339.31
	RDB (10)	2.18E-10	1.80E-07	2.63E-09	3.88E-11	4.70E-09	1.69E-08	0.0021	1.3664	6.26E-14
	I. Criteria	-6.575	-6.130	-6.972	-7.785	-23.832	-6.130	-3.981	-8.157	-7.504
	Q(20)	2.5436	167.760	139.972 ***	99.6922 ***	0.0069	103.137	4.0148	2.7105	15.8465
	$Q^2(20)$	0.0076	5.6149	12.4021	7.0942	0.0069	73.0977	0.0142	0.0075	0.0864
UK	ARCH(10)	0.0004	1.9385	0.0006	0.0007	-	0.0046	0.0007	0.0003	0.0004
	J. Nyblom	651.59	616.09	624.47	569.28	615.3180	663.73	422.20	701.51	647.42
	A.P G.o.f	6712.97	7477.76	7192.07	9846.84	12727.38	2626.12	6955.95	13502.33	7236.52
	RDB (10)	4.75E-17	10.3849	7.22E-05	4.90E-05	1.31E-14	0.0006	2.75E-05	1.55E-12	7.66E-08
	I. Criteria	-5.957	-12.223	-5.576	-5.974	-5.403	-5.971	-5.095	-5.840	-7.350

Ukraine

Table 1.5: Results of the diagnostic tests for the 38 worlwide countries (*Continued*)

		Models								
Countries		**GARCH**	**ERGARCH**	**GJR**	**APARCH**	**IGARCH**	**FIGARCH**	**FIEGARCH**	**FIAPARCH**	**HYGARCH**
	Q(20)	0.0000	884.481 ***	136.035 ***	0.011	2.0310	4.1195	15.5804	0.2173	162.703 ***
	Q^2(20)	0.0223	801.556 ***	151.049 ***	0.061	0.1073	0.1000	0.3402	0.0339	187.622 ***
	ARCH(10)	0.0011	105.8400 ***	0.0084	0.0030	0.0056	0.0037	0.0318	0.0017	5.8859 ***
	J. Nyblom	79.77	970.74	188.02	183.33	174.09	83.57	62.30	122.79	300.18
	A.P G.o.f	4790.74	48665.73	9862.01	4277.79	4961.98	5513.99	10353.01	9309.59	11230.89
	RDB (10)	3.20E-14	139.62	0.0002	8.30E-13	2.26E-05	7.67E-07	1.0228	7.34E-08	63.1099 ***
USA	I. Criteria	-3.343	-3.219	-3.343	-3.343	-3.333	-3.385	-3.218	-3.394	-3.475
	Q(20)	22.1954	20.9911	22.6308	23.2446	25.8119	21.7770	20.9958	18.9781	21.4223
	Q^2(20)	0.6640	0.6783	0.6768	0.7894	1.2310	1.0326	0.6784	0.5677	0.2415
	ARCH(10)	0.0343	0.0249	0.0361	0.0441	0.0762	0.0392	0.0249	0.2338	0.0196
	J. Nyblom	2.10	70.44	2.90	3.33	1.73	18.30	134.90	40.45	15.65
	A.P G.o.f	30069.34	10179.22	30020.77	2994.64	29578.64	29371.73	10202.40	29411.16	27477.49
	RDB (10)	0.3515	0.3611	0.3693	0.4664	0.8526	0.2184	0.3621	0.2197	0.1690
Venezuela	I. Criteria	-4.433	-4.335	-4.433	-4.450	-4.409	-4.410	-4.518	-4.771	-4.861
	Q(20)	16.8322	22.2545	16.1177	16.2001	16.9461	18.3256	84.5941 ***	44.4650 ***	183.998 ***
	Q^2(20)	7.8329	8.0298	9.7585	51.5638 ***	23.4663	13.0599	0.1977	81.4568 ***	32.3894 **
	ARCH(10)	0.4800	0.2973	0.6520	4.2005 ***	1.7687	0.7184	0.0138	8.4904 ***	3.2795 ***
	J. Nyblom	2.83	69.96	2.68	2.39	1.5400	75.83	238.36	149.77	237.86
	A.P G.o.f	738.70	590.98	905.20	1071.96	1025.57	720.43	200.46	340.07	403.25
	RDB (10)	4.5171	4.5980	4.3576	2.1091	33.6120	14.4391	0.1152	4.0510	169.0970

Q(20) and Q^2(20) are the Box-Pierce Q statistics under the null hypothesis of no serial correlation in the 20^{th} lags order of respectively the standardized residuals and the squared standardized residuals. ARCH (10) is the Engle's ARCH-LM test with 10 lag orders, used to detect ARCH effects in the series under the null hypothesis of no autocorrelations in the squared residuals. The J. Nyblom is a stability test under the null hypothesis of parameters joint constancy over time against the alternative of parameters shift at an undefined breakpoint. The A.P. G.o.f is the adjusted Pearson goodness-of-fit test up to 50 cells that verifies whether the residuals' empirical distribution matches or not the theoretical distribution. RDB denotes the Residuals-Based Diagnostic test that checks for conditional Heteroscedasticity, by complementing and filling the gaps of the Box-Pierce Q statistics. *, ** and *** denote the statistical significance at respectively 1%, 5% and 10% levels.

1.7 Appendix: Maximum Likelihood estimation

Pan et al. (2002) argue that the Generalized Least Square (GLS)-based inference holds statistical consistency and asymptotically normal distribution for the ordinary univariate models. However, this guideline becomes inaccurate and complicated when it comes to more sophisticated regression models. Therefore, since most of our studied models are non-linear, we base the estimation of the regression coefficients on the Maximum Likelihood (ML) rather than on the linear Generalized Least Square estimate[1]. The likelihood-based determination of our models' coefficients (Ω) is considered as follows:

$$\widehat{\Omega} = arg \ \underset{(\Omega)}{m}ax\{L(\Omega, \Lambda)\}. \tag{1.18}$$

Where $L(\Omega)$ is the likelihood function and $\widehat{\Omega}$ are the statistical estimates (parameters values) of our models, maximizing the likelihood function (making the data most probable), given a set observed data (Λ)[2]. As reported by Aldrich et al. (1997), using the log-likelihood function $(ln\ L(\Omega, \Lambda))$ is completely equivalent to the ordinary likelihood function inference, given that the natural logarithm is an increasing function.

The quasi-maximum likelihood estimator could have been consistent in estimating our conditional mean and conditional variance equations if the residuals of our time series had been normally distributed (Bollerslev and Wooldridge, 1992). However, CDS series' innovations do not necessarily follow a Gaussian distribution and the maximum likelihood is thus better adapted. In fact, financial time series are characterized by a departure from normality with a high observed kurtosis (as stated by Palm and Vlaar (1997)), and the use of fat-tailed distributions is therefore more consistent.

The log-likelihood function can be expressed in four ways following the innovations' distribution assumptions (Gauss, Student, GED, Skewed Student).

$$L_{Gauss} = -\frac{1}{2}\sum_{t=1}^{T}[log(2\pi) + log(\sigma_t^2) + \varepsilon_t^2], \tag{1.19}$$

With T is the number of observations.

$$L_{Student} = T[log\Gamma(\frac{\nu+1}{2}) - log\Gamma(\frac{\nu}{2}) - \frac{1}{2}log(\pi(\nu-2))] - \frac{1}{2}\sum_{t=1}^{T}[log(\sigma_t^2) + (1+\nu)log(1+\frac{\varepsilon_t^2}{\nu-2})], \tag{1.20}$$

With ν is the number of the degrees of freedom.

$$L_{GED} = \sum_{t=1}^{T}[log(\frac{\nu}{\tau_\nu}) - 0.5 \mid \frac{\varepsilon_t}{\tau_\nu} \mid^{\nu} -(1+\nu^{-1})log(2) - log\Gamma(\frac{1}{\nu}) - 0.5log(\sigma_t^2)], \tag{1.21}$$

[1] According to Pan et al. (2002), the ML and the GLS give the same estimators in only one special case, that is Rao's simple covariance structure.

[2] Maximizing the likelihood function means that the number of available observations tends towards infinity, then the estimator $\widehat{\Omega}$ correspond to their true values Ω.

Where $\tau_{\nu} = \sqrt{\frac{\Gamma(1/\nu)2^{(-2/\nu)}}{\Gamma(3/\nu)}}$.

$$L_{Skewed_Student} = T[log\Gamma(\frac{\nu+1}{2}) - log\Gamma(\frac{\nu}{2}) - 0.5(\pi - (\nu-2)) + log(\frac{2}{\xi+1/\xi}) + log(s)] \\ -0.5\sum_{t=1}^{T}[log(\sigma_t^2) + (1+\nu)log(1+\frac{(s\varepsilon_t+m)^2}{\nu-2})\xi^{-2I_t}], \tag{1.22}$$

With ξ denotes the asymmetry parameter, $s = \sqrt{(\xi^2 + \frac{1}{\xi^2} - 1) - m^2}$, $m = \frac{\Gamma(\frac{\nu+1}{2})\sqrt{\nu-2}}{\sqrt{\pi}\Gamma(\nu/2)}(\xi - \frac{1}{\xi})$ and

$$I_t = \begin{cases} 1, \text{if } \varepsilon_t \geq -\frac{m}{s} \\ -1, \text{if } \varepsilon_t < -\frac{m}{s}. \end{cases}$$

As already mentioned, all the above-written functions take into account (except the log-likelihood function with ε following a Gaussian distribution, L_{Gauss}) take into account the large kurtosis properties of the CDS series, however only the $L_{Skewed} - Student$ function considers for the asymmetry of the probability distribution.

Several numerical optimization algorithms exist in the literature to solve nonlinear functions: BHHH (Bhattacharya et al., 1974), BFGS Broyden et al. (1986), MaxSA (Goffe et al., 1994), BFGS-Bounds (Nocedal and Wright, 1999)...

The Berndt–Hall–Hall–Hausman (BHHH) algorithm is an iterative nonlinear equivalent to the Gauss-Newton algorithm, that is only adequate to maximize least-square functions with no strong interactions between parameters. The BHHH is consequently highly inefficient in our case. Contrary to the previous algorithm, the Broyden, Fletcher, Goldfarb and Shanno (BFGS) - based on the quasi-Newton methods - is able to solve real-valued functions. According to Lawrence and Tits (2001), this numerical technique solves the (log-)likelihood functions in an iterative way by allowing the parameters values (Ω) to range in the interval $]-\infty, +\infty[$. A more restrictive version of the BFGS is used to estimate the GARCH-class models in this essay, so-called BFGS-bounds, in which the Ω estimated values are restrained to a smaller interval. Lawrence and Tits (2001) propose an algorithm is which the maximization is established through a sequential quadratic programming technique and conducted under some non-linear constraints, so we can control the stationarity of the models and the positivity of some parameters during the estimation. The same problem is treated in Yuan and Lu (2011). The authors improve the effectiveness of the optimization techniques by imposing a lower and an upper boundaries between which the parameters can possibly range at each iteration, enforcing all iterations and the model convergence to be feasible, as well, for a large-scale dataset. Finally, optimizing non-smooth functions with possible multiple local maxima can be conducted through a Simulated Annealing algorithm, so-called MaxSA. The robustness of this algorithm is justified by the fact that it allows to easily distinguish between local and global optima while maximizing difficult functions (Goffe, 1995)[1]. Even though the latter numerical optimization program seems to be relevant in our case, it has not been used since it doesn't properly converge in most cases.

[1]See Fletcher (2013), for example, for an exhaustive survey on the different aspects (unconstrained and constrained) of optimization methods used in solving mathematical functions and the way they empirically perform.

In fact, in practice, the estimated model may not converge conveniently due to some optimization problems. The FIAPARCH is the most complicated models with the highest number of direct miss-convergences: either the $L(\Omega, \Lambda)$ function cannot reach a supremum belonging to Ω and no maximum estimate is found or at the opposite, the optimization algorithm finds several values that maximize the function.

Chapter 2

On the Informational Market Efficiency of the Worldwide Sovereign Credit Default Swap

In this globalizing world, the search for predictions of asset returns across financial markets has challenged practitioners and academics for decades.

Aware of this issue importance in developing investment strategy, we aim in this chapter to give new evidences on the efficiency degree of the Sovereign CDS markets. The new framework, used in this chapter, combing a VECM and a FIGARCH models by a 3-step estimation allows us to greatly improve the accuracy of the econometric estimates.

Using data from 37 countries all over the world, throughout the period spanning from January 2006 to March 2017, our study provides worldwide evidence rejecting in some extent, conversely to the results of the literature, the randomness of the credit derivative markets. The implication of our results is that speculators can beat the market by predicting CDS performances, especially during crisis periods.

Keywords : Market Efficiency, Worldwide Sovereign CDS, VECM-FIGARCH.

2.1 Introduction

Over the last few decades, the predictability of financial asset prices and the Efficient Market Hypothesis (EMH) legitimacy have been the most difficult financial challenges in both academic and non-academic areas. While economists and researchers seem to be unanimous about the efficiency of international equity markets, many questions and criticisms are perpetually raised concerning the efficiency of derivatives markets. Particularly, the credit derivatives prices are castigated for being irrational and predictable, which explains allowing market participants to use them in speculative and arbitrage transactions rather than as part of the hedging process. Hence, whether the Credit Default Swaps (CDS) markets are informationally efficient or not is a controversy subject, especially during the recent financial crises in which financial markets have behaved unexpectedly. This essay aims to pay more attention to the international sovereign CDS markets by providing additional evidence on their weak-form informational efficiency hypothesis and its validity during the Global Financial Crisis and the Sovereign Debt Crisis.

A number of authors in the literature, beginning with Fama (1970), focuses on the extent and speed with which past information is incorporated into current asset prices. Whether in its weak, semi-strong or strong form, a market is considered efficient if its assets instantly reflect relevant information sets in their prices, evolve unpredictably, and are consistent with the random walk theory. In other words, if the randomness of the financial assets is verified, then an undeniable conclusion about the market efficiency can be drawn. Based on this reasoning pattern, several empirical studies have investigated the CDS spreads efficiency in both corporate and sovereign markets (Zhang and Zhang, 2013; Avino and Nneji, 2014; Kiesel et al., 2016; Chang et al., 2015; Norden, 2017). Despite the growing need for conclusive and robust results, the empirical evidence of the sovereign CDS predictability remains an open issue that suggests a contradictory conclusion. Moreover, to the best of our knowledge, only one article studies the impact of crises on the efficiency degree in sovereign credit derivatives market presents questionable results (see Sensoy et al. (2017)). In fact, these authors argue that financial troubles have no impact on the efficiency of CDS spreads, which is preposterously incoherent from a realistic perspective as some favorable arbitrage and speculative strategies based on credit derivatives were observed, leading to financial instability. Furthermore, the future pattern of financial assets in general and CDS spreads in particular is difficult to predict and the existing empirical tests can only give a preliminary insight of the market effectiveness characteristics. As these tools are not strict enough, and since CDS market highly impacts the real economy through its risk-transfer role, more studies using further approaches are needed to be sure about the market efficiency. Finally, in the literature focusing of the financial markets efficiency, the authors either use the VECM model without considering for the heteroscedasticity issue or apply the GARCH framework on stationarised series which can weaken the long-term equilibrium relationship. As far as we are concerned, none of the aforementioned papers uses these two models in a single framework.

Our essay contributes to the literature in several ways. First, contrarily to previous studies, our methodological framework is heteroscedasticity-robust and is the only one that takes into account, simultaneously, the long-run properties, the volatility clustering and long-memory behavior of financial data. Combing both models in a unique econometric framework provides more robust estimates and allows us to detect some degrees of inefficiency. Second, we complement the few existing empirical studies on the efficiency of CDS spreads and give international evidence by using daily spreads of 37 worldwide heterogeneous countries, ranging from January 2^{nd}, 2006 to March 31^{st}, 2017. As far as we are concerned, our database is the largest dataset ever used in studying sovereign CDS efficiency in terms of size and time-period. The analysis is conducted on both the whole studied period and four sub-periods (pre-crisis, crisis and post-crisis phases) defined according to range-based volatility, so we can assess the impact of crises on market effectiveness. Third, apart from what is commonly agreed in the study of the weak-form market efficiency, the current investigation attempts to detect any reflection of past information into current CDS spreads that are available not only in the CDS market but also in the corresponding bond market.

While the existing literature seems to give a common evidence about the efficiency of sovereign CDS markets, our findings show that spreads composing our sample are predictable from both their own historical values and the past values of the underlying bond yields. Furthermore, crises negatively impact the randomness of CDS spreads with a significant increase in the number of forecastle prices, especially during the Sovereign Debt Crisis. According to our heterogeneous results, we notice that timeless general conclusion should not be given on worldwide CDS markets and a perpetual revision of regulatory operations and investment strategies should take place according to whether the market is impeccably efficient or glossy inefficient.

The rest of the chapter is organized as follows: section 2.2 gives a brief review on theoretical background on the Efficiency Market Hypothesis and the related empirical evidence of CDS efficiency. We present the empirical data and the methodological framework used to detect randomness in section 2.3. section 2.4 displays the data analysis and the model estimation, while the section 2.5 concludes the chapter.

2.2 Literature review

This section provides a brief review of theoretical and empirical works on the efficiency hypothesis and the related theories, in the first place. Next, an exhaustive literature review of the CDS spreads informational efficiency is presented.

2.2.1 Theoretical background on the Efficient Market Hypothesis

By taking stock of the theoretical and empirical existing literature concerning market efficiency, we notice a particular definition that is commonly used by researchers and according to which, the financial market is considered as efficient if its assets' prices always completely, instantaneously and properly [1] reflect available and relevant information (Fama, 1970; Bollerslev and Hodrick, 1992).

This definition gives rise to three interpretations: First, given an information set, the expected returns of financial assets are assumed to follow a "fair game" model in which the equilibrium prices are determined according to their risk levels. This implies that long-term equilibrium prices should not exceed limits fixed by expectation model and that the excess volatility is a sign of market inefficiency (Shiller, 1979, 1981, 1992; Cuthbertson and Hyde, 2002). Second, in an efficient market context, next period's asset prices - respecting the current information sequence - are greater than the actual prices. This means that the conditional expected prices are following a sub-martingale model[2](LeRoy, 1989). Third, the financial market efficiency analysis is intimately related to the random walk theory. This theory denotes that the assets' prices fluctuate randomly, meaning that successive price changes are independent and identically distributed (Samuelson, 1965; Lo and MacKinlay, 1988; Fama, 1995). Yet, Malkiel (2003) explains this random walk idea by the fact that financial time series have no long-run or short-run memory and that today's prices are independent from previous prices and only depends on today's available and known information.

This immediate and fully incorporation of information flows into asset prices is based on the assumption of market rationality and the nonexistence of arbitrage opportunities[3]: On the one hand, the information must be translated and understood in the same way by all the market participants who implement their investment strategies on the basis of reflective and profit-maximization reasoning. On the other hand, since new information flows randomly, prices should be unpredictable making investors unable to realize better returns than what

[1]The term properly in this essay means without bias.

[2]The sub-martingale model is defined by the following equations: $E(x_{t+1}/\mathcal{F}_t >= x_t)$ and $E(y_{t+1}/\mathcal{F}_t >= 0)$ where x_{t+1} and y_{t+1} are respectively the expected return and the expected returns changes, and $\mathcal{F}_t$ is the information set available at the time t.

[3]Several conditions must be met to reach the informational efficiency of financial markets, namely: assets are traded without any transactions fees and the information is transparent and free for all investors.

they could expect from another randomly selected portfolio with the same risk-level, as argued by Malkiel (2003). However, the analysis of stock markets behavior shows that several irregularities exist, hindering a correctly price formation. In fact, Malkiel (2005) underlines some irrational investment activities notably during the dot-com bubble when investors excessively speculate on unreasonable positions. The behavioral finance supports this market irrationality and argues that investors' decisions are based on considerations unrelated to fundamentals and are affected by systemic psychological errors in the way that market participants think (Fama, 1998; Ritter, 2003; Hirshleifer et al., 2006). Yet, Lo and MacKinlay (1988), Huang (1995) and Urrutia (1995), among other authors, argue that financial assets do not necessarily follow a random walk and are rather characterized by a predictable pattern which rejects the nonexistence of arbitrage opportunities' assumption. However, Fama (1970) argues that the non-respect of this condition does not necessarily imply the inefficiency of financial markets.

While emphasizing the fact that efficient market theory is based on a timely incorporation of relevant information into asset prices, authors distinguish three forms of market efficiency (Roberts, 1959; Fama, 1970): (i) a weak form where the available information concerns only the historical prices and market's past behavior (Sensoy et al., 2017), (ii) a semi-strong form in which the information sequence is rather composed by publicly released information (earnings surprises, rating publications, credit events, M&A announcements, financial accounts disclosure...) (Norden and Weber, 2004; Zhang and Zhang, 2013; da Silva et al., 2015; Jenkins et al., 2016; Kiesel et al., 2016; Norden, 2017), and (iii) a strong form in which the information set made of pertinent private information - initially held by investors or financial groups in a monopolistic way - that have been recently released.

Several parametric and non-parametric statistics are used to test for the weak-form of the EMH. Bollerslev and Hodrick (1992) review the empirical literature on the theory of the efficient market and provide a selective synthesis of the existing econometric approaches to test for the efficiency in the stock markets using data[1] on NYSE-traded stocks. Serial correlation tests in the short-term and the long-term, multi-period regression tests and variance bounds tests are discussed in their article and reject, for the most, the market efficiency. A similar study is conducted by Mollah (2007) for emerging markets using a triangulation econometric. Serial autocorrelation is detected , indicating the predictability of the stock returns. Another approach to test for the market efficiency hypothesis is to focus on the assets volatility rather than on their predictability. This econometric method is based on the idea that the excess volatility indicates the inefficiency of the market: Financial markets are too volatile to be efficient (Fakhry and Richter, 2015; Fakhry et al., 2016; Richter and Fakhry, 2016). Combining these two aforementioned methodological frameworks, Vieito et al. (2013) are among the first authors that investigate the weak-form efficiency of the developed markets (G-20 countries). These authors show that the studied stock indexes are efficient with an improvement of this market efficiency during crisis period.

2.2.2 The efficiency of the CDS market

Following the primary objective of this essay, the forthcoming literature review is only limited to the existing works on the CDS markets. Even though there are several works studying the dynamic of CDS spreads, very few of them focus on the efficiency of the CDS markets and even less on the sovereign CDS markets. Norden and Weber (2004) study the information

[1]Prices, dividends and returns.

efficiency of the CDS market and the stock market of 1000 corporate and sovereign entities over the period spanning from 2000 to 2002. The authors use a univariate and a comparative event study to argue that the rating announcements significantly impact the direction and the magnitude in which the studied CDS spreads and stock returns move. Results also show that downgrades events by Standard&Poor's and Moody's are reflected in a greater extent than the reviews downgrade of the other rating agencies. Cserna and Imbierowicz (2008) apply several structural credit risk models[1] to CDS spreads of 808 firms belonging to 10 different industries from 2002 to 2006. The authors find strong strategies of arbitrage opportunities given the convergence between the produced spreads and the observed ones. The market efficiency hypothesis is still rejected even after controlling for the transactions fees. Using copula methodology, Gatfaoui (2010) study the predictable pattern that may exist from the financial market fundamentals to the CDS spreads (the spreads of eight Dow Jones credit derivative indexes (CDX indexes)). Results show that CDS are negatively linked with market price and positively linked with market volatility risk, supporting the existence of a forecastable trend of common correlation between the credit risk and the financial securities.

In the same context of semi-strong efficiency study, Zhang and Zhang (2013) use a sample composed by 633 US firms to study the information efficiency and the reaction of the single-name CDS spreads following earnings announcements from 2001 to 2005. Results show that positive and negative earnings news significantly impact CDS spreads in different extents confirming the efficiency theory. Nonetheless, the sensitivity extent and the time of reactions are different for investment-grade firms and speculative-grade firms. Similarly, da Silva et al. (2015) argue that the CDS market is more efficient than the stock market. These authors analyze the patterns of CDS spreads and the stock prices of US and Western European firms before and after the announcements of Mergers and Acquisitions (M&A) events from 2006 to 2013. Results show that private information is reflected in CDS spreads before its assimilation into stock prices.

Most recently, a number of policy makers and regulator authorities have expressed concerns regarding sophisticated market players entering uncovered or naked positions in credit default swaps (CDS)

By analyzing the iTraxx Europe index From September 2005 to September 2010, Avino and Nneji (2014) find that the corporate CDS spreads exhibit a predictable pattern, rejecting, thus, the weak-form efficiency market hypothesis. Results of this forecasting ability are based on both linear (least square method) and non-linear (Markov switching and Markov Switching structural model) approaches explaining CDS spreads by their lagged values. Everlastingly focusing on the weak-form efficiency, Kiesel et al. (2016) study the information efficiency of corporate CDS and the corresponding equity markets for countries from the US and Europe. Based on an event study approach and by concentrating the studied period around credit events, the authors find, among others, that the CDS market is lagging the equity market in the price formation process though both markets are relatively efficient, confirming that investors are not able to rigorously and timely assess the effect of sudden events. Similarly, Fei et al. (2017) propose a flexible dynamic copula with Markov-switching model to forecast the iTraxx Europe CDS market based on the underlying equity market. Results show that the value of the European CDS index is extremely dependent to the stock market index particularly during the global financial crisis and the sovereign debt crisis. Lately, Norden (2017) analyzes the reactions of 95 international industrial and financial companies towards

[1]The CreditGrades, Leland and Toft (1996) and Zhou(2001) models (Cserna and Imbierowicz, 2008).

credit rating announcements from 2000 to 2006. Based on the results of an event study and multiple regression analysis, these authors show that financial news is reliably and instantly reflected into CDS spreads and that the corporate CDS market is in line with the efficiency hypothesis. Moreover, the CDS markets' efficiency ranks of companies with important bank interconnections are the greatest.

The study of sovereign CDS efficiency has started more recently with Gündüz and Kaya (2013) who test the presence of a long memory behavior in the sovereign CDS markets of 10 Eurozone countries using both CDS changes and the corresponding volatility as proxies for respectively the price efficiency and the sovereign risk. Results show, among other findings, that the CDS markets are efficient given that no long-run dependence is observed between CDS spreads changes' observations. These results are negated by Capponi and Larsson (2014), who argue that derivative instruments and particularly sovereign CDS contracts are not efficient, but can rather threaten the financial stability. The authors explain that CDS are kind of predictable, making the market subject to excessive speculation on naked CDS, which leads to a systemic risk in the overall economy. Likewise, Chang et al. (2015) study the arbitrage condition between the European CDS markets and the corresponding bond markets during the sovereign debt crisis from 2010 to 2013. Results show that the efficiency hypothesis between these credit markets is only confirmed in the long-run.

The recent study conducted in the context of sovereign weak-form market efficiency is conducted by Sensoy et al. (2017). Based on a permutation entropy method, the authors study the weak-form efficiency of CDS markets of 15 sovereigns. Results of these authors show that the efficiency-level differs from one country to another and that crisis periods don't affect the markets' efficiency degrees. Unlike previous studies, Sensoy et al. (2017) do not impose a single fixed efficiency degree throughout the studied period and allow, thus, more flexibility to the approach. Yet, in order to not reduce the statistical reliability of the permutation entropy approach, the volatility clustering behavior and the ARCH effect exhibited in the CDS spreads data are taking into account by requiring the analysis to rather be based on GARCH filtered data.

2.2.3 Limits of the CDS efficient market studies

As already shown, the literature comprises a restricted number of nine articles that empirically examine the efficiency of CDS spreads, among which only 4 studies deal with the sovereign markets. Broadly, studies are based either on European countries or on emerging countries where the credit risk is known to be misestimated especially during crisis episodes. Evidences show, mostly, that the informational market efficiency is supported even during crisis periods, which is an antagonist to economists and practitioners' opinions who argue that CDS allow for profitable speculative and arbitrage operations. Our essay fills this gap by considering a wide range of heterogeneous cross-country sample representative of the worldwide sovereign CDS markets. For sake of accuracy, the studied period is divided into 4 sub-periods during which financial markets effectiveness is expected to behave abnormally.

On the other hand, most of the above-mentioned studies - whether on private or sovereign CDS markets - present some methodological shortcomings. First, the several statistic tests for the random walk hypothesis have only power to detect alternatives to randomness, which is neither necessary nor sufficiency to affirm with certainty or discredit the EMH. Second, except for Sensoy et al. (2017) who use a GARCH filter that takes into account ARCH effects, the other econometric methods used in the CDS literature don't control for financial markets' stylized facts (Volatility clustering, asymmetries, fat tails...). Yet, Da Fonseca and Wang (2016) use a Markow regime-switching VAR framework to analyze two constituents of the North American investment grade Credit Default Swap index, which is quite interesting when it comes to take into account different volatility regimes. However, this econometric model does not consider for the long-term equilibrium. In a like manner, Coudert and Gex (2010) study the interaction between the CDS and the underlying bond market using a VECM model that does not take into account the heteroscedasticity issues presented in both CDS and bond series. As opposed to these studies, our econometric approach takes into account, at the same time, long-run properties, volatility clustering and long-memory behavior while investigating the price efficiency of sovereign CDS.

Finally, weak-form empirical investigations in the literature are conducted in such a way that it only takes account of the impact of recent accessible information in the CDS markets. However, as derivatives and credit markets highly comove[1], it is interesting to consider for the past information available in both CDS and the underlying bond prices and their reflection into current CDS spreads. In this essay, the long-run properties between these two markets and their impact of the dynamic spreads formation are taken into consideration through a two-step VECM model.

2.3 Data and methodology

2.3.1 Sample and data description

The sample under study in this chapter is composed by 37 countries that cover five geographical areas from all over the world (Eastern Europe, South and Central America, Asia and Western Europe) and belong to different economic categories (developed countries, newly industrialized countries and emerging countries). The complete list of these countries with their economic and geographical status is given in Table 2.1.

To examine the efficiency of these sovereign CDS markets, daily CDS spreads (and their underlying bond yields) with 5-year maturity with a USD denomination are collected from Thomson Reuters ® for a period going from January 2^{nd}, 2006 to March 31^{st}, 2017. As mentioned before, to the best of our knowledge, our database is the largest dataset ever used in studying sovereign CDS efficiency in terms of size and time-period.

2.3.2 Econometric methodology: a VECM-FIGARCH methodology

By inspiring from the work of Sogiakas and Karathanassis (2015) on spot and derivative markets, our analysis is based on a VECM-FIGARCH(1,d,1)-DCC model. This approach assesses the contribution degree of each market in the information efficiency of the worldwide CDS markets. The VECM-FIGARCH-DCC model allows to take into account simultaneously the non-stationarity of our time series in the conditional mean equation and the volatility clustering, the heteroscedasticity and the long-memory behavior in the conditional variance equation.

The informational efficiency of the credit derivative market is investigated following three iterative steps:

[1]See for example Sabkha et al. (2018*c*) for an empirical study on the interconnectedness and the risk spillover between CDS and the corresponding bond markets.

Table 2.1: Sample and countries classification into economic categories and geographical positions

Country	Geographical position	Country	Geographical position
Developed countries (20)		***Newly industrialized countries (6)***	
Austria	Western Europe	Brazil	South America
Belgium	Western Europe	China	Asia
Denmark	Western Europe	Mexico	North America
Finland	Western Europe	Philippines	Asia
France	Western Europe	Thailand	Asia
Germany	Western Europe		
Ireland	Western Europe		
Italy	Western Europe	***Emerging countries (11)***	
Japan	Asia	Bulgaria	Eastern Europe
Latvia	Eastern Europe	Croatia	Eastern Europe
Lithuania	Eastern Europe	Czech	Eastern Europe
Netherlands	Western Europe	Hungary	Western Europe
Norway	Western Europe	Greece	Western Europe
Portugal	Western Europe	Indonesia	Asia
Slovakia	Eastern Europe	Poland	Eastern Europe
Slovenia	Eastern Europe	Romania	Eastern Europe
Spain	Western Europe	Russia	Asia
Sweden	Western Europe	Ukraine	Eastern Europe
UK	Western Europe	Venezuela	South America
USA	North America		

Countries decomposition into these categories is made according to the NU, the CIA world Factbook, the IMF and the world Bank criteria.

Step 1. Estimation of the Conditional mean equation through the VECM model

This model assesses each market's contribution in the innovations of the random walk efficient price. The VECM is used rather than the unrestricted VAR to avoid information loss and to avoid linking disrupt between variables due to stationarity techniques. Taking account the long-run properties of the CDS-Bond relationship, the VECM model can be expressed as functions of the cointegrating terms and their mutual lagged values:

$$\Delta X_t = \mu + \Gamma \Xi' X_{t-1} + \sum_{k=1}^{p} \Pi_k \Delta X_{t-k} + \upsilon_t, \tag{2.1}$$

With X_t is a vector of 2 variables (CDS spreads and bond yields) at time t, Π is $2\times$ 2 parameters matrix of the short-run relationship, Γ and Ξ' denote matrices of receptively the error correction terms and the long-run coefficients, μ is a deterministic component and υ_t represents the innovations. In a simpler way, the cointegrated vector autoregressive model, can be written, through two equations where the CDS spreads and the bond yields are expressed as functions of the cointegrating terms and their mutual lagged values:

$$\Delta x_{1,t} = \lambda_1 \xi_{t-1} + \sum_{k=1}^{p} \gamma_1 \Delta x_{1,t-k} + \sum_{k=1}^{p} \delta_1 \Delta x_{2,t-k} + \upsilon_{1,t}, \quad (2.2)$$

$$\Delta x_{2,t} = \lambda_2 \xi_{t-1} + \sum_{k=1}^{p} \gamma_2 \Delta x_{2,t-k} + \sum_{k=1}^{p} \delta_2 \Delta x_{1,t-k} + \upsilon_{2,t}, \quad (2.3)$$

where x_1 and x_2 represent respectively the sovereign CDS spreads and the government bonds yields, λ is the adjustment coefficient of each market and ξ_t is the deviation from the long-run equilibrium estimated from the following equation: $x_{1,t} = c_0 + c_1 x_{2,t} + \xi_t$. $\upsilon_{1,t}$ and $\upsilon_{2,t}$ are the residuals of the VECM models.

Step 2. Estimation of the FIGARCH(1,d,1) model

The volatility model is applied to the residuals of the VECM model ($\upsilon_{1,t}$ and $\upsilon_{2,t}$). This univariate model is estimated following a more flexible class of GARCH models that take into account a new feature of the unit root for the variance, proposed by Baillie et al. (1996) and so-called FIGARCH. This model highlights the fact that, unlike basic models where the persistence of volatility shocks is subject to an exponential decay, in real financial time series, the impact of lagged errors on future volatility occurs at a slow hyperbolic rate of decay. The FIGARCH model allows, thus, to capture the long memory of autocorrelations in volatility processes with a complete flexibility regarding the persistence degree via the differencing fractional parameter (d). The use of such a model-class is recommended by Sabkha et al. (2018*b*). These authors argue that the non-linear GARCH-class models, that allows for leverage effects, unsymmetrical dependencies and long-range memory in the volatility model are the best fitting to sovereign CDS data[1]. The FIGARCH (1,d,1) is written as follows:

$$\upsilon_t \sim \mathcal{D}(0, \sigma_t^2), \quad (2.4)$$

$$\sigma_{i,t}^2 = \alpha_0 + [1 - (1 - \Theta(L))^{-1}(1 - \phi(L))(1 - L)^d]\upsilon_{i,t}^2 + \beta \sigma_{i,t-1}^2, \quad (2.5)$$

where $\upsilon_t = e_t \sigma_t^2$, with e_t are independent and identically distributed random variables and σ_t is the conditional volatility of υ_t given the information set at the moment $t-1$ ($\mathcal{F}_{t-1}$), (d) is the differencing fractional parameter such as $0 < d < 1$ and $\mathcal{D}$ is a law of probability that might be a Gaussian, a student, a GED or a skewed student's distribution. When d=1, the FIGARCH (1,d,1) is equivalent to an IGARCH (1,1) where the persistence of conditional variance is supposed to be complete, while when d=0, it is rather equivalent to a GARCH (1,1) with no volatility persistence is taken into consideration. L is the lag operator and $(1-L)^d$ is the financial fractional differencing operator.

Step 3. Re-estimating the VECM model using transformed data

To overcome non-stationarity, heteroscedasticity and long-memory issues and take account, at the same, time of the long-run cointegration properties characterizing financial data, the VECM is once again estimated using not the raw data but reconstructed time

[1] Similarly, Sabkha et al. (2018*d*) use a long-memory model, namely the FIAPARCH(1,d,1), to model the volatility of the sovereign CDS markets.

series. We propose a special treatment that is applied to each series of each country though the following transformation-equation:

$$y_1 = x_1, \tag{2.6}$$

$$y_t = \hat{\omega} + y_{t-1} + \frac{\hat{\varepsilon}_t}{\hat{\sigma}_t}, \text{ for } t = 2, \ldots, T, \tag{2.7}$$

with

$$\hat{\omega} = \frac{1}{T-1} \sum_{t=2}^{T} \Delta x_t \tag{2.8}$$

and

$$\hat{\varepsilon}_t = \Delta x_t + \hat{\omega}, \tag{2.9}$$

where y_t is the new transformed time series, x_t is the CDS spreads (or Bond yields) spread at time t, μ_t and σ_t^2 are respectively the conditional mean and the conditional variance obtained from the estimation of the univariate FIGARCH model. In this way, heteroscedastic properties and long-memory behavior of CDS and bond spreads are considered in the converted-time series.

The VECM model, applied to transformed time series, is re-written as follows:

$$\Delta y_{1,t} = \lambda_1^{'} \xi_{t-1}^{'} + \sum_{k=1}^{p} \gamma_1^{'} \Delta y_{1,t-k} + \sum_{k=1}^{p} \delta_1^{'} \Delta y_{2,t-k} + v_{1,t}^{'}, \tag{2.10}$$

$$\Delta y_{2,t} = \lambda_2^{'} \xi_{t-1}^{'} + \sum_{k=1}^{p} \gamma_2^{'} \Delta y_{2,t-k} + \sum_{k=1}^{p} \delta_2^{'} \Delta y_{1,t-k} + v_{2,t}^{'}. \tag{2.11}$$

If only one coefficient of the lagged variables ($\gamma_1^{'}, \gamma_2^{'}, \delta_1^{'}$ or $\delta_2^{'}$) is statistically significant, then a predictable pattern is detected and the EMH doesn't hold in the Sovereign CDS market.

2.3.3 Market efficiency during crisis periods

The impact of crises on the Sovereign CDS markets is investigated through the same VECM-FIGARCH (1,d,1) explained above. The third step VECM(2) is once again applied on the reconstructed time series over four subperiods: a pre-crisis period, a first-crisis period (Global Financial Crisis), a second-crisis period (European Debt Crisis) and a post-crisis period. Analysis of the statistically significance of the lagged coefficients is based on the results of the Block Exogeneity and Lag Exclusion Wald Tests over these sub-periods.

Crises timeline is defined in this essay is the same way as in Sabkha et al. (2018*a*). As mentioned before, our data period covers both the Global Financial Crisis and the Sovereign Debt Crisis. By referring to the timeline produced by the BIS (2009), the length as well as the crisis sub-periods of the crisis can be defined as follows: (i) A tranquil period going from January 2006 to the third quarter of 2007, in which the financial climate was globally healthy. (ii) A 1$^{\text{st}}$ turmoil period, characterized by an increase of market participants' misperception of some risky credit derivatives, and spans from July 2007 to mid-September 2008. (iii) A 2$^{\text{nd}}$ trouble phase starting up from mid-September 2008 until late 2008, during which the financial financial market is subject to sharp deterioration following the Lehman Brothers Bankruptcy. The 3$^{\text{rd}}$ turmoil phase extends from late 2008 to the end of the first quarter of 2009 and is characterized by a decrease in the economic health due to the implementation of some rescue packages in the financial system.

On the other hand, the Sovereign Debt Crisis spans from October 2009 to April 2012 according to Thomson Reuters official publications. This crisis goes through four phases: (i) From October 2009 to April 2010, the public finances' real situation of Greece is unrevealed, showing that the budget deficit was much higher than what the country announced. (ii) The 2^{nd} phase, running from May 2010 to June 2011, is triggered following the adoption of EU and IMF bailout packages. (iii) A worsening of the situation is recorded and the sovereign risk reached the highest levels from July 2011 to March 2012. (iv) The Eurozone reports the first signs of recovery in April 2012, following the setting up of a rescue fund whose purpose is to keep countries and banks' credit risk a reasonable level.

Next, since financial crises are characterized by a sharp increase in financial assets volatility, we check the phases of excessive volatility for each of the CDS markets using Markov's switching ARMA model. As explained by Sabkha et al. (2018*a*), this model class takes into account structural breaks with two regimes: stable and volatile, where 0 corresponds to a low conditional volatility and 1 to a high conditional volatility. Thus, this model allows us to define different crisis sub-periods. Results of the regime classification based on smoothed probabilities are presented in Table 2.8 (section 2.6).

Thus, by taking stock of the results of these two previous methods, the period studied can be divided into 4 sub-periods (See Figure 2.5, section 2.7):

- From January 2006 to June 2007: a reference period (Quiet period);
- From July 2007 to March 2009: 1^{st} crisis period (Global Financial Crisis);
- From April 2009 to March 2012: 2^{nd} crisis period (European Debt crisis);
- From March 2012 to March 2017: Post-crisis period (Recovery period).

2.4 Empirical results

This section displays descriptive statistics and brief analysis of the preliminary properties of credit markets. It models, as well, the joint dynamics of the CDS spreads and their underlying bond yields using a VECM-FIGARCH model in order to capture at the same time cointegrating relations, clustering volatility and long memory behavior.

2.4.1 Descriptive statistics

Table 2.3 shows descriptive statistics for the CDS spreads and their corresponding bond yields. Panels A, B and C correspond respectively to developed countries, newly industrialized countries and emerging countries. Time series of each country under study are composed by 2936 observations.

Unsurprisingly, the highest spreads are recorded in the Greek market during the sovereign debt crisis, followed by Ukraine (15028 bp) and Venezuela (10995 bp). These high values are reported respectively during the European Debt crisis, the Ukrainian political crisis[1] and the

[1]Even though the crisis in Ukraine has started in 2013, the highest levels in CDS spreads are recorded during 2015 when economists affirm that "*Ukraine Sovereign CDS Spreads are back to pre-war/pre-revolution levels*".

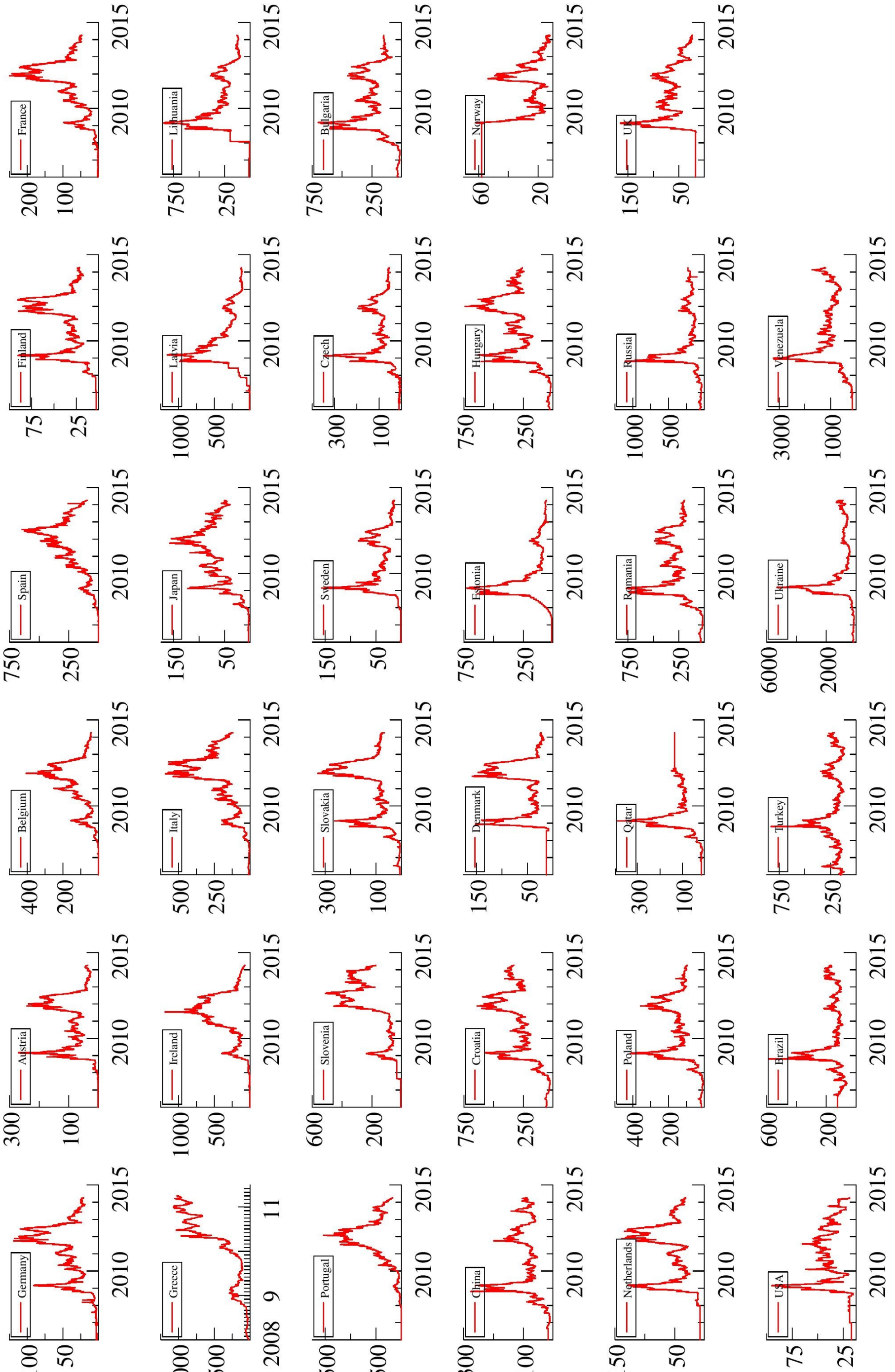

Figure 2.1: Time-varying evolution of CDS spreads of some countries

Table 2.3: Descriptive statistics and non-stationary tests of CDS spreads and bond yields

		Obs.	Min	Mean	Max	Std. Dev	LLC test Statistic	Number of CI relations Trace test	Max-Eig test
Panel A: Developed countries									
Austria	CDS	2936	1.40	36.13	132.77	24.96	0.38327	2	2
	BOND	2936	-0.51	1.93	4.88	1.58			
Belgium	CDS	2936	2.05	72.39	398.78	74.62	0.43877	1	0
	BOND	2936	-0.52	2.14	5.62	1.60			
Denmark	CDS	2936	11.25	36.65	157.46	32.94	-0.12334	2	2
	BOND	2936	-0.50	1.83	5.09	1.62			
Finland	CDS	2936	2.69	26.85	94.00	19.24	-0.75381	2	2
	BOND	2936	-0.53	1.78	4.88	1.56			
France	CDS	2936	1.50	54.30	245.27	50.56	0.09455	1	0
	BOND	2936	-0.46	1.92	4.91	1.50			
Germany	CDS	2936	1.40	28.77	118.38	24.50	-0.83017	1	1
	BOND	2936	-0.62	1.61	4.77	1.56			
Ireland	CDS	2936	1.75	188.89	1249.30	234.02	0.11659	1	1
	BOND	2936	-0.34	3.40	17.61	2.79			
Italy	CDS	2936	5.58	151.75	586.70	127.38	-0.88370	1	1
	BOND	2936	0.20	3.01	7.78	1.59			
Japan	CDS	2936	2.13	49.26	152.64	33.28	-0.83411	1	1
	BOND	2936	-0.37	0.49	1.60	0.47			
Latvia	CDS	2936	5.50	210.89	1176.30	216.13	-0.26628	1	0
	BOND	2936	0.10	4.02	16.49	3.21			
Lithuania	CDS	2936	6.00	169.21	850.00	154.01	0.03087	2	2
	BOND	2936	0.05	4.06	13.70	2.97			
Netherlands	CDS	2936	7.67	37.13	133.84	29.50	-0.48263	2	2
	BOND	2936	-0.57	1.78	4.88	1.56			
Norway	CDS	2936	10.59	30.95	62.00	17.82	-0.99822	2	2
	BOND	2936	0.53	2.52	5.39	1.34			
Portugal	CDS	2936	4.02	289.89	1600.98	323.68	-0.02785	1	1
	BOND	2936	0.84	4.89	23.42	4.02			
Slovakia	CDS	2936	5.33	77.52	306.01	66.71	-0.33187	2	2
	BOND	2936	-0.33	2.74	5.76	1.83			
Slovenia	CDS	2936	4.25	131.24	488.58	114.88	-0.40258	1	0
	BOND	2936	-0.07	3.07	6.92	2.17			
Spain	CDS	2936	2.55	144.63	634.35	135.01	-0.40593	1	1
	BOND	2936	0.04	3.00	7.73	1.62			
Sweden	CDS	2936	1.63	27.17	159.00	25.70	-0.78589	2	2
	BOND	2936	-0.40	1.92	4.74	1.44			
UK	CDS	2936	16.50	42.89	165.00	28.11	-1.04744	2	2
	BOND	2936	0.16	2.33	5.76	1.56			
USA	CDS	2936	10.02	24.01	90.00	11.11	-1.86194	2	2
	BOND	2936	0.54	2.15	5.24	1.26			
Panel B: Newly Industrialized countries									
Brazil	CDS	2936	61.50	178.55	606.31	94.86	-0.61737	2	0
	BOND	2935	4.79	11.61	17.86	2.51			
China	CDS	2936	10.00	82.44	276.30	43.56	-0.60868	2	0
	BOND	2936	2.38	4.22	5.99	0.64			
Mexico	CDS	2936	64.17	141.89	613.11	59.36	-0.43577	1	0
	Bond	2936	4.07	6.31	9.42	1.27			
Philippines	CDS	2936	78.30	188.72	840.00	101.70	-0.70327	2	2
	BOND	2936	2.39	5.37	11.04	1.70			
Thailand	CDS	2936	51.01	120.94	500.00	41.89	-0.40863	2	2
	BOND	2936	1.42	3.31	5.75	0.97			
Turkey	CDS	2936	109.82	217.65	835.01	72.41	-0.52148	2	2
	BOND	2936	5.65	11.64	24.62	4.08			
Panel C: Emerging countries									
Bulgaria	CDS	2936	13.22	180.37	692.65	121.88	0.06721	2	2
	BOND	2936	0.41	3.63	7.74	1.87			
Croatia	CDS	2936	24.88	244.20	592.50	128.47	0.17809	1	1
	BOND	2936	1.54	4.55	7.52	1.41			
Czech	CDS	2931	3.41	66.89	350.00	49.54	0.56910	1	0
	BOND	2936	-0.36	2.21	5.32	1.59			
Greece	CDS	2936	5.20	9508.85	37081.41	15351.1	-0.17131	1	1
	BOND	2936	3.06	17.40	64.99	18.84			
Hungary	CDS	2936	17.34	225.98	729.89	153.05	-1.00460	2	2
	BOND	2936	1.77	6.29	13.69	2.57			
Indonesia	CDS	2936	118.09	219.29	1240.00	116.83	-0.27096	2	2
	BOND	2936	4.39	8.36	19.65	2.30			
Poland	CDS	2936	7.67	101.35	421.00	73.12	0.00223	1	0
	BOND	2936	1.68	4.41	7.61	1.40			
Romania	CDS	2936	0.00	204.20	767.70	144.27	-1.01639	2	2
	BOND	2936	2.07	6.51	15.50	3.01			
Russia	CDS	2936	0.00	209.09	1106.01	147.92	0.28748	2	2
	BOND	2936	6.05	8.29	17.94	2.21			
Ukraine	CDS	2936	1.00	2173.76	15028.76	3969.28	0.06110	2	2
	BOND	2936	9.07	17.10	28.00	2.70			
Venezuela	CDS	2936	124.62	1771.08	10995.67	1869.79	-0.40778	2	0
	BOND	2936	4.68	12.91	19.93	4.34			

The table reports descriptive statistics for the daily CDS spreads expressed in basis points. Min., Max. and Std. Dev. refer respectively to the minimum, the maximum and the standard deviation. LLC denotes the panel unit root of Levin, Lin and Chu (with individual intercept in the test equation): The null hypothesis is the presence of a unit root in all the processes (non stationary time series). Finally, number of CI relations denotes the number of cointegration relations based on Trace test and Max-Eig test (denoting trace and maximum eigenvalues tests) in the Johansen Cointegraion model with quadratic specification.

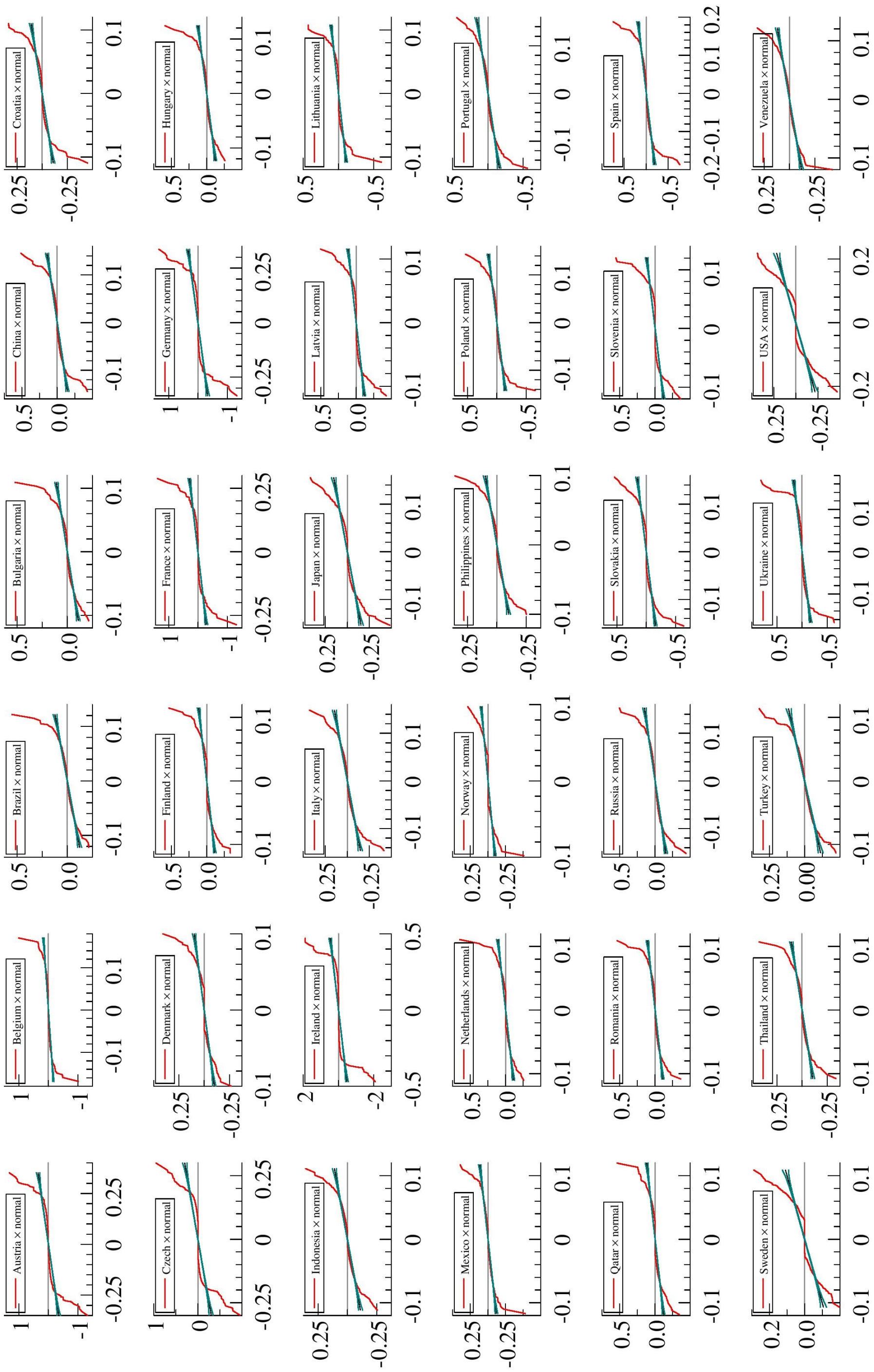

Figure 2.2: Sample Quantiles and Normal theoretical Quantiles

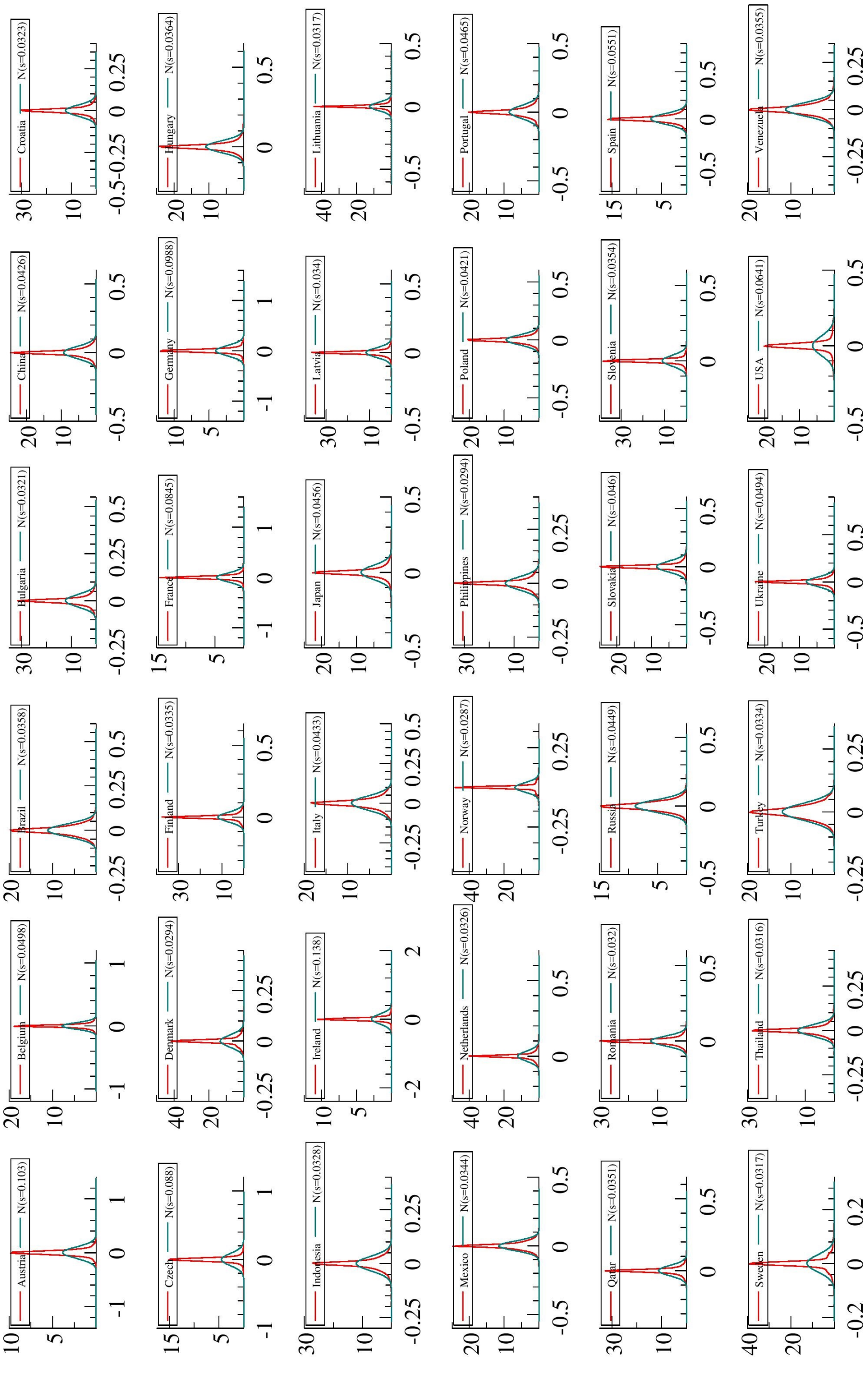

Figure 2.3: Empirical Density and Normal Distribution Fit

Venezuelan economic recession[1], as shown in Figure 2.1. The situation is also dramatic in other countries (Ireland, Latvia, Portugal, Indonesia and Russia) but in a lesser extent. This can be explained by the considerable and long-lasting impact of the two recent worldwide financial crises on these economies. Interestingly, the highest bond yields are recorded in almost the same countries (Ireland, Latvia, Portugal, Ukraine, Venezuela...) which makes sense with the common result found in literature regarding the positive correlation between the CDS and the underlying bond markets (Sabkha et al., 2018*a*).

The Levin et al. (2002) panel unit root test does not reject the null hypothesis of the unit root presence and confirms the common non-stationarity of the CDS spreads and bond yields. Yet, the Johansen Cointegration test, based on the quadratic specification, exhibits at least one cointerating relation between the two-time series of each studied country. Results of both stationarity and cointegration tests are suitable for modeling our credit data using a Vector autoregressive with error correction.

The Q-Q probability charts and the empirical density of each stationnarized time-series, as displayed in Figure 2.2 and Figure 2.3, compare the probability distribution of our time series against the normal distribution. Graphs clearly show that these CDS spreads are not normally distributed. In fact, the scatter points are not close enough to the reference line (Figure 2.2) and the probability density functions are not in shape of the standard Gaussian distribution curve (Figure 2.3). Given that the random walk hypothesis is based on the assumption of normal distribution, based on the results of the normality tests, we can ostensibly say that the sovereign CDS markets are not efficient. However, the normality of our data's distribution is necessary but not sufficient condition to confirm or refute the predictability of these studied non-cash assets' prices. That's why, deeper analysis is proposed in this essay.

Preliminary tests on the residuals of the VECM mean equation confirm the appropriate use of FIGARCH(1,d,1) to model the conditional variance equation (Table 2.4). First, regardless the lag order, ARCH effects are detected in almost all the considered series (Except for CDS of Norway, Greece and Ukraine and Bond of Venezuela). Second, strong evidence of credit markets' long-memory behavior is found using the Rescaled Range test. Yet, the proxied unconditional volatility of all studied countries are following a fractionally integrated process (Exception for CDS Greece and Ukraine, and Bond of Croatia and Venezuela). Finally, results of the Jarque-Bera test, confirmed by significant Skewness excess of Kurtosis, show that the studied time series exhibit leptokurtic properties, confirming the rejection of the null hypothesis of normality. To overcome the distribution issue, residuals are allowed to follow a Gaussian, a student and a Generalized Error Distribution (G.E.D)[2].

Table 2.4: Preliminary tests on the VECM mean equation's residuals

		Skweness		Excess Kurtosis		Jarque-Bera		ARCH-LM(2)		ARCH-LM(5)		ARCH-LM(10)		R/S	
Panel A: Developed countries															
Austria	CDS	0.37	***	24.33	***	72376	***	34.21	***	59.07	***	31.31	***	2.56	***
	Bond	0.67	***	7.92	***	7886	***	25.36	***	26.49		21.29	***	4.08	***
Belgium	CDS	-0.69	***	28.87	***	10207	***	120.58	***	64.52	***	52.91	***	3.65	***
	Bond	0.17	***	10.483	***	13440	***	144.19	***	119.95	***	68.545	***	3.60	***
Denmark	CDS	0.22	***	25.92	***	82	***	100.28	***	59.27	***	53.71	***	3.37	***
	Bond	-0.31	***	26.55	***	86142	***	24.00	***	13.21		10.90	***	2.63	***
Finland	CDS	0.23	***	18.06	***	39869	***	116.97	***	89.33	***	47.59	***	3.83	***
	Bond	-0.66	***	25.85	***	81853	***	16.46	***	7.91		9.95	***	2.84	***
France	CDS	-0.08	*	19.21	***	45075	***	152.09	***	94.54	***	59.71	***	3.80	***
	Bond	0.21	***	3.78	***	1770	***	53.30	***	41.09		25.58	***	4.43	***

[1]Venezuela has been in socioeconomic crisis since 2014, but by 2016 (The year during which spreads stood at their highest levels in its history) the situation in this country got worse with an 800% inflation rate.

[2]Innovations of the variance equation are allowed, as well, to follow a skewed student distribution, but no optimal estimation with this distribution is found.

Table 2.4: Preliminary tests on the VECM mean equation's residuals (*Continued*)

		Skweness		Excess Kurtosis		Jarque-Bera		ARCH-LM(2)		ARCH-LM(5)		ARCH-LM(10)		R/S	
Germany	CDS	-0.30	***	24.97	***	76220	***	262.48	***	135.23	***	69.04	***	3.16	***
	Bond	-0.85	***	40.17	***	19746	***	8.84	***	4.19		4.51	***	2.94	***
Ireland	CDS	-0.82	***	31.94	***	12495	***	165.99	***	98.30	***	58.36	***	3.30	***
	Bond	0.18	***	28.68	***	10048	***	100.30	***	67.70		49.04	***	2.91	***
Italy	CDS	0.25	***	31.16	***	11862	***	188.52	***	84.95	***	46.00	***	3.23	***
	Bond	-0.61	***	50.38	***	50	***	51.66	***	32.92		17.52	***	3.23	***
Japan	CDS	0.73	***	34.78	***	14802	***	127.61	***	60.12	***	30.59	***	2.85	***
	Bond	-0.13	***	24.70	***	74552	***	77.11	***	34.92		16.50	***	3.02	***
Latvia	CDS	0.63	***	54.36	***	36114	***	382.16	***	344.83	***	179.29	***	2.58	***
	Bond	3.66	***	165.57	***	33554	***	14.64	***	12.39		7.72	***	2.27	***
Lithuania	CDS	-0.18	***	67.27	***	55289	***	650.39	***	263.93	***	136.74	***	2.28	***
	Bond	-1.57	***	78.72	***	75822	***	79.58	***	60.67		34.18	***	2.85	***
Netherlands	CDS	0.41	***	20.94	***	53663	***	105.78	***	68.51	***	37.33	***	3.93	***
	Bond	-0.54	***	24.03	***	70679	***	15.63	***	6.83		6.94	***	2.89	***
Norway	CDS	-6.04	***	202.76	***	50405	***	0.18		0.19		0.19		1.93	**
	Bond	-0.40	***	29.14	***	10383	***	31.31	***	12.94		8.14	***	2.42	***
Portugal	CDS	-0.70	***	32.93	***	13267	***	70.22	***	49.67	***	30.62	***	3.71	***
	Bond	-3.47	***	181.81	***	40442	***	3.54	**	1.71		4.06	***	2.58	***
Slovakia	CDS	1.52	***	50.53	***	31299	***	111.63	***	152.14	***	93.48	***	2.31	***
	Bond	0.10	**	49.19	***	29561	***	56.34	***	32.69		18.63	***	1.76	*
Slovenia	CDS	5.20	***	111.03	***	15193	***	6.72	***	3.59	***	8.99	***	2.06	**
	Bond	4.69	***	94.75	***	11076	***	168.43	***	92.50		46.30	***	1.89	**
Spain	CDS	-0.46	***	15.13	***	28050	***	96.00	***	68.44	***	42.11	***	4.39	***
	Bond	0.27	***	50.70	***	31403	***	54.75	***	45.41		23.76	***	2.73	***
Sweden	CDS	0.93	***	34.49	***	14577	***	72.69	***	50.56	***	35.50	***	3.41	***
	Bond	-0.41	***	46.85	***	26827	***	22.54	***	10.95		6.31	***	2.54	***
UK	CDS	-0.08	*	20.18	***	49731	***	119.50	***	61.39	***	43.94	***	4.07	***
	Bond	-0.44	***	32.20	***	12678	***	20.47	***	9.01		5.17	***	2.68	***
USA	CDS	1.02	***	15.82	***	31060	***	85.82	***	55.41	***	31.48	***	3.64	***
	Bond	-0.64	***	26.29	***	84607	***	43.49	***	18.58		9.99	***	3.22	***
Panel B: Newly Industrialized countries															
Brazil	CDS	4.94	***	142.95	***	25083	***	19.73	***	44.21	***	27.45	***	2.08	**
	Bond	0.80	***	112.00	***	15327	***	288.84	***	138.41		109.60	***	2.30	***
China	CDS	0.29	***	52.26	***	33372	***	177.83	***	158.89	***	121.85	***	1.93	**
	Bond	1.02	***	64.35	***	50643	***	93.06	***	39.78		50.00	***	2.62	***
Mexico	CDS	3.29	***	124.43	***	18967	***	312.76	***	163.55	***	128.74	***	1.76	*
	Bond	0.59	***	12.89	***	20471	***	108.68	***	45.59		23.55	***	2.01	**
Philippines	CDS	4.09	***	169.29	***	35094	***	465.60	***	267.59	**	191.10	***	3.04	***
	Bond	0.75	***	17.98	***	39760	***	242.38	***	103.70		53.68	***	2.35	***
Thailand	CDS	1.54	***	133.05	***	21637	***	156.01	***	273.22	***	209.41	***	2.94	***
	Bond	0.26	***	9.77	***	11705	***	19.54	***	11.87		10.41	***	3.38	***
Turkey	Bond	2.53	***	57.66	***	40928	***	94.00	***	335.74	***	182.61	***	1.98	**
	CDS	0.25	***	23.90	***	69793	***	87.82	***	40.73		44.22	***	2.70	***
Panel C: Emerging countries															
Bulgaria	CDS	1.20	***	47.54	***	27683	***	73.25	***	82.57	***	58.45	***	2.64	***
	Bond	-0.85	***	35.88	***	15764	***	23.90	***	11.68		9.42	***	2.38	***
Croatia	CDS	-0.55	***	23.26	***	66235	***	128.65	***	122.05	***	67.42	***	2.90	***
	Bond	4.51	***	115.28	***	16336	***	14.60	***	5.93		3.00	***	0.97	
Czech	CDS	-0.24	***	52.55	***	33737	***	173.41	***	124.38	***	97.48	***	2.59	***
	Bond	1.27	***	15.04	***	28416	***	105.35	***	87.47		46.64	***	2.94	***
Greece	CDS	-45.08	***	2324.30	***	661010	***	0.00		0.00		0.00		0.99	
	Bond	-2.22	***	175.84	***	37796	***	24.48	***	11.97		6.32	***	2.08	**
Hungary	CDS	1.45	***	39.04	***	18721	***	128.55	***	103.60	***	60.36	***	2.57	***
	Bond	-0.94	***	50.02	***	30605	***	57.28	***	23.24		29.95	***	2.54	***
Indonesia	CDS	2.70	***	119.09	***	17362	***	355.20	***	227.61	***	165.31	***	1.82	*
	Bond	-0.16	***	50.38	***	31014	***	200.01	***	83.83		42.73	***	2.46	***
Poland	CDS	-0.26	***	41.40	***	20946	***	266.88	***	133.10	***	84.45	***	2.69	***
	Bond	1.56	***	45.83	***	25782	***	3.12	**	8.48		4.73	***	1.82	*
Romania	CDS	2.17	***	86.22	***	91053	***	178.12	***	124.79	***	67.63	***	2.06	***
	Bond	-0.05		54.25	***	35947	***	35.29	***	18.15		15.90	***	3.37	***
Russia	CDS	2.41	***	73.30	***	65924	***	164.87	***	100.62	***	86.31	***	2.15	***
	Bond	2.60	***	77.56	***	73824	***	188.10	***	90.96		63.97	***	1.91	**
Ukraine	CDS	-24.41	***	1339.10	***	219370	***	0.00		0.36		0.18		1.24	
	Bond	3.92	***	248.67	***	7561	***	60.40	***	24.71		12.39	***	2.12	***
Venezuela	CDS	-1.46	***	49.04	***	29485	***	62.32	***	75.00	***	41.32	***	3.51	***
	Bond	52.83	***	2834.50	***	982930	***	7,3e-05		1,8e-04		2,7e-04		1.00	

The Engle's ARCH-LM test with 2, 5 and 10 lag orders is used to detect ARCH effects in the series under the null hypothesis of no autocorrelations in the squared residuals. R/S denotes the rescaled range test (number of autocorrelations=10) is applied to the squared arithmetic returns (as proxy for unconditional volatility) to detect any long-term dependence under the null assumption of no long-memory behavior in the volatility process. *, ** and *** denote statistical significance at respectively 10%, 5% and 1%.

2.4.2 Model estimation

As mentioned before, volatility clustering, long-memory behavior as well as the long-run relationship between CDS spreads and bond yields are taken into account through a VECM(2)-FIGARCH(1,d,1) model. Results of the model estimation, presented in Table 2.5, confirm the appropriate use of the fractionally integrated model since the coefficients are statistically significant in most cases. The specification of the mean equation is chosen according to the

Table 2.5: Estimation results of the VECM-FIGARCH(1,d,1)

		Mean Equation						**Variance Equation**					
		Cst(M)	λ	γ_1	γ_2	δ_1	δ_2	Cst(V)	d-Figarch	ARCH (ϕ)	GARCH (θ)	Student	GED
Panel A: Developed countries													
Austria	CDS	0,01603	-0,00478 **	-0,03434 *	0,02044	-2,19492 **	-0,46027	0,15926	0,35091 ***	0,16434 *	0,26916 ***		0,82062 ***
		(0,0398)	(0,0018)	(0,0185)	(0,0185)	(0,7872)	(0,7879)	(0,1062)	(0,0423)	(0,0948)	(0,0898)		(0,0425)
	Bond	-0,00109	-0,00008 *	0,01162	0,02311	0,00083 *	0,00054	44,74156 ***	0,57020 ***	0,26470 ***	0,75206 ***	4,44826 ***	
		(0,0009)	(4,32E-5)	(0,0185)	(0,0185)	(0,0004)	(0,0004)	(15,6380)	(0,0593)	(0,0456)	(0,0548)	(0,3076)	
Belgium	CDS	0,00919	-0,00191 *	0,22410 **	-0,03939 **	0,05011	2,04255 **	4,00333 ***	0,73178 ***	0,18314 **	0,58550 ***	0,70555 ***	
		(0,0747)	(0,0010)	(0,0185)	(0,0190)	(0,9912)	(0,9722)	(0,9359)	(0,0325)	(0,0895)	(0,1021)	(0,0252)	
	Bond	-0,00135	-0,00002	-0,16186 **	0,01659	0,00398 **	0,00155 **	83,38401 ***	0,60637 ***	0,26714 ***	0,67713 ***	4,40646 ***	
		(0,0014)	(1,87E-5)	(0,0185)	(0,0181)	(0,0003)	(0,0004)	(29,4730)	(0,0478)	(0,0720)	(0,0862)	(0,3036)	
Denmark	CDS	0,00027	-0,00166 **	0,33109 **	-0,03665 **	-0,58729 **	-0,17622	7,44651 ***	0,85723 ***	0,42648 ***	0,79704 ***		0,65911 ***
		(0,0325)	(0,0007)	(0,0185)	(0,0185)	(0,2153)	(0,2154)	(2,0686)	(0,0456)	(0,0577)	(0,0484)		(0,0255)
	Bond	-0,00137	0,00004	-0,21589 **	-0,04875 **	-0,00467 **	0,00202	100,00 **	0,25162 ***	0,46915 ***	0,65631 ***		
		(0,0028)	(0,0001)	(0,0185)	(0,0185)	(0,0016)	(0,0016)	(38,7710)	(0,0606)	(0,0871)	(0,1030)		
Finland	CDS	0,00540	-0,00229 *	0,11074 **	0,10112 **	-0,02232	-0,07267	0,02767	0,60166 ***	0,30476 ***	0,79598 ***		
		(0,0215)	(0,0012)	(0,0184)	(0,0184)	(0,1541)	(0,1540)	(0,0272)	(0,1328)	(0,1078)	(0,1119)		
	Bond	-0,00143	-0,00019	-0,20423 **	-0,03340 *	-0,00257	0,00527 **	100,00 **	0,37079 ***	0,47838 ***	0,75442 ***		
		(0,0026)	(0,0001)	(0,0185)	(0,0185)	(0,0022)	(0,0022)	(41,9140)	(0,0679)	(0,0803)	(0,0555)		
France	CDS	0,01390	-0,00193 *	0,20179 **	0,00663	-2,43449 **	3,17249 **	2,76390 ***	0,69188 ***	0,24183 ***	0,64285 ***	2,91107 ***	
		(0,0500)	(0,0010)	(0,0185)	(0,0185)	(1,0517)	(1,0520)	(0,7750)	(0,0390)	(0,0660)	(0,0621)	(0,0787)	
	Bond	-0,00101	-0,00003	0,01923	-0,00852	0,00057 *	0,00041	30,18740 **	0,57653 ***	0,35885 ***	0,80313 ***	5,53744 ***	
		(0,0009)	(1,81E-5)	(0,0185)	(0,0185)	(0,0003)	(0,0003)	(12,5470)	(0,0776)	(0,0533)	(0,0597)	(0,4872)	
Germany	CDS	0,00401	-0,00029	0,06087 **	0,03404 *	-0,51639 **	-0,15535	0,43204	0,73315 ***	0,16224 **	0,60483 ***		0,54262 ***
		(0,0298)	(0,0002)	(0,0185)	(0,0185)	(0,1990)	(0,1990)	(0,8962)	(0,0457)	(0,0753)	(0,0874)		(0,0163)
	Bond	-0,00144	0,00003 *	-0,17283 **	-0,05248 **	-0,00366 **	0,00093	100,00 ***	0,16440 ***	0,68666 ***	0,08239 ***	2,25694 ***	
		(0,0028)	(1,89E-5)	(0,0185)	(0,0185)	(0,0017)	(0,0017)	(16,9510)	(0,0350)	(0,0439)	(0,0242)	(0,0164)	
Ireland	CDS	0,02705	-0,00331 **	0,16995 **	-0,01138	9,68159 **	2,39312 *	1,43914 ***	0,44356 ***	0,49708 ***	0,11800 ***		4,31264 ***
		(0,1849)	(0,0013)	(0,0201)	(0,0199)	(1,3520)	(1,3592)	(0,5277)	(0,0015)	(0,0015)	(5,94E-9)		(4,66E-9)
	Bond	-0,00108	-0,00001	-0,06383 **	0,00049	0,00257 **	0,00062 **	2,74285	0,42861 ***	0,23201 **	0,55353 ***		
		(0,0028)	(1,90E-5)	(0,0202)	(0,0203)	(0,0003)	(0,0003)	(3,7186)	(0,1429)	(0,1133)	(0,1689)		
Italy	CDS	0,04924	0,00004	0,13713 **	-0,05450 **	0,38080	-0,60704	0,36451 *	0,54841 ***	0,13240 **	0,50672 ***		
		(0,1472)	(0,0002)	(0,0186)	-(0,0186)	(0,5832)	(0,5814)	(0,1869)	(0,0578)	(0,0593)	(0,0711)		
	Bond	-0,00111	0,00002 **	-0,25248 **	-0,09682 **	0,00266 **	0,00087	1,00E+06	0,41285 ***	0,44200 ***	0,77822 ***		
		(0,0047)	(7,60E-6)	(0,0186)	(0,0185)	(0,0006)	(0,0006)	(66,9460)	(0,0878)	(0,0730)	(0,0466)		
Japan	CDS	0,00644	-0,00079	0,04652 **	0,04519 **	-0,50771	-0,21344	0,00639	0,50589 ***	0,36320 ***	0,75457 ***		
		(0,0394)	(0,0011)	(0,0185)	(0,0185)	(0,7727)	(0,7717)	(0,0060)	(0,1105)	(0,0678)	(0,1041)		
	Bond	-0,00045	-0,00007 **	-0,26790 **	-0,06039 **	-0,00028	0,00035	1,00E+06 **	0,32859 ***	0,60090 ***	0,11405 ***		0,44246 ***
		(0,0009)	(2,59E-5)	(0,0185)	(0,0184)	(0,0004)	(0,0004)	(47,2770)	(0,0536)	(0,0421)	(0,0194)		(0,0111)
Latvia	CDS	0,01685	-0,00263 *	-0,29721 **	0,31165 **	1,98336	-1,13320	100,00 ***	0,81164 ***	0,00000	0,37281 ***		0,67256 ***
		(0,2639)	(0,0015)	(0,0176)	(0,0176)	(1,2496)	(1,2500)	(25,6350)	(0,0247)	(0,0682)	(0,0685)		(0,0421)
	Bond	-0,00153	0,00005 **	-0,09567 **	-0,10780 **	-0,00018	-0,00034	1,00E+06 **	0,12500 *	0,39570 **	0,50097 ***		
		(0,0039)	(2,10E-5)	(0,0184)	(0,0184)	(0,0003)	(0,0003)	(50,9610)	(0,0730)	(0,1829)	(0,2225)		
Lithuania	CDS	0,01595	-0,00120	-0,21318 **	0,21932 **	0,11452	-0,12791	43,00145 **	0,80289 ***	0,00000	0,40491 ***		0,61263 ***
		(0,1806)	(0,0014)	(0,0181)	(0,0181)	(0,3013)	(0,2981)	(18,2760)	(0,0366)	(0,0673)	(0,0726)		(0,0537)
	Bond	-0,00138	0,00056 **	-0,31713 **	-0,10274 **	-0,00486 **	-0,00370 **	2,66029 ***	0,48697 ***	0,50907 ***	0,14093 ***	2,31539 ***	
		(0,0111)	(0,0001)	(0,0185)	(0,0183)	(0,0011)	(0,0011)	(0,2975)	(0,0130)	(0,0116)	(0,0014)	(0,0228)	
Netherlands	CDS	0,00455	-0,00219 **	0,24003 **	-0,01865	-0,11769	-0,04119	0,47512	0,57924 ***	0,35482 ***	0,74616 ***		
		(0,0311)	-(0,0010)	-(0,0185)	-(0,0185)	-(0,2297)	-(0,2297)	(0,6550)	(0,1034)	(0,1312)	(0,0790)		
	Bond	-0,00137	-0,00002	-0,20379 **	-0,04724 **	-0,00121	0,00048	1,00E+06 ***	0,11001 ***	0,76971 ***	0,10800 ***	2,23201 ***	
		(0,0025)	-(0,0001)	-(0,0185)	-(0,0185)	-(0,0015)	-(0,0015)	(0,0009)	(0,0000)	(0,0000)	(0,0000)	(0,0162)	
Norway	CDS	-0,01310	-0,00222 *	0,03828 **	0,02197	-0,09738	-0,03504	5,75E+05	0,26970 ***	0,58814 ***	0,08793 ***		1,54461 ***
		(0,0155)	(0,0012)	(0,0185)	(0,0185)	(0,0938)	(0,0935)	(70,3760)	(0,6738)	5,2485-e1	(0,5227)		(0,1735)
	Bond	-0,00127	0,00119 **	-0,17959 **	-0,04881 **	-0,00774 **	-0,00667 *	1,00E+06 ***	0,37703 ***	0,42225 ***	0,72932 ***		
		(0,0031)	(0,0002)	(0,0185)	(0,0185)	(0,0037)	(0,0037)	(57,8020)	(0,0743)	(0,0561)	(0,0572)		
Portugal	CDS	0,06646	-0,00470 **	0,14837 **	0,05766 **	8,25213 **	-3,22191 **	36,28834 ***	0,57136 ***	0,16088 **	0,44539 ***	3,55517 ***	
		(0,2829)	(0,0018)	(0,0193)	(0,0192)	(1,4001)	(1,4067)	(7,7017)	(0,0449)	(0,0769)	(0,0948)	(0,2007)	
	Bond	-0,00037	0,00003	0,05749 **	-0,01623	0,00124 **	-0,00007	1,00E+06 **	0,48261 ***	0,66683 ***	0,90662 ***		
		(0,0039)	(2,50E-5)	(0,0194)	(0,0194)	(0,0003)	(0,0003)	(40,4060)	(0,0833)	(0,0774)	(0,0347)		

Table 2.4: Estimation results of the VECM-FIGARCH(1,d,1) *(Continued)*

		Mean Equation						Variance Equation					
		Cst(M)	λ	γ_1	γ_2	δ_1	δ_2	Cst(V)	d-Figarch	ARCH (ϕ)	GARCH (θ)	Student	GED
Slovakia	CDS	0,01024	-0,00209 **	0,10633 **	0,04317 **	0,06044	-0,08743	63,05347 ***	0,86935 ***	0,29401 ***	0,75353 ***	0,50624 ***	
		(0,0689)	(0,0009)	(0,0185)	(0,0185)	(0,4396)	(0,4392)	(17,0370)	(0,0247)	(0,0605)	(0,0507)	(0,0126)	
	Bond	-0,00181	-4,34E-06	-0,32638 **	-0,13672 **	0,00114	0,00065	597,86000	0,73861 ***	0,54819 ***	0,36158 ***	4,02731 ***	
		(0,0029)	(3,90E-5)	(0,0183)	(0,0183)	(0,0008)	(0,0008)	(6,1551)	(0,0002)	(0,0003)	(0,0002)	(1,0849)	
Slovenia	CDS	0,02085	-0,00060 *	0,14145 **	0,07850 **	0,18194	0,24342	11,31456	0,53317 ***	0,00000	0,42984 ***		
		(0,0864)	(0,0004)	(0,0184)	(0,0184)	(0,2426)	(0,2415)	(10,3120)	(0,0492)	(0,1452)	(0,1397)		
	Bond	-0,00015	0,00007 **	-0,44532 **	-0,24149 **	0,00287 **	0,00066	1,00E+06 ***	0,63715 ***	0,77353 ***	0,59658 ***	2,46385 ***	
		(0,0064)	(2,73E-5)	(0,0181)	(0,0180)	(0,0014)	(0,0014)	(10,3080)	(0,0038)	(0,0000)	(0,0023)	(0,0193)	
Spain	CDS	0,02288	-0,00028	0,18851 **	-0,06424 **	0,26451	0,40324	0,06823	0,47131 ***	0,02794	0,37120		
		(0,1394)	(0,0006)	(0,0186)	(0,0187)	(0,6269)	(0,6249)	(0,0651)	(0,1346)	(0,1365)	(0,2416)		
	Bond	-0,00129	0,00005 **	-0,28558 **	-0,11048 **	0,00299 **	0,00072	1,00E+06	0,47228 ***	0,44768 ***	0,82142 ***		
		(0,0041)	(1,90E-5)	(0,0186)	(0,0185)	(0,0006)	(0,0006)	(78,3650)	(0,0854)	(0,0976)	(0,0637)		
Sweden	CDS	0,00401	-0,00014	0,26484 **	0,01940	-0,02763	-0,24443	1,25541 ***	0,79675 ***	0,35970 ***	0,63089 ***	2,67061 ***	
		(0,0284)	(0,0001)	(0,0185)	(0,0185)	(0,1617)	(0,1615)	(0,4065)	(0,0471)	(0,1260)	(0,1423)	(0,0614)	
	Bond	-0,00134	0,00003 **	-0,19281 **	-0,04177 **	-0,00075	0,00053	1,00E+06	0,42504 ***	0,41349 ***	0,77124 ***		
		(0,0032)	(1,36E-5)	(0,0185)	(0,0185)	(0,0021)	(0,0021)	(79,8630)	(0,0783)	(0,0703)	(0,0517)		
UK	CDS	0,00333	0,00015	0,15226 **	0,02203	-0,23835	-0,03585	0,04708 ***	0,64598 ***	0,16182 **	0,48919 ***	2,69709 ***	
		(0,0339)	(0,0004)	(0,0185)	(0,0185)	(0,1874)	(0,1871)	(0,0149)	(0,0456)	(0,0817)	(0,0909)	(0,0666)	
	Bond	-0,00152	-0,00011 **	-0,19866 **	-0,05309 **	-0,00429 **	-0,00019	1,00E+06 **	0,33443 ***	0,47171 ***	0,72979 ***		
		(0,0033)	(4,17E-5)	(0,0185)	(0,0184)	(0,0018)	(0,0018)	(48,6240)	(0,0662)	(0,0844)	(0,0635)		
USA	CDS	-0,00040	-0,00559 **	-0,23325 **	-0,05240 **	-0,01238	-0,07957	1,00E+06 ***	0,10410 ***	0,61118 ***	0,05296 **	0,44407 ***	0,44407 ***
		(0,0318)	(0,0024)	(0,0185)	(0,0185)	(0,1729)	(0,1727)	(27,8850)	(0,0239)	(0,0512)	(0,0233)	(0,0115)	(0,0115)
	Bond	-0,00107	-0,00060 **	-0,26256 **	-0,06776 **	-0,00192	-0,00045	0,08131	0,68046 ***	0,46002 ***	0,23625 ***	4,41477 ***	
		(0,0034)	(0,0003)	(0,0185)	(0,0184)	(0,0020)	(0,0020)	(4,1059)	(7,40E-6)	(5,49E-6)	(6,46E-6)	(0,1152)	
Panel B: Newly Industrialized countries													
Brazil	CDS	0,02884	-0,00225 *	0,14705 **	-0,01815	0,03594	0,13663	10,26098 ***	0,60344 ***	0,01630	0,49738 ***		0,99958 ***
		(0,1645)	(0,0011)	(0,0186)	(0,0186)	(0,3103)	(0,3083)	(1,9567)	(0,0718)	(0,0582)	(0,0919)		(0,0746)
	Bond	0,00206	0,00027 **	-0,32622 **	-0,19957 **	0,00221 **	0,00183 *	11,44751	0,73946 ***	0,08976	0,76523 ***		1,68271 ***
		(0,0097)	(0,0001)	(0,0183)	(0,0182)	(0,0011)	(0,0011)	(60,5660)	(0,0931)	(0,1013)	(0,1379)		(0,2368)
China	CDS	0,02229	-0,00116	0,10633 **	0,15876 **	0,09830	0,31921	0,06302 ***	0,68063 ***	0,45991 ***	0,23619 ***	4,41389 ***	
		(0,0714)	(0,0007)	(0,0182)	(0,0183)	(0,6784)	(0,6763)	(0,0242)	(5,53E-6)	(6,22E-6)	(0,0000)	(0,1239)	
	Bond	0,00096	0,00007 **	-0,31402 **	-0,12686 **	-0,00076	-0,00030	30,28539 ***	0,28642 ***	0,67920 ***	0,53845 ***	3,42428 ***	
		(0,0019)	(2,E-05)	(0,0184)	(0,0183)	(0,0005)	(0,0005)	(9,0091)	(0,0548)	(0,0996)	(0,1217)	(0,1389)	
Mexico	CDS	0,00097	-0,01235 **	0,19612 **	-0,10331 **	10,71790 **	0,59183	4,57495 **	0,59541 ***	0,00	0,40579 **		1,22862 ***
		(0,1484)	(0,0028)	(0,0187)	(0,0186)	(2,0145)	(2,0234)	(2,0607)	(0,0518)	(0,1223)	(0,1688)		(0,0585)
	Bond	-0,00031	-0,00005 *	-0,07956 **	-0,01530	0,00067 **	-0,00009	6,05E+05	0,47652 ***	0,74209 ***	0,88748 ***	3,69180 ***	
		(0,0014)	(0,0000)	(0,0189)	(0,0190)	(0,0002)	(0,0002)	(40,5720)	(0,0797)	(0,0715)	(0,0347)	(0,1974)	
Philippines	CDS	-0,06587	-0,00814 **	0,25989 **	-0,04700 **	-2,62345 **	0,64073	1,35335 *	0,64848 ***	0,00000	0,38748 ***	5,06109 ***	
		(0,1528)	(0,0026)	(0,0186)	(0,0190)	(1,1865)	(1,1754)	(0,7190)	(0,0380)	(0,0856)	(0,1039)	(0,3808)	
	Bond	-0,00163	0,00013 **	-0,19287 **	0,05929 **	0,00294 **	0,00037	0,05004 ***	0,28555 ***	0,73621 ***	0,46634 ***		0,70932 ***
		(0,0024)	(0,0000)	(0,0185)	(0,0184)	(0,0003)	(0,0003)	(0,0160)	(0,0879)	(0,1078)	(0,0740)		(0,0230)
Thailand	CDS	-0,01502	-0,01346 **	0,13940 **	0,15801 **	-2,54222	-0,15094	0,15566 **	0,60816 ***	0,03382	0,42950 ***	3,95321 ***	
		(0,1077)	(0,0026)	(0,0182)	(0,0183)	(2,0300)	(2,0301)	(0,0755)	(0,0431)	(0,0556)	(0,0796)	(0,2081)	
	Bond	-0,00103	-0,00009 **	-0,02009	0,01618	0,00018	-0,00024	4,97E+05 ***	0,39529 ***	0,33306 **	0,52026 ***	3,33148 ***	
		(0,0010)	(0,0000)	(0,0185)	(0,0185)	(0,0002)	(0,0002)	(16,9480)	(0,0440)	(0,1327)	(0,1351)	(0,1674)	
Turkey	CDS	0,02619	-0,01296 **	0,18354 **	0,06516 **	0,29428	-0,13366	100,00 **	0,57427 ***	0,03005	0,45329 ***	0,90203 ***	
		(0,1767)	(0,0026)	(0,0184)	(0,0185)	(0,2454)	(0,2452)	(46,4680)	(0,0792)	(0,0627)	(0,1219)	(0,0660)	
	Bond	-0,00160	0,00004	-0,37733 **	-0,16636 **	0,00445 **	0,00197	1,45284 ***	0,36173 ***	0,81993 ***	0,52211 ***		0,46137 ***
		(0,0132)	(0,0002)	(0,0183)	(0,0183)	(0,0014)	(0,0014)	(0,0802)	(0,0002)	(0,0000)	(0,0290)		(0,0116)
Panel C: Emerging countries													
Bulgaria	CDS	0,02141	-0,00354 **	0,16659 **	0,01015	-0,11537	-1,26700	100,00 ***	0,77076 ***	0,11981 *	0,57715 ***		0,68215 ***
		(0,1485)	(0,0013)	(0,0185)	(0,0185)	(1,1182)	(1,1180)	(25,9070)	(0,0367)	(0,0659)	(0,0633)		(0,0391)
	Bond	-0,00153	0,00001	-0,28567 **	-0,17039 **	0,00001	-0,00012	100,00000 *	0,92953 ***	0,00000	0,46211 ***		0,39534 ***
		(0,0024)	(0,0000)	(0,0182)	(0,0182)	(0,0003)	(0,0003)	(53,8920)	(0,0170)	(0,0400)	(0,0375)		(0,0159)
Croatia	CDS	0,03188	-0,00289 **	0,16267 **	0,07176 **	-0,01363	0,53836	1,77963 **	0,48741 ***	0,30045 **	0,57255 ***		
		(0,1340)	(0,0012)	(0,0184)	(0,0185)	(1,2996)	(1,2976)	(0,8565)	(0,0625)	(0,1229)	(0,1255)		
	Bond	-0,00078	0,00000	-0,31422 **	-0,08297 **	0,00067 **	0,00035	9,91E+03 ***	0,09800 ***	0,86944 ***	0,38441 ***		

Table 2.4: Estimation results of the VECM-FIGARCH(1,d,1) *(Continued)*

		Mean Equation						Variance Equation					
		Cst(M)	λ	γ_1	γ_2	δ_1	δ_2	Cst(V)	d-Figarch	ARCH (ϕ)	GARCH (θ)	Student	GED
		(0,0019)	(0,0000)	(0,0184)	(0,0184)	(0,0003)	(0,0003)	(0,1453)	(0,0277)	(0,0133)	(0,0386)		
Czech	CDS	0,02252	-0,00459 **	-0,00596	0,00812	5,27601 **	4,54805 **	17,15734 ***	0,78626 ***	0,13992 *	0,67917 ***		0,58558 ***
		(0,0836)	(0,0017)	(0,0185)	(0,0185)	(1,4499)	(1,4509)	(6,4380)	(0,0290)	(0,0806)	(0,0725)		(0,0168)
	Bond	-0,00125	0,00001	-0,20060 **	-0,02795	0,00071 **	0,00000	100,00 ***	0,51234 ***	0,61883 ***	0,76943 ***	3,23696 ***	
		(0,0011)	(0,0000)	(0,0185)	(0,0185)	(0,0002)	(0,0002)	(35,6350)	(0,0590)	(0,1767)	(0,1573)	(0,1541)	
Greece	CDS	0,29641	-0,00401 **	0,02315	0,02745	-11,42562 *	1,89926	100,00	0,40841 ***	0,58252 ***	0,84346 ***		
		(13,0929)	(0,0009)	(0,0184)	(0,0184)	(5,9338)	(5,9214)	(6,5014)	(0,0002)	(0,0002)	(0,0759)		
	Bond	0,00063	0,00001 **	-0,20140 **	-0,05316 **	4,49E-06	0,00003	0,14810	0,28294 **	0,48685 **	0,72087 ***		
		(0,0410)	(3,E-06)	(0,0186)	(0,0185)	(0,0001)	(0,0001)	(0,3414)	(0,1099)	(0,2162)	(0,0830)		-
Hungary	CDS	0,02714	-0,00131 *	0,14437 **	0,03725 **	0,38841	1,20304 **	17,86708 ***	0,63346 ***	0,23725 ***	0,60049 ***	2,94579 ***	
		(0,1800)	(0,0007)	(0,0185)	(0,0185)	(0,4574)	(0,4558)	(4,8448)	(0,0372)	(0,0755)	(0,0811)	(0,0845)	
	Bond	-0,00226	0,00008 **	-0,27094 **	-0,07078 **	0,00251 **	-0,00009	0,49454 *	0,34083 ***	0,77885 ***	0,36075 ***	2,20248 ***	
		(0,0073)	(0,0000)	(0,0185)	(0,0185)	(0,0007)	(0,0007)	(0,2568)	(0,0742)	(0,0474)	(0,0834)	(0,0164)	
Indonesia	CDS	-0,03233	-0,01391 **	0,10943 **	-0,01999	0,99331	0,94208	1,06795	0,65562 ***	0,02897	0,42251 **		1,00722 ***
		(0,2529)	(0,0031)	(0,0187)	(0,0193)	(1,4399)	(1,4073)	(1,3898)	(0,0401)	(0,1414)	(0,1686)		(0,0513)
	Bond	-0,00250	-0,00002	-0,20864 **	-0,04579 **	0,00331 **	0,00205 **	0,03550	0,47946 ***	0,14024	0,28483 **	3,07308 ***	
		(0,0033)	(0,0000)	(0,0186)	(0,0182)	(0,0002)	(0,0002)	(0,0236)	(0,0465)	(0,1255)	(0,1324)	(0,1277)	
Poland	CDS	0,02833	-0,00359 **	0,08299 **	-0,00432	10,07558 **	5,01618 **	29,02422 ***	0,76106 ***	0,20041 ***	0,62960 ***	3,22280 ***	
		(0,1020)	(0,0014)	(0,0188)	(0,0187)	(1,7540)	(1,7636)	(8,7048)	(0,0342)	(0,0624)	(0,0560)	(0,1138)	
	Bond	-0,00062	-0,00001	0,04857 **	0,02401	-0,00008	-0,00041 **	3,63E+05 **	0,24290 **	0,90117 ***	0,94021 ***		
		(0,0011)	(0,0000)	(0,0188)	(0,0189)	(0,0002)	(0,0002)	(16,3030)	(0,1025)	(0,0377)	(0,0129)		
Romania	CDS	0,02133	-0,00352 **	0,08813 **	-0,08616 **	0,60358	-1,21065 **	46,30649 ***	0,68704 ***	0,00000	0,47018 ***	3,12447 ***	
		(0,1951)	(0,0012)	(0,0184)	(0,0184)	(0,5103)	(0,5095)	(9,6511)	(0,0276)	(0,0820)	(0,0791)	(0,1406)	
	Bond	-0,00183	0,00011 **	-0,26456 **	-0,01888	-0,00104	-0,00056	1,00E+06 *	0,36877 ***	0,57785	0,83154 ***		
		(0,0071)	(0,0000)	(0,0185)	(0,0185)	(0,0007)	(0,0007)	(52,9530)	(0,1293)	(0,3690)	(0,0964)		
Russia	CDS	0,03032	-0,01612 **	0,01354	0,06830 **	0,30100	0,15939	68,74330 ***	0,68865 ***	0,10692 *	0,51764 ***	4,05454 ***	
		(0,3196)	(0,0040)	(0,0188)	(0,0188)	(1,3772)	(1,3735)	(17,9620)	(0,0338)	(0,0558)	(0,0627)	(0,2596)	
	Bond	0,00074	0,00024 **	-0,27322 **	0,01728	0,00088 **	0,00056 **	1,00E+06 **	0,32281 ***	0,91632 ***	0,78973 ***		0,71952 ***
		(0,0044)	(0,0001)	(0,0187)	(0,0187)	(0,0003)	(0,0003)	(48,6280)	(0,0854)	(0,0300)	(0,0343)		(0,0270)
Ukraine	CDS	0,36862	0,00025	-0,00215	-0,01409	1,55053	0,36856	87,89872	0,24316 ***	0,65661 ***	0,80777 ***		
		(5,3959)	(0,0005)	(0,0185)	(0,0185)	(9,1411)	(9,1293)	(67,2750)	(0,5863)	(0,5870)	(0,5868)		
	Bond	-0,00050	0,00001 **	-0,05046 **	-0,17064 **	-0,00001	-0,00001	0,25005 ***	0,44288 ***	0,09842 ***	0,40942 ***		1,96857 ***
		(0,0108)	(0,0000)	(0,0182)	(0,0182)	(0,0000)	(0,0000)	(0,0108)	(0,0802)	(0,0304)	(0,0200)		(0,0269)
Venezuela	CDS	0,98589	-0,00001	0,20342 **	0,02869	-0,04938	-0,02799	4,85856 ***	0,41161 ***	0,00000	0,17876	4,85686 ***	
		(2,4423)	(0,0000)	(0,0185)	(0,0185)	(0,1016)	(0,0723)	(0,9018)	(0,0338)	(0,1693)	(0,1905)	(0,3035)	
	Bond	-0,00324	0,00014 **	-0,02448	-0,01215	-0,00032	0,00011	239,49000	0,67768 ***	0,46262 ***	0,23737 ***	4,39446 ***	
		(0,6243)	(0,0000)	(0,0260)	(0,0185)	(0,0047)	(0,0047)	(4,8438)	(0,0001)	(0,0001)	(0,0001)	(0,1430)	

This table reports the results of the VECM-FIGARCH(1,d,1) model for each studied country. *, ** and *** denote statistical significance at respectively 10%, 5% and 1%.

AIC information criterion that selects 2 as the number of lag intervals for exogenous. The lagged term γ_1 (γ_2) is significant in 33 (22) CDS markets and 33 (25) bond markets, which suggest that market information is rapidly reflected in CDS spreads and bond yields of most studied countries.

The conditional volatility of worldwide CDS and bond markets seem to exhibit common behavior. The conditional variance is more sensitive to its own lagged values (97% of the estimated equations) than to its lagged errors (78%). ARCH and GARCH terms are always positive suggesting that the current conditional market volatility is positively dependent with past shocks and volatility. The magnitude of these coefficients vary greatly from one market to another and from one country to another, which indicates that the volatility evolves continuously over time with regard to the corresponding impact degree of impulsion in both past errors and volatility. The persistence behavior of volatility process is captured as well with the fractional integration parameter (d) that is highly significant in all cases, justifying, once again, the accuracy of the FIGARCH(1,d,1). The d parameter varies from 0.10 to 0.92 depending on both the market and the country, with the memory degree of the FIGARCH increase as it gets closer to zero. Drawing on the idea of Charfeddine and Khediri (2016), the markets' efficiency is ranked according to the value of the integrated long-memory parameter (d): the greater the parameter is, the fewer the market is efficient. The estimators provide heterogeneous efficiency levels for the studied countries, which confirms that worldwide sovereign CDS spreads exhibit different long-memory behavior and different efficiency nature. Thus, estimates show that, the most efficient market seems to be the USA, followed by Ukraine, whils the least efficient is Slovakia. Nonetheless, this ranking method supposes that the markets are already found to be efficient which is not the case.

2.4.3 The whole period market efficiency testing

In the second step, the long-run cointegration relationship between the transformed time series is modeled through a VECM. If only one coefficient of the lagged variables ($\gamma_1^{'}, \gamma_2^{'}, \delta_1^{'}$ or $\delta_2^{'}$) is statistically significant, then a predictable pattern is detected and the EMH doesn't hold in the Sovereign CDS market.

Since the aim of this essay is to examine the CDS market efficiency, we only focus on the regression equation of CDS spreads (Table 2.6). Referring to the theoretical foundation, the CDS spreads and the Bond yields should fluctuate in the same direction, which is clearly proved in our results with the coefficient λ mainly negative. We also find that the one-period autoregressive term, designed by the coefficient γ_1, significantly impacts current sovereign CDS spreads in almost all the studied countries (Except for Austria and Latvia), while the two-period autoregressive term, represented by γ_2, is significantly different from zero in 62% of the sample countries (The two-period lagged value of CDS Austria insignificant as well, whereas the lagged value of Latvia CDS becomes statistically significant at 1% level). These findings imply a short-run predictability in CDS prices of all studied countries, except Austria. Furthermore, the lagged values of bond yields at the first (second) order, as denoted by γ_1 (γ_2), are statistically significant in 52%(24%) of the cases, which implies that a significant dependence between current CDS spreads and past bond yields exists in some countries, including Austria. Whether based on former realizations of CDS or bond prices, the non-randomness detected in these countries suggest a direct evidence of CDS predictability. Therefore, our novel econometric framework helps to generally reveal that the weak-form market efficiency hypothesis is rejected in the global sovereign CDS markets, even though the inefficiency magnitude orders are small in several countries (Austria, Latvia, Norway, Brazil, China, Indonesia. . .).

Table 2.6: Estimation of the VECM(2) model for the transformed time series during the whole period

		VECM(2)													
		Cst(M)		λ		γ_1		γ_2		δ_1		δ_2	
Panel A: Developed countries													
Austria	CDS	0,01844		-0,00189	*	0,01153		0,01250		-0,05401	***	-0,00878	
		(0,0133)		(0,0008)		(0,0189)		(0,0188)		(0,0148)		(0,0148)	
	Bond	-0,05661	***	-0,00239	*	-0,01246		0,00667		0,02756		0,01241	
		(0,0170)		(0,0010)		(0,0189)		(0,0189)		(0,0241)		(0,0240)	
Belgium	CDS	0,01147		-0,00066	*	0,18464	***	0,01723		-0,00451		0,03412	**
		(0,0136)		(0,0003)		(0,0185)		(0,0185)		(0,0164)		(0,0163)	
	Bond	-0,04703	***	-0,00056	*	-0,09803	***	0,01146		0,09674	***	0,01934	
		(0,0154)		(0,0003)		(0,0185)		(0,0184)		(0,0208)		(0,0209)	
Denmark	CDS	-0,00617		-0,00106	*	0,16685	***	0,02496		-0,05629	***	-0,05124	***
		(0,0120)		(0,0005)		(0,0185)		(0,0184)		(0,0167)		(0,0168)	
	Bond	-0,02184		-0,00001		-0,22211	***	-0,06050	***	-0,03132		0,01096	
		(0,0133)		(0,0005)		(0,0185)		(0,0185)		(0,0204)		(0,0204)	
Finland	CDS	0,03678	***	-0,00149	***	0,06951	***	0,07099	***	-0,01609		-0,00274	
		(0,0138)		(0,0005)		(0,0184)		(0,0184)		(0,0194)		(0,0194)	
	Bond	-0,02090		-0,00069		-0,23443	***	-0,04543	*	-0,02195		0,03535	**
		(0,0131)		(0,0005)		(0,0185)		(0,0185)		(0,0175)		(0,0175)	
France	CDS	0,02315	*	-0,00088	*	0,19616	***	0,06023	***	-0,04784	***	0,03651	**
		(0,0133)		(0,0005)		(0,0184)		(0,0184)		(0,0149)		(0,0149)	
	Bond	-0,04713	***	-0,00103	*	0,00705		-0,02528		0,00522		-0,01060	
		(0,0165)		(0,0006)		(0,0185)		(0,0185)		(0,0228)		(0,0228)	
Germany	CDS	0,00791		-0,00093	*	0,10675	***	0,05165	***	-0,04988	***	-0,00188	
		(0,0127)		(0,0004)		(0,0185)		(0,0184)		(0,0182)		(0,0182)	
	Bond	-0,02140	*	-0,00007		-0,22913	***	-0,08028	***	-0,03504	*	-0,00528	
		(0,0129)		(0,0004)		(0,0185)		(0,0185)		(0,0188)		(0,0187)	
Ireland	CDS	0,08732	***	-		0,13807	***	-0,13887	***	0,09155	***	-0,09099	***
		(0,0294)				(0,0189)		(0,0189)		(0,0177)		(0,0177)	
	Bond	-0,01760		-		0,93369	***	0,06639	***	0,16257	***	-0,16269	***
		(0,0316)				(0,0190)		(0,0190)		(0,0203)		(0,0203)	
Italy	CDS	0,10302	***	-0,00085	***	0,15543	***	-0,00312		0,00106		-0,00523	
		(0,0158)		(0,0002)		(0,0186)		(0,0186)		(0,0228)		(0,0228)	
	Bond	-0,01309		-0,00021		-0,26703	***	-0,10280	***	0,04807	***	-0,01069	
		(0,0128)		(0,0002)		(0,0185)		(0,0185)		(0,0151)		(0,0151)	
Japan	CDS	0,01731		-0,00118	*	0,05575	***	0,06345	***	-0,00243		0,01507	
		(0,0151)		(0,0005)		(0,0185)		(0,0185)		(0,0242)		(0,0242)	
	Bond	-0,01768		-0,00046		-0,22114	***	-0,05700	***	-0,01879		-0,00511	
		(0,0116)		(0,0004)		(0,0185)		(0,0185)		(0,0141)		(0,0141)	
Latvia	CDS	0,00426		-0,00131	*	0,00156		0,15906	***	0,04553	*	0,02671	
		(0,0102)		(0,0005)		(0,0183)		(0,0183)		(0,0232)		(0,0233)	
	Bond	-0,03567	***	-0,00034		-0,16054	***	-0,06624	***	-0,01661		-0,01045	
		(0,0081)		(0,0004)		(0,0185)		(0,0186)		(0,0145)		(0,0145)	
Lithuania	CDS	0,00236		-0,00084		0,10602	***	0,11277	***	-0,00883		0,00834	
		(0,0090)		(0,0009)		(0,0184)		(0,0184)		(0,0142)		(0,0142)	
	Bond	-0,00734		0,00370	***	-0,30032	***	-0,09937	***	-0,02391		-0,01519	
		(0,0117)		(0,0012)		(0,0184)		(0,0184)		(0,0238)		(0,0238)	
Netherlands	CDS	0,01102		-0,00149	*	0,15226	***	0,02475		-0,03567	*	-0,00076	
		(0,0131)		(0,0007)		(0,0185)		(0,0185)		(0,0195)		(0,0195)	
	Bond	-0,02059	*	-0,00037		-0,23589	***	-0,06423	***	-0,01861		-0,00797	
		(0,0124)		(0,0006)		(0,0185)		(0,0185)		(0,0175)		(0,0175)	
Norway	CDS	-0,04335	***	-0,00095		0,06429	***	0,02598		-0,00950		-0,00266	
		(0,0079)		(0,0007)		(0,0185)		(0,0185)		(0,0106)		(0,0105)	
	Bond	-0,02044		0,00631	***	-0,19415	***	-0,06451	***	-0,06389	*	-0,05145	
		(0,0139)		(0,0012)		(0,0185)		(0,0184)		(0,0325)		(0,0325)	
Portugal	CDS	0,09666	***	-0,00029	***	0,18304	***	0,02889		0,09451	***	-0,04032	*
		(0,0145)		(0,0001)		(0,0191)		(0,0190)		(0,0194)		(0,0195)	
	Bond	-0,00933		-0,00006		0,05103	***	0,00164		0,07792	***	-0,01353	
		(0,0142)		(0,0001)		(0,0191)		(0,0192)		(0,0188)		(0,0187)	
Slovakia	CDS	0,01292		-0,00085	*	0,08461	***	0,05586	***	0,01586		-0,00890	
		(0,0115)		(0,0004)		(0,0185)		(0,0185)		(0,0176)		(0,0176)	
	Bond	-0,03540	***	0,00002		-0,32445	***	-0,12066	***	0,02342		0,00853	
		(0,0120)		(0,0004)		(0,0184)		(0,0184)		(0,0192)		(0,0192)	
Slovenia	CDS	0,99973	***	-		0,15128	***	-0,15067	***	0,04188		-0,03799	
		(0,9997)				(0,0183)		(0,0183)		(0,0357)		(0,0357)	
	Bond	0,99818	***	-		0,71141	***	0,28681	***	0,03007	***	-0,03040	***
		(0,9982)				(0,0177)		(0,0177)		(0,0091)		(0,0091)	
Spain	CDS	0,06493	***	-0,00075	***	0,14065	***	0,01597		-0,00613		-0,00727	
		(0,0163)		(0,0002)		(0,0186)		(0,0187)		(0,0248)		(0,0248)	
	Bond	-0,01865		0,00000		-0,25869	***	-0,08985	***	0,05226	***	0,00546	
		(0,0122)		(0,0002)		(0,0186)		(0,0186)		(0,0140)		(0,0140)	
Sweden	CDS	0,02242	*	-0,00107	***	0,10317	***	0,06259	***	-0,03521	*	-0,02030	
		(0,0119)		(0,0003)		(0,0184)		(0,0184)		(0,0180)		(0,0180)	
	Bond	-0,01982		-0,00017		-0,25198	***	-0,06017	***	-0,03424	*	-0,01623	
		(0,0122)		(0,0004)		(0,0185)		(0,0185)		(0,0189)		(0,0189)	
UK	CDS	0,01348		-0,00107	***	0,15833	***	0,04593	**	-0,04814	*	0,00518	
		(0,0137)		(0,0004)		(0,0185)		(0,0185)		(0,0202)		(0,0202)	
	Bond	-0,01727		0,00009		-0,21803	***	-0,06988	***	-0,05041	***	-0,00634	
		(0,0126)		(0,0003)		(0,0185)		(0,0185)		(0,0169)		(0,0169)	
USA	CDS	-0,00350		-0,00440	*	-0,23041	***	-0,02717		0,00255		-0,01917	

Table 2.6: Estimation of the VECM(2) model for the transformed time series during the whole period(*Continued*)

		VECM(2)											
		Cst(M)		λ		γ_1		γ_2		δ_1		δ_2	
		(0,0107)		(0,0018)		(0,0185)		(0,0185)		(0,0170)		(0,0170)	
	Bond	-0,01502		0,00161		-0,26591	***	-0,08238	***	-0,03592	*	-0,02805	
		(0,0116)		(0,0019)		(0,0184)		(0,0184)		(0,0201)		(0,0201)	
Panel B: Newly Industrialized countries													
Brazil	CDS	0,03334	**	-0,00147		0,09586	***	0,00586		0,05387	**	0,03251	
		(0,0146)		(0,0009)		(0,0191)		(0,0190)		(0,0218)		(0,0218)	
	Bond	0,02653	**	0,00139	*	-0,14160	***	-0,01601		0,06930	***	0,01357	
		(0,0127)		(0,0008)		(0,0191)		(0,0191)		(0,0167)		(0,0166)	
China	CDS	0,05476	***	-0,00033		0,03587	*	0,09022	***	-0,00374		0,01668	
		(0,0123)		(0,0003)		(0,0184)		(0,0184)		(0,0160)		(0,0159)	
	Bond	0,01706		0,00092	***	-0,13934	***	-0,07111	***	-0,03902	*	-0,01460	
		(0,0143)		(0,0004)		(0,0185)		(0,0184)		(0,0213)		(0,0213)	
Mexico	CDS	0,99468	***	-		0,11019	***	-0,11028	***	0,07209	***	-0,07255	***
		(0,9947)				(0,0185)		(0,0185)		(0,0211)		(0,0211)	
	Bond	0,99924	***	-		0,02762	***	-0,02806		0,02824	*	-0,02845	*
		(0,9992)				(0,0187)		(0,0187)		(0,0163)		(0,0163)	
Philippines	CDS	-0,12461	***	0,00006		0,06525	***	0,02365		-0,06389	***	0,01379	
		(0,0136)		(0,0001)		(0,0185)		(0,0186)		(0,0196)		(0,0196)	
	Bond	-0,03545	***	0,00042	***	-0,15396	***	0,05181	***	0,07965	***	0,01561	
		(0,0129)		(0,0001)		(0,0185)		(0,0185)		(0,0175)		(0,0176)	
Thailand	CDS	0,2668	**	-		0,087077	***	-0,0902	***	0,00234		-0,00048	
		(0,1219)				(0,0184)		(0,0184)		(0,0188)		(0,0188)	
	Bond	0,1012		-		0,015255	***	-0,0146		0,01248		-0,01437	
		(0,1201)				(0,0185)		(0,0185)		(0,0181)		(0,0181)	
Turkey	CDS	0,02338	*	-0,00248	*	0,15177	***	-0,00567		0,05174	**	0,02405	
		(0,0142)		(0,0010)		(0,0186)		(0,0183)		(0,0234)		(0,0233)	
	Bond	-0,01486		-0,00176	*	-0,32566	***	-0,08959	***	0,06598	***	0,01930	
		(0,0113)		(0,0008)		(0,0186)		(0,0185)		(0,0148)		(0,0145)	
Panel C: Emerging countries													
Bulgaria	CDS	0,02091	*	-0,00100	*	0,17708	***	0,07387	***	-0,00595		-0,01642	
		(0,0116)		(0,0005)		(0,0184)		(0,0184)		(0,0196)		(0,0196)	
	Bond	-0,02679	*	-0,00077	*	-0,40603	***	-0,21580	***	0,01769		-0,00578	
		(0,0107)		(0,0005)		(0,0181)		(0,0181)		(0,0170)		(0,0169)	
Croatia	CDS	0,04542	***	-0,00038	*	0,15920	***	0,11147	***	-0,00714		-0,00435	
		(0,0142)		(0,0002)		(0,0184)		(0,0184)		(0,0300)		(0,0300)	
	Bond	-0,02107	*	-0,00015		-0,36170	***	-0,11586	***	0,03036	***	0,01094	
		(0,0087)		(0,0001)		(0,0184)		(0,0183)		(0,0112)		(0,0113)	
Czech	CDS	0,01984		-0,00785	***	-0,50708	***	-0,21857	***	0,06894		-0,04298	
		(0,0469)		(0,0029)		(0,0181)		(0,0180)		(0,0606)		(0,0606)	
	Bond	-0,07180	***	-0,00172	*	-0,18678	***	-0,01123		0,01258	**	0,00691	
		(0,0143)		(0,0009)		(0,0185)		(0,0185)		(0,0055)		(0,0055)	
Greece	CDS	0,23069	***	-0,00009	*	0,19289	***	0,13450	***	-0,04113	***	0,02340	*
		(0,0102)		(4,90E-5)		(0,0183)		(0,0183)		(0,0128)		(0,0127)	
	Bond	-0,02340		0,00035	***	-0,21263	***	-0,07824	***	0,03525		0,04990	*
		(0,0148)		(0,0001)		(0,0185)		(0,0185)		(0,0267)		(0,0266)	
Hungary	CDS	0,02208		-0,00109	*	0,16388	***	0,05257	***	0,03216		0,02799	
		(0,0135)		(0,0004)		(0,0185)		(0,0185)		(0,0217)		(0,0217)	
	Bond	-0,01663		-0,00004		-0,25745	***	-0,07581	***	0,05792	***	0,03060	*
		(0,0115)		(0,0004)		(0,0185)		(0,0185)		(0,0158)		(0,0158)	
Indonesia	CDS	-0,06048	***	-0,00202	*	0,09486	***	0,02760		0,04759	**	-0,00600	
		(0,0146)		(0,0009)		(0,0188)		(0,0191)		(0,0210)		(0,0208)	
	Bond	-0,02828	*	0,00079		-0,05999	***	0,01914		0,15989	***	0,07701	***
		(0,0130)		(0,0008)		(0,0188)		(0,0186)		(0,0168)		(0,0171)	
Poland	CDS	0,02882	**	-0,00119	*	0,09776	***	0,04387	**	0,12516	***	0,06215	***
		(0,0126)		(0,0006)		(0,0187)		(0,0185)		(0,0199)		(0,0201)	
	Bond	-0,03086	***	-0,00092		0,02084		0,00045		0,05258	***	-0,02359	
		(0,0118)		(0,0006)		(0,0187)		(0,0188)		(0,0175)		(0,0174)	
Romania	CDS	0,01230		-0,00127	*	0,17604	***	0,07531	***	0,00774		-0,01375	
		(0,0097)		(0,0005)		(0,0184)		(0,0184)		(0,0156)		(0,0156)	
	Bond	-0,02052	*	-0,00025		-0,34011	***	-0,06467	***	0,02022		0,04570	**
		(0,0115)		(0,0006)		(0,0184)		(0,0184)		(0,0218)		(0,0218)	
Russia	CDS	0,99961	***	-		1,07394	***	-0,07368	***	0,08130	***	-0,08151	***
		(0,9996)				(0,0193)		(0,0193)		(0,0184)		(0,0184)	
	Bond	0,99763	***	-		0,88846	***	0,11009	***	0,14091	***	-0,14076	***
		(0,9976)				(0,0193)		(0,0193)		(0,0202)		(0,0202)	
Ukraine	CDS	0,32911	***	-0,00004	***	0,12320	***	0,06489	***	0,03285	**	0,00878	
		(0,0143)		(9,60E-6)		(0,0185)		(0,0184)		(0,0150)		(0,0150)	
	Bond	-0,01866		-0,00004	***	-0,08300	***	-0,06478	***	-0,00145		0,03250	
		(0,0177)		(1,20E-5)		(0,0185)		(0,0185)		(0,0228)		(0,0228)	
Venezuela	CDS	0,98589		-0,00001		0,20342	***	0,02869		-0,04938		-0,02799	
		(2,4423)		(1,74E-5)		(0,0185)		(0,0185)		(0,1016)		(0,0723)	
	Bond	-0,00324		0,00014	***	-0,02448		-0,01215		-0,00032		0,00011	
		(0,6243)		(4,45E-6)		(0,0260)		(0,0185)		(0,0047)		(0,0047)	

This table reports the results of the VECM model applied to the restructured time series for each studied country. The lag order is defined according to the AIC information criterion. For Ireland, Slovenia, Mexico, Thailand and Russia, a VAR(2) is estimated rather than the VECM (No cointegrating relationship is found between CDS spreads and Bond yields of these countries). *, ** and *** denote statistical significance at respectively 10%, 5% and 1%.

2.4.4 The sub-period market efficiency testing

In order to better understand the reaction of markets to crises, the VECM(2) is once again applied on the reconstructed time series over four subperiods: a pre-crisis period, a first-crisis period (Global Financial Crisis), a second-crisis period (The European Debt Crisis) and a post-crisis period. Estimation results are not reported here but can be provided upon request. However, we depict in Table 2.7 the Block Exogeneity and Lag Exclusion Wald post-estimation tests over the sub-periods. The aim of this test is to analysis the statistically significance of the lagged coefficients.

Unlike the VECM(2) results over the full period, Wald tests show that, depending on the period or on the country, CDS spreads can be predicted or not from its past values. Focusing on the pre-crisis period, the coefficient δ_1 is significant in at least 10% level in 27% of the studied period. With the start of turmoil subperiods, the number of significant lagged bond yields coefficients have increased to 48% and 62% respectively during the Global Financial Crisis and the European Debt crisis. Interestingly, Wald tests don't detect any significant coefficient during the post-crisis period.

The results of the short run predictability show that during the period prior to financial tensions, the efficient market hypothesis is rejected in 10 countries (Denmark, France, Netherlands, the UK, the USA, China, Mexico, Philippines, Czech and Poland). The CDS spreads of these countries can thus be predicted not from their previous prices but rather from previous values of their underlying bond yields. Crises have, obviously, changed some markets' behavior in an unexpected way. Interestingly, more CDS markets become inefficient during crises. In fact, whether during the first or the second crisis, the number of markets in which the null hypothesis of randomness is rejected, sharply increases to 18 countries and 23 countries respectively during the Global Financial crisis and the Sovereign Debt crisis. While the markets that are initially broadly efficient, become less sensitive to fundamentals during crisis periods, the opposite reaction is observed during the post-crisis period. After the financial situation being calmed by mid 2012, the null hypothesis is accepted in all the 37 studied markets. That is, the CDS spreads in these countries exhibit an unpredictable behavior accepting, therefore, the random walk and the efficiency hypotheses.

2.4.5 Robustness check

As mentioned before, the inefficiency of the CDS market is detected when the impact of the lagged values of the CDS spreads or the bond yields on the current CDS level is statistically significant. Our results can be confirmed if the parameters capturing this inefficiency increased during crisis periods compared to the reference period. To do this, we get interested in the evolution of the parameters (γ and δ) values during the four sub-periods studied. Estimates are made, this time, upon a synthetic CDS index representing the global CDS market.

This global CDS index is constructed using the value-weighting technique and suppose that, whether for the CDS or the bond portfolios, each country's weight is defined by dividing its transaction volume (outstanding debt amount) by the total transaction volume of the portfolio, such as: $I_G = \sum_{i=1}^{N} w_i y_i$, where I_G is the synthetic index, N is the number of CDS markets composing the index, y_i transformed the CDS (or Bond) series and $w_i = \frac{v_i}{v_I}$ with v_i is the country's transaction volume on the credit market and v_I is the total transaction volume of all the countries composing the portfolio.

The inefficiency parameters evolution, presented in Figure 2.4, confirms our previous find-

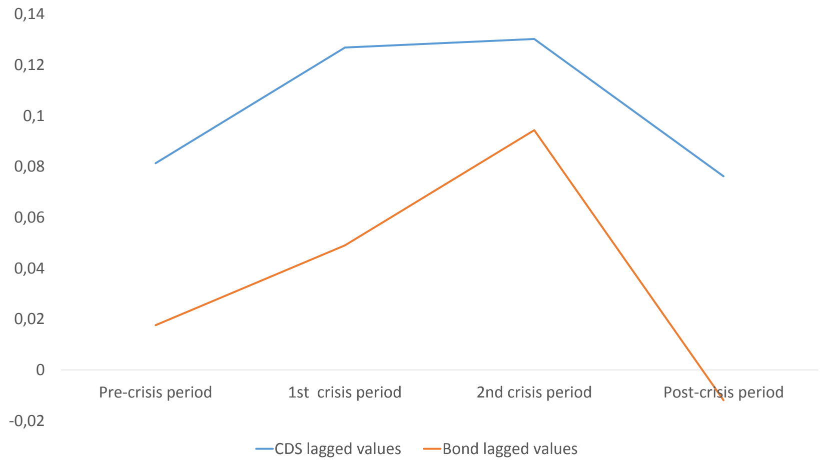

Figure 2.4: Evolution of the inefficiency parameters over the four studied sub-periods

ings: During the pre-crisis period, the pattern of CDS spreads can be, in some extent, predictable based on the lagged values of CDS spreads and bond yields. This extent increases during the global financial crisis and the European debt crisis, implying a more important predictability of CDS spreads and more interesting speculative opportunities. The impact of the lagged values of the CDS and the Bonds decreases after the markets' financial situation has returned to calm, suggesting some changes in the CDS behavior. During the post-crisis period a more important independence between current and past prices is observed, which implies that the CDS spreads become less predictable.

2.4.6 Discussion

As mentioned before, the study of the Sovereign CDS spreads efficiency is a substantial research issue that concerns both academic and non-academic communities. In fact, a good understanding of the spreads evolution's pattern is crucial to implement an allocative efficiency of credit markets and ensure financial stability of the real sphere.

Preliminary analysis shows that, whatever the degree of indebtedness or credit risk, all the studied countries exhibit inefficient credit markets where historical data significantly impact the direction of future CDS prices fluctuations. This is a particularly important finding given that our sample is composed by economically heterogeneous countries with different liquidity and risk characteristics. Since the random walk hypothesis is globally rejected, it can be understandable that these markets are potentially used to speculation and to achieve excess returns from arbitrage strategies. These irregularities imply, as well, that investors of sovereign CDS markets are obviously interpreting prices evolution in an inefficient way due to the financial sector complexity. This inefficiency can be explained by several reasons: (i) The transaction costs are not taken into account in the value of CDS spreads, making this predictability difficult to exploit in practice. (ii) Even though the sovereign CDS and the bond markets have undergone a remarkable development during the recent decades, their liquidity remains less important compared to other financial markets, (iii) it may be caused, to one degree or another, by the algorithm method used to fill the missing data and the outliers in some countries (the UK, Mexico, Romania. . .) and (iii) the macroeconomic variables do not freely fluctuate, making the interest rates (and eventually the CDS spreads) evolution kind of

Table 2.7: Block Exogeneity and Lag Exclusion Wald Tests during the sub-periods

	Pre-crisis period			1^{st} crisis period			2^{nd} crisis period			Post-crisis period		
	$\gamma_{1,1}$	$\gamma_{1,2}$	δ_1	$\gamma_{1,1}$	$\gamma_{1,2}$	δ_1	$\gamma_{1,1}$	$\gamma_{1,2}$	δ_1	$\gamma_{1,1}$	$\gamma_{1,2}$	δ_1
Panel A: Developed countries												
Austria	48,95	17,78	0,66	1,98	7,86	2,16 *	1,1E-8	0,07	0,01 **	1,2E-4	4,5E-3	0,00
Belgium	66,18	14,19	2,28	5,73	1,17	1,06	7,7E-8	0,31	0,07 *	4,0E-9	0,12	0,16
Denmark	36,20	28,79	98,84 ***	96,91	1,94	6,91 **	5,4E-9	0,41	0,21	0,20	1,9E-3	0,01
Finland	3,10	5,35	3,33	14,02	6,00	0,45	2,5E-5	0,50	0,05 *	0,24	0,11	0,30
France	14,06	49,22	5,34 *	15,54	1,60	1,35 *	5,2E-13	0,04	6,0E-4 ***	7,3E-9	0,01	0,37
Germany	32,13	17,25	0,10	6,00	9,03	1,08 *	1,3E-6	0,96	0,03 **	1,7E-3	2,1E-3	0,14
Ireland	14,16	2,09	0,02	0,20	10,04	0,78	1,2E-9	0,63	3,0E-3 ***	2,3E-12	1,5E-3	1,4E-3
Italy	8,71	1,04	4,44	3,58	8,29	8,19 **	3,0E-11	0,12	0,96 **	3,9E-8	0,76	0,69
Japan	29,78	16,33	1,46	12,06	0,94	0,92	0,05	0,33	0,75	1,9E-4	4,8E-3	0,82
Latvia	1,46	4,05	0,93	11,87	13,93	3,39	0,04	0,03	0,23	0,15	0,09	0,40
Lithuania	1,62	0,63	1,74	9,71	10,45	3,17	0,01	0,20	0,57 *	1,3E-8	0,01	0,79
Netherlands	1,34	1,25	0,86 ***	39,36	4,22	0,14 **	8,5E-8	0,41	0,33 **	0,13	0,44	0,69
Norway	2,08	27,74	3,71	53,20	2,21	0,33	5,4E-4	0,84	0,83	0,24	0,36	0,71
Portugal	47,43	15,38	2,34	0,05	9,06	9,08 **	1,9E-9	0,08	0,04 **	0,00	0,26	2,0E-4
Slovakia	13,88	2,22	0,97	13,88	2,22	0,97	2,4E-5	0,33	0,52	0,37	0,09	0,42
Slovenia	0,04	20,26	0,03	7,34	3,37	0,12	4,3E-7	0,17	0,17	2,5E-4	0,03	0,12
Spain	32,13	12,70	1,31	1,66	9,42	8,68 **	9,2E-7	0,59	0,97 **	4,0E-7	0,32	0,44
Sweden	8,35	2,81	2,78	46,02	5,43	5,50 *	4,5E-5	0,45	0,25	0,14	0,06	0,00
UK	2,82	10,07	26,09 ***	23,95	1,55	1,59	1,1E-6	0,20	0,23 ***	2,0E-4	4,8E-3	0,02
USA	1,15	2,68	2,95 ***	27,69	2,42	0,41 *	4,8E-5	0,60	0,94 *	0,00	2,8E-5	0,20
Panel B: Newly Industrialized countries												
Brazil	5,74	3,97	3,43	4,95	2,93	4,26	0,03	0,02	0,08 *	1,8E-5	0,67	0,01
China	25,51	1,52	4,67 *	4,38	7,92	2,35 **	0,97	0,25	0,79	0,18	6,5E-4	0,11
Mexico	1,10	0,70	0,14 ***	16,66	2,11	12,18 ***	0,01	0,20	0,54	1,3E-5	0,99	0,09
Philippines	3,27	0,23	32,48 ***	7,18	3,43	1,98 **	0,85	0,40	0,77 *	2,4E-4	0,56	1,8E-3
Thailand	1,51	0,19	0,05 ***	10,02	4,19	1,69	0,52	0,04	0,97	3,8E-3	0,34	1,8E-1
Turkey	20,21	0,70	0,96	11,98	0,42	1,75	2,3E-3	0,85	0,73	1,4E-6	0,69	0,60
Panel C: Emerging countries												
Bulgaria	7,93	4,27	1,01	17,64	10,39	7,02 **	9,1E-8	0,07	0,46 **	2,9E-5	0,15	0,30
Croatia	0,69	5,71	0,26	11,48	5,73	0,53	4,4E-8	0,15	0,54	2,9E-6	5,5E-5	0,62
Czech	0,36	12,40	6,76 **	2,09	1,99	1,36	2,1E-4	0,53	0,89 *	0,00	3,3E-16	0,22
Greece	76,47	1,19	1,31	24,53	9,85	3,47	8,0E-6	0,01	0,56 ***	0,00	2,9E-3	0,00
Hungary	11,31	8,12	3,69	4,68	4,60	3,49	9,0E-6	0,42	0,47	1,7E-12	0,13	0,56
Indonesia	0,35	1,51	2,74	1,96	1,61	1,30	0,70	0,25	0,55 **	1,8E-7	0,44	0,08
Poland	20,56	8,84	25,37 ***	14,91	9,16	12,21 ***	7,1E-6	0,01	0,01 ***	3,2E-9	0,17	0,00
Romania	10,43	7,51	0,04	8,90	4,69	0,66	5,5E-7	0,12	0,57 **	6,7E-7	0,24	0,96
Russia	7,25	2,48	3,32	11,46	1,22	5,18 *	2,7E-4	0,34	0,56	4,2E-5	0,47	0,00
Ukraine	4,95	0,61	0,32	21,37	9,13	11,14 ***	2,0E-4	0,22	0,01 **	0,01	0,04	0,74
Venezuela	61,96	5,63	1,86	36,12	5,38	4,98 *	5,1E-9	0,84	0,08 *	0,00	0,70	0,00

The Wald Chi-Squared Test is a parametric econometric test that verifies whether the parameters are statistically significant or not, based on a prior model estimation. $\gamma_{1,1}$ and $\gamma_{1,2}$ denote the single parameters of CDS lags values; whilst δ_1 denote the joint/multiple parameters of the Bond lags values. The parameters are tested in order to verify their significant impact on the price formation (Dependent variable: D[CDS]). *, ** and *** denote statistical significance at respectively 10%, 5% and 1%.

predictable.

The credit prices predictability of Sovereigns raises a serious concern about their potential exposure to common risk during periods of financial tensions, given that credit derivatives markets can contribute to the increase of financial market instability because of their huge outstanding amounts. Our results, based on a sub-period analysis, confirm this perception and reveal that the number of inefficient markets increases during the Global Financial Crisis and the Sovereign Debt crisis, and even right after the earliest signs of the crisis (pre-crisis period). This implies that market efficiency is a time-varying phenomenon characterized by a regime switching during tension episodes.

Focusing on the second sub-period representing the Global Financial Crisis, the Wald tests detect several significant relationship between current and past observations in Portugal, Ireland, Estonia and Ukraine. The second crisis is also characterized by a change in the markets nature with an increase in the number of forecastle prices based on previous credit market behavior. In general, we can see that crises negatively impact the randomness of the CDS markets with a more important decrease in the number of efficient countries compared to the whole studied period, particularly during the second crisis. This suggests that, since the European Debt Crisis intensity and severity are more important than in the Global Financial Crisis, the misperception of financial signals by investors is all the more important that the crisis is harsh.

The random walk analysis gives heterogeneous efficiency status for each studied country and for each sub-period. The overall consistency between our results is that a timeless general conclusion should not be given on worldwide CDS markets and that regulators and market participants should perpetually revise their strategies according to whether the market is impeccably efficient or glossy inefficient.

2.5 Conclusion

The aim of this essay is to empirically investigate the weak-form EMH on 37 worldwide sovereign CDS markets, from January 2006 to March 2017. Similar studies are scarce, and for the most part the evidence wholly supports the randomness of CDS regardless of the crises' effects and the country risk profile. Our study tries to fill this gap by focusing on countries with different economic and financial status and conducting the analysis throughout the entire period as well as over sub-periods of strong and weak financial tensions. Our methodological framework is particularly suitable to the context, as it takes into account most of CDS markets' stylized facts. Yet, the examination of CDS spreads' predictability is based on past information available not only on the CDS market but also on the underlying bond market.

Results of the VECM-FIGARCH(1,d,1) framework on the whole period are not in line with common findings and suggest that sovereign CDS markets of developed, newly industrialized and emerging countries are not weak-form efficient. Further, as opposed to previous studies, our sub-period analysis reveals that the efficiency of the major studied markets is actually impacted by financial tensions even before the crisis-official onset and that the global randomness is observed exclusively during the post-crisis period. Surprisingly current CDS spreads are found to be only predictable from the past bond markets information with no role played by previous CDS fluctuations. Finally, our findings show that the structural breaks in countries' efficiency behavior do not depend on the sovereign credit risk degree.

In this constantly evolving worldwide credit market, the study of the CDS spreads efficiency needs to keep pace with this change. First, as these markets are becoming less efficient during crisis periods, then we expect a detection of the CDS spreads predictability by practitioners, and upgraded trading strategies, a readapted portfolio management techniques and an implementation of beneficial speculative and arbitrage operations. At the opposite, the validity of the CDS markets efficiency all along the post-crisis period implies less trading profitability and better asset pricing. Second, since the CDS markets have become a financial stability indicator used in the assessment of the real economy suitability and sovereign creditworthiness in particular, CDS spreads should completely and appropriately reflect all the available information. Hence, based on our results, policymakers have to examine the reasons behind market anomalies observed in some countries during pre-crisis period, the Global Financial Crisis and the European Debt Crisis. Authorities should, as well, avoid market inefficiency by ensuring compliance with random walk conditions (costless CDS trading, free and transparent information for all investors . . .). Until the CDS market becomes efficient again - due to multiple transactions carried out to profit from irregularities - a regulatory framework should be put in place: National and international regulators can make the market more liquid, through securitization operations (such as Collateralized Debt Obligations and Mortgage-Backed Securities) for example, or increase transaction costs as to be more important than the arbitrage and speculation's expected benefits making trading structure worthless and fruitless.

This research essay can be pursued in two ways. First, an empirical investigation on the determinants of these inefficiency degrees with a particular focus on the role played by the macroeconomic variables of each country in the predictability of the CDS spreads. Second, it can be interesting to concretely implement a trading strategy based on the detected predictions, in order to verify whether our results can be used to generate additional profit.

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Appendices

2.6 Appendix: Regime Switching classification

Table 2.8: Regime Switching classification

Date	Days	Average probability
Regime 0		
2006-01-02 - 2007-11-21	493	0.999
Total: 493 days (16.79%) with average duration of 493.00 days.		
Regime 1		
2007-11-21 - 2012-05-31	1181	0.998
Total: 1181 days (40.22%) with average duration of 1181.00 days.		
Regime 0		
2012-03-31 - 2017-05-31	1262	0.999
Total: 1262 days (42.98%) with average duration of 1262.00 days.		

2.7 Appendix: Time-varying average CDS spreads between the studied countries

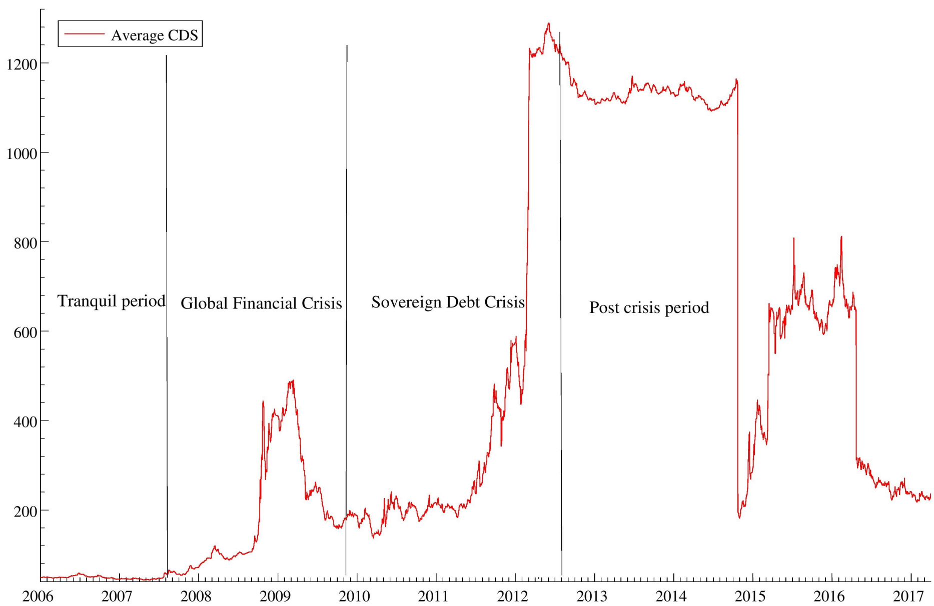

Figure 2.5: Time-varying average CDS spreads between the studied countries

Chapter 3

Nonlinearities in the oil fluctuation effects on the sovereign credit risk: A Self-Exciting Threshold Autoregressive approach

The unquenchable thirst of several sectors to crude oil in the recent years makes a common belief regarding its key role towards the acceleration of the recent economic recession and financial instability.

This chapter aims to examine the nonlinear impact of oil shocks on the sovereign credit risk for a sample of 38 worldwide oil-producing and non-oil producing countries, over a period ranging from January 2006 to March 2017. In contrast to the existing literature, CDS volatility is employed as a measure for the creditworthiness level, rather than the commonly used CDS spreads first-order moment. The methodological framework used in this essay goes beyond previous studies and takes into account more financial data features (long memory behavior, asymmetric effects and nonlinearities) according to a self-exciting regime switching model.

Results reveal some dissimilarities in the explanatory power of the exogenous variables between regimes and across countries. Particularly, restricted evidence of oil significant impact on sovereign CDS volatility are detected during the stable regime, whilst during the risky regime credit volatility becomes more sensitive to oil market conditions for most of the studied markets. Generally, the decline in oil price worsens the public finances tenability whether the country is oil-related or not.

Keywords : Sovereign CDS volatility, Oil market, FIAPARCH, SETAR, Threshold regime-switching.

3.1 Introduction

Because of its highly required usage in countries' economic development, and considering the sharp increasing uncertainty around the role played by the credit market in the accentuation of the financial instability, academic and non-academic researchers are more and more interested in understanding the main drivers of the credit risk, proxied notably by the Credit Default

Swap (CDS, hereafter) spreads. As the CDS market does not only reflect the creditworthiness but also quantifies the degree of investors' risk aversion and gives an insight on the systemic risk transfer, studying the credit risk determinants is widely useful for worldwide regulators and market participants so they can detect the risk source and properly adjust the policy-decisions during extreme situations. This essay aims to investigate whether price fluctuations can help to explain conditional sovereign CDS volatility, after controlling for local and global economy-wide factors.

Several papers exist in literature regarding the determinants of the corporate and sovereign credit risk. Using various economic and financial variables, authors show mainly that the country's creditworthiness depends on local and global economy-wide factors (Ericsson et al., 2009; Naifar, 2011; Oliveira et al., 2012; Costantini et al., 2014; Fontana and Scheicher, 2016; Srivastava et al., 2016)[1]. If studies on macroeconomic factors and their impact on credit risk multiply, a relatively few of them get interested into the potential role of the energy sector in the determination of the sovereigns' solvency level. This might be due to the fact that oil prices were generally stable until recently when prices start to exhibit some volatile behavior. The strand of literature related to the purpose of our essay remains relatively limited and includes only few studies. On the one hand, Sharma and Thuraisamy (2013) and Wegener et al. (2016) find a significant linear relationship between oil price and the investors' apprehension of sovereign credit risk. On the other hand, Results, of the quantile regression and the causality-in-quantiles approaches (Naifar et al., 2017) and rolling-window causality approach and the cross-quantilogram approach (Shahzad, Naifar, Hammoudeh and Roubaud, 2017) analyzes, show some asymmetric nonlinearities in the risk transfer between the oil market and the sovereign CDS market.

Our contribution to the existing literature is threefold: First, as far as we are concerned, this study is the first to give an in-depth investigation on the relationship between the oil price and the sovereign credit risk using not the CDS spreads as an indicator of the creditworthiness but rather the CDS volatility. In fact, using the volatility of CDS as a measure of credit risk seems to be more appropriate than its first-order moment for several reasons: On the one hand, initially developed to hedge governments' debts, CDS spreads were closely related to the default probability of a reference entity and their values seemed therefore suitable to measure how risky a country is. However, as time goes on, naked CDS are becoming to be increasingly used for speculation, which makes their spread levels dissociated from the inherent credit risk degree. Using sovereign CDS in a gain-making vision can have perverse effects as was the case during the recent sovereign debt crisis. In the case of Greece in particular, investors were betting on an increase in the country's probability of default by massively buying Greek CDS (even if this anticipation is not justified), leading thus to raise the spreads levels. In doing so, the price of protections on Greek debt effectively increased because of the increased demand on the market. Greece has therefore been subject to higher interest rates because of this speculative mechanism rather than because of its public finances' deterioration. In our view, CDS spreads seem, therefore, to be a controversial measure of risk for investors since high spreads do not necessarily imply a high probability of a credit event occurring but rather a high volume of speculation. On the other hand, we believe that solvency risk should not be limited to the government's default probability, but should also take into account market instability and uncertainty about the investors' risk perception. The objective is, thus, to measure this

[1]Only some recent references, investigating the variables that influence the level of CDS spreads, are cited here as examples. For a more exhaustive list, please refer to the literature review in section 3.2.

'complementary' market risk in order to properly assess the countries' creditworthiness. Our reasoning is all the more true since a certain paradox is observed during the first half of 2011 as regards the evolution of French CDS. During this period, CDS spreads - reaching 190 basis points - outpaced those of some much riskier countries like Brazil or the Philippines, despite the improvement in France's credit conditions and the decline in its bonds' interest rates. This increase in French spreads, despite the good health of the country's fundamentals and despite the fact that French debt is still sought by investors, seems to be rather related to a high liquidity caused by rumors about the deterioration of the France sovereign rating. Therefore this situation reflects the limits of CDS spreads as a measure of credit risk, especially in periods of high risk aversion and permanent rumors.

Second, we use a novel methodological framework that considers simultaneously for several statistical features characterizing the CDS market such as the volatility clustering, long memory behavior, asymmetry and nonlinearity. Third, our time period spans over a relatively long interval covering the recent two financial crises and the precipitous fluctuations in oil prices by half of 2014. Yet, the current study includes several countries with different financial characteristics (not only highly oil-related countries), notably the less-studied countries in which oil price has outwardly no effect on the economic health.

The empirical findings show that the countries under study react in a heterogeneous way to economic and financial shocks and a regime-switching behavior is observed over time. Particularly, positive changes in oil market conditions negatively impact the sovereign CDS volatility for most cases, especially during the high-risk period (2^{nd} regime), while limited evidence of significant relationship between these two markets are found during the stable regime. Our results confirm that the oil price is another relevant driving force of public finances tenability and thus an appropriate factor to be considered in the appreciation of sovereign credit risk for both oil-producing and oil-consuming countries.

The rest of the chapter is structured as follows. An overall review of the literature studying the determinants of credit risk is presented in section 3.2, with a particular emphasis on papers dealing with the impact of oil price. section 3.3 presents a brief description of the potential risk factors and the methodological framework. Results are presented is section 3.4, while section 3.5 discusses the empirical findings. Concluding remarks are presented in section 3.6.

3.2 Literature review

Empirical papers investigating the key determinants of the CDS spreads can be divided into two categories depending on whether the reference entity is a company or a sovereign state. We start this section by an overview of the major studies belonging to these literature strands. Then, we provide a survey on the few papers particularly analyzing the impact of oil price on the CDS spreads fluctuations.

3.2.1 Corporate CDS analysis

Inspired by Merton's theoretical model, several authors empirically develop and assess companies' credit risk, using different methodological frameworks and econometric tools. From the early ones, Collin-Dufresn et al. (2001) use monthly industrial bond to show that surprisingly the logical theoretical determinants don't impact the fluctuation of credit spreads. Based on the results of a principal component analysis, no significant explanatory power is detected from macroeconomic and financial variables and liquidity proxies. Credit risk spreads depend only on the local supply and demand shocks. At the opposite and based on a linear regression framework, Abid and Naifar (2006) use a large set of explanatory variables to study the determinants of CDS premiums. Authors argue that the majority of the credit-risk fundamentals (credit rating, riskless interest rate, volatility, maturity and slope of the yield) significantly explain credit spreads. Similarly, using a simple linear regression of CDS spreads on some theoretical credit-risk factors, Ericsson et al. (2009) present some empirical evidence of the significant role played by corporate leverage, volatility and risk-free rate in default-risk premium determination.

Tang and Yan (2010) investigate the role played by firm-level features and macroeconomic variables in the corporate credit spreads pricing. Results show that investor sentiment and the cash-flow volatility are the most important factors in explaining CDS spreads. Using a Markov-switching models, Naifar (2011) also finds that the iTraxx Japan CDS spreads changes are explained by stock market and macroeconomic characteristics with a strengthening of these relationships during the crisis period. Having the same purpose, Annaert et al. (2013) focus on the credit risk of 32 European banks' debts. The major result obtained from this study shows that the explanatory power of the liquidity component, the bank-level variables and market factors is constantly changing over time and across the studied banks.

More lately, Galil et al. (2014) analyze the determinants of CDS spreads of 718 US companies from 2002 to 2003. Through a linear regression estimation, these authors show that common factors have a significant role in the spreads' formation only after taking into account the firm-specific variables. The authors find, furthermore, that three factors play the dominant role in the explanation of the corporate credit risk, namely, the stock returns, the stock market volatility's changes and the market conditions. Focusing their analysis on North America area, Chan and Marsden (2014) study the factors explaining the corporate credit risk of two CDX categories (investment grade and high-yield). Based on a Markov-switching analysis, the results confirm that several macroeconomic variables significantly explain daily CDX spreads changes with a reinforced relationship during turmoil crisis periods. Market sentiment and liquidity proxies (market default premium and VIX) positively impact the risk spread while interest rate and financial factors (stock index returns and Fama-French-Cahart momentum factor) have a negative impact.

Avino and Nneji (2014) go beyond the common research context and investigate the prediction ability of some pricing models developed in the literature. Even though these models are empirically proved to explain CDS spreads, the authors show that this is not always true when it comes to the forecasting performances of the iTraxx European index based on linear and non-linear techniques. Finally, using a data sample composed by emerging and developed countries, Ismailescu and Phillips (2015) show, through an event-study analysis, that CDS trading initiation[1] is significantly affected by country-specific volatility index, regional and international CDS indexes, currency exchange rates and the percentage of external debt.

3.2.2 Sovereign CDS analysis

Initially overlooked by investors, the sovereign credit risk has been reassessed upward since the 2000s which has contributed to awaken the interest of researchers in the determinants of sovereign CDS spreads. Andritzky and Singh (2007) are amongst the first authors to be interested in the pricing of sovereign credit risk. These authors focus on the Brazilian economic

[1]CDS trading initiation refers to the CDS spreads quoted at the first appearance of the reference entity.

crisis of 2002 and use sovereign CDS data to show that the pricing of these credit spreads is mainly dependent on the underlying bond's recovery rate. Oliveira et al. (2012) provide further evidence on the determinants of credit spreads changes using sovereign bonds. Authors show that before the outbreak of the Global Financial Crisis, prices on the credit market are driven by the domestic factors, while after the 2007, credit spreads are rather determined by macroeconomic variables and global risk factor. Similarly, and by considering the fact that CDS time series exhibit volatility clustering properties, Fender et al. (2012) examine the CDS spreads changes of 12 emerging countries from different geographical regions. The authors find that during crisis period the commonly studied global factors have the most important role in the CDS price formation.

Using a simple regression analysis, Eyssell et al. (2013) show that China's CDS spreads, in level and changes, are explained by financial drivers in both country and global levels. The study is conducted over a period running from 2001 to 2010 and is interested in the sensitivity of spreads to the local stock market index, the real interest rate, the government foreign debt, the GDP, the total reserves, the VIX and the non-North America global index among other variables. Beirne and Fratzscher (2013) conduct the same analysis on 31 developed and emerging countries during the European debt crisis. The estimation results of a standard panel model with fixed effects show that countries fundamentals are the main drivers of the sovereign risk and that these factors' explanatory power is accentuated during this crisis period. Besides the macroeconomic variables abundantly studied in the literature, Aizenman et al. (2013) include two ratios (sovereign debt/tax revenue and fiscal deficit/tax) in their CDS pricing model as proxies for fiscal space. Authors show that fiscal space is not only important in explaining European credit risk but also in predicting sovereign CDS spreads.

Eichler (2014) goes beyond the fundamental determinants of credit spreads studied in the literature and gets interested in the political context and its impact on the sovereign bond yields. Results show that sovereign spreads of the presidential regimes' countries are less than those in parliamentary countries. Political stability is found to play a significant role in the credit prices' formation while the degree of democracy has no impact. Using a panel cointegration framework on bond spreads of 9 Euro-area countries, Costantini et al. (2014) argue that the main components of the credit yields are the fiscal imbalances, the liquidity premiums and the cumulated inflation differentials. Authors also show that these results are drawn only for countries not belonging to the Optimal Currency Area.

Whether represented by the CDS spreads or the bond spreads, Fontana and Scheicher (2016) show that the sovereign risk is mostly explained by common drivers such as the riskless rate, the risk aversion level, the corporate CDS index defined by the iTraxx, the total government debt and the stock market volatility. Using a vector auto-regression framework over a period spanning from 2001 to 2010, Srivastava et al. (2016) find evidence of significant unidirectional relationship from the VIX, the currency exchange rate and the bond to the CDS spreads. Besides the country-specific factors (the currency rate and the bond yield), the VIX has the most important role in reducing predicting errors.

More recently, Ho (2016) uses quarterly data of 8 emerging countries from 2008 to 2013 to distinguish between the CDS spreads determinants in short-term and in the long-term. Results of a panel cointegration estimation reveal that three local economic indicators (current account, foreign debt and international reserves) are the main drivers of sovereign risk with the most important role played by international reserves. The author also shows that an increase in these fundamentals improves the government's solvency and reduces, thus, the sovereign spreads. However, this cointegration relationship is not statistically significant in the short-run for all countries. At the opposite, Blommestein et al. (2016) find that local macroeconomic factors have low impact on the spreads formation of 5 Euro-area countries. These authors show, on the other hand, that global factors, and more particularly European Monetary Union factors, play a predominant role in the pricing of the CDS changes.

3.2.3 The impact of oil prices on the CDS spreads

Because of the sharp uncertainty about the energy sector fluctuations during recent years, researchers are more and more interested in the interaction between the energy market and the credit market either in a bivariate framework or by incorporating oil price as a global-wide explanatory variable in the credit risk pricing models. Guo et al. (2011) are the first authors to study the shock transmission between the credit default swap market and the energy market through a regime-switching Vector Autoregressive context. Using data from 2003 to 2009, the authors find, among others, that oil price and the stock price play the predominant role in explaining the North American DCX index fluctuation, especially during risk regimes. More particularly, Hammoudeh et al. (2013) focus on the determinants of CDS spreads of US oil-related sectors from 2004 to 2011. The sectoral CDS index is found to have significant causal relationship with the VIX and the SMOVE[1] indexes.

Da Fonseca et al. (2016) study the interaction between the corporate CDS market and the energy market from 2004 to 2013. Focusing on the joint behavior of the CDS energy sector index and CDS spreads of different credit rating categories with the light sweet crude oil futures contracts, and using a linear regression approach, the authors show that jumps in the volatility of these futures contracts have a significant impact on the CDS changes. These markets interact more during financial turmoil phases. Similarly, Lahiani et al. (2016) examine the financial, economic and energy determinants of the US CDS index of three sectors, banking, financial services and insurance, over a period spanning from 2004 until 2014. Results of the NARDL methodology reveal asymmetries and nonlinearities between the three-month libor, the three-month Treasury rate, the federal funds rate, the VIX and the oil price and the CDS changes in both the short and the long-runs. Shahzad, Nor, Ferrer and Hammoudeh (2017) conduct the same investigation on the industry sector and base their analysis on a NARDL approach, as well, to capture asymmetries in the short and long-runs. These authors study a period spanning from 2007 to 2015 and find an asymmetric cointegrated relationship between the CDS spreads index of US industrial firms and the corresponding industry stock indices, the US stock market volatility, the 5-year treasury bond yields and the crude oil price.

Regarding the sovereign market, Naifar et al. (2017) examines the pricing of the CDS spreads of 16 countries from 2009 to 2016 using the most important financial and risk drivers, namely, the VIX, the 10-year US Treasury rate, the MOVE index[2], the West Texas Intermediate (WTI) price and the OVX index. Based on the quantile regression and the causality-in-quantiles approaches, the analysis reveal a nonlinear relationship between the studied factors and the sovereign spreads, depending on the market state (bearish, bullish or normal). Moreover, results show that the oil price is the most important determinant of CDS spreads particularly in oil-exporting countries and that sovereign risk is more sensitive to bond market uncertainties than to stock market uncertainties. Shahzad, Naifar, Hammoudeh and Roubaud (2017) study the pattern predictability of the risk transfer from the oil market to the sovereign

[1]The swapotion volatility index.
[2]The MOVE index is the VIX's analogous on the bond market.

CDS market. Using both rolling-window causality approach and the cross-quantilogram approach, these authors focus on the sovereign markets of 11 countries belonging to the Gulf Cooperation Council and to other oil-producing countries from 2009 to 2016. Results show that there is a directional predictability from the oil market to most of oil-exporting markets particularly during the crash of oil price.

3.2.4 Limits and contributions

Most of the aforementioned studies investigating the impact of financial and macroeconomic factors on credit risk, use the CDS spreads as dependent variable to proxy the credit risk level, which does not seem totally relevant, at least if it is not associated with any other economic or financial indicator. In fact, this approach is based on the assumption of a risk-neutral market so the default probabilities can be properly reflected in the CDS spreads. However, in reality, economic agents are risk-averse, with different levels of aversion. They require therefore an additional premium that results in the overvaluation of CDS. Because of their averse nature, investors may also request a counterparty risk premium linked not only to the reference entity but also to the default probability of the CDS seller itself. Finally, trading CDS for speculative purposes means that CDS spreads also contain a third bias related to the liquidity premium, which can lead to conflicting signals. For all these reasons, we propose in this essay an assumption in which using the volatility of CDS as a measure of credit risk is more appropriate than its first-order moment. Yet, studying the determinants of CDS volatility is still a sparse or at least an under-investigated financial issue[1]. Given the afore stated postulate, we are motivated to study the impact of some explanatory factors on the CDS volatility, with a particular emphasis on the impact of oil price and oil instability.

Some of the existence literature supposes a linear relationship between credit risk and oil price, using linear regression or an ARDL approaches, which ignores the fact that financial series clearly exhibit complex and nonlinear nature (Hammoudeh et al., 2013; Da Fonseca et al., 2016). This time series' joint characteristic is easily admitted since financial markets are highly unstable and crisis periods are frequently occurring, making CDS series subject to structural breaks, outliers and potential asymmetric effects. To overcome these gaps, Lahiani et al. (2016), Shahzad, Nor, Ferrer and Hammoudeh (2017) and Naifar et al. (2017) introduce the nonlinearity and asymmetries while studying the dynamics of CDS spreads. However, the adopted econometric approaches still neglect a prominent stylized fact of financial series, that is the long memory behavior. We use, in this essay, an extensive framework, that takes into account simultaneously long memory behavior and leverage effects, through a FIAPARCH model, and the nonlinearity of CDS volatility and the economic factors' asymmetric impacts, through a SETAR model.

3.3 Data and Methodology

This section presents the data sample and the financial and economic variables used as factors in the sovereign CDS spreads explanation. Yet, the cubic spline interpolation methodology

[1]As far as we are concerned, the only paper taking into account the volatility of CDS spreads, while studying the credit risk determinants is presented by Fender et al. (2012). Although the authors use a GARCH framework, they still only interested into the sensitivity of CDS and CDS spread changes to international and local risk factors.

used to convert quarterly and monthly time series into daily is introduced. Lastly, the econometric framework, including the FIAPARCH volatility model and the SETAR model, is as well displayed in this section.

3.3.1 Sample and variables description

The studied sample in this chapter is composed by some of the world's 25 biggest oil-producing countries and other worldwide countries belonging to different economic categories (developed countries, newly industrialized countries and emerging countries) and different geographical areas (Eastern Europe, South and Central America, Asia and Western Europe), leading to a total dataset of 38 countries. Table 3.1 presents the countries' sample with their economic and geographical status.

Table 3.1: Countries classification

	Country	Economic Status	Geographical position
Oil-producing countries	Norway	**Developed countries**	Western Europe
	UK		Western Europe
	USA		North America
	Brazil	**Newly industrialized countries**	South America
	China		Asia
	Mexico		North America
	Qatar		Asia
	Thailand		Asia
	Indonesia	**Emerging countries**	Asia
	Russia		Asia
	Venezuela		South America
Other worldwide countries	Austria	**Developed countries**	Western Europe
	Belgium		Western Europe
	Denmark		Western Europe
	Finland		Western Europe
	France		Western Europe
	Germany		Western Europe
	Ireland		Western Europe
	Italy		Western Europe
	Japan		Asia
	Latvia		Eastern Europe
	Lithuania		Eastern Europe
	Netherlands		Western Europe
	Portugal		Western Europe
	Slovakia		Eastern Europe
	Slovenia		Eastern Europe
	Spain		Western Europe
	Sweden		Western Europe
	Philippines	**Newly industrialized countries**	Asia
	Turkey		Asia
	Bulgaria	**Emerging countries**	Eastern Europe
	Croatia		Eastern Europe
	Czech		Eastern Europe
	Hungary		Western Europe
	Greece		Western Europe
	Poland		Eastern Europe
	Romania		Eastern Europe
	Ukraine		Eastern Europe

The list of oil-producing countries is collected from the Monthly Energy Review (May 2017) of the US Energy Information Administration (EIA). Countries classification into these categories is made according to the NU, the CIA world Factbook, the IMF and the World Bank criteria.

Daily 5-year sovereign CDS spreads, Brent crude oil price and the other explanatory variables are extracted from Thomson Reuters ®. The studied period ranges from January 2^{nd}, 2006 to March 31^{st}, 2017, comprising 2936 observations. To our knowledge, the period considered is the longest and the most recent timeline among the CDS studies. The use of daily frequency seems to be more relevant than other frequencies since it provides a huge amount of information with a better capture of short and mid-range spreads movements.

The explanatory factors used as exogenous variables in the SETAR model are presented in Table 3.2. Beyond the theoretical and empirical determinants identified in the literature and used as control variables, our regressions incorporate as well the consumer confidence index as a country-specific factor and the Thomson Reuters global index, the Brent crude oil price and the CBOE Crude Oil Volatility Index[1] as common factors. The use of these control variables is inspired by their potential explanatory power of credit risk level shown in the empirical literature. The first set of variables includes several financial and macroeconomic measures of the country's fundamentals, while the second set is comprised by global economy-wide factors to account for the international environment conditions. Note that the purpose of this essay is not to predict nor to explain credit spreads, but rather to investigate the sensitivity of credit risk to changes in oil market conditions.

Table 3.2: Variables description

Variables	Description	Expected relationship
Country-specific factors		
SMR	Daily log returns of national stock market index. This index measures the value of the most locally traded significant companies and is used to proxy the financial sector's health and the country's future prospects.	Positive financial market performance should reassure investors about the market outlook regarding its financial stability. A negative relation is thus expected between stock returns and the country's default risk.
RBY	Daily log returns of sovereign bond yields. This variable measures the default risk premium required by investors and proxies the country's credit risk category.	An increase in the bond yield implies an increase in risk perceptions by investors which is expected to lead to a rise in the market volatility and thus the credit risk level.
RGDP	Daily log returns of the nominal Gross Domestic Product. This variable measures the country's economic growth.	The economic expansion drives the diminishing of the future debt real weight which is expected to improve repayment ability and reduce the country's credit risk.
RDEBT	Daily log returns of the government total debt. As the leverage ratio for firms, the debt level should impact the country's default probability.	The more the debt burden is important, the more the economy is weak. A positive relationship is expected between the level of government indebtedness and the perceived default risk.
REDEBT	Daily log returns of the government external debt.	The level of foreign debt is expected to negatively impact the country's economic growth rate and thus its default probability. As the foreign debt is amplifying, the country international competitiveness is lessening.

[1]The OVX measures the Chicago Board Options Exchange's expectation of 30-day volatility of crude oil prices. This measure uses the same estimation methodology as the VIX. It is used in this essay to proxy the oil market uncertainty, as in Shahzad, Naifar, Hammoudeh and Roubaud (2017).

INF	Daily log returns of the Harmonized Consumer Prices (HICP-all items). The inflation is used as one of the government's public finances indicators.	No particular sign is expected for the relationship between inflation and the sovereign credit risk. In fact prices' increase may have different effects: Inflation was associated with economic growth during the 30 glorious years. However, during the 1970s a shift in the market reaction is observed (stagflation) due to economies' openness and international competitiveness harshness.
RCCI	Daily log returns of the Consumer confidence index. This measure is used as a proxy for the consumer sentiment toward the country's risk.	If the CCI decreases, then investors upward their perception of the sovereign risk and may require higher loan interest rates, burdening the public borrowing cost. Thus, a negative relation is expected between the consumer confidence level and the sovereign risk level.
Common factors		
RTRGI	Daily log returns of the Thomson Reuters global index. This index is highly representative of the international stock market performance, covering over 97% market caps from 51 worldwide markets.	Stock returns are closely related to the economic growth and should thus negatively impact credit risk. So, the higher this index is, the less probably the default is expected to occur.
VIX	Daily volatility index based on the implied volatility of the S&P500 index options for the next 30 days. This measure proxies the investors' aversion towards worldwide credit risk.	The more this index is high, the more the uncertainty and risk aversion are observed on the global stock market. The VIX is thus expected to be positively correlated with the default likelihood.
RWTI	Daily log returns of the West Texas Intermediate Brent crude oil prices	-
OVX	Daily CBOE Crude Oil Volatility Index	-

Logically, a positive shock on oil price drives to a deterioration in the economic situation of oil-consuming countries, whilst this leads to an improvement in the financial and macroeconomic conditions of the oil-producing countries. In fact, an increase in oil price is expected to rise the financial health, the public finances sustainability and thus the creditworthiness uncertainty of oil-related countries. Contrarily, a negative relationship is expected between oil shocks and the economic growth of oil-consuming countries, which implies that a rise in energy prices leads to weaken the ability of these countries to repay their debts and awaken investors credit risk aversion. In fact, the more the oil price is important, the more the import costs are high, the greater budgetary expenditures are and the more the country's public health is consistent - as reflected in the CDS spreads volatility. Finally, some statistically insignificant relationships should be observed between oil prices and CDS volatility of some countries that are not big producers of oil but are self-reliant with their oil needs. In these countries the government reimbursement ability is not or very little sensitive to oil fluctuations.

3.3.2 Data treatment: A cubic spline interpolation

As larger frequency data improves estimation results in macroeconomic field (Andreou et al., 2013), we use a daily interval time series data. Although our main data (CDS spreads and oil price) are directly extracted in the right frequency, some macroeconomic series are only available in monthly, quarterly or even annual frequency (GDP, Total debt, HICP ...). We need, thus, to convert time series with lower frequency to the same time interval through one of the most commonly used method: the Cubic Spline Interpolation, following Boateng et al. (2015), Li and Chau (2016) and Abeygunawardana et al. (2017).

This approximation technique allows us to get a smooth estimate of unknown observations. Between each two points, a piecewise continuous curve is drawn to connect them, using a 3^{rd} degree polynomial function. The detailed step-by-step method is presented in section 3.8.

3.3.3 Econometric models

The sensitivity of sovereign CDS volatility to oil shocks is investigated, through a two-step process: **(1)** A univariate FIAPARCH volatility models are fit for the CDS spreads series to obtain the conditional volatility $\sigma_{i,t}$ of each market. **(2)** The estimated volatility is explained with regard to its own lagged values and local and global variables chosen from the literature. We use a nonlinear time series model that allows for regime-switching, so-called Self-Exciting Threshold Auto-Regressive (SETAR).

Step1. AR(1)-FIAPARCH(1,d,1):

We employ the univariate FIAPARCH model as an estimator of CDS historical volatility. The use of such class of model is motivated by the work of Sabkha and de Peretti (2018), in which they show that the use of Fractionally-Integrated Generalized AutoRegressive Conditionally Heteroskedastic class of models instead of a standard GARCH model improves the conditional variance flexibility and takes account of more GARCH specifications in the volatility process. For each country, time series are assumed to follow an AR(1) process such as,

$$x_t = ln(S_t) - ln(S_{t-1}) = a_0 + a_1 x_{t-1} + \varepsilon_t, \tag{3.1}$$

with S_t denotes the time series of a country from the sample at time t, a_0 is a constant, $|a_1| < 1$ and $\varepsilon_t = e_t \sigma_t$, with e_t constitutes a white noise with $E(e_{t-1}^2) = 1$. σ_t^2 is a positive parameter representing the conditional variance of x_t such as $\sigma_t^2 = Var(x_t|\mathcal{F}_{t-1})$ with $\mathcal{F}_t$ is the market information set at a given moment t.

The FIAPARCH model of Tse (1998) is estimated as follows:

$$\sigma_t^\delta = \alpha_0(1-\beta)^{-1} + [1-(1-\beta(L))^{-1}\phi(L)(1-L)^d](\mid \varepsilon_t \mid -\gamma\varepsilon_t)^\delta. \tag{3.2}$$

With $0 < d < 1$, L is the lag operator and $(1-L)^d$ is the financial fractional differencing operator. δ depicts the Box-Cox power transformation of the conditional volatility (σ_t), and satisfies the condition of $\delta >= 0$.

The FIAPARCH is an extension of the conventional fractionally integrated GARCH model (FIGARCH) (Baillie et al., 1996). This new approach combines the long-range dependencies feature and the asymmetric impact of lagged positive and negative shocks on future volatility in one fractionally integrated model.

Step 2. Self-Exciting Threshold Auto-Regressive (SETAR):

The CDS conditional volatility estimated from the FIAPARCH(1,d,1) is incorporated as a dependent variable in a short-run time series model, called a Self-Exciting Threshold Auto-Regressive model (Tong and Lim, 2009) with exogenous variables. The adoption of a regime-switching model seems to be useful and appropriate, since the oil price and the other control variables are not supposed to play a constant role over time, and may be subject to structural changes.

The two-regime SETAR model for a time series y_t with two-regime is written as follows:

$$y_t = [(\omega_1+\sum_{i=1}^{k}\theta_{1,i}y_{t-i}+\sum_{j=1}^{n}\Phi_{1,j}y_{j,t}^{'}+\xi_{1,t})\zeta(y_{t-h}\leq\chi)]+[(\omega_2+\sum_{i=1}^{k}\theta_{2,i}y_{t-i}+\sum_{j=1}^{n}\Phi_{2,j}y_{j,t}^{'}+\xi_{2,t})\zeta(y_{t-h}>\chi)], \tag{3.3}$$

with y_t is the estimated conditional volatility of the CDS spreads at time t, k and n are respectively the lag order of the autoregressive process and the number of exogenous variables in the model and $\xi_{m,t}$ are the residuals such as $\xi_{m,t} \sim \mathcal{D}(0,\sigma_m^2)$ with $m = \{1,2\}$ represents the regime. $\zeta(.)$ is an indicative function that equals to 1 if the condition in parentheses is respected and 0 otherwise, h is the length delay and χ is the threshold parameter chosen automatically by the numerical optimization based on the Broyden-Fletcher-Goldfarb-Shanno (BFGS) method (Shanno, 1985).

We follow in this essay the three-step Tong's method (Tong and Yeung, 1991) for estimating the SETAR model. Other methods exist in the literature as to the appropriate technique for estimating the model parameters (Hansen's method (Hansen, 1997), Tsay's method (Tsay, 1989)...) (See Fırat (2017) for a detailed discussion on modeling SETAR based on these latter methods, for European GDP data and euro, dollar and Turkish pound exchange rates respectively). First, the relevant autoregressive level (k) is determined using the partial auto-correlation coefficients function (PACF). The lag order selection may also be done according to the AIC (or another information criterion), by supposing that h and χ are constant, such as:

$$\widehat{k} = min\{AIC(y_k)\}, \text{for } k = 1,2,3. \tag{3.4}$$

However, Tsay (1989) argue that the presence of a non-linear dynamism in our estimated process makes information criteria irrelevant in selecting the autoregression order. Second, the threshold variable (y_{t-h}), that leads to switch from one regime to another, is nothing but a lagged value of the dependent variable (conditional volatility here). The appropriate lag specification (h)is assumed to be known (constant) while the threshold value (χ) is chosen automatically using the information criterion AIC (χ parameter that minimizes the value of the $AIC(h,\widehat{\chi})$ is selected among all the possible threshold values), such as:

$$(\widehat{h},\widehat{\chi}) = min\{AIC(h,\chi)\}. \tag{3.5}$$

Third, after determining k and χ values, the threshold variable's lag specification h is selected is such a way that minimizes the NAIC(h) criterion. According to Tong and Yeung (1991), since the value of h will impact the number of observations (T) in each sub-sample of the two regimes, using the NAIC criterion instead of the ordinary AIC criterion is more appropriate.

$$\widehat{h} = min\{NAIC(k,\chi\}, \text{with } NAIC = \frac{AIC}{T-T_h}. \tag{3.6}$$

Usually and following the recommendation of the Tong's method, we should use the information criteria to select the best fitted model. However, since the number of our model parameters isn't time-varying then, minimizing the sum of squared residuals (SSR) gives the same result as minimizing the information criteria. The h selection is therefore determined such as:

$$\widehat{h} = min\{SSR(k, \chi\} \tag{3.7}$$

The self-exciting model is more adequate because it considers more features of the volatility series than what is usually considered in conventional linear model: Unlike basic autoregressive models where the parameters are constant at any time, ω_m, θ_m, Φ_m and ξ_m are allowed, in the threshold autoregressive model, to change between regimes and to have two values depending on whether the market is upward or downward.

Along with these lines, a self-exciting model is proposed to explain the volatility rather than the commonly used linear model for several reasons: (i) the nonlinearities of our volatility series are taken into account, (ii) the flexibility of the model regarding the parameters' behavior during the regime switching and (iii) the threshold variable is set as to depend on the past values of the dependent variable (the CDS volatility here).

3.4 Results

3.4.1 Data analysis

Table 3.3 displays summary statistics on the oil price and the CDS spreads of each country. The mean value of the oil price is 76.90 USD over the 195 studied months. Figure 3.1 shows that the price of a barrel of crude oil reaches historical levels by the end of 2007 - probably due to strong demand and weakness of the dollar exchange rate. These reactions result from the increase in the investors' aversion after the appearance of the first signals of the US recession. Countries CDS spreads present dissimilar variability, with the maximum values recorded in Venezuela, Greece and Ukraine. The average CDS spread highly fluctuates from one country to another and doesn't seem to depend on whether the country is an oil-producer or not. CDS spreads exhibit high standard deviations, which indicates that the time series present several extreme values (This could be explained by the fact that our studied period includes several financial turmoil that causes unusual changes, such as the enormous increases in CDS levels after the European sovereign debt outbreak.). Finally, the Augmented-Dickey Fuller test show that the oil crude prices and the CDS spreads of each country are not stationary at 5% level, implying that the studied CDS series exhibit leptokurtic properties.

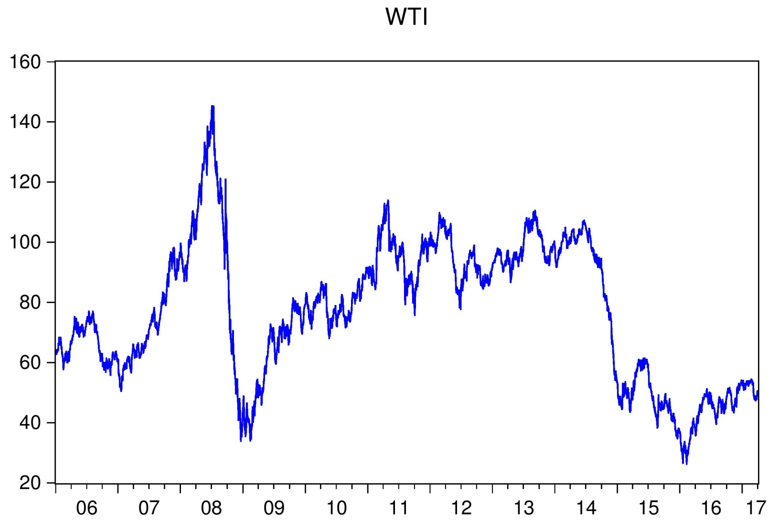

Figure 3.1: West Texas Intermediate oil price

As we need relevant statistics, the exogenous variables included in the SETAR have to be stationary as well. These time series properties are further investigated through the Augmented-Dickey Fuller unit root test (Results are presented in Table 3.7, section 3.9). Results show that our explanatory economic and financial variables exhibit non-stationary behavior at least at the 5% statistical level, and need thus to be stationarized through the use of mathematical techniques. For each country under study and each variable, daily returns are calculated following $y_t^{'} = ln(\frac{p_t}{p_{t-1}})$, with p_t is the variable value at time t. The logarithmic return transformation is used in this essay rather than the first difference because it allows for better suitability of time series' distributional characteristics.

Table 3.3: Descriptive statistics and non-stationary tests of CDS spreads and oil prices

	Obs.	**Min**	**Mean**	**Max**	**Std. Dev**	**ADF statistics**	
Oil Price reference							
West Texas Intermediate (WTI)	2936	26.21	76.90	145.29	22.96	-1.82	
CDS spreads							
Panel A: Oil-producing countries							
Norway	2936	10.59	30.95	62.00	17.82	-1.68	
UK	2936	16.50	42.89	165.00	28.11	-2.07	
USA	2936	10.02	24.01	90.00	11.11	-3.58	*
Brazil	2936	61.50	178.55	606.31	94.86	-2.46	

China	2936	10.00	82.44	276.30	43.56	-2.82	*
Mexico	2936	64.17	141.89	613.11	59.36	-3.03	*
Qatar	2936	7.80	83.13	390.00	53.89	-2.12	
Thailand	2936	51.01	120.94	500.00	41.89	-3.64	*
Indonesia	2936	118.09	219.29	1240.00	116.83	-2.63	*
Russia	2936	36.88	209.09	1106.01	147.84	-2.95	*
Venezuela	2936	124.62	1771.08	10995.67	1869.79	-2.00	
Panel B: Other worldwide countries							
Austria	2936	1.40	36.13	132.77	24.96	-2.45	
Belgium	2936	2.05	72.39	398.78	74.62	-1.67	
Denmark	2936	11.25	36.65	157.46	32.94	-2.17	
Finland	2936	2.69	26.85	94.00	19.24	-2.33	
France	2936	1.50	54.30	245.27	50.56	-1.71	
Germany	2936	1.40	28.77	118.38	24.50	-2.05	
Ireland	2936	1.75	188.89	1249.30	234.02	-1.36	
Italy	2936	5.57	151.75	586.7	127.38	-1.79	
Japan	2936	2.13	49.26	152.64	33.28	-1.94	
Latvia	2936	5.50	210.89	1176.30	216.13	-1.62	
Lithuania	2936	6.00	169.21	850.00	154.01	-1.90	
Netherlands	2936	7.67	37.13	133.84	29.50	-2.00	
Portugal	2936	4.02	289.89	1600.98	323.68	-1.60	
Slovakia	2936	5.33	77.52	306.01	66.71	-2.03	
Slovenia	2936	4.25	131.24	488.58	114.88	-1.65	
Spain	2936	2.55	144.63	634.35	135.01	-1.56	
Sweden	2936	1.63	27.17	159.00	25.70	-2.64	*
Philippines	2936	78.30	188.72	840.00	101.70	-1.77	
Turkey	2936	109.82	217.65	835.01	72.41	-3.72	*
Bulgaria	2936	13.22	180.37	692.65	121.88	-2.25	
Croatia	2936	24.88	244.20	592.50	128.47	-2.15	
Czech	2936	3.41	66.89	350.00	49.54	-2.62	*
Hungary	2936	17.34	225.98	729.89	153.05	-2.18	
Greece	2936	5.20	9508.85	37081.41	15351.1	-1.46	
Poland	2936	7.67	101.35	421.00	73.12	-2.32	
Romania	2936	17.00	204.20	767.70	144.17	-2.09	
Ukraine	2936	1.00	2173.76	15028.76	3969.28	-2.15	

The table reports descriptive statistics for the daily WTI oil price and CDS spreads expressed in basis points. Min., Max. and Std. Dev. denotes respectively to the minimum, the maximum and the standard deviation. The Augmented-Dickey Fuller (Individual intercept included in the test equation) is a stationary test, with the null hypothesis is defined as the presence of a unit root in the process (non-stationary time series). *, ** and *** refer to statistical significance at respectively 10%, 5% and 1%.

Results of the preliminary statistical tests on the CDS spreads log returns (Table 3.4) show that no time series is normally distributed, with the highest Excess Kurtosis values are observed for Ireland, Greece and Ukraine. Residuals are, thus, allowed to follow a Gaussian, a student and a Generalized Error Distribution (G.E.D). The Engle's ARCH-LM test with 2, 5 and 10 lag orders detects autocorrelations in the squared residuals and confirms the presence of ARCH effects in all the studied time series (Except for CDS of Greece). CDS spreads also exhibit high persistence in volatility (Except for CDS of Greece), according to the results of the log periodogram test of Geweke and Porter-Hudak (1983). The box plots, displayed in Figure 3.2, show that the median is in most cases not in the center of the box, indicating that the dataset is asymmetric. The use of FIAPARCH(1,d,1) model to estimate the dynamic

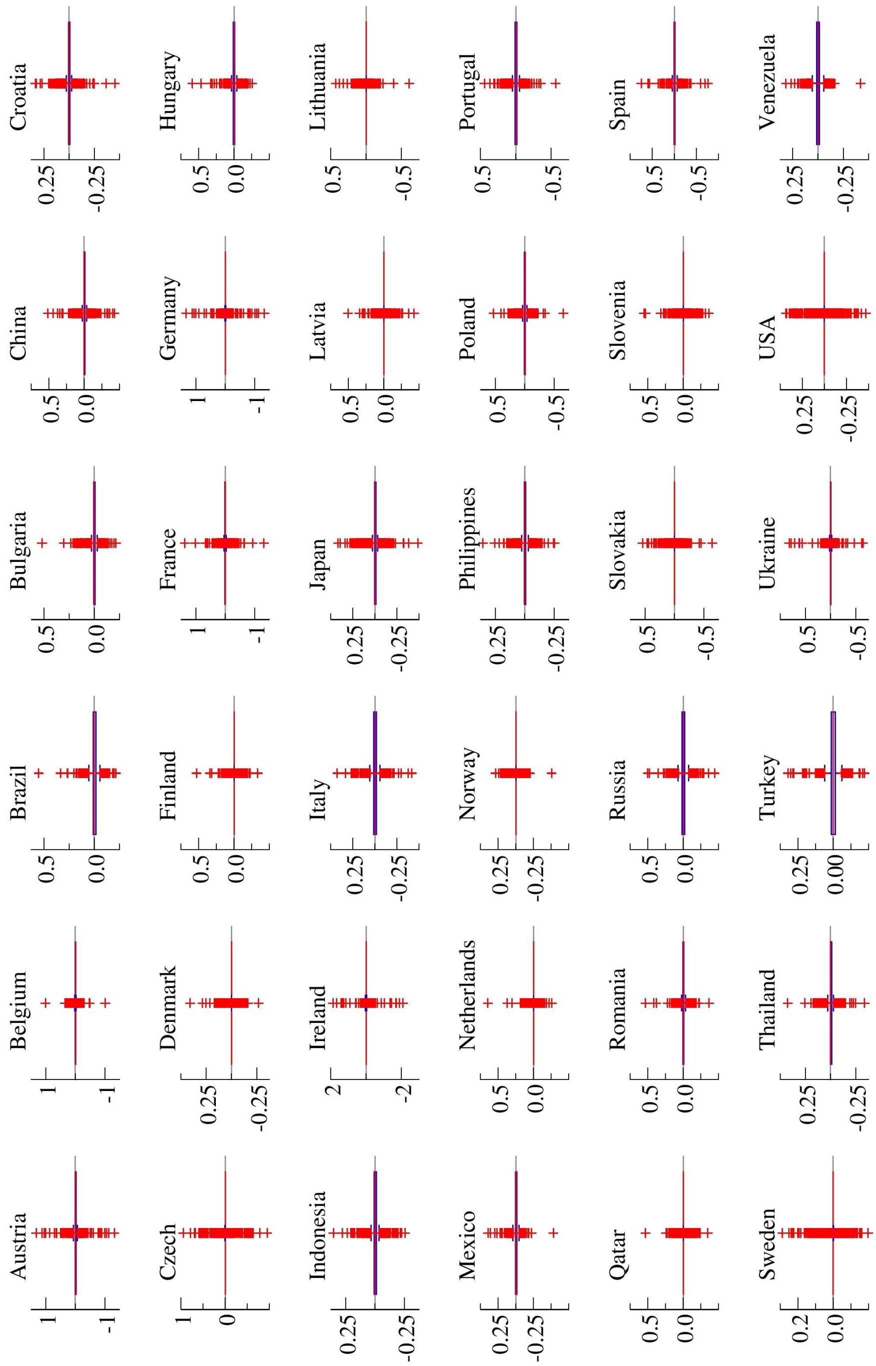

Figure 3.2: Box plots for daily CDS spreads

conditional volatility - allowing for long-memory behavior and asymmetric effects - is, thus, justified.

Table 3.4: Preliminary tests on the CDS log-returns

	Skweness		Excess Kurtosis		Jarque-Bera		ARCH-LM (2)		ARCH-LM (5)		ARCH-LM (10)		GPH	
Panel A: Oil-producing countries														
Norway	-1.15	***	47.63	***	2.8E+05	***	3.22	***	2.46	***	2.06	***	0.05	**
UK	0.89	***	21.38	***	56263	***	27.33	***	21.12	***	23.19	***	0.11	***
USA	0.33	***	12.64	***	19581	***	94.96	***	46.67	***	24.57	***	0.18	***
Brazil	1.89	***	27.49	***	94159	***	25.01	***	43.70	***	37.71	***	0.11	***
China	0.67	***	33.49	***	1.4E+05	***	120.85	***	63.09	***	39.00	***	0.22	***
Mexico	0.20	***	35.65	***	1.5E+05	***	356.35	***	160.17	***	127.50	***	0.39	***
Qatar	1.38	***	32.85	***	1.3E+05	***	37.65	***	17.33	***	9.55	***	0.09	***
Thailand	0.63	***	24.38	***	72831	***	81.52	***	120.36	***	96.33	***	0.17	***
Indonesia	0.80	***	17.02	***	35720	***	139.82	***	105.31	***	61.49	***	0.23	***
Russia	0.69	***	20.97	***	54004	***	258.09	***	117.58	***	65.50	***	0.29	***
Venezuela	0.25	***	13.51	***	22350	***	36.17	***	38.56	***	22.73	***	0.11	***
Panel B: Other worldwide countries														
Austria	-0.28	***	60.66	***	4.5E+05	***	249.75	***	127.05	***	72.58	***	0.29	***
Belgium	0.02		127.85	***	2.0E+06	***	508.94	***	237.99	***	120.84	***	0.18	***
Denmark	1.63	***	27.89	***	96409	***	87.27	***	41.66	***	24.36	***	0.21	***
Finland	1.66	***	42.55	***	2.2E+05	***	13.79	***	7.98	***	4.43	***	0.05	***
France	0.59	***	68.15	***	5.7E+05	***	276.95	***	120.56	***	62.86	***	0.20	***
Germany	-0.28	***	72.62	***	6.4E+05	***	252.46	***	128.31	***	73.27	***	0.29	***
Ireland	-0.56	***	113.67	***	1.6E+06	***	218.63	***	103.01	***	63.33	***	0.18	***
Italy	0.23	***	15.55	***	29572	***	127.35	***	60.46	***	35.18	***	0.19	***
Japan	0.44	***	19.96	***	48796	***	71.53	***	31.30	***	21.68	***	0.13	***
Latvia	0.95	***	55.28	***	3.7E+05	***	152.57	***	68.47	***	35.36	***	0.26	***
Lithuania	-0.29	***	95.62	***	1.1E+06	***	56.75	***	26.91	***	13.56	***	0.15	***
Netherlands	3.52	***	69.22	***	5.9E+05	***	10.79	***	4.33	***	5.59	***	0.05	***
Portugal	0.00	***	18.84	***	43385	***	53.57	***	42.23	***	22.61	***	0.17	***
Slovakia	0.66	***	41.44	***	2.1E+05	***	25.14	***	24.62	***	19.31	***	0.11	***
Slovenia	2.59	***	65.14	***	5.2E+05	***	13.23	***	9.82	***	34.88	***	0.11	***
Spain	-0.09	***	50.27	***	3.1E+05	***	195.02	***	78.80	***	39.98	***	0.19	**
Sweden	1.30	***	14.67	***	27127	***	69.49	***	30.82	***	20.72	***	0.16	***
Philippines	0.68	***	18.97	***	44205	***	154.83	***	127.66	***	90.03	***	0.23	***
Turkey	1.12	***	13.91	***	24252	***	69.04	***	86.65	***	46.84	***	0.21	***
Bulgaria	2.37	***	34.43	***	1.5E+05	***	12.71	***	10.36	***	6.72	***	0.08	***
Croatia	-0.50	***	37.86	***	1.8E+05	***	137.90	***	58.87	***	47.62	***	0.26	***
Czech	-0.19	***	36.85	***	1.7E+05	***	62.52	***	46.01	***	29.50	***	0.14	***
Hungary	2.78	***	42.73	***	2.3E+05	***	14.48	***	15.20	***	8.67	***	0.10	***
Greece	-29.18	***	129.45	***	2.1E+08	***	5.E-04		4.E-04		6.E-04		-4.E-04	
Poland	0.22	**	41.33	**	2.1E+05	**	311.98	**	135.64	**	75.78	**	0.21	***
Romania	2.55	***	55.64	***	3.8E+05	***	57.88	***	33.74	***	17.50	***	0.17	***
Ukraine	3.99	***	106.61	***	1.4E+06	***	60.42	***	32.53	***	17.13	***	0.11	***

The Engle's ARCH-LM test with 2, 5 and 10 lag orders informs about the presence of ARCH effects in the series, under the null hypothesis of no autocorrelations in the squared residuals. GPH (Geweke and Porter-Hudak) is the log periodogram test of Geweke and Porter-Hudak (1983) with d-parameter m=1467. This test is applied to the squared logarithmic returns (as proxy for unconditional volatility) to detect any long-range dependence under the null assumption of no long-memory behavior in the volatility process. *, ** and *** denote significance at respectively 10%, 5% and 1% statistical levels.

3.4.2 Empirical findings

As the first step of our econometric framework is to estimate the conditional volatility, we present in Table 3.8 (section 3.10) the results of the AR(1)-FIAPARCH(1,d,1) estimation for each country. The autoregressive term in the mean equation is almost always significantly positive, which indicates the instantaneous incorporation of past information into current CDS spreads. All CDS spreads (Other than Norway, China and Thailand) exhibit statistically significant fractional differencing parameters (d), which implies that the persistence of a shock on the conditional volatility of CDS spreads follows a hyperbolic rate of decay and supports thus the use of fractional integrated model. The GARCH parameters (ϕ and β) are positive and mainly significant, respecting the model condition of nonnegativity. The leverage effect parameter (γ) is significant, as well, in most cases, which means that losses on CDS operations have a bigger impact on future volatility than do gains. These coefficients estimators confirm, thus, once again, the appropriate use of the AR(1)-FIAPARCH(1,d,1).

The behavioral analysis of the generated time series is conducted through the Bai and Perron (2003) test. In this essay, the structural breaks test accounts for only two regimes: a 1^{st} stable regime corresponds to a low conditional volatility and a 2^{nd} risky regime with a high conditional volatility. Results, presented in Table 3.9 (section 3.11), show a strong evidence of regime shifts pattern in all volatility series with a rejection at 5% significance level of the null hypothesis of a zero threshold transition. Therefore, the CDS volatility series of the 38 studied countries are characterized by significant nonlinearities over time, justifying the use of a regime-switching model.

As already mentioned, the optimal number of lags in the threshold variable specification is chosen based on the sum of squared residuals criteria (See Table 3.5). It is clearly found that the optimal number of lag specifications is different from one country to another. The threshold variable is set using the Bai-Perron breakpoint tests (Bai and Perron, 2003) with a maximum break of 1 and a trimming percentage[1] equal to 15.

Results of the self-excited TAR model with exogenous variables, reported in Table 3.6 and Table 3.10 (section 3.12), reveal some interesting findings. The threshold parameter ($\widehat{\chi}$) is positive for all the studied countries. The highest threshold value is observed in France (0.0168), meaning that this CDS market needs greater volatility increase than the other markets, to get excited. Yet, Belgium ($\widehat{\chi} = 0.0001$), Netherlands ($\widehat{\chi} = 0.0002$), Greece ($\widehat{\chi} = 0.0003$) and Romania ($\widehat{\chi} = 0.0002$) record the lowest threshold values, making them easily excitable with a higher likelihood of switching to the 2^{nd} regime.

Table 3.5: Selection of the threshold variable specification

Sum of Squared Residuals (SSR)						
	VOL_{t-1}	VOL_{t-2}	VOL_{t-3}	VOL_{t-4}	VOL_{t-5}	VOL_{t-6}
Panel A: Oil-producing countries						
Norway	0.0030	0.0031	0.0031	0.0031	0.0031	0.0031
UK	0.0064	0.0065	0.0065	0.0065	0.0066	0.0064
USA	0.1096	0.1126	0.1126	0.1162	0.1151	0.1168
Brazil	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003
China	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003
Mexico	0.0031	0.0031	0.0031	0.0031	0.0031	0.0032
Qatar	0.0009	0.0009	0.0009	0.0009	0.0009	0.0009
Thailand	0.0026	0.0025	0.0026	0.0026	0.0026	0.0026
Indonesia	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003
Russia	0.0127	0.0128	0.0129	0.0129	0.0127	0.0128
Venezuela	0.0082	0.0083	0.0083	0.0083	0.0084	0.0085
Panel B: Other worldwide countries						
Austria	0.0076	0.0074	0.0072	0.0074	0.0072	0.0074
Belgium	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Denmark	0.0049	0.0049	0.0049	0.0050	0.0050	0.0050
Finland	0.0126	0.0122	0.0126	0.0126	0.0126	0.0126

[1]The minimum length of each sub-sample is equal to 15% of the total observations number.

France	0.5935	0.5733	0.5873	0.5920	0.5864	0.5849
Germany	1.7902	1.6109	1.6897	1.8114	1.7599	1.7756
Ireland	2.1551	1.9232	2.0980	2.0811	2.1505	2.1566
Italy	0.0257	0.0247	0.0258	0.0251	0.0259	0.0257
Japan	0.0086	0.0085	0.0086	0.0086	0.0087	0.0087
Latvia	0.0752	0.0755	0.0749	0.0748	0.0758	0.0752
Lithuania	0.0432	0.0431	0.0434	0.0434	0.0434	0.0435
Netherlands	0.0042	0.0042	0.0043	0.0038	0.0039	0.0041
Portugal	0.1495	0.1468	0.1472	0.1479	0.1462	0.1484
Slovakia	0.0882	0.0891	0.0890	0.0902	0.0904	0.0900
Slovenia	0.0204	0.0204	0.0207	0.0207	0.0209	0.0209
Spain	0.0679	0.0612	0.0671	0.0674	0.0675	0.0655
Sweden	0.0019	0.0019	0.0020	0.0019	0.0020	0.0020
Philippines	0.0661	0.0675	0.0682	0.0690	0.0701	0.0698
Turkey	0.0021	0.0020	0.0021	0.0020	0.0021	0.0022
Bulgaria	0.1210	0.1215	0.1197	0.1209	0.1211	0.1214
Croatia	0.0160	0.0156	0.0161	0.0163	0.0163	0.0161
Czech	0.0139	0.0139	0.0139	0.0140	0.0140	0.0142
Hungary	0.0829	0.0818	0.0817	0.0820	0.0827	0.0825
Greece	0.0049	0.0028	0.0028	0.0047	0.0049	0.0049
Poland	0.0258	0.0256	0.0260	0.0259	0.0258	0.0258
Romania	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Ukraine	0.0346	0.0339	0.0339	0.0339	0.0339	0.0340

This table reports the Sum of Squared Residuals (SSR) for each model with lag orders from 1 to 6. The chosen model is the one that minimizes the SSR.

As expected, the coefficient estimates of the regressors (ω, θ_i, Φ_j) vary from one regime to another. Some dissimilarities in the explanatory power of the exogenous variables are observed between regimes and across countries. Even though its past value coefficient is always highly positive and significant regardless the regime, CDS volatility seems to be, for the most, more sensitive to previous shocks during the stable state compared to the risky state. Regarding the control variables, no common determinants are observed for the studied countries and reaction degree of CDS volatility to economic and financial factors seems to vary strongly from one country to another and from one regime to another.

Since the purpose of this essay is to study the impact of oil price and uncertainty on CDS volatility, we are more interested in the WTI and OXV coefficients. During the stable period (1^{st} regime), the role played by oil price and oil uncertainty in determining the level of credit risk is, to say the least, trivial with a significant impact only detected in respectively one (Bulgaria) and 7 countries, out of the 38 studied countries. None of these impacted countries belong to the oil-producing category. The explanatory power of oil price seems to be more important during the 2^{nd} regime. Oil price significantly impacts, henceforth, the CDS volatility of 25 countries, representing 66% of our studied sample. More particularly, CDS volatility of oil-producing countries are more sensitive to oil price fluctuations, with significant coefficients in 91% of the sub-sample. Similarly, CDS markets become more sensitive to oil uncertainty, though in a lesser extent, with only 18 countries involved. Thus, movements in the international oil market have greater influence on credit volatility when the CDS markets are excited.

Focusing on oil-producing countries during the 2^{nd} regime, oil price has a negative impact in most cases (A positive relationship is only observed in the USA, Brazil and Thailand), although with varied magnitudes. With a threshold value equal to 0.0018, Thailand is the most sensitive CDS market to oil price fluctuations, even though the expected sign is not respected.

Table 3.6: Estimation results of the SETAR(1) for oil-producing countries

	Norway		UK		USA		Brazil		China	
T. variable	VOL_{t-1}		VOL_{t-6}		VOL_{t-1}		VOL_{t-2}		VOL_{t-4}	
T. value	0.0014		0.0010		0.0090		0.0013		0.0012	
	Regime 1	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***
Obs.	2492	439	2451	469	2492	443	2492	442	2393	539
C	-0.0002***	0.0017***	0.0006*	-0.0002	-0.0017	0.0396***	-0.0001	-0.0009***	-0.0003**	-0.0003
	(0.0001)	(0.0002)	(0.0004)	(0.0015)	(0.0020)	(0.0056)	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Vol_{t-1}	1.0932***	0.0656***	0.4038***	0.6995***	1.1258***	0.1748***	0.9485***	0.9022***	1.1121***	0.9708***
	(0.0633)	(0.0212)	(0.0210)	(0.0214)	(0.0582)	(0.0225)	(0.0178)	(0.0085)	(0.0178)	(0.0050)
SMR	0.0022	-0.0046*	-0.0032	0.0169***	-0.0059	-0.0029	0.0020***	0.0050***	-0.0002	-0.0007
	(0.0014)	(0.0027)	(0.0030)	(0.0051)	(0.0108)	(0.0269)	(0.0005)	(0.0008)	(0.0004)	(0.0006)
RBY	0.0002	-0.0002	0.0000	0.0018**	-0.0001	-0.0051**	0.0000	-0.0004	0.0000	-0.0010**
	(0.0003)	(0.0004)	(0.0002)	(0.0007)	(0.0012)	(0.0026)	(0.0001)	(0.0003)	(0.0003)	(0.0004)
RGDP	-0.0442	0.2754*	-0.1517***	-0.0450	1.8165	12.0490	2.8085	-276.3434	0.0164	-0.0337
	(0.0706)	(0.1618)	(0.0541)	(0.0988)	(3.2376)	(10.5445)	(97.6948)	(269.8486)	(0.0378)	(0.1701)
RDEBT	0.0036	0.1067***	-0.4487***	0.0831	0.1640	1.3727*	-2.8121	276.1857	0.0390	0.0057
	(0.0084)	(0.0397)	(0.1419)	(0.5204)	(0.3323)	(0.8208)	(97.6948)	(269.8482)	(0.0365)	(0.0868)
REDEBT	0.0086	-0.0184	-0.0056	-0.0595	-1.4768	-23.7262***	-0.0064	-0.1153***	-0.0208	-0.0224
	(0.0266)	(0.0771)	(0.0456)	(0.0899)	(1.3564)	(4.0890)	(0.0135)	(0.0312)	(0.0130)	(0.0482)
INF	0.0086	-0.4853**	0.1058	0.2641	-0.0731	-0.5608	-0.0102	0.2196	0.0035	0.2375***
	(0.0837)	(0.1885)	(0.2144)	(0.5193)	(0.8853)	(2.6548)	(0.0582)	(0.1760)	(0.0265)	(0.0526)
RCCI	0.0001	-0.0057**	-3.79E-05	0.0042***	0.0216	-0.3348***	0.0004	-0.0708***	-0.0024	0.0195
	(0.0002)	(0.0026)	(0.0002)	(0.0005)	(0.0242)	(0.0613)	(0.0043)	(0.0104)	(0.0064)	(0.0199)
RTRGI	3.33E-06	0.0000**	-5.20E-06***	2.33E-06	9.64E-06	-0.0002***	7.70E-07*	4.55E-06***	1.18E-06**	9.40E-07
	(2.61E-06)	(0.0000)	(1.98E-06)	(8.93E-06)	(8.51E-06)	(2.82E-05)	(4.65E-07)	(1.27E-06)	(5.94E-07)	(1.18E-06)
VIX	7.28E-06*	0.0000***	3.63E-05***	3.64E-05**	3.65E-05	4.03E-05	4.49E-06**	2.75E-05***	8.96E-07	7.59E-06***
	(3.80E-06)	(0.0000)	(8.38E-06)	(1.52E-05)	(3.06E-05)	(0.0001)	(1.77E-06)	(3.01E-06)	(1.86E-06)	(2.78E-06)
RWTI	-0.0012*	-0.0012*	-0.0005	-0.0067**	0.0060	0.0356**	0.0005	0.0038***	0.0001	-0.0017***
	(0.0011)	(0.0021)	(0.0015)	(0.0032)	(0.0060)	(0.0165)	(0.0003)	(0.0006)	(0.0003)	(0.0005)
OVX	-	-	-3.20E-06	-1.32E-05	6.06E-06	-0.0001**	-8.43E-07	-3.77E-06*	4.76E-07	-9.94E-07
	-	-	(3.75E-06)	(8.19E-06)	(1.51E-05)	(3.89E-05)	(8.89E-07)	(1.98E-06)	(8.00E-07)	(1.98E-06)

	Mexico		Qatar		Thailand		Indonesia		Russia	
T. variable	VOL_{t-2}		VOL_{t-5}		VOL_{t-2}		VOL_{t-2}		VOL_{t-5}	
T. value	0.0018		0.0007		0.0018		0.0011		0.0025	
	Regime 1	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***
Obs.	2481	453	2492	439	2494	440	2493	441	2427	498
C	-0.0001	-0.0023***	-0.0002	-0.0007**	0.0000	-0.0048***	0.0000	-0.0008***	-0.0010*	-0.0007
	(0.0003)	(0.0009)	(0.0002)	(0.0004)	(0.0002)	(0.0008)	(0.0001)	(0.0003)	(0.0006)	(0.0013)
VOL_{t-1}	0.9639***	0.9287***	0.7574***	0.8549***	1.0175***	0.8092***	0.9790***	0.9611***	0.6695***	0.8676***
	(0.0384)	(0.0067)	(0.0205)	(0.0114)	(0.0334)	(0.0113)	(0.0227)	(0.0071)	(0.0253)	(0.0106)
SMR	-0.0025	-0.0131***	-0.0013	- -	0.0010	0.0196***	-0.0001	-0.0017*	-0.0034	-0.0083***
	(0.0020)	(0.0032)	(0.0009)	-	(0.0017)	(0.0026)	(0.0006)	(0.0009)	(0.0025)	(0.0030)
RBY	0.0009	0.0152***	-	-0.0043***	-0.0009	0.0057***	0.0002	-0.0022***	0.0021	-0.0013
	(0.0018)	(0.0033)	-	(0.0013)	(0.0012)	(0.0018)	(0.0004)	(0.0007)	(0.0023)	(0.0033)
RGDP	0.0179	0.0922	0.0043	-0.1005***	0.0164	0.3815***	-0.0035	-0.1466***	0.0234	0.1777***
	(0.0532)	(0.1236)	(0.0129)	(0.0302)	(0.0334)	(0.1051)	(0.0150)	(0.0462)	(0.0200)	(0.0478)
RDEBT	-0.0043	-0.4194***	0.0154	0.0853	-0.0058	-0.0561	0.0065	0.2614***	-0.0775	0.6869**
	(0.0290)	(0.0540)	(0.0251)	(0.0763)	(0.0304)	(0.0662)	(0.0175)	(0.0552)	(0.1291)	(0.2983)
REDEBT	-0.0106	-0.3085***	-0.0177	-0.0941	-0.0372	0.3405***	0.0012	-0.0640	-0.0516	-0.3717***
	(0.0393)	(0.0883)	(0.0286)	(0.0946)	(0.0348)	(0.0977)	(0.0135)	(0.0553)	(0.0588)	(0.1331)
INF	0.0136	-0.0174	-0.0692	-0.1633	0.0164	-0.9505***	0.0042	0.1050*	0.0000	0.0006
	(0.1248)	(0.3380)	(0.0773)	(0.2694)	(0.0822)	(0.1608)	(0.0295)	(0.0614)	(0.0001)	(0.0008)
RCCI	-0.0027	-0.1611***	-	-	-0.0065	-0.2137***	-0.0013	0.0295**	0.0002	-0.0001
	(0.0124)	(0.0405)	-	-	(0.0204)	(0.0501)	(0.0042)	(0.0129)	(0.0004)	(0.0011)

Table 3.6: Estimation results of the SETAR(1) for oil-producing countries(*Continued*)

	Mexico		Qatar		Thailand		Indonesia		Russia	
T. variable	VOL_{t-2}		VOL_{t-5}		VOL_{t-2}		VOL_{t-2}		VOL_{t-5}	
T. value	0.0018		0.0007		0.0018		0.0011		0.0025	
	Regime 1	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***
RTRGI	6.71E-08	1.40E-05 ***	1.13E-06	7.65E-06 ***	-2.77E-07	2.04E-05 ***	4.33E-09	2.54E-06	6.76E-06 **	-2.21E-06
	(0.0000)	(4.35E-06)	(8.54E-07)	(1.92E-06)	(1.28E-06)	(4.20E-06)	(4.31E-07)	(1.62E-06)	(3.03E-06)	(0.0000)
VIX	4.33E-06	0.0001 ***	9.06E-06 ***	4.05E-05 ***	7.09E-06	0.8285 ***	1.75E-06	9.80E-06 **	3.88E-05 ***	0.0001 ***
	(5.64E-06)	(1.17E-05)	(3.48E-06)	(4.93E-06)	(4.86E-06)	(9.58E-06)	(1.76E-06)	(3.88E-06)	(1.35E-05)	(1.60E-05)
RWTI	-0.0011	-0.0128 ***	-0.0004	-0.0042 ***	-0.0001	0.8272 ***	0.0001	-3.91E-05	-0.0006	-0.0250 ***
	(0.0011)	(0.0018)	(0.0006)	(0.0009)	(0.0010)	(0.0015)	(0.0003)	(0.0006)	(0.0023)	(0.0037)
OVX	4.66E-08	-2.89E-05 ***	-1.22E-06	-2.51E-05 ***	-1.02E-06	0.0006	-1.79E-07	6.41E-06 ***	-5.31E-06	-1.08E-05
	(2.82E-06)	(5.39E-06)	(1.38E-06)	(3.68E-06)	(2.27E-06)	(6.51E-06)	(8.18E-07)	(2.43E-06)	(5.63E-06)	(1.10E-05)

	Venezuela	
T. variable	VOL_{t-1}	
T. value	0.0018	
	Regime 1	***Regime 2***
Obs.	2433	469
C	3.31E-05	-0.0170 ***
	(0.0014)	(0.0057)
VOL_{t-1}	0.8598 ***	0.4030 ***
	(0.0967)	(0.0181)
SMR	0.0008	-0.0039
	(0.0021)	(0.0033)
RBY	-	-
	-	-
RGDP	0.0667	-0.3936
	(0.0651)	(0.2506)
RDEBT	-0.0286	-0.1355
	(0.0289)	(0.0967)
REDEBT	-0.1375	0.0763
	(0.1383)	(0.6043)
INF	0.0501	-0.0060
	(0.0430)	(0.0639)
RCCI	-	-
	-	-
RTRGI	2.29E-06	4.49E-05 ***
	(2.71E-06)	(8.80E-06)
VIX	8.36E-06	0.0002 ***
	(6.57E-06)	(1.47E-05)
RWTI	-0.0013	-0.0233 ***
	(0.0017)	(0.0028)
OVX	-4.68E-10	1.20E-08
	(1.86E-09)	(7.67E-09)

T. variable and T. value refer to the threshold chosen variable and the threshold value used. Regime 1(2) corresponds to the period where Threshold variable chosen < Threshold value (Threshold variable chosen >= Threshold value). *, ** and *** denote significance at respectively 10%, 5% and 1% statistical levels.

A 1% increase in oil price leads to an increase in CDS volatility by 82.72%, which is not explained by the reasoning previously supposed. This divergent behavior might be explained by the fact that, even though the oil production in Thailand is increasing during recent years, it still not cover its consumption needs. To get closer from its needs satisfaction, Thailand has to go through with importations, which weaken its public finances and thus its ability to repay debts. Credit risk sensitivity to oil price shocks can, as well, be explained in the USA and Brazil, as a result of the large quantity of necessary imports to help meet demand, despite the fact that these countries are respectively ranked as the 3^{rd} and the 10^{th} in the world oil production countries.

Interestingly, the impact of oil uncertainty - as proxied by the OVX index - on the CDS volatility during the risky regime, is mostly negative except that in Thailand, Indonesia, Venezuela and Ukraine, where the sign matches the expected relationship. Reasonably, an increase in the oil market volatility should higher the sovereign credit risk, though this is mainly not the revealed relationship by our empirical findings. This may be attributed to spurious relationships caused by irrational behavior of investors following the frequent occurrence of crisis periods in both CDS and oil markets.

3.5 Discussion

The study of the credit risk determinants, with a particular emphasis on the impact of oil market conditions seems to be interesting all the more during the current unstable context of energy and climate policies and the recent episodes of pumping up and down in oil price. An increase in oil price is expected to raise the financial health and thus the creditworthiness uncertainty of oil-related countries, though this reasoning perspective doesn't always hold for all studied countries and during all periods.

The increase in oil price leads, in the majority of the studied countries, to a worsening of the government's financial health and thus to increase its credit risk. At the opposite, a decline in the oil market conditions potentially raises the country's incomes, which leads to lower the sovereign debt burden and the financing costs, in turn. If the country spends less money serving the debt, then it will hold over revenues, implying a greater indebtedness ability. Interestingly, our findings show that this relationship does not hold for some of the studied countries, in which the CDS volatility divergently behave to oil shocks (the USA, Brazil, Thailand, Sweden, Bulgaria and Hungary). These countries are characterized by a diversified economy: Even though some of them are ranked as the world top oil-producing countries, they still rely on importations to cover their oil consumption needs. The increase in oil price leads, indubitably, to higher imports charges and less government's revenue, which weakens the country's public finances. This leads, in turn, to deteriorate the stability of sovereign solvency, which increases the credit risk and tightens the financing conditions (as reflected in CDS volatility). In some other countries the relationship between oil and CDS markets are statistically insignificant (Finland, Ireland, Spain, Philippines, Greece, Romania and Ukraine). This can be explained by the fact that these countries are not big producers of oil but are self-reliant with their oil needs. In these countries the government reimbursement ability is not or very little sensitive to oil price fluctuations.

Reactions of CDS volatility to higher uncertainty in the oil market is, surprisingly, negative for most cases. This spurious relationship can be explained by irrational trading strategies during the recent crisis periods in both CDS and oil markets. However, these empirical results remain inconclusive.

Our findings are of prominent importance for both regulators and investors. From a policymaker point of view, understanding the source of sovereign risk is a crucial step to properly adjust the policy-decision during extreme situations. Our first result is that the sovereign CDS market, as an indicator of the credit risk, is subject to regime shifts, and its determinants are depending on whether it is highly volatile (and thus risky) or low volatile (and thus safe). This suggests that the key drivers of the credit risk should be continually investigated in order to keep the economic measures and policies viable. Yet, the impact of oil market conditions on CDS volatility was, initially, trivial, but becomes a significant factor in the sovereign risk appreciation, during the risky period. This finding proposes to take inti account current, historical and forecasted oil price while elaborating crisis exit solutions.

Understanding the impact of changes in the energy market conditions on the sovereign credit risk is also of critical usefulness for financial markets participants because CDS contracts are widely traded in a speculative purpose. In fact, investors use this credit derivative not only to transfer credit risk but also to generate extra returns by forecasting its prices based on the market psychology. Our results can be helpful for fund managers, so they can make investment profits from simultaneous trading on oil assets and CDS contracts, by basing their strategies on volatility trend of each market. For example, we suggest increasing the oil investment weight in the portfolio if the energy market is bullish and decreasing, at the same time, the CDS investment weight.

3.6 Conclusion

This chapter investigates the impact of oil prices fluctuations on sovereign credit risk, after controlling for local and global economy-wide factors. Using the CDS volatility as a complementary risk measure, our results confirm, firstly, the nonlinearity pattern of the dynamic evolution of the CDS market volatility. Secondly, some dissimilarities in the explanatory power of the exogenous variables are observed between regimes and across countries. Thirdly, in most cases, the role played by the oil market is trivial in the determination of credit risk during the stable regime, whilst it becomes significant when the market switches to the risky regime. The majority of the studied countries exhibit a similar behavior, that is the increase in oil price leads to an improvement of the government's creditworthiness, reflected in the CDS volatility decline.

Our essay contributes to the literature in several conclusions: First, investigating the determinants of worldwide CDS volatility is of a prominent issue since understanding the credit risk source may help to better implement crisis exit solutions and to readjust the investment strategies based on the countries' particular features. Second, since oil price decline may lead to the deterioration of the repayment ability of some states, during volatile period, policymakers should settle some rescue packages with respect to the anticipated fluctuations in oil market conditions. And third, market participants should avoid investing simultaneously in the oil market and the sovereign CDS market of some countries during periods of accelerating volatility and instability, because of their close comovement.

Further investigation is needed to explain the unexpected relationship between oil market uncertainty, as proxied by the OVX, and the sovereign CDS volatility. Preliminary findings, revealed in this essay, slightly suggest a miss-appreciation of oil volatility by the CDS market investors, but still not conclusive. Including a variable measuring the political risk of countries in the studied model could provide an early answer to this question.

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Appendices

3.8 Appendix: Cubic Spline Interpolation

As mentioned before, to obtain a daily data from a monthly, quarterly or annual observations, we need to use a mathematical technique that enables to construct a regular continuous curve that passes by all known points. The Spline Interpolation method is one of the most widely used process that allows to create a $\mathcal{C}^2$ function starting with $n+1$ couples $(x_i, f(x_i))_{i \in [\![0,n]\!]}$. A spline is a special function defined piecewise by polynomials. In our case, we chose to use degree 3 polynomials, which is the lowest degree allowing to build the $\mathcal{C}^2$ function.

Let's start from the given points of Figure 3.3, our goal is to draw the $\mathcal{C}^2$ function as displayed in Figure 3.4.

On each sub-interval $[x_i, x_{i+1}]$, we aim to build a polynomial, based on a third-order Taylor polynomial of the sought function written in the neighborhood of x_i, such as:

$$p_i(x) = f_i + f_i'(x - x_i) + \frac{f_i''}{2!}(x - x_i)^2 + \frac{f_i'''}{3!}(x - x_i)^3, \quad i \in [\![0, n-1]\!] \tag{3.8}$$

The goal is then to explicit the constants $(f_i, f_i', f_i'', f_i''')_{i \in [\![0,n-1]\!]}$ using the known information i.e. the couples $(x_i, f(x_i))_{i \in [\![0,n]\!]}$, under certain conditions:

- We want the curve to pass by our points $(x_i, f(x_i)) \Rightarrow \forall i \in [\![0, n-1]\!], p_i(x_i) = f(x_i)$ and also at the right endpoint of the interval : $p_{n-1}(x_n) = f(x_n)$,
- The function must be $\mathcal{C}^0 \Rightarrow \forall i \in [\![0, n-2]\!], p_i(x_{i+1}) = p_{i+1}(x_{i+1})$,
- The function must be $\mathcal{C}^1 \Rightarrow \forall i \in [\![0, n-2]\!], p_i'(x_{i+1}) = p_{i+1}'(x_{i+1})$,
- The function must be $\mathcal{C}^2 \Rightarrow \forall i \in [\![0, n-2]\!], p_i''(x_{i+1}) = p_{i+1}''(x_{i+1})$.

The constants $(f_i', f_i''')_{i \in [\![0,n-1]\!]}$ are first expressed depending on $(f_i'')_{i \in [\![0,n]\!]}$, since those are directly written with the known variables. Indeed, the final equations are :

$$f_i = f(x_i), \forall i \in [\![0, n-1]\!] \tag{3.9}$$

$$f_i' = \frac{f(x_{i+1}) - f(x_i)}{h} - h\left[\frac{f_i''}{3} + \frac{f_{i+1}''}{6}\right], \quad \forall i \in [\![0, n-1]\!] \tag{3.10}$$

$$f_i''' = \frac{f_{i+1}'' - f_i''}{h}, \qquad \forall i \in [\![0, n-1]\!] \tag{3.11}$$

$$f_i'' + 4f_{i+1}'' + f_{i+2}'' = \frac{6}{h^2}[2f(x_{i+1}) - f(x_{i+2}) - f(x_i)], \qquad \forall i \in [\![0, n-2]\!] \tag{3.12}$$

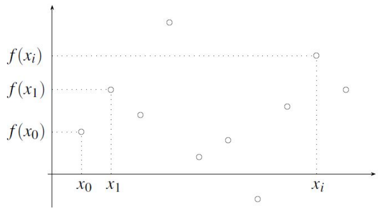

Figure 3.3: Available data $(x_i, f(x_i))$

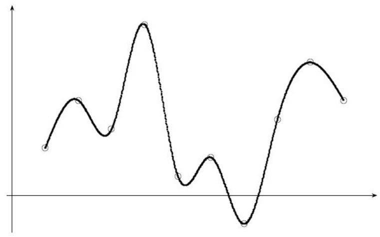

Figure 3.4: Constructed $\mathcal{C}^2$ using natural cubic spline interpolation

At this point, an algorithm is enough to find an explicit solution to the (f_i'') and thus to the entire problem. The great advantage of our hypothesis is that the main difficulty in the algorithm is the calculation of the inverse of a symmetrical tridiagonal matrix (as shown in Equation 3.9), which is quite time effective.

3.9 Appendix: Unit root test on daily explanatory variables

Table 3.7: Unit root test for the exogenous variables

	Augmented Dickey-Fuller statistics						
Common factors	TRGI	VIX	WTI	OVX			
	-1.53	-3.34 **	-1.82	-3.11 ***			
Country-specific factors	Stock market indexes	Bond yields	GDP	Total debt	Foreign debt	HICP	CCI
Panel A: Oil-producing countries							
Norway	-2.10	-1.99	-1.05	-1.68	-3.87 *	-0.05	-1.18
UK	-1.76	-1.92	-1.36	-4.15 *	-2.17	-1.79	-1.47
USA	0.24	-2.83 *	3.51	-0.55	0.59	-1.25	-1.16
Brazil	-2.44	-2.93 *	4.39	4.39	-1.67	5.40	-1.28
China	-2.46	-3.73 *	-4.16 *	6.21	1.01	-0.87	-2.64 *
Mexico	-1.46	-1.80	0.67	0.84	0.09	0.88	-1.96
Qatar	-1.91	-	-1.88	-0.94	-0.93	1.04	-
Thailand	-0.58	-2.06	-0.36	0.28	-1.01	-1.97	-3.14 *
Indonesia	-0.94	-2.50	0.86	2.54	0.73	0.42	-2.15
Russia	-1.85	-2.51	-2.02	3.51	-2.50	-5.23 *	-1.67
Venezuela	4.40	-4.90 *	-3.47 *	-0.93	-5.38 *	3.07	-
Panel B: Other worldwide countries							
Austria	-1.57	-0.43	-3.34 *	-0.79	-1.19	-0.68	-1.75
Belgium	-1.23	-0.48	-0.34	1.99	-1.98	-1.26	-2.56
Denmark	-0.48	-1.23	-1.74	-1.06	-0.01	-2.24	-2.48
Finland	-0.84	-1.16	-1.49	-0.16	-2.05	-1.78	-2.15
France	-1.66	-0.58	1.58	-3.90 *	-3.33 *	-1.70	-1.54
Germany	-0.50	-1.45	-0.38	-2.09	-1.94	-1.44	-1.77

Ireland	-1.09	-1.47		1.04		-3.64	*	-1.71		-3.32	*	-1.42	
Italy	-1.52	-2.94	*	-2.16		-1.22		-2.95	*	-2.53		-1.57	
Japan	-1.51	-1.56		-0.45		-0.43		-0.85		-1.05		-2.20	
Latvia	-0.57	-1.16		-1.86		-1.85		-4.28	*	-3.91	*	-1.51	
Lithuania	-1.03	-4.02	*	-2.47		-3.42	*	-2.32		-3.00	*	-1.33	
Netherlands	-1.32	-1.21		-0.62		-1.35		-3.14	*	-1.29		-0.81	
Portugal	-0.96	-1.53		-0.45		-0.04		-3.31	*	-1.65		-0.80	
Slovakia	-1.35	-1.02		-2.66	*	-0.05		-0.52		-2.17		-1.75	
Slovenia	-0.78	-3.01	*	-1.85		0.24		-0.64		-2.34		-2.31	
Spain	-1.79	-2.65	*	-4.09	*	0.52		-4.03	*	-2.02		-1.41	
Sweden	-2.54	-1.94		-1.47		-1.51		-1.05		-2.04		-2.35	
Philippines	-0.81	-0.81		-1.24		-2.04		-2.93	*	-1.40		-0.86	
Turkey	-1.24	-3.30	*	-0.39		2.49		-1.88		2.68		-2.94	*
Bulgaria	-1.14	-0.57		-3.59	*	1.08		-4.63	*	-4.71	*	-0.99	
Croatia	-1.27	-1.02		-3.71	*	-3.42	*	-0.84		-2.37		-1.26	
Czech	-1.67	-0.48		0.16		-1.62		-0.39		-1.79		-1.31	
Hungary	-1.09	-2.69	*	-3.29	*	-1.39		-2.56		-5.45	*	-1.42	
Greece	-0.97	-2.15		-1.20		-1.88		-2.18		-2.17		-1.81	
Poland	-1.77	-0.97		-2.00		-0.53		-2.59	*	-2.69	*	-1.07	
Romania	-0.15	-2.62	*	-2.86	*	0.60		-1.96		-0.21		-0.98	
Ukraine	-1.38	-4.98	*	0.81		1.92		-5.08	*	-4.85	*	-2.37	

This table reports the Augmented-Dickey Fuller statistics. GDP, HICP, CCI and TRGI refer to the Gross Domestic Product, the Harmonized Consumer Prices, the Consumer confidence index and Thomson Reuters Global index. *, ** and *** denote significance at respectively 10%, 5% and 1% statistical levels.

3.10 Appendix: Univariate FIAPARCH(1,d,1)

Table 3.8: Estimation results of the AR(1)-FIAPARCH(1,d,1)

	Mean Equation		Variance Equation							
	Cst (a_0)	AR(1)	Cst (a_0)	d-Figarch	ARCH (ϕ)	GARCH (β)	APARCH (γ)	APARCH (δ)	Student (df)	G.E.D (r)
Panel A: Oil-producing countries										
Norway	0.9960 ***	0.4681 ***	0.8583 ***	0.0432	0.0104	-0.2359 ***	1.2339 ***	-	6.1064 ***	-
	(0.0075)	(0.0114)	(0.1307)	(0.1366)	(0.0255)	(0.0734)	(0.0391)		(0.9118)	-
UK	-5.9E-06	0.9742 ***	0.1638 ***	0.8412 ***	0.2070 ***	0.4596 ***	0.0078	0.8948 ***	5.8629 ***	-
	(9.3E-06)	(0.0128)	(0.0046)	(0.0113)	(0.0370)	(0.0662)	(0.0307)	(0.0254)	(0.8157)	-
USA	2.6E-06	0.3051 ***	0.8562 ***	0.6989 ***	0.3683 ***	0.2248 ***	-0.4818 ***	1.0242 ***	3.9837 ***	-
	(6.6E-06)	(0.0194)	(0.0378)	(0.0121)	(0.0626)	(0.8002)	(0.0327)	(0.0374)	(0.2604)	-
Brazil	-0.0001	0.0946 ***	0.0021	0.9767 ***	0.0355	0.8860 ***	-0.7420 **	1.4484 ***	-	0.6818 ***
	(0.0001)	(0.0013)	(0.0245)	(0.0519)	(0.0431)	(0.0201)	(0.3748)	(0.2005)	-	(0.1159)
China	0.0003	-0.0126	0.0616	0.1333	0.8138 ***	-0.7194 **	-0.1789 **	2.2654 ***	-	-
	(0.0004)	(0.0337)	(0.2376)	(0.2295)	(0.1588)	(0.3248)	(0.0898)	(0.8115)	-	-
Mexico	-0.0002 ***	0.5305 **	0.0104 ***	0.3902 ***	0.0363	0.3986 ***	0.0241	1.9781 ***		1.0584 ***
	(0.0001)	(0.2549)	(0.0010)	(0.0902)	(0.0849)	(0.1507)	(0.5305)	(0.0950)		(0.1638)
Qatar	2.4E-05 *	0.0521	2.5522 ***	0.9881 ***	0.0000	0.8198 ***	-0.4823 ***	0.8543 ***	2.2854 ***	-
	(1.3E-05)	(0.0512)	(0.1825)	(0.0561)	(0.0903)	(0.0165)	(0.1620)	(0.0920)	(0.0740)	-
Thailand	3.2E-05	0.6541 ***	6.7892 ***	0.5138	0.2091	0.5123 ***	0.0718	1.1961 *	-	0.6983 ***
	(4.2E-05)	(0.0372)	(0.2028)	(0.6185)	(0.5873)	(0.1101)	(0.4927)	(0.6896)	-	(0.0975)
Indonesia	-0.0004	1.0000 ***	0.7568 ***	0.9683 ***	0.0499	0.9086 ***	-0.1556 ***	0.5404 ***	3.4702 ***	-
	(0.0025)	(0.0000)	(0.0370)	(0.0147)	(0.0433)	(0.0022)	(0.0166)	(0.0108)	(0.0918)	-
Russia	-0.0010	0.1158 ***	100.00 ***	0.4613 ***	0.1432 **	0.3882	-0.2066	1.6963	4.3007 ***	-
	(0.0006)	(0.0234)	(38.4700)	(0.0679)	(0.0695)	(0.0834)	(0.0732)	(0.1238)	(0.3528)	-
Venezuela	0.0000	0.5959 ***	0.0038 ***	0.3994 ***	0.3320 ***	0.3885 ***	-0.1213 ***	1.6164 ***	3.1431 ***	-
	(1.8E-05)	(0.0672)	(0.0002)	(0.0135)	(0.1221)	(0.0945)	(0.6052)	(0.0971)	(0.1146)	-
Panel B: Other worldwide countries										
Austria	1.0E-05	-0.0341 ***	39.5958 *	0.9382 ***	0.4147 **	0.9602 ***	-0.2099	0.2635 ***	2.9992 ***	-
	(0.0001)	(0.0010)	(20.4910)	(0.1901)	(0.2025)	(0.0197)	(0.1429)	(0.0277)	(0.1996)	-
Belgium	-4.0E-06	0.0388 ***	1.5824 ***	0.7369 ***	0.1080 ***	0.7577 ***	-0.4750 ***	0.5281 ***	3.0627 ***	-
	(0.0001)	(0.0010)	(0.6094)	(0.0308)	(0.0357)	(0.0237)	(0.0405)	(0.0392)	(0.1495)	-
Denmark	-4.5E-05	1.0000 ***	0.2629 ***	0.5051 ***	0.6319 ***	0.3446 ***	-0.2553 ***	0.5460 ***	2.5852 ***	-
	(4.1E-05)	(0.0000)	(0.0565)	(0.0114)	(0.0188)	(0.0407)	(0.0290)	(0.0175)	(0.0973)	-
Finland	0.0003	0.0958 **	0.2053	0.5392 ***	0.3092	0.6321 ***	-0.1162	2.1773 ***	-	-
	(4.9E-04)	(0.0428)	(0.2640)	(0.1859)	(0.2000)	(0.1915)	(0.0900)	(0.2192)	-	-

Table 3.8: Estimation results of the AR(1)-FIAPARCH(1,d,1) (*Continued*)

	Mean Equation		**Variance Equation**								
	Cst (a_0)	AR(1)	Cst (α_0)	d-Figarch	ARCH (ϕ)	GARCH (β)	APARCH (γ)	APARCH (δ)	Student (df)	G.E.D (r)
France	0.0004	0.1914	0.9147	0.7236 ***	0.4845	0.8189 ***	-0.3096 ***	1.8632 ***	-	-
	(0.0011)	(0.0334)	(0.8887)	(0.1843)	(0.1424)	(0.0847)	(0.1078)	(0.1907)	-	-
Germany	-1.2E-05	0.1239 ***	0.0000	0.7854 *	0.2904	0.8039 ***	0.0185	2.3219 ***	-	-
	(0.0006)	(0.0407)	(366.19)	(0.4769)	(0.4486)	(0.1384)	(0.1381)	(0.5546)	-	-
Ireland	3.1E-06	0.5931 ***	0.6048	0.5984 ***	0.5132 ***	0.7446 ***	-0.4985 ***	0.9510 ***	-	0.8050 ***
	(1.2E-05)	(0.0012)	(3.0596)	(0.1278)	(0.1078)	(0.0709)	(0.1279)	(0.0957)	-	(0.1512)
Italy	4.0E-06	-0.0150 ***	28.9289 ***	0.2371 ***	0.0999	0.2421	0.5267 ***	1.8154 ***	-	0.4207 ***
	(4.0E-05)	(0.0002)	(9.3825)	(0.0369)	(0.3112)	(0.2950)	(0.0727)	(0.0197)	-	(0.0172)
Japan	4.2E-06	-0.1754 ***	2.9038	0.4586 ***	0.1235 *	0.4793 ***	-0.2276 **	1.1998 ***	-	0.3499 ***
	(2.8E-05)	(0.0015)	(2.1909)	(0.0194)	(0.0632)	(0.0653)	(0.1035)	(0.0477)	-	(0.0147)
Latvia	0.0008 ***	1.0000 ***	0.8645 ***	0.1804 ***	0.3471 ***	-0.4528 ***	0.7669 ***		2.3917 ***	-
	(0.0002)	(0.0000)	(0.1355)	(0.0233)	(0.0644)	(0.0431)	(0.0280)	(0.0309)	(0.0178)	-
Lithuania	0.0010	1.0000 ***	0.9963	0.2129 ***	0.5767 ***	0.0455 ***	0.1362 ***	0.3717 ***	2.5459 ***	-
	(0.0214)	(0.0000)	(1.5096)	(0.0148)	(0.0311)	(0.0076)	(0.0244)	(0.0122)	(0.0528)	-
Netherlands	-0.0007 ***	0.9958 ***	0.4748 ***	0.6730 ***	0.4273 ***	0.2205 ***	0.5973 ***	1.3690 ***	5.5211 ***	-
	(0.0002)	(0.0010)	(0.0270)	(0.1983)	(0.1432)	(0.0510)	(0.0234)	(0.1113)	(0.4420)	-
Portugal	2.5E-06	-0.0030 ***	7.6097 ***	0.8289 ***	0.6103 ***	0.4807 ***	0.3632 ***	1.9409 ***	-	0.2870 ***
	(0.0001)	(0.0002)	(0.1962)	(0.0628)	(0.0542)	(0.0190)	(0.1372)	(0.0608)	-	(0.0129)
Slovakia	-0.0004	0.0100	78.2647	0.6446 ***	0.3152 **	0.6794 ***	-0.1810 **	2.0817 ***	-	-
	(0.0006)	(0.0437)	(157.92)	(0.1089)	(0.1490)	(0.1388)	(0.0898)	(0.2664)	-	-
Slovenia	0.0001 ***	0.7297 ***	56.5384	0.7847 ****	0.0983	0.4199 ***	0.3005 ***	0.8035 ***	-	0.5497 ***
	(1.9E-05)	(0.0502)	(103.00)	(0.0541)	(0.0764)	(0.0800)	(0.1040)	(0.1498)	-	(0.1761)
Spain	1.0E-06	0.0017	0.2929 ***	0.3499 ***	0.2038 ***	0.4288 ***	-0.8369 ***	1.3025 ***	2.8175 ***	-
	(1.1E-05)	(0.0028)	(0.0560)	(0.0204)	(0.0671)	(0.0702)	(0.0540)	(0.0666)	(0.0664)	-
Sweden	-0.0016 **	1.0000 ***	0.9497 **	0.4985 ***	0.4875 ***	0.5810 ***	0.4466 ***	0.4208 ***	3.1075 ***	-
	(0.0006)	(0.0000)	(0.3799)	(0.0127)	(0.0308)	(0.0209)	(0.0352)	(0.0171)	(0.2523)	-
Philippines	-2.0E-06	0.9359 ***	0.0035 ***	0.1621 ***	0.0006	0.1602 **	0.6934	1.5075 ***	9.2233 ***	
	(1.5E-05)	(0.0386)	(0.0001)	(0.0237)	(0.0785)	(0.0643)	(0.3209)	(0.0425)	(2.1216)	
Turkey	-0.0001	0.1172 ***	1.4295	0.9945 ***	0.1632 ***	0.9096 ***	-0.1958 *	1.1906 ***	4.4236 ***	-
	(4.9E-05)	(0.0253)	(495.05)	(0.0046)	(0.0252)	(0.0091)	(0.1055)	(0.1426)	(0.2202)	-
Bulgaria	-0.0006	0.1181 ***	0.0146	0.3142 **	0.3050 **	0.3755 ***	-0.1885 *	2.2343 ***	-	-
	(0.0004)	(0.0404)	(0.1077)	(0.1370)	(0.1369)	(0.1222)	(0.1079)	(0.1983)	-	-

Table 3.8: Estimation results of the AR(1)-FIAPARCH(1,d,1) (*Continued*)

	Mean Equation		**Variance Equation**							
	Cst (a_0)	AR(1)	Cst (α_0)	d-Figarch	ARCH (ϕ)	GARCH (β)	APARCH (γ)	APARCH (δ)	Student (df)	G.E.D (r)
Croatia	-0.0006 **	0.0393	0.1297 .	0.4667 ***	0.5412 ***	0.7003 ***	-0.1181	1.9222 ***	-	-
	(0.0003)	(0.0280)	(0.1356)	(0.1274)	(0.1759)	(0.1387)	(0.0890)	(0.1266)	-	-
Czech	-9.0E-06	0.7460 ***	1.0048	0.6785 ***	0.4933 ***	0.6371 ***	-0.3313 ***	0.9161 ***	-	0.3628 ***
	(2.4E-05)	(0.0027)	(1.2575)	(0.0473)	(0.0369)	(0.0720)	(0.0474)	(0.1370)	-	(0.0156)
Hungary	-2.0E-06	-0.0066 ***	18.1272 ***	0.7805 ***	0.5517 ***	0.8093 ***	0.9226 ***	2.4153 ***	-	0.3704 ***
	(4.5E-05)	(0.0020)	(2.8926)	(0.0204)	(0.0224)	(0.0153)	(0.0231)	(0.0501)	-	(0.0208)
Greece	-8.0E-06	0.7439 ***	12.2720	0.7346 ***	0.3918 ***	0.4788 ***	-0.3299 ***	0.9905 ***	-	0.7215 ***
	(1.5E-05)	(0.0251)	(16.58)	(0.1396)	(0.0811)	(0.0648)	(0.0365)	(0.3447)	-	(0.0359)
Poland	-0.0003 ***	0.0331 *	0.0000	0.5332 ***	0.2019 ***	0.4802 ***	-0.3219 ***	1.6923 ***	2.9626 ***	-
	(0.0001)	(0.0171)	(0.0384)	(0.0476)	(0.0745)	(0.0726)	(0.1035)	(0.0756)	(0.1053)	-
Romania	-0.0003	0.1361 ***	5.4566	0.6071 ***	0.7873 ***	0.9508 ***	-0.3709 ***	2.0033 ***	-	-
	(0.0004)	(0.0413)	(9.1640)	(0.1411)	(0.0913)	(0.0220)	(0.1252)	(0.0980)	-	-
Ukraine	1.5E-06	0.4106 ***	0.0000	0.8731 ***	0.1905 *	0.5730 ***	-0.0804 **	1.1093 ***	4.6197 ***	-
	(5.0E-06)	(0.0409)	(0.0364)	(0.0311)	(0.1012)	(0.0438)	(0.0387)	(0.0409)	(1.6281)	-

*, ** and *** refer to significance at respectively 10%, 5% and 1% statistical levels.

3.11 Appendix: Results of the structural breaks test

Table 3.9: Thresholds F-statistics (0 Vs. 1 test)

Country	F-statistic	Scaled F-statistic	
Panel A: Oil-producing countries			
Norway	38.60	463.17	**
UK	17.86	232.23	**
USA	34.78	452.16	**
Brazil	13.97	181.60	**
China	7.66	99.62	**
Mexico	16.50	214.53	**
Qatar	13.03	143.28	**
Thailand	11.70	152.13	**
Indonesia	3.83	49.79	**
Russia	11.44	148.67	**
Venezuela	24.13	265.47	**
Panel B: Other worldwide countries			
Austria	21.74	282.60	**
Belgium	14.84	192.92	**
Denmark	26.37	342.81	**
Finland	16.33	212.30	**
France	42.33	550.27	**
Germany	43.00	558.94	**
Ireland	24.69	320.95	**
Italy	17.68	229.82	**
Japan	37.61	488.97	**
Latvia	8.63	112.13	**
Lithuania	7.12	92.59	**
Netherlands	34.47	448.08	**
Portugal	21.49	279.41	**
Slovakia	10.16	132.12	**
Slovenia	10.65	138.51	**
Spain	30.35	394.60	**
Sweden	20.34	264.47	**
Philippines	21.81	283.55	**
Turkey	32.52	422.71	**
Bulgaria	8.71	113.26	**
Croatia	16.05	208.65	**
Czech	14.58	189.56	**
Hungary	10.60	137.79	**
Greece	174.22	2264.90	**
Poland	8.66	112.60	**
Romania	9.10	118.35	**
Ukraine	12.46	161.98	**

This table reports the results of the structural breaks test proposed by Bai and Perron (2003). The test investigates the presence of a regime-switching under the null hypothesis of zero thresholds (one-regime). A maximum of one threshold and a 15% trimming percentage are authorized. The Bai-Perron critical value is equal to 27.03. ** denotes statistical significance at the 5% level.

3.12 Appendix: SETAR(1) results

Table 3.10: Estimation results of the SETAR(1) for oil consuming countries

	Austria		Belgium		Denmark		Finland		France	
T. variable	VOL_{t-1}		VOL_{t-3}		VOL_{t-4}		VOL_{t-1}		VOL_{t-2}	
T. value	0.0046		0.0001		0.0015		0.0021		0.0168	
	Regime 1	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***
Obs.	2467	438	1472	431	2445	432	2425	482	2481	439
C	0.0007	-0.0040 ***	0.0000	-0.0002 **	0.0000	-0.0025 ***	0.0001	-0.0035 **	0.0050	-0.0688 ***
	(0.0004)	(0.0015)	(0.0001)	(0.0001)	(0.0004)	(0.0009)	(0.0005)	(0.0014)	(0.0036)	(0.0124)
Vol_{t-1}	0.7745 ***	0.6492 ***	1.4089 ***	0.9259 ***	1.0820 ***	0.3661 ***	0.4911 ***	0.7488 ***	0.7257 ***	0.2803 ***
	(0.0212)	(0.0167)	(0.0373)	(0.0066)	(0.0917)	(0.0198)	(0.0205)	(0.0208)	(0.0378)	(0.0193)
SMR	0.0035 *	-0.0036	-0.0002	-0.0015 ***	-0.0040 *	0.0161 ***	0.0016	0.0042	-0.0046	-0.0285
	(0.0021)	(0.0060)	(0.0005)	(0.0004)	(0.0024)	(0.0036)	(0.0033)	(0.0050)	(0.0212)	(0.0497)
RBY	0.0000	0.0065 ***	0.0000	0.0001	0.0000	-0.0005	0.0000	0.0007	-0.0006	0.0577 **
	(0.0002)	(0.0020)	(0.0000)	(0.0001)	(0.0001)	(0.0003)	(0.0002)	(0.0007)	(0.0013)	(0.0250)
RGDP	-0.0389	0.8920 ***	-0.0127	0.1588 ***	-0.0020	-0.0047	-0.3530	0.9080 *	1.3847	73.2032 ***
	(0.0513)	(0.1340)	(0.0437)	(0.0508)	(0.0469)	(0.1326)	(0.2840)	(0.4876)	(2.3898)	(14.4836)
RDEBT	-0.1339	0.5229	-0.0008	-0.0169	0.0046	-0.2304 ***	-0.0037	0.0950 **	4.0723	43.2009 ***
	(0.2009)	(0.4537)	(0.0150)	(0.0174)	(0.0120)	(0.0256)	(0.0274)	(0.0455)	(3.7942)	(14.8959)
REDEBT	0.1271	-0.7624	-0.0020	0.0007	0.0045	0.1308 ***	0.0064	0.0672	0.1660	4.7704 ***
	(0.2712)	(0.6255)	(0.0062)	(0.0079)	(0.0042)	(0.0111)	(0.0454)	(0.1415)	(0.4213)	(0.9245)
INF	-0.0377	0.8552 **	0.0041	0.0036	0.0307	-0.5027	0.1116	1.6386 ***	1.0174	32.4333 ***
	(0.1418)	(0.3669)	(0.0093)	(0.0091)	(0.1645)	(0.3887)	(0.2632)	(0.5587)	(1.5256)	(4.8469)
RCCI	-0.0001	-0.0002	1.46E-05	-1.30E-08	1.91E-05	-0.0001	-0.0001	-1.41E-05	0.2662	-1.1384 *
	(0.0002)	(0.0004)	(2.87E-05)	(2.86E-05)	(0.0002)	(0.0002)	(0.0004)	(0.0005)	(0.3219)	(0.6068)
RTRGI	-1.25E-06	3.93E-05 ***	3.30E-08	9.09E-07 ***	-1.03E-06	2.19E-05 ***	-1.56E-06	2.17E-05 ***	-2.32E-05	0.0004 ***
	(2.18E-06)	(0.0000)	(3.45E-07)	(3.40E-07)	(1.94E-06)	(5.41E-06)	(2.78E-06)	(6.43E-06)	(1.93E-05)	(0.0001)
VIX	1.94E-05 ***	0.0001 ***	1.03E-06	4.32E-06 ***	1.02E-05	0.0001 ***	3.52E-05 ***	0.0001 ***	3.43E-05	0.0006 ***
	(7.44E-06)	(2.14E-05)	(0.0000)	(1.23E-06)	(6.49E-06)	(1.29E-05)	(1.10E-05)	(1.97E-05)	(0.0001)	(0.0002)
RWTI	-0.0013	-0.0058	-0.0001	-0.0006 **	-0.0017	-0.0028	-0.0012	0.0039	-0.0004	-0.0901 **
	(0.0015)	(0.0046)	(0.0002)	(0.0002)	(0.0014)	(0.0024)	(0.0022)	(0.0036)	(0.0137)	(0.0417)
OVX	-1.11E-05 ***	-1.95E-05	-4.37E-08	-8.93E-07	1.56E-06	-2.76E-05 ***	-2.50E-06	-8.24E-06	-4.75E-05	-0.0001
	(3.99E-06)	(1.75E-05)	(5.42E-07)	(7.56E-07)	(2.87E-06)	(7.90E-06)	(4.87E-06)	(1.48E-05)	(3.40E-05)	(0.0002)

	Germany		Ireland		Italy		Japan		Latvia	
T. variable	VOL_{t-2}		VOL_{t-2}		VOL_{t-2}		VOL_{t-2}		VOL_{t-4}	
T. value	0.0108		0.0068		0.0031		0.0019		0.0019	
	Regime 1	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***
Obs.	2454	432	1811	434	2494	440	2476	453	2491	439
C	-0.0012	0.0741 ***	0.0004	0.0194	0.0003	-0.0042 **	0.0003	-0.0070 ***	1.06E-05	-0.0037
	(0.0061)	(0.0162)	(0.0104)	(0.0285)	(0.0007)	(0.0016)	(0.0004)	(0.0012)	(0.0013)	(0.0031)
Vol_{t-1}	1.5377 ***	0.7145 ***	0.8852	1.9770 ***	0.5309 ***	0.6222 ***	0.4912 ***	0.4831 ***	0.6632 ***	0.6854 ***
	(0.0401)	(0.0118)	(0.9345)	(0.0650)	(0.0369)	(0.0160)	(0.0333)	(0.0185)	(0.0314)	(0.0150)
SMR	-0.0105	0.3748 ***	-0.0002	-0.0127	-0.0052	0.0812 ***	0.0012	0.0152 ***	-0.0068	0.0008
	(0.0369)	(0.0880)	(0.0562)	(0.0670)	(0.0040)	(0.0077)	(0.0025)	(0.0051)	(0.0087)	(0.0155)
RBY	0.0002	0.0140	0.0000	0.0103	0.0000	0.0032 *	0.0000	-0.0022 **	0.0003	-0.0031
	(0.0020)	(0.0211)	(0.0018)	(0.0445)	(0.0005)	(0.0017)	(0.0002)	(0.0011)	(0.0020)	(0.0062)
RGDP	0.4539	-33.6538 ***	-0.0076	-34.4161 ***	0.0861	2.6594 *	0.0949	-1.1204 *	-0.4275	-54.8466 ***
	(1.5736)	(4.8163)	(0.8803)	(5.3309)	(0.6176)	(1.4887)	(0.2129)	(0.6035)	(2.0556)	(14.3406)
RDEBT	-0.2121	1.6266	0.1123	12.6201 ***	-0.1883	-0.6934	0.0087	0.1837	0.4297	56.5873 ***
	(1.1673)	(2.8161)	(2.4737)	(3.2414)	(0.2475)	(0.5735)	(0.0777)	(0.1777)	(2.0927)	(14.6039)
REDEBT	-0.5148	-20.0540 ***	0.0090	10.4688 ***	0.0528	-0.0572	0.0164	-0.0624	0.1377	-0.8915 *
	(0.5630)	(2.6034)	(1.0444)	(1.6775)	(0.0705)	(0.1379)	(0.0431)	(0.0780)	(0.1838)	(0.5154)
INF	-0.1063	49.8596 ***	-0.0364	11.7209	0.4092	6.3225 ***	-0.0745	2.7190 ***	0.0504	-0.9187
	(2.2674)	(8.6431)	(3.2062)	(9.3267)	(0.5736)	(1.4568)	(0.2347)	(0.5655)	(0.3840)	(0.7628)
RCCI	0.0000	-0.0024	-0.0020	-0.2768	0.0037	-0.0180	-0.0026	0.1229 **	0.0002	-0.1907 ***
	(0.0030)	(0.0064)	(0.1695)	(0.3594)	(0.0482)	(0.1296)	(0.0240)	(0.0605)	(0.0019)	(0.0275)
RTRGI	4.61E-06	-0.0001	-1.41E-06	-1.87E-05	1.80E-06	1.90E-05 **	-1.38E-06	0.0001 ***	-9.38E-07	3.73E-05 **

Table 3.10: Estimation results of the SETAR(1) for oil consuming countries(*Continued*)

	(3.21E-05)	(0.0001)	(0.0001)	(0.0002)	(3.87E-06)	(7.98E-06)	(2.49E-06)	(6.14E-06)	(6.75E-06)	(1.63E-05)
VIX	-1.22E-05	0.0009 ***	-5.29E-06	-0.0014 ***	3.37E-05 **	0.0002 ***	9.94E-06	0.0002 ***	1.50E-05	0.0002 ***
	(0.0001)	(0.0003)	(0.0002)	(0.0005)	(0.0000)	(2.99E-05)	(8.71E-06)	(2.06E-05)	(2.73E-05)	(4.91E-05)

	Germany		Ireland		Italy		Japan		Latvia	
T. variable	VOL_{t-2}		VOL_{t-2}		VOL_{t-2}		VOL_{t-2}		VOL_{t-4}	
T. value	0.0108		0.0068		0.0031		0.0019		0.0019	
	Regime 1	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***
RWTI	-0.0034	-0.3874 ***	-0.0005	0.0255	-0.0007	-0.0601 ***	0.0020	-0.0115 ***	-0.0025	-0.0047
	(0.0234)	(0.0614)	(0.0332)	(0.0542)	(0.0029)	(0.0070)	(0.0016)	(0.0037)	(0.0050)	(0.0091)
OVX	-6.01E-06	-0.0016 ***	0.0000	-0.0002	-1.34E-05	-2.93E-05	-1.14E-06	-0.0001 ***	3.21E-06	-0.0001 **
	(0.0001)	(0.0003)	(0.0001)	(0.0002)	(8.44E-06)	(2.32E-05)	(4.02E-06)	(1.52E-05)	(1.16E-05)	(3.75E-05)

	Lithuania		Netherlands		Portugal		Slovakia		Slovenia	
T. variable	VOL_{t-2}		VOL_{t-4}		VOL_{t-5}		VOL_{t-1}		VOL_{t-1}	
T. value	0.0015		0.0002		0.0106		0.0019		0.0017	
	Regime 1	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***
Obs.	2488	440	2013	887	2489	442	2427	463	2488	440
C	0.0003	0.0045	-0.0002	0.0009 *	-0.0017	0.0073 *	-0.0010	-0.0091 **	0.0001	0.0010
	(0.0010)	(0.0028)	(0.0003)	(0.0005)	(0.0018)	(0.0042)	(0.0016)	(0.0037)	(0.0007)	(0.0023)
Vol_{t-1}	0.6364 ***	0.5008 ***	0.7743 ***	0.2208 ***	0.4479 ***	0.2354 ***	1.4113 ***	0.5306 ***	0.8943 ***	0.7766 ***
	(0.0385)	(0.0173)	(0.0203)	(0.0223)	(0.0252)	(0.0236)	(0.2755)	(0.0170)	(0.1782)	(0.0121)
SMR	0.0006	-0.0379 ***	-0.0017	0.0007	-0.0160	0.0244	0.0051	0.0456 *	-0.0010	0.0252 ***
	(0.0086)	(0.0116)	(0.0023)	(0.0028)	(0.0120)	(0.0247)	(0.0098)	(0.0271)	(0.0050)	(0.0085)
RBY	3.64E-05	0.0006	1.01E-06	0.0001	0.0107 **	0.0133	0.0001	-0.0035	0.0000	0.0038 *
	(0.0006)	(0.0012)	(0.0001)	(0.0003)	(0.0045)	(0.0138)	(0.0004)	(0.0043)	(0.0001)	(0.0022)
RGDP	0.0128	-0.0980	0.1058	1.7230 ***	-0.2354	7.3111 ***	0.1133	-0.6990 *	-0.2761	3.5671 ***
	(0.0578)	(0.1563)	(0.2800)	(0.4152)	(0.4767)	(1.3285)	(0.1159)	(0.3728)	(0.3408)	(1.0606)
RDEBT	0.0335	-0.7162 ***	0.3018 ***	-0.1446 **	-0.0077	-1.1650 **	-0.2692	0.7244	0.0417	-0.5563 ***
	(0.0746)	(0.2482)	(0.0447)	(0.0695)	(0.1987)	(0.5335)	(0.2067)	(0.4785)	(0.0629)	(0.1500)
REDEBT	0.1123	1.5889 **	-0.0124	0.0989 **	-0.1657	4.1281 ***	0.1086	0.1434	-0.0028	0.2693 ***
	(0.1300)	(0.6228)	(0.0331)	(0.0478)	(0.4964)	(1.0401)	(0.0761)	(0.1315)	(0.0174)	(0.0469)
INF	0.1360	1.5855 **	-0.0611	-0.0655	0.5094	1.7293	0.4916	-4.4028 *	-0.0090	-0.0490
	(0.3282)	(0.6981)	(0.0928)	(0.1334)	(0.4782)	(1.4013)	(0.7450)	(2.4805)	(0.1969)	(0.6040)
RCCI	0.0001	-0.0172	-4.67E-05	4.22E-05	0.0402 **	0.1457 **	-0.0001	0.0004	0.0003	0.0920 ***
	(0.0007)	(0.0200)	(0.0001)	(0.0005)	(0.0173)	(0.0623)	(0.0025)	(0.0009)	(0.0034)	(0.0127)
RTRGI	-1.92E-06	-1.97E-05	6.38E-08	-5.84E-06 **	2.19E-05 **	1.82E-05	3.26E-06	0.0001 ***	-1.96E-06	-1.45E-05
	(5.15E-06)	(1.53E-05)	(1.66E-06)	(2.81E-06)	(9.80E-06)	(2.21E-05)	(8.37E-06)	(1.93E-05)	(3.60E-06)	(1.27E-05)
VIX	2.71E-05	0.0001 ***	2.09E-05 ***	2.70E-05 ***	0.0001 ***	0.0005 ***	3.84E-05	0.0005 ***	5.07E-06	0.0001 ***
	(2.08E-05)	(3.60E-05)	(6.33E-06)	(8.93E-06)	(3.52E-05)	(0.0001)	(2.95E-05)	(0.0001)	(1.39E-05)	(2.53E-05)
RWTI	-2.19E-05	-0.0353 ***	-0.0017	-0.0010	0.0036	-0.0332 *	0.0002	-0.0627 ***	0.0005	-0.0092 **
	(0.0041)	(0.0059)	(0.0013)	(0.0020)	(0.0069)	(0.0174)	(0.0054)	(0.0108)	(0.0027)	(0.0043)
OVX	-6.61E-06	-0.0001 ***	-4.61E-06	-6.86E-06	-4.39E-05 ***	-0.0003 ***	-1.99E-06	-0.0002 ***	6.43E-06	-5.39E-06
	(9.62E-06)	(3.08E-05)	(3.01E-06)	(5.04E-06)	(1.64E-05)	(0.0001)	(1.35E-05)	(4.83E-05)	(6.33E-06)	(1.82E-05)

	Spain		Sweden		Philippines		Turkey		Bulgaria	
T. variable	VOL_{t-2}		VOL_{t-1}		VOL_{t-1}		VOL_{t-2}		VOL_{t-3}	
T. value	0.0006		0.0007		0.0018		0.0011		0.0015	
	Regime 1	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***
Obs.	1209	721	2468	440	2491	443	2493	441	2344	589
C	-0.0004	0.0017	0.0001	0.0001	2.76E-05	-0.0137 ***	0.0002	-0.0013 **	0.0002	-0.0075 **
	(0.0019)	(0.0015)	(0.0002)	(0.0005)	(0.0015)	(0.0037)	(0.0002)	(0.0005)	(0.0017)	(0.0034)
Vol_{t-1}	2.2998 ***	0.7907 ***	1.2309 ***	0.1755 ***	1.4865 ***	0.0492 **	0.3296 ***	0.4738 ***	0.0931 ***	0.0519 *
	(0.0769)	(0.0103)	(0.1007)	(0.0232)	(0.2311)	(0.0205)	(0.0323)	(0.0184)	(0.0229)	(0.0297)

Table 3.10: Estimation results of the SETAR(1) for oil consuming countries(*Continued*)

SMR	-0.0021	-0.0036	0.0022 *	0.0029	0.0248 ***	0.0404 ***	-0.0047 ***	-0.0115 ***	0.0285 **	0.1391 ***
	(0.0102)	(0.0072)	(0.0013)	(0.0021)	(0.0081)	(0.0149)	(0.0011)	(0.0018)	(0.0133)	(0.0167)
RBY	0.0003	0.0003	0.0000	0.0002	-0.0015	0.0434 ***	0.0002	-0.0001	-0.0003	-0.0078
	(0.0009)	(0.0012)	(0.0001)	(0.0002)	(0.0034)	(0.0080)	(0.0003)	(0.0006)	(0.0029)	(0.0085)
RGDP	0.0770	0.0819	-0.0230	-1.93E-05	0.0206	0.4976 ***	-0.0091	-0.0076	0.0126	0.2428 **
	(0.1815)	(0.1504)	(0.0163)	(0.0428)	(0.0597)	(0.1339)	(0.0103)	(0.0287)	(0.0508)	(0.1110)

	Spain		Sweden		Philippines		Turkey		Bulgaria	
T. variable	VOL_{t-2}		VOL_{t-1}		VOL_{t-1}		VOL_{t-2}		VOL_{t-3}	
T. value	0.0006		0.0007		0.0018		0.0011		0.0015	
	Regime 1	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***
RDEBT	-0.0224	-0.8593 **	0.0168	0.1152 ***	-0.0436	0.1940 *	-0.0301	-0.2472 ***	-0.0085	0.6869 ***
	(0.4075)	(0.4162)	(0.0125)	(0.0284)	(0.0510)	(0.1154)	(0.0287)	(0.0706)	(0.0704)	(0.1717)
REDEBT	0.2477	1.6958 ***	0.0089	-0.0206 *	-0.1500	-5.4229 ***	0.0170	-0.7293 ***	0.1093	-0.5280
	(0.4438)	(0.4003)	(0.0077)	(0.0110)	(0.6958)	(1.6489)	(0.0439)	(0.1041)	(0.1575)	(0.3845)
INF	0.1392	0.5522	0.0670	-0.1891	-0.8323	0.3563	0.0813 *	-1.0011 ***	0.8735 *	-1.0385
	(0.5461)	(0.4801)	(0.0883)	(0.2381)	(0.5986)	(1.8880)	(0.0462)	(0.1177)	(0.5065)	(1.0326)
RCCI	-0.0002	0.0001	-0.0089	-0.0686 ***	0.0005	-0.0171	-0.0019	-0.1791 ***	-0.0623	0.4091 **
	(0.0015)	(0.0007)	(0.0095)	(0.0199)	(0.0022)	(0.0171)	(0.0088)	(0.0222)	(0.0882)	(0.1785)
RTRGI	5.67E-08	-6.76E-06	-7.01E-07	2.28E-06	-1.80E-06	0.0001 ***	-4.11E-07	1.39E-05 ***	-1.53E-06	4.24E-05 **
	(1.04E-05)	(8.45E-06)	(1.09E-06)	(2.87E-06)	(8.06E-06)	(2.12E-05)	(1.10E-06)	(2.82E-06)	(8.86E-06)	(1.82E-05)
VIX	5.06E-06	3.85E-05 *	1.32E-05 ***	3.73E-05 ***	0.0001 **	0.0005 ***	1.47E-05 ***	0.0001 ***	0.0001 ***	0.0003 ***
	(4.78E-05)	(2.26E-05)	(3.92E-06)	(7.53E-06)	(2.31E-05)	(4.87E-05)	(4.50E-06)	(7.56E-06)	(3.47E-05)	(0.0001)
RWTI	-0.0023	0.0004	0.0004	0.0078 ***	0.0026	0.0246 ***	-0.0002	-0.0064 ***	0.0125 *	0.0320 ***
	(0.0067)	(0.0053)	(0.0008)	(0.0017)	(0.0047)	(0.0088)	(0.0008)	(0.0016)	(0.0065)	(0.0110)
OVX	-3.29E-06	-1.94E-05	-3.94E-06 **	-4.92E-06	-7.46E-06	-0.0001 ***	-3.52E-06 *	-3.76E-05 ***	-2.58E-05 *	-3.62E-05
	(1.69E-05)	(1.36E-05)	(1.88E-06)	(5.38E-06)	(1.15E-05)	(2.39E-05)	(2.13E-06)	(5.12E-06)	(1.52E-05)	(4.27E-05)

	Croatia		Czech		Hungary		Greece		Poland	
T. variable	VOL_{t-2}		VOL_{t-3}		VOL_{t-3}		VOL_{t-3}		VOL_{t-2}	
T. value	0.0009		0.0011		0.0035		0.0003		0.0023	
	Regime 1	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***	***Regime 1***	***Regime 2***
Obs.	2208	726	2458	440	2493	440	638	294	2492	442
C	-0.0026 ***	-0.0045 ***	0.0003	-0.0057 ***	-0.0007	-0.0061 *	-0.0009	-0.0003	-0.0021 **	-0.0027
	(0.0008)	(0.0011)	(0.0006)	(0.0013)	(0.0013)	(0.0033)	(0.0012)	(0.0002)	(0.0008)	(0.0019)
Vol_{t-1}	2.0911 ***	0.5518 ***	0.6812 ***	0.6298 ***	0.2574 ***	0.4644 ***	11.0991 ***	0.9499 ***	0.9426 ***	0.6944 ***
	(0.1188)	(0.0152)	(0.0388)	(0.0159)	(0.0225)	(0.0257)	(0.2183)	(0.0043)	(0.0399)	(0.0137)
SMR	-0.0114 *	-0.0070	-0.0023	0.0045	0.0743 ***	0.0517 ***	-0.0006	-0.0015	-0.0095 *	-0.0396 ***
	(0.0067)	(0.0048)	(0.0038)	(0.0051)	(0.0076)	(0.0132)	(0.0020)	(0.0010)	(0.0058)	(0.0084)
RBY	-0.0010	-0.0002	2.61E-06	0.0024	0.0001	-0.0039	0.0000	-0.0002	0.0010	0.0422 ***
	(0.0018)	(0.0036)	(0.0002)	(0.0057)	(0.0019)	(0.0042)	(0.0004)	(0.0002)	(0.0038)	(0.0108)
RGDP	-0.0329	-0.2689 ***	0.5412	-0.8231	0.0574	0.3391 **	-0.0107	0.0030	-0.0106	-0.2135 *
	(0.0435)	(0.0921)	(0.3521)	(0.7476)	(0.0559)	(0.1549)	(0.0352)	(0.0172)	(0.0384)	(0.1242)
RDEBT	0.1223	1.9840 ***	0.0435	0.0225	0.3480 ***	-0.5910 **	0.0647	-0.0251	0.0947	2.7959 ***
	(0.2111)	(0.4885)	(0.0560)	(0.1189)	(0.1147)	(0.2790)	(0.1632)	(0.0249)	(0.1461)	(0.4581)
REDEBT	-0.0192	-0.0221	0.0427	-0.3907 ***	0.3049 **	0.3832	-0.0039	0.0293 **	0.1117 *	-0.0545
	(0.0242)	(0.0608)	(0.0913)	(0.1514)	(0.1516)	(0.3133)	(0.0476)	(0.0142)	(0.0673)	(0.1427)
INF	0.4061	-0.0182	0.0913	-0.6346 *	-0.8000 **	0.7832	-0.0104	0.1245 ***	0.1826	1.9984
	(0.2830)	(0.4926)	(0.1776)	(0.3448)	(0.3650)	(0.7187)	(0.0674)	(0.0394)	(0.4242)	(1.2738)
RCCI	0.0052	-0.0181	0.0002	-0.0035 ***	-0.0042	-0.0013	-0.0003	0.0067 *	0.0002	-0.0284 **
	(0.0121)	(0.0134)	(0.0004)	(0.0011)	(0.0149)	(0.0438)	(0.0136)	(0.0037)	(0.0046)	(0.0125)
RTRGI	1.47E-05 ***	2.43E-05 ***	-2.57E-06	0.0001 ***	2.36E-07	3.64E-05 **	4.54E-06	2.02E-06	1.07E-05 **	1.57E-05 *
	(4.02E-06)	(5.51E-06)	(3.34E-06)	(6.90E-06)	(7.14E-06)	(1.65E-05)	(6.12E-06)	(1.28E-06)	(4.32E-06)	(8.64E-06)

Table 3.10: Estimation results of the SETAR(1) for oil consuming countries(*Continued*)

VIX	5.58E-06	0.0001 ***	6.02E-06	0.0001 **	0.0001 ***	0.0003 ***	-5.99E-06	5.07E-06	0.0001 ***	0.0001 ***
	(1.46E-05)	(1.65E-05)	(1.18E-05)	(2.79E-05)	(2.77E-05)	(4.55E-05)	(2.27E-05)	(4.07E-06)	(1.84E-05)	(2.64E-05)
RWTI	-0.0014	-0.0053	0.0015	-0.0014	-3.30E-05	0.0276 ***	0.0004	0.0010	-0.0028	-0.0096 *
	(0.0025)	(0.0034)	(0.0022)	(0.0050)	(0.0053)	(0.0103)	(0.0034)	(0.0009)	(0.0031)	(0.0055)
OVX	-7.58E-07	-4.87E-05 ***	-1.60E-06	-1.45E-05	-2.26E-05 *	-4.99E-05	1.23E-05	-1.86E-07	-1.25E-05	-0.0001 ***
	(5.29E-06)	(1.16E-05)	(5.21E-06)	(2.67E-05)	(1.25E-05)	(3.56E-05)	(1.48E-05)	(2.37E-06)	(7.77E-06)	(2.10E-05)

	Romania		Ukraine	
T. variable	VOL_{t-4}		VOL_{t-4}	
T. value	0.0002		0.0013	
	Regime 1	***Regime 2***	***Regime 1***	***Regime 2***
Obs.	975	206	439	493
C	0.0002	0.0003	-0.0136 ***	-0.0015 *
	(0.0002)	(0.0003)	(0.0033)	(0.0008)
Vol_{t-1}	0.5855 ***	0.7248 ***	0.1455 ***	0.6049 ***
	(0.0274)	(0.0348)	(0.0431)	(0.0162)
SMR	-0.0002	-0.0088 ***	0.0731 ***	0.0048
	(0.0010)	(0.0024)	(0.0094)	(0.0041)
RBY	0.0000	0.0003	0.0011	-0.0006
	(0.0001)	(0.0003)	(0.0055)	(0.0018)
RGDP	0.0011	0.0220 ***	0.2958 **	-0.0036
	(0.0021)	(0.0061)	(0.1164)	(0.0353)
RDEBT	0.0146	0.1387	1.3540 ***	0.0842 ***
	(0.0452)	(0.1032)	(0.2143)	(0.0235)
REDEBT	0.0138	-0.0903 ***	-1.9779 ***	-0.1987 *
	(0.0111)	(0.0288)	(0.3708)	(0.1046)
INF	0.0000	0.0004 *	-1.1548 **	0.0408
	(0.0000)	(0.0002)	(0.5733)	(0.0880)
RCCI	0.0003	-0.0040	-0.6113 **	-0.0052
	(0.0016)	(0.0052)	(0.3069)	(0.0697)
RTRGI	-1.08E-06	-3.64E-06 **	0.0001 ***	0.0000 **
	(8.49E-07)	(1.67E-06)	(2.06E-05)	(4.42E-06)
VIX	5.17E-06	3.93E-05 ***	3.53E-07	4.07E-05 ***
	(3.28E-06)	(7.23E-06)	(0.0001)	(1.55E-05)
RWTI	3.17E-05	0.0006	0.0055	0.0025
	(0.0004)	(0.0007)	(0.0095)	(0.0031)
OVX	-6.54E-07	-5.22E-06 ***	0.0002 ***	1.17E-06
	(7.58E-07)	(1.93E-06)	(2.90E-05)	(8.07E-06)

T. variable and T. value refer to the threshold chosen variable and the threshold value used. Regime 1(2) corresponds to the period where Threshold variable chosen < Threshold value (Threshold variable chosen >= Threshold value). *, ** and *** denote significance at respectively 10%, 5% and 1% statistical levels.

Chapter 4

International risk spillover in the sovereign credit markets: An empirical analysis

The occurrence of more and more financial crises characterized not only by their persistence but especially by their severity and magnitude encourages further investigation on portfolio diversification and financial assets' comovements.

This essay, forthcoming in ***Managerial Finance***, studies the volatility spillover among 33 worldwide Sovereign Credit Default Swap markets and their underlying bond markets. Conversely to the studies of the literature, heteroscedasticity, asymmetric leverage effect and long-memory features of sovereign credit spreads are simultaneously taken into account through a bivariate FIEGARCH model and a Bayesian cointegrated VAR model.

Similarly to the literature, our findings confirm strong evidences of credit risk spillover between credit markets accentuated during crisis periods. However, our country by country analysis allows us to show that countries exhibit different sensitivity levels and reactions' divergences to financial shocks. Further, we show that the bidirectional interrelationship evolves over time and across countries emphasizing the necessity of time-varying national regulatory policies and trading positions.

Keywords : *Sovereign CDS and bond markets, Dynamic Conditional Correlation, Bayesian cointegrated VAR, Contagion, Risk spillover.*

4.1 Introduction

Aiming to control the financial stability, to anticipate financial turmoil and to appropriately balance risk against profitability in investment mix, portfolio managers and policy makers assign a high priority to understand the risk spillover over time and among various credit markets. This issue is, actually, to be addressed to determine and develop both the optimal level of portfolio diversification with the associated risks and the indispensable regulatory policies for macroeconomic-level financial supervision. With remaining questions about the financial markets' comovement dynamics, a particular interest is given to interrelationships between the credit derivatives and the bond markets in both academic and non-academic backgrounds. Despite the perpetually increasing number of studies on the proper credit risk assessment, the lead-lag relationship of the credit spreads' second order remains of importance and needs deeper investigation particularly after the world credit markets integration and the occurrence of financial crises. In fact, the necessity of comprehending and assessing the interaction between credit spreads volatility and the spillover effect between credit derivatives and their underlying markets remains a crucial issue in financial research, whether to avail of arbitrage opportunities, to realize some hedging operations or to speculate on the predictability of the borrowing cost. Understanding the direction and intensity of shocks spreading among credit derivative and debt markets is very important. With better understanding of spillover effects during crises, economists, regulators and policy makers can anticipate credit markets' reactions and reduce financial instability.

Several works consider the interrelationship between derivative assets and their underlying markets and focus, notably, on the co-movement dynamics of the CDS and the bond markets. This strand of research can be divided into three groups following the purpose: First, research focus on the identification of the price discovery process origin. Second, another part of the literature works on the explanation of the price difference between CDS spreads and bond spreads (CDS-Bond basis) by means of several financial and economic variables. Third, other empirical works consider this dynamic relation in the context of a shock transmission and contagion mechanism. Our essay fits in the third category and examines the interrelationship between the sovereign CDS market and the underlying government bond market of 33 countries in order to detect volatility spillover during the period going from January 2006 until April 2014 covering the Global Financial Crisis and the European Debt Crisis.

Prior studies, studying shocks transmission between CDS and bond generally focus on the spreads' first moment and suppose a non-informational volatility interaction[1]. These studies are also based on empirical approaches and methodologies that present some econometric issues: For example, the use of a Vector AutoRegressive (VAR) model in its different forms is not necessary heteroskedasticity robust which distorts the results of cointegration and causality. Further, the use of joint volatility processes, through multivariate Dynamic Conditional Correlation (DCC) or BEKK models, is not sufficient if the credit spreads statistical properties are not all taken into account. Moreover, most of the studies samples are composed by regional countries and gives thus only restricted evidence that is not straightforwardly suitable for other regions exhibiting different characteristics.

This essay contributes to the existing literature in several ways while studying the dynamic volatility transmission between the underlying bond market and their sovereign Credit Default Swaps (CDS, hereafter). First, unlike most of the previous studies, the aforementioned methodological shortcomings are filled by providing an improvement in the usual econometric framework: our results rely on both a reduced-form of the VAR model and an extensive-form of the multivariate GARCH model. Second, in order to assess the interconnectedness and the volatility spillover effects among the CDS and the bond markets, a class of model based on the AR(1)-FIEGARCH(1,d,1)-DCC is carried out, whose relevance is justified by the identification of the credit markets' particular properties. And so, the leverage effect, the asymmetric power and the long memory behavior of sovereign CDS and bond spreads are taken into consideration in the volatility spillover estimation. As proved by the results of our model, admitting these specifications in a multivariate model's computation adds more robustness to the empirical results and provides more relevant decision-making process. Third,

[1]For volatility spillover analysis, Tamakoshi and Hamori (2016) examine corporate indexes for banking, life insurance and other UK financial sectors over a period spanning from 2008 until 2013.

our econometric technique controls and exploits the heteroscedasticity in the Bayesian Vector Error Correction model which allows the Granger-Causality test in mean to capture both small and extreme risk propagation. Fourth, we use a sample composed by countries across the world, representing the international context so we can study the risk spillover among countries with different economic characteristics and financial features and give, thus; some general evidences. Fifth, unlike previous study, our data covers the Global Financial Crisis as well as the Sovereign Crisis during which trading CDS contracts no longer only concerns hedging operations but also arbitrage and speculation. The studied period allows us, then, to examine the impact of crises on risk spillover dynamics. Finally, our study is not limited to country-by-country analysis but also investigates the reactions of synthetic financial portfolios constructed using economic growth, regional and credit rating criteria.

Even though several researchers studied the co-movement relationship between the CDS market and the underlying bond market, our essay is the first to include further significant credit spreads properties in the volatility transmission estimation model which gives more robustness to the results. In fact, the investigation through the FIEGARCH-DCC model and the Bayesian Vector Error Correction model (BVECM) detects greater shock transmission across worldwide credit derivative and their underlying markets. The study of such phenomenon during a long period covering the recent two financial crises reveals that the risk transmission is even more important during turmoil phases. Yet the analysis of countries with dissimilar characteristics shows different sensitivity degree and reaction direction that fluctuate over time and across markets. Finally, besides the country-by-country credit spreads analysis, our essay examines the volatility spillover between synthetic financial portfolios constructed following several criteria: the economic growth, the region and the credit rating.

The rest of the chapter is organized as follows: section 4.2 depicts the literature reviews on the comovement between the CDS and their underlying markets. section 4.3 displays the data used and the econometric framework. Empirical results and discussion are presented in section 4.4, while section 4.5 is dedicated to the concluding remarks and implications.

4.2 Literature review on CDS and underlying bonds

The interconnectedness between capital markets have been abundantly assessed in the financial literature. A specific strand of these researchers, focusing on information and/or shock transfer between the CDS and the underlying bond markets, is of particular interest in this essay. Even though the approach is the same, these various studies can be divided into three groups following the purpose.

4.2.1 The price discovery process

Researchers, focusing on the price discovery process, aim to determine the origin of the credit price formation. The earliest study conducted by Zhu (2006) shows that CDS takes the lead in the price adjustment process. Focusing on the Japanese mega-banks' credit spreads, Baba et al. (2007) empirically find, as well, that corporate CDS market plays the primary and the dominant role in the price discovery process of credit risk to the detriment of the underlying bond market. In contrast, using daily data of 8 emerging countries, Bowe et al. (2009) show that - even though the average price difference is positive reflecting the preeminence of the CDS spreads over the Bond spreads - the CDS market does not take the lead of the price discovery process. Coudert and Gex (2013) concentrate the analysis on the GM and Ford crisis periods and confirm the previous findings. These authors study the interaction between corporate credit markets during the General Motors and Ford crisis and reveal that these two markets trace each other and that corporate CDS market influences the bond one with an intensification of this interaction pattern during turmoil phases. When it comes to sovereign markets, the interrelationship seems to reverse and the low-yield bond market gets back on top of the price discovery process. Based on results of country-level analysis and using a time varying vector autoregression on five-year and ten-year maturity contracts, Calice et al. (2013) show that these two markets comove closely. However, the main finding of this essay is that the liquidity of the CDS market has an important impact on the bond spread. Furthermore, authors empirically demonstrate that this information transmission and interaction mechanism differ from one country to another and depends on maturities. Yet, this trend is more important during turmoil period where the CDS market clearly overtakes the bond market in most cases. This study is only limited to European countries. More recently, Fontana and Scheicher (2016) present different findings where the price discovery process depends not only on the countries' specifications but also on arbitrage and liquidity effects. Focusing on sovereign CDS of then euro area countries over a period spanning from 2006 to 2010, the authors show that, as expected, the price adjustment is initially observed in the CDS market but after September 2008, the mechanism changes the direction and takes place in the bond market.

4.2.2 The determinants of the price divergence

Another strand of the literature tries to explain the price divergence between CDS spreads and Bond spreads (CDS-Bond basis) by using several domestic and international variables as proxies for assets' properties. Cossin et al. (2005) show that, unlike the theoretical parity, corporate CDS premiums and bond spreads of the 180 most liquid European companies are not closely related in the short run, and they show that this pricing difference is mainly explained by the liquidity premium and the contract specifications (the cheapest to deliver option). Blanco et al. (2005) find an equilibrium relationship between these credit derivatives and the corresponding bond spreads in the long-run. These authors argue that the parity deviation in the short-run arises from the CDS contracts' imperfections and from, eventually, some measurement errors of the bond spread due to risk-free rate inappropriateness. Studying 33 private reference entities mainly from the USA, the UK, France and Germany, belonging to more than four sectors, the authors subsequently suggest that the credit risk part in the CDS spreads is upper-estimated while it is undervalued in the bond spreads especially in Europe. Longstaff et al. (2005) investigate the same issue in an international context represented by data on European and American firms. They explain the divergence in corporate credit risk spreads by a non-default risk component related to bond-specific illiquidity and macroeconomic fundamentals of the credit market. Using a panel VECM, Zhu (2006) also finds that the theoretical parity between CDS and bond spreads is only valid in the long-run. However, this cointegration relationship does not exist in the short-run because of the differences in reactions to some credit conditions. The author affirms that the liquidity premium greatly impacts the credit risk pricing while the cash market plays a neglected role, especially in the US market from 1999 to 2002. The same conclusions are drawn for the sovereign credit markets by Ammer and Cai (2011) using a sample of nine emerging countries. Bai and Collin-Dufresne (2013) examine the cross-sectional determinants of the price difference between the two contracts and explain that the more the counterparty risk component, the risk premium and the collateral margin of the bond are important, the more the difference measure is large.

More lately, Gilchrist and Mojon (2016) investigate credit risk measures of financial and non-financial Euro companies and find that the Global Financial crisis has negatively impacted the borrowing cost reflected in the bond spread of these firms, while the US doc-com bubble of 2000s has only impacted the non-financial corporations. Authors find, as well, that the financial crisis has widened the cross-countries price difference between the CDS and the bond spreads due to national and not euro area credit conditions. All these cited studies point out the shortcoming of the arbitrage theory that supposes a non-arbitrage necessary condition between the two markets.

4.2.3 The dynamic relation of shock transmission

Other empirical works consider this dynamic relation in the context of a shock transmission and contagion mechanism. Different empirical approaches - controlling for endogeneity or serial correlation - are used to assess the risk spillover across these two markets. Baba et al. (2007) find empirically that shocks spill over from the CDS to the bond market but no feedback transmission is found. Norden and Weber (2009) give interesting findings about the comovement relationship between CDS, bonds and stock markets in the private sector over a very short period of two years (2000–2002). Using a VAR model, these authors show that financial shocks first affect the stock market before spreading to the CDS and the bond markets. Besides, further evidences are displayed and reveal that, in most countries under focus, the CDS market is more vulnerable to shocks than the bond one. The CDS market contributes more than the bond market in the credit risk transmission channel. Forte and Pena (2009) study the credit risk discovery process of 17 non-financial companies from North America and Europe and confirm that shock transmission takes place from the CDS to the corresponding bond market. Delatte et al. (2012) study the mutual influence between the CDS and the underlying bond market during a relatively short period, as well, spanning from 2009 to 2010. They figure out that this interconnection is more intense during distress period and that the non-linear risk transfer from the sovereign CDS market to the bond market depends on the market conditions. The direction of the credit markets dynamics gets reverse when it comes to core-European countries.

4.2.4 The risk-free reference rate

Because of a homogeneity issue, the majority of the above-cited studies transform the bond yields into bond spreads regarding the risk-free rate. A large body of the literature addresses the appropriate choice issue of the risk-neutral reference rate. Longstaff et al. (2005) and Ismailescu and Phillips (2015) promote the use of the US treasury yield when it comes to studying an extensive dataset of European and American corporate bonds while other authors are more flexible and use yields of bonds issued by the lowest risky government in the area. For instance, to construct bond spreads of the Euro area, authors use the German federal government securities as a risk-free rate while they use the US treasury yield for American reference entities[1] (Blanco et al., 2005; Delatte et al., 2012; Coudert and Gex, 2013; Gyntelberg et al., 2013; Costantini et al., 2014; Eichler, 2014; Fontana and Scheicher, 2016; Gilchrist and Mojon, 2016).

[1] Calice et al. (2013) use the five-year German bund as a risk-free rate for EU and Turkish banks and the UK gilt rate for US banks.

In the same context, Cossin et al. (2005) use the five-year JPMorgan EMU government investment-grade bond index as a proxy for the risk-free rate to calculate the European corporate bond spread. Working on an assessment of the deterministic dynamics of credit spreads in emerging countries, Delatte et al. (2012) use relatively the same reference rate with different EMBI[1] JPMorgan index for each geographical region. Finally, Zhu (2006) prefers the use of the zero-coupon treasury.

Another strand of the literature argues that governments are no more considered as riskless entities and their issued government yields cannot be a good proxy for the risk-free rate due to tax charges, legal factors and other macroeconomics factors (Bai and Collin-Dufresne, 2013). That's why, the US swap rate is used as the risk-neutral rate instead of the government bond yield (Blanco et al., 2005; Forte and Pena, 2009; Ammer and Cai, 2011; Bai and Collin-Dufresne, 2013; Fontana and Scheicher, 2016). The swap rate seems to be an accurate choice since derivatives traders commonly use it as a reference in their pricing models. Yet, Hull et al. (2004) prove empirically that swap rate is more representative of the risk-free rate than US treasuries rates. Nevertheless, the use of swap rates does not seem relevant for European countries. Indeed, being low risky, the bonds issued by these countries have very low yields, with negative spreads in most cases. The literature based on emerging countries, where credit risk is quite high, proposes an alternative approach.

Since there is no certainty about the most appropriate benchmark, Norden and Weber (2009) use several free interest rate term structures: government bond yield curves of Deutsche Bundesbank, the Federal Reserve Board and the bank of England, the swap rate curves denominated in USD, EUR and GBP and they include a synthetic Euro yield curve.

4.2.5 Econometric approaches and literature limits

Focusing on the third strand of the literature dealing with the contagion phenomenon in financial markets in general and the risk spillover between CDS and Bond markets particularly, econometric approaches can be classified into two frameworks: On the one hand, some authors employ a Vector autoregressions framework analysis and its extended and reduced forms (structural VAR, Vector Error Correction, Bayesian VAR, VARX...) (Blanco et al., 2005; Zhu, 2006; Baba et al., 2007; Forte and Pena, 2009; Longstaff, 2010; Ammer and Cai, 2011; Delatte et al., 2012; Coudert and Gex, 2013; Lee et al., 2015; Srivastava et al., 2016; Fontana and Scheicher, 2016; Gilchrist and Mojon, 2016; Yu, 2017). On the other hand, other authors propose a multivariate GARCH framework (Baek and Jun, 2011; Calice and Ioannidis, 2012; Audige, 2013; Youssef and Belkacem, 2015; Buchholz and Tonzer, 2016; Tamakoshi and Hamori, 2016). We note that the mentioned studies and many others are based on research methodologies presenting some econometric issues. First, the use of different VAR models to study the dynamics of a shock transfer in financial cross-markets is questionable and subject to several criticisms because of insufficiency in theoretical underpinnings (Lee et al., 2015). Yet, these models have no direct heteroskedasticity-robustness which distorts the results of cointegration and causality. Second, most of the GARCH-type multivariate models used to detect shock transmission does not recognize all the credit spreads specifications which leads to less relevant and significant empirical results. Third, results of the multivariate GARCH studies are based solely on the fact that the transmission of financial shocks from one market to another is identified by a significant increase in assets' dynamic correlations. However, we

[1]Emerging Market bond index.

believe that increasing correlations is justified, in some cases, not by a change in price transmission mechanisms within a country's credit markets, but rather by economic and geographical dependence or by a simple increase in prices' volatility on these financial markets. While the volatility of a financial market increases considerably, its correlation with other financial markets also increases automatically. This is evident even if the underlying relationship between these markets remains constant (Forbes and Chinn, 2004). Thus, this methodological choice seems in this case not totally relevant, at least if it is not associated with any other methodologies or econometric techniques.

Despite the econometric issues, literature on CDS and bond markets presents some further limits. In fact, studies of international context using worldwide samples are scarce. The majority of the studied samples are, indeed, composed by regional countries and since we believe that each country presents different economic and financial characteristics, these regional findings cannot be interpreted as global evidences. Moreover, most of these studies generally focus on the spreads' first moment and suppose a non-informational volatility interaction. We believe that risk spillover is rather detected using conditional volatility rather than spread or log returns.

4.3 Data and Methodology

4.3.1 Data description: CDS and bond spreads

This essay focuses on the analysis of the interrelationship between the sovereign CDS market and the underlying government bond market in order to detect volatility spillover during the period going from January 2006 until April 2014 covering the Global Financial Crisis and the European Debt Crisis. The sample used is composed by 33 worldwide countries belonging to four different economic status: low economic growth countries (Portugal, Ireland, Italy, Greece and Spain), developed countries (Austria, Belgium, Denmark, Finland, France, Germany, Japan, Latvia, Lithuania, Netherlands, Norway, Slovakia, Slovenia, Sweden, the UK, and the USA), newly industrialized countries (Brazil, China and Turkey) and emerging countries (Bulgaria, Croatia, Czech, Hungary, Poland, Romania, Russia, Ukraine and Venezuela). The economic classification of these countries is made according to the NU, the CIA World Factbook, the IMF and the World Bank criteria, so as to have homogeneous sample in each category.

The five-year CDS spreads and the corresponding bond yields are obtained from Bloomberg ® and Thomson Reuters ®. For sake of homogeneity, five-year bond yields are transformed into spreads regarding the risk-free interest rate. In this essay, the bond spreads are constructed by relying on the work of Norden and Weber (2009). We choose the five-year German federal government bond as a reference rate for European countries, and the United States sovereign bonds for American and Asian countries. In order to not reduce our sample size, the Euro-area generic bond is used as a benchmark yield for Germany, and the US Treasury Zero-Coupon Yield Curve for the United States.

4.3.2 Econometric Methodology

The econometric framework adopted in this essay includes two dependent approaches. First, a Dynamic Conditional Correlation model is estimated within the CDS and bond markets of each country following the AR(1)-FIEGARCH(1,1)-DCC model. Next, a Bayesian specification of the cointegrated VAR model is applied to transformed-time series in order to analyze credit risk transmission across markets.

The AR(1)-DCC-FIEGARCH(1,1) framework

The adopted methodology, in this first step, is inspired by the work of Sabkha et al. (2018) who used this model to identify contagion effect among sovereign CDS markets. The FIEGARCH model of Bollerslev and Mikkelsen (1996) is employed in its multivariate dimension. The accuracy of this model relies on the findings of the preliminary tests that clearly defines the particular features of the sovereign credit markets: a volatility clustering, an asymmetric response of volatility to positive and negative news, a leverage effect and a long-range volatility dependence. Furthermore, the use of this class of model is empirically recommended since it allows for conditional variance flexibility and takes into account previous cross markets' specifications (Conrad et al., 2011; Fantazzini, 2011).

Bivariate dynamic conditional correlation coefficients are estimated following the DCC specifications as proposed by Engle (2002). For each country, time series are assumed to follow an AR(1) process with a t-student marginal distribution.

$$\begin{cases} x_{1,t} = a_{1,0} + a_{1,1}x_{1,t-1} + u_{1,t} \\ x_{2,t} = a_{2,0} + a_{2,1}x_{2,t-1} + u_{2,t}, \end{cases} \tag{4.1}$$

where $x_{1,t}$ and $x_{2,t}$ are respectively the CDS first-differences and the bond first-differences at time t. For $i = 1, 2$, $a_{i,0}$, are constant $\in [0, \infty)$ and $|a_{i,1}| < 1$. $u_{i,t} = \sigma_{i,t}\varepsilon_{i,t}$ where $\varepsilon_{i,t}$ constitute weak white noises such as $E_t(\varepsilon^2_{i,t-1}) = 1$. $\sigma^2_{i,t}$ is positive representing the conditional variance of $x_{i,t}$ such as $\sigma^2_{i,t} = Var(x_{i,t}|\mathcal{F}_{t-1})$ with $\mathcal{F}_t$ is the market information set at a given moment t.

In its general form, the DCC model is defined as a time varying variance-covariance structure:

$$\Omega_t = D_t H_t D_t, \tag{4.2}$$

Where D_t is a diagonal matrix of the conditional standard deviation obtained from the univariate models and H_t is the 2×2 time-varying correlation matrix of the standardized error terms ε_t (of x_t) such as:

$$H_t = Q_t^{-1} Q_t Q_t^{-1}, \tag{4.3}$$

where Q_t is symmetric covariance matrix that can be written as follows:

$$Q_t = \overline{Q}(1 - \alpha - \beta) + \alpha(\varepsilon_{t-1}\varepsilon'_{t-1}) + \beta Q_{t-1}, \tag{4.4}$$

With $\overline{Q}$ is a symmetric time invariant matrix of the unconditional correlation coefficients ($\overline{\rho_{12}}$) between $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$. α and β parameters are positive and respect the stationarity constraint of $\alpha + \beta < 1$. The bivariate dynamic conditional correlation coefficient of Engle (2002) is, thus, defined as:

$$\rho_{12,t} = \frac{\overline{q_{12}}(1 - \alpha - \beta) + \alpha(\varepsilon_{1,t-1}\varepsilon_{2,t-1}) + \beta q_{12,t-1}}{\sqrt{(\overline{q_{11}}(1 - \alpha - \beta) + \alpha\varepsilon^2_{11,t-1} + \beta q_{11,t-1})(\overline{q_{22}}(1 - \alpha - \beta) + \alpha\varepsilon^2_{22,t-1} + \beta q_{22,t-1})}}. \tag{4.5}$$

A prior step to the DCC estimation is to run a univariate FIEGARCH (1,d,1) model for each of the time series in order to obtain the conditional standard deviations, $\sigma_{1,t}$ and

$\sigma_{2,t}$. According to Bollerslev and Mikkelsen (1996), a FIEGARCH (p,d,q) model is written as follows:

$$ln(\sigma_t^2) = \omega_0 + \phi(L)^{-1}(1-L)^{-d}[1+\psi(L)]g(\varepsilon_{t-1}). \tag{4.6}$$

With $\phi(L)$ and $\psi(L)$ are lag polynomials, $(1-L)^{-d}$ is the financial fractional differencing operator and $g(e_t)$ is a quantization function of information flows such as $g(e_t) = \theta e_t + \gamma[| e_t | - E(| e_t |)]$ where γ is the leverage coefficient. When $\gamma > 0$, it means that the impact of bad news (negative shocks) on volatility is more important than the impact of good news (negative shocks with the same absolute magnitude), leading to an increase of the conditional variance in a more proportional way and vise versa. The FIEGARCH (1,d,1) is automatically well-defined and does not need any non-negativity restrictions.

As mentioned in the literature (Kalbaska and Gątkowski, 2012; Dimitriou et al., 2013; Kenourgios and Dimitriou, 2015), contagion and risk spillover phenomena are highly associated with an increase in the dependency between financial markets during crisis periods, compared with their interconnection beyond the shocks occurrence. In other words, it is assumed that risk transfer between the CDS market and the bond market occurs when in time of crises correlation between price co-movements in these markets is much higher than what it was beyond these periods. Since contagion is only detected when there is a statistically significant increase in the correlation, we follow the previously mentioned works and we propose to regress conditional correlations (ρ_t) on their lagged values (ρ_{t-1}) and dummy variables representing different crisis periods (D_k). We follow this approach and we consider the following equation:

$$\rho_t = \mu_0 + a_1\rho_{t-1} + b_k D_k + \eta_t. \tag{4.7}$$

where α_0 is a constant $\in [0, \infty)$, ρ_t is the time-varying conditional correlation between the CDS and the bond markets. k corresponds to the crisis index, it is equal to one when it's about the first financial crisis and equal to two when it comes to the sovereign crisis. In this essay, we use the same length and crises' timeline as Sabkha et al. (2018) and divide our studied period into four sub-periods:

- From January 2006 to June 2007: a reference period;
- From July 2007 to March 2009: 1^{st} crisis period (financial crisis);
- From November 2009 to March 2012: 2^{nd} crisis period (Sovereign Debt crisis);
- From March 2012 to April 2014: Post-crisis period (tranquil period).

Using the time periods defined above, if the lagged variable coefficient (b_k) is statistically significant, this indicates that the country's CDS market and bond market are more cointegrated during the period of financial turmoil, and therefore there is a risk spillover between these credit markets. The econometric implication of this hypothesis is that large shocks are more important that the small ones in terms of transmission, making risks more easily spread between these two markets during crisis periods. This implies that changes in CDS spread volatilities impact the volatility of bond spreads, and vise versa.

The Bayesian VECM framework

The analysis of the credit risk spillover goes through studying the lead-lag relationship between financial assets. This dynamic relation is frequently modeled using the vector autoregressive

(VAR). This estimation method does not explicitly consider for several financial data properties such as endogeneity, serial correlation or non-normality. To overcome these shortcomings in this essay, a restricted form of the VAR method is applied to transformed time series. The transformation technique allows us to take into account the presence of heteroscedasticity, among other features, in the spreads under investigation.

For each spread, a special treatment is applied to each time series though the following transformation-equation: $y_t = \frac{x_t - \mu_t}{\sigma_t^2}$. With y_t is the new transformed time series, x_t is the CDS (or Bond) spread at time t, μ_t and σ_t^2 are respectively the conditional mean and the conditional variance of the spread obtained from the estimation of the univariate FIEGARCH model. In this way, heteroscedastic properties, asymmetric leverage effect and long-memory behavior of CDS and bond spreads are considered in the converted-time series.

To overcome information loss due to stationary techniques, the restricted form of VAR, as proposed by Johansen et al. (1991) considering for the non-stationarity and the cointegration of macroeconomic and financial time series is employed in this essay rather than the commonly used unrestricted VAR model of Sims (1980). The main idea of this model is to restrain the long-run paths of explicative variables by forcing the convergence to the cointegration coefficient (error correction term), while the adjustment of the short-run behavior remains unrestricted.

$$\Delta Y_t = \mu + \Gamma \beta' Y_{t-1} + \sum_{k=1}^{p} \Pi_k \Delta Y_{t-k} + a_t, \tag{4.8}$$

Where Y_t is a vector of N explicative variables ($N = 2$ in our case) at time t, Π is $N \times N$ parameters matrix of the short-run relationship, Γ and β' denote matrices of receptively the error correction terms and the the long-run coefficients μ is a deterministic component and a_t represents the innovations.

Another restrictive version of the general vector autoregressions is the Bayesian VAR introduced by Litterman (1986). This new class of model avoids the estimation problem of over-parameterization by proposing some restrictions in the prior distribution functions. Initial specifications allow for calibrating the prior residual covariance matrix parameters by controlling the prior mean and the tightness of the variance. The use of the Bayesian form is recommended when the studied period is short and the number of observations is limited (Cuestas, 2017).

Given that our series contain stochastic trends (random walk process) and show highly significant cointegrating relationships (results can be given upon request), and in order to avoid over-fitting issues, the use a Bayesian Vector Error correction model combining specifications of both previous restrictive models, is appropriate. This approach concedes more reliability and efficiency to the parameters estimates with particular respect to the long-run equilibrium. In consideration of several non-identification issues, prior elicitation in multivariate models is an important step. Our analysis, being based upon this Bayesian econometrics, is relevant as it has been already used in the macroeconomic context knowing that financial variables exhibit the same statistical properties as macro-aggregates. In fact, macroeconomic application shows that the Bayesian VAR with an error correction parametrization outperforms both standard and cointegrated VAR (Félix et al., 2003; Koop et al., 2005).

We follow the work of Amisano and Serati (1999) and give some informative prior to the Γ and β' (factor loadings coefficients) matrices. Restrictions are imposed to the estimated adjustments terms using the results of the Johansen system cointegration test[1]. The loadings factor matrices allow us to give more importance to the cointegrating relationships - with no restriction in the short-run dynamics - and to define the speed of their convergence.

The interrelationship between the CDS and the bond markets can be expressed, through the Bayesian vector autoregressions with error correction, as functions of the cointegrating terms and their mutual lagged values:

$$\begin{aligned}\Delta y_{1,t} &= \lambda_1 e_{t-1} + \sum_{k=1}^{p} \gamma_1 \Delta y_{1,t-k} + \sum_{k=1}^{p} \delta_1 \Delta y_{2,t-k} + a_{1,t},\\ \Delta y_{2,t} &= \lambda_2 e_{t-1} + \sum_{k=1}^{p} \gamma_2 \Delta y_{2,t-k} + \sum_{k=1}^{p} \delta_2 \Delta y_{1,t-k} + a_{2,t}.\end{aligned} \tag{4.9}$$

with y_1 and y_2 represent respectively the transformed time series of the sovereign CDS and the government bonds, λ is the adjustment coefficient of each market and e_t is a deviation from the long-run equilibrium estimated from the following equation: $y_{1,t} = c_0 + c_1 y_{2,t} + e_t$.

After estimating the BVECM, a Granger causality (GC, hereafter) test is applied in order to detect any contagion phenomenon between the two markets and to check for the risk transfer direction. The main problem with the classical Granger causality test in mean, is that it assumes conditional homoscedasticity, which distorts the results since most financial time series exhibit autocorrelation behavior (Hong, 2001; Srivastava et al., 2016). This problem is not encountered in our essay since we control for the ARCH-type effect by using transformed data[2]. The general GC test formalization, as proposed by Granger (1969), supposes the null hypothesis of independence between past values of y_2 and the present and future values of y_1 (no bivariate causality). If y_2 doesn't Granger cause y_1 in the strict sense, then:

$$P[y_{1,t}|\mathcal{F}_{t-1}] = P[y_{1,t}|(\mathcal{F}_{t-1} - y_{2,t-h}^{h})], \tag{4.10}$$

where $P(y_t|\mathcal{F}_{t-1})$ is the conditional probability distribution of the y_t and $\mathcal{F}_{t-1}$ is the information set available at time $t-1$. y_t^h is the h-length lagged vector of the transformed time series such as $y_t^h \equiv (y_{t-h}, y_{t-h+1} ... y_{t-1})$. Furthermore, y_2 doesn't instantaneously Granger cause y_1 when:

$$P(y_{1,t}|\mathcal{F}_{t-1}) = P[y_{1,t}|(\mathcal{F}_{t-1} + y_{2,t})]. \tag{4.11}$$

When the null hypothesis is rejected (Equation 4.10 and Equation 4.11), we can say that y_2 Granger causes y_1.

As already mentioned, in our case, the GC test is used to detect the direction of the pattern of correlation between the CDS market and the underlying bond market. For example, in case the CDS volatilities Granger cause the bond volatilities, this implies that a risk spillover is detected from the CDS market to the bond market. In other words, the volatility of these two credit markets is related in the sens that the occurrence of financial shocks in CDS prices entails some changes in prices and level of risk of bonds.

[1]Besides the cointegration rank, the Johansen test estimates unrestricted and normalized cointegrating coefficients and unrestricted error correction coefficients.

[2]Other solutions exist as to take into account the heteroscedasticity. Hong (2001) proposes a specific Granger-causality test in the mean that considers for the serial correlation and infinite unconditional variance, while Srivastava et al. (2016) suggest resolving the problem by conducting the test on the conditional variance.

4.3.3 Synthetic portfolios' construction

As mentioned before, our essay is not limited to country-by-country analysis, but it examines as well the volatility spillover between CDS and bond markets of synthetic financial portfolios constructed in concordance with the economic growth, the region and the credit rating. Several studies exist in the literature regarding the optimal non-cash asset allocation weight methods (Equal-weight, volatility weight, value-weight...). We are inspired by the value-weighting technique and suppose that, whether for the CDS or the bond portfolios, each country's weight is defined by dividing its transaction volume (outstanding debt amount) by the total transaction volume of the portfolio, such as:

$$P = \sum_{i=1}^{N} w_i x_i \tag{4.12}$$

Where P is the synthetic portfolio, N is the number of non-cash assets in the portfolio, x_i is the CDS (or Bond) spreads and $w_i = \frac{v_i}{v_p}$ with v_i is the country's transaction volume on the credit market and v_p is the total transaction volume of all the countries composing the portfolio.

The synthetic portfolios are used as proxies to reproduce the credit markets of some areas or some economic categories. The objective of replicating portfolios in this essay is to aggregate and study countries in the same region, with the same economic level and/or with the same credit risk classification.

4.4 Empirical results

4.4.1 Descriptive statistics

Table 4.1 reports descriptive statistics of the time series for each studied country. CDS and Bond daily spreads of different countries fluctuate from -191.85 bp to 5304.9 (Except for Greece that reaches 37688 bp). Different countries' average spreads are not at the same level - which is explained by the heterogeneity of our sample - but are almost always positive (for Germany, USA and Japan the average bond spread is negative). Negative credit spreads have several explanations. First, during financial turmoil, market participants choose to invest in government riskless assets rather than in corporate assets, which explains that some countries (Germany among others) issue bonds with negative yields (Dolvin, 2012). Second, Beber et al. (2009) and Bhanot and Guo (2011) interpret the negative spreads as a temporary liquidity problem making interest rate downgrade. And third, this phenomenon can also be explained by a bad choice of the risk-free rate. Almost all our time series exhibit significant excess kurtosis and positive skewness coefficients, which implies a presence of several extreme values and a bigger fat tail than what expected from a Gaussian distribution. These results are in line with the Jarque-Bera test that confirms the non-normality of the data distribution at the 1% statistical level of significance. As expected, CDS and bond spreads are found to be non-stationary according to the Augmented Dickey-Fuller's test.

To overcome the presence of unit-roots in our time series, first-differences are estimated for each country such as $X_t = x_t - x_{t-1}$ with x_t is the CDS (or the Bond) spread at time t.The over time CDS and bond first-differences plots[1] clearly show that changes are stationary. CDS and bond spreads changes exhibit a relatively similar time-varying evolution dynamic.

[1]These plots are not reported here but are available upon request.

Table 4.1: Descriptive statistics of daily CDS and Bond spreads from January 2006 to April 2014

		Obs.	Min.	Mean	Max.	Std. Dev.	Skweness	Excess Kurtosis	Jarque-Bera	ADF statistics
Panel A: PIIGS										
Portugal	CDS	2154	4.02	311.23	1527.00	356.15	1.21 ***	0.45 ***	544.65 ***	-0.99
	Bond	2154	-11.40	368.93	2264.00	462.05	1.45 ***	1.15 ***	875.16 ***	-1.06
Ireland	CDS	2154	1.75	232.90	1191.50	249.26	1.08 ***	0.00	414.84 ***	-0.99
	Bond	2154	-26.50	228.07	1578.00	278.79	1.51 ***	2.10 ***	1211.50 ***	-1.20
Italy	CDS	2154	5.58	161.93	591.54	148.52	0.95 ***	0.13	327.70 ***	-0.97
	Bond	2154	-4.10	148.90	676.50	146.96	1.14 ***	0.52 ***	493.68 ***	-1.11
Greece	CDS	2009	5.20	8068.60	37081	14532.00	1.45 ***	0.18 *	711.20 ***	-1.51
	Bond	2154	-121.60	9994.00	37688	14984.00	0.98 ***	-0.95 ***	428.78 ***	3.09
Spain	CDS	2154	2.55	165.66	641.98	153.97	0.79 ***	-0.21 **	226.37 ***	-0.99
	Bond	2154	-13.90	153.58	740.80	157.06	0.89 ***	-0.04	285.30 ***	-1.10
Panel B: Developed countries										
Austria	CDS	2154	1.75	61.13	268.98	58.57	1.03 ***	0.42 ***	393.32 ***	-1.28
	Bond	2154	-16.60	36.04	213	33.51	1.44 ***	2.88 ***	1488.70 ***	-2.01
Belgium	CDS	2154	2.05	83.61	406.12	85.62	1.20 ***	0.63 ***	556.10 ***	-1.09
	Bond	2154	-6.00	62.18	438.90	66.30	1.74 ***	3.60 ***	2254.10 ***	-1.88
Denmark	CDS	2154	9.00	42.71	158.23	37.26	1.39 ***	0.66 ***	736.64 ***	-1.06
	Bond	2154	-32.40	23.62	121.30	28.43	0.68 ***	0.18 *	171.12 ***	-1.80
Finland	CDS	2154	2.69	28.12	90.84	22.55	0.92 ***	0.14	302.63 ***	-0.98
	Bond	2154	-14.00	18.67	93.90	18.68	1.11 ***	0.96 ***	0.96 ***	-2.52
France	CDS	2154	1.50	60.58	249.63	59.07	1.14 ***	0.64 ***	504.73 ***	-0.99
	Bond	2154	-5.90	30.32	184.80	29.55	1.72 ***	3.43 ***	2117.20 ***	-1.89
Germany	CDS	2154	1.40	32.95	119.17	28.02	0.93 ***	0.20 *	317.04 ***	-1.06
	Bond	2154	-107.70	-45.61	3.90	20.79	-0.60 ***	-0.23 **	135.11 ***	-1.16
Japan	CDS	2154	2.13	52.63	157.21	38.33	0.18 ***	-0.88 ***	80.66 ***	-0.84
	Bond	2154	-191.85	-86.22	-18.05	51.87	-0.60 ***	-0.91 ***	203.23 ***	-1.75
Latvia	CDS	2154	5.50	258.32	1163.00	236.02	1.13 ***	1.35 ***	789.36 ***	-1.10
	Bond	2154	112.20	343.09	1418.30	269.86	2.25 ***	4.20 ***	3402.20 ***	-1.09
Lithuania	CDS	2154	6.00	203.03	847.50	171.73	1.09 ***	1.42 ***	609.11 ***	-0.94
	Bond	2154	-8.30	288.82	145.10	273.38	1.46 ***	1.72 ***	1033.90 ***	-1.86
Netherlands	CDS	2154	7.67	42.61	139.84	33.41	0.92 ***	0.07	306.13 ***	-0.95
	Bond	2154	-15.50	20.02	89.40	19.92	0.84 ***	0.21 **	256.60 ***	-2.39
Norway	CDS	2154	11.94	37.11	62.16	18.12	0.11 **	-1.77 ***	285.76 ***	-1.49
	Bond	2154	8.10	79.45	168.70	33.13	0.31 ***	-0.26 **	40.77 ***	-0.84
Slovakia	CDS	2154	5.33	87.73	328.25	74.34	1.16 ***	0.83 ***	544.60 ***	-0.96
	Bond	2154	-14.80	116.46	389.40	69.66	1.23 ***	2.20 ***	979.36 ***	-0.96
Slovenia	CDS	2154	4.25	138.52	511.07	136.61	0.86 ***	-0.65 ***	300.37 ***	-0.65
	Bond	2154	17.30	210.14	635.00	155.37	0.70 ***	-0.67 ***	218.18 ***	-1.08
Sweden	CDS	2154	1.63	29.15	156.36	26.48	1.26 ***	2.33 ***	1056.00 ***	-1.25
	Bond	2154	-32.80	34.76	120.10	36.06	0.32 ***	-0.99 ***	124.19 ***	-1.26
UK	CDS	2154	16.50	49.04	164.79	30.52	0.76 ***	0.20 *	211.84 ***	-0.95
	Bond	2154	-64.40	53.99	143.10	41.52	-0.13 **	-0.57 ***	35.13 ***	-1.14

Table 4.1: Descriptive statistics of daily CDS and Bond spreads from January 2006 to April 2014 (*Continued*)

		Obs.	**Min.**	**Mean**	**Max.**	Std. Dev.	**Skweness**		**Excess Kurtosis**		**Jarque-Bera**		**ADF statistics**
USA	CDS	2154	15.00	32.82	95.00	14.57	24.81	***	693.69	***	4340.90	***	-0.94
	Bond	2154	-165.24	-32.61	112.70	32.71	0.13	**	4.29	***	1655.90	***	-0.98
Panel C: Newly Industrialized Countries													
Brazil	CDS	2154	61.50	145.15	586.86	65.13	2.58	***	8.06	***	8218.20	***	-1.48
	Bond	2154	24.30	855.47	1529.20	328.58	-1.48	***	1.26	***	92.62	***	-0.74
China	CDS	2154	10.00	75.87	276.30	48.68	1.02	***	1.57	***	592.67	***	-1.40
	Bond	2154	-146.30	95.06	394.70	149.29	0.18	***	-1.22	***	145.84	***	0.45
Turkey	CDS	2154	110.95	214.85	831.31	82.51	2.25	***	7.82	***	7299.30	***	-1.31
	Bond	2154	525.10	1024.50	2345.20	349.16	0.80	***	0.01		227.52	***	-0.48
Panel D: Emerging countries													
Bulgaria	CDS	2154	13.22	198.11	699.39	140.48	0.76	***	0.40	***	222.85	***	-1.00
	Bond	2154	3.10	212.22	535.60	139.19	0.43	***	-0.86	***	134.71	***	-1.10
Croatia	CDS	2154	24.88	247.41	636.36	153.87	0.19	***	-0.87	***	81.84	***	-0.55
	Bond	2154	91.70	351.33	641.50	114.64	0.31	***	-0.42	***	51.59	***	-0.12
Czech	CDS	2154	3.41	73.94	350.00	55.81	1.25	***	2.79	***	1264.70	***	-1.19
	Bond	2154	-78.50	66.61	257.90	70.15	0.06		-0.50	***	23.45	***	-1.49
Hungary	CDS	2154	17.34	255.41	738.60	171.24	0.24	***	-0.77	***	73.97	***	-0.91
	Bond	2154	25.30	531.43	1167	172.90	0.79	***	0.37	***	236.35	***	-0.66
Poland	CDS	2154	7.67	119.28	415.00	84.84	0.63	***	0.20		141.88	***	-1.03
	Bond	2154	66.90	282.47	468.20	99.71	-0.42	***	-0.85	***	126.10	***	-0.34
Romania	CDS	2154	17.00	236.50	764.75	158.49	0.68	***	0.59	***	197.19	***	-1.01
	Bond	2154	293.80	548.99	1317.70	206.93	0.87	***	0.63	***	306.16	***	-0.55
Russia	CDS	2154	36.88	191.78	1113.40	154.53	2.54	***	7.70	***	7627.10	***	-1.83
	Bond	2154	171.10	527.03	1567.80	253.39	0.51	***	-0.03		92.08	***	-0.25
Ukraine	CDS	2154	126.13	767.11	5304.90	760.94	2.67	***	8.33	***	8783.40	***	-1.29
	Bond	2154	723.10	1087.20	2802.50	462.45	1.55	***	1.28	***	1009.30	***	-0.56
Venezuela	CDS	2154	124.62	876.06	3239.30	560.93	2.67	***	8.33	***	8783.40	***	-0.63
	Bond	2154	-73.50	1048.10	1899.40	558.29	-0.54	***	-1.07	***	206.90	***	-1.85

The table reports descriptive statistics for the daily CDS spreads expressed in basis points. Min.. Max. and Std. Dev. refer respectively to the minimum , the maximum and the standard deviation. The Augmented Dickey-Fuller (ADF. with intercept and no trend in the test equation) is a unit root tests is a unit root tests that informs about the time series stationarity. The null hypothesis is defined as the presence of a unit root in the process (non stationary time series).

Table 2: Preliminary tests on the changes of the CDS and Bond spreads

		Normality test			ARCH-LM test	Ljung-Box test (raw series)	Ljung-Box test (squared raw series)	Log memory test
		Skewness	***Excess Kurtosis***	***Jarque-Bera***	***ARCH-LM statistics (10)***	***Q-statistics (10)***	***Q-statistics (10)***	***R/S (hurst)***
Panel A: PIIGS								
Portugal	CDS	-0,49 ***	20,42 ***	37496 ***	38,05 ***	192,78 ***	756,03 ***	1,88 ***
	Bond	1,64 ***	53,46 ***	25735 ***	44,11 ***	100,14 ***	540,45 ***	1,93 ***
Ireland	CDS	-0,64 ***	27,73 ***	69122 ***	72,91 ***	249,61 ***	1283,54 ***	2,15 ***
	Bond	-0,18 ***	26,80 ***	64447 ***	50,33 ***	110,96 ***	1054,04 ***	2,02 ***
Italy	CDS	0,03	14,00 ***	17590 ***	25,46 ***	99,61 ***	486,92 ***	1,27 ***
	Bond	-0,07	15,38 ***	21208 ***	44,22 ***	116,32 ***	1024,01 ***	1,29 ***
Greece	CDS	-39,12	1736,4 ***	27102 ***	3,01E-04	11,38	3,03E-03	0,97 ***
	Bond	12,36 ***	388,47 ***	13592 ***	3,79 ***	205,98 ***	41,31 ***	2,45 ***
Spain	CDS	-0,25 ***	31,25 ***	87614 ***	56,53 ***	58,25 ***	427,28 ***	1,24 ***
	Bond	-0,84 ***	11,87 ***	12897 ***	23,58 ***	73,83 ***	468,97 ***	1,41 ***
Panel B: Developed countries								
Austria	CDS	0,88 ***	42,75 ***	16424 ***	194,03 ***	190,37 ***	2625,78 ***	1,09 ***
	Bond	0,65 ***	6,51 ***	3957 ***	28,80 ***	120,57 ***	510,36 ***	0,90 ***
Belgium	CDS	-0,25 ***	21,89 ***	42997 ***	36,78 ***	151,75 ***	693,74 ***	1,60 ***
	Bond	-0,05	8,05 ***	5818 ***	44,61 ***	130,42 ***	973,13 ***	1,06 ***
Denmark	CDS	0,94 ***	28,42 ***	72792 ***	17,04 ***	102,52 ***	313,13 ***	1,42 ***
	Bond	1,77 ***	21,02 ***	40747 ***	4,40 ***	290,36 ***	54,31 ***	0,75 ***
Finland	CDS	0,51 ***	12,23 ***	13517 ***	26,01 ***	41,17 ***	534,37 ***	1,28 ***
	Bond	0,89 ***	11,14 ***	11422 ***	17,77 ***	355,95 ***	220,89 ***	0,48 ***
France	CDS	-0,33 ***	12,47 ***	13991 ***	41,53 ***	58,94 ***	909,05 ***	1,41 ***
	Bond	0,54 ***	13,24 ***	15837 ***	24,43 ***	41,27 ***	449,36 ***	0,99 ***
Germany	CDS	0,05 ***	19,27 ***	33300 ***	34,92 ***	16,35 ***	399,63 ***	1,19 ***
	Bond	0,14 ***	4,87 ***	2137,4 ***	33,96 ***	346,46 ***	588,01 ***	0,45 ***
Japan	CDS	1,81 ***	45,79 ***	18929 ***	11,20 ***	52,38 ***	129,29 ***	1,18 ***
	Bond	0,08	3,46 ***	1077,7 ***	32,47 ***	130,71 ***	563,18 ***	0,90 ***
Latvia	CDS	1,72 ***	46,88 ***	19823 ***	28,18 ***	93,86 ***	526,84 ***	1,71 ***
	Bond	2,95 ***	122,23 ***	13433 ***	6,15 ***	100,73 ***	80,56 ***	1,12 ***
Lithuania	CDS	1,03 ***	46,84 ***	19723 ***	28,79 ***	47,68 ***	459,63 ***	1,59 ***
	Bond	-0,17 ***	116,48 ***	12170 ***	48,37 ***	393,16 ***	500,72 ***	0,43 ***
Netherlands	CDS	0,12 **	11,98 ***	12879 ***	38,62 ***	74,17 ***	914,05 ***	1,27 ***
	Bond	0,68 ***	8,89 ***	7253,7 ***	18,05 ***	289,88 ***	278,26 ***	0,47 ***
Norway	CDS	-0,10 **	11,14 ***	11128 ***	38,00 ***	17,04 *	798,03 ***	1,30 ***
	Bond	47814 ***	8,08 ***	5943,5 ***	4,70 ***	38,66 ***	64,91 ***	0,60 ***
Slovakia	CDS	0,79 ***	22,29 ***	44802 ***	50,06 ***	34,62 ***	730,58 ***	1,38 ***
	Bond	0,34 ***	10,30 ***	9558,4 ***	78,31 ***	325,73 ***	928,74 ***	0,96 ***
Slovenia	CDS	0,19 ***	19,38 ***	33722 ***	35,84 ***	43,07 ***	487,94 ***	1,32 ***
	Bond	0,98 ***	53,22 ***	25445 ***	53,39 ***	204,93 ***	463,68 ***	0,67 ***
Sweden	CDS	10,15 ***	330,98 ***	98643 ***	17,50 ***	90,14 ***	154,30 ***	1,34 ***
	Bond	0,55 ***	5,59 ***	2912,9 ***	9,14 ***	124,50 ***	123,58 ***	0,59 ***

Table 2: Preliminary tests on the changes of the CDS and Bond spreads (*Continued*)

		Normality test			ARCH-LM test	Ljung-Box test (raw series)	Ljung-Box test (squared raw series)	Log memory test
		Skewness	***Excess Kurtosis***	***Jarque-Bera***	***ARCH-LM statistics (10)***	***Q-statistics (10)***	***Q-statistics (10)***	***R/S (hurst)***
UK	CDS	0,33 ***	16,42 ***	24234 ***	19,59 ***	46,36 ***	279,91 ***	1,52 ***
	Bond	0,32 ***	6,52 ***	3849,1 ***	7,97 ***	47,82 ***	102,23 ***	1,03 ***
USA	CDS	-0,20 ***	604,92 ***	32827 ***	45,12 ***	304,34 ***	377,39 ***	0,59 ***
	Bond	-0,32 ***	11,83 ***	12599 ***	38,36 ***	228,93 ***	604,29 ***	0,71 ***
Panel C: Newly Industrialized Countries								
Brazil	CDS	2,70 ***	121,52 ***	13275 ***	67,84 ***	363,59 ***	717,88 ***	1,25 ***
	Bond	0,45 ***	99,11 ***	88126 ***	70,06 ***	265,83 ***	988,77 ***	0,43 ***
China	CDS	0,46 ***	49,00 ***	21549 ***	98,75 ***	230,04 ***	1241,14 ***	1,22 ***
	Bond	0,03	2,93 ***	770 ***	22,94 ***	162,18 ***	353,99 ***	0,60 ***
Turkey	CDS	0,16 ***	33,75 ***	10221 ***	122,56 ***	244,86 ***	2602,62 ***	1,53 ***
	Bond	0,04	9,36 ***	7852,8 ***	37,60 ***	83,05 ***	804,72 ***	1,56 ***
Panel D: Emerging countries								
Bulgaria	CDS	0,33 ***	16,66 ***	24933 ***	67,46 ***	118,25 ***	1600,83 ***	1,54 ***
	Bond	0,00	7,66 ***	5264,5 ***	18,87 ***	233,62 ***	337,67 ***	0,52 ***
Croatia	CDS	0,10 *	9,19 ***	7586,1 ***	26,53 ***	27,14 ***	491,17 ***	1,05 ***
	Bond	-0,15 ***	10,12 ***	9202,6 ***	42,46 ***	189,86 ***	849,38 ***	1,01 ***
Czech	CDS	0,42 ***	36,37 ***	11781 ***	62,61 ***	43,68 ***	913,95 ***	1,55 ***
	Bond	0,77 ***	7,39 ***	5108 ***	34,44 ***	115,11 ***	526,35 ***	0,88 ***
Hungary	CDS	0,60 ***	15,48 ***	21614 ***	50,97 ***	118,56 ***	1028,28 ***	1,19 ***
	Bond	0,13 **	10,81 ***	10478 ***	24,67 ***	61,46 ***	462,65 ***	1,32 ***
Poland	CDS	0,03	11,69 ***	1226 ***	48,04 ***	63,40 ***	1142,91 ***	1,38 ***
	Bond	0,70 ***	9,53 ***	8328,4 ***	21,34 ***	12,90	233,40 ***	0,91 ***
Romania	CDS	0,22 ***	16,55 ***	24583 ***	61,90 ***	141,55 ***	1540,10 ***	1,49 ***
	Bond	-0,51 ***	81,23 ***	59206 ***	52,39 ***	373,44 ***	540,75 ***	0,78 ***
Russia	CDS	1,79 ***	65,42 ***	38505 ***	171,66 ***	541,43 ***	2849,71 ***	1,63 ***
	Bond	0,08	65,89 ***	38947 ***	134,49 ***	319,81 ***	1835,02 ***	1,14 ***
Ukraine	CDS	-0,41 ***	90,01 ***	72691 ***	76,88 ***	355,67 ***	1071,62 ***	1,76 ***
	Bond	4,78 ***	166,73 ***	25021 ***	12,15 ***	129,87 ***	113,04 ***	0,55 ***
Venezuela	CDS	1,43 ***	24,74 ***	55634 ***	41,03 ***	335,09 ***	596,16 ***	2,34 ***
	Bond	1,50 ***	55,79 ***	28004 ***	22,12 ***	115,28 ***	211,88 ***	0,39 ***

The Jarque Bera test checks for the marginal distribution of our time series under the null hypothesis of normality. ARCH-LM is the Lagrange Multiplier test for autoregressive conditional heteroscedasticity, with a null hypothesis corresponding to homoscedastic innovations. Jung-Box statistics aslo check for the presence of ARCH-type effects in the mean and variance equations under the null hypothesis of no serial correlation. Rescaled-Range (R/S) tests detect any long-run dependance with a null hypothesis of no correlation process in the Hurst test (Hurst, 1951)and a null hypothesis of a short memory process in the Lo test (Lo, 1989). GPH denotes the Log Periodogram Regression of Geweke and Porter-Hudak (1983). *,** and *** encode the statistical significance at respectively 1%, 5% and 10%.

Preliminary tests are reported in Table 4.2. As in the level data analysis, spreads changes exhibit significant skewness and excess kurtosis implying the presence of several extreme values. The non-normality of spreads' changes is confirmed by the Jarque-Bera test at the 1% significant level. To suit the leptokurtic properties of both series, bivariate innovations are allowed to follow a student, a G.E.D (Generalized Error Distribution) or a skewed student distribution. ARCH-type effects are clearly observed and heteroscedastic features are detected. The Ljung-Box statistics show significant autocorrelations with a high order for all countries for both mean and variance equations. Results of the GPH and the Rescaled-Range tests on squared arithmetic returns[1] show that credit spreads exhibit long-memory behavior. Results of these preliminary analysis justify the relevant use of the FIEGARCH(1,d,1)-DCC model[2].

4.4.2 Empirical Findings

Results of the AR(1)-FIEGARCH(1,d,1)-DCC application to the CDS and bond spreads changes are reported in Table 4.3 and Table 4.4. The parameter estimates of the AR(1)-FIEGARCH univariate model are only reported in Table 4.7 and Table 4.8 (section 4.6). The autoregressive term in the mean equation is significantly positive in the majority of the cases whether concerning the country-level or the synthetic portfolios-level analysis. All CDS spreads (other than Italy and Russia) and bond series exhibit statistically significant fractional differencing parameters (d), which implies that the persistence of the shock on the conditional volatility of our studied series follows a hyperbolic rate of decay and supports thus the use of fractional integrated model. Estimates of the (d) parameter range for the CDS spreads from 0.2881 (Portugal) to 0.9232 (Belgium) and for the bond spreads from 0.0545 (Finland) to 0.9999 (Slovakia). The GARCH parameters (ϕ, θ_1 and θ_2) are positive and mainly significant, respecting the model condition of nonnegativity. The leverage effect parameter (γ) is significant, as well, in most cases (85% and 79% of respectively the CDS and bond equations), which means that losses on CDS and bond trading have a bigger impact on future volatility than do gains. These coefficients estimators confirm once again, the appropriate use of the AR(1)-FIEPARCH(1,d,1).

The country-by-country analysis show that the average conditional correlation is significant in 76% of the sample and considerably fluctuates from one country to another which underlines once again the heterogeneity of our studied countries. The Beta coefficient is always significant and close to one (Except for Finland, Sweden, the USA and Ukraine) which implies a great multivariate persistence between the CDS market and the bond market. The leverage effect is statistically significant emphasizing, as well, the important impact of negative innovations on worldwide credit markets. Moreover, the degree of freedom coefficient is always significant at the 1% statistic level which confirms the results of the Jarque-Bera test. Results show that there is no misspecification in our model estimation.

The time-varying correlations between the CDS and the bond spreads of some constructed portfolios are presented in Figure 4.1. Graphs show some dissimilarity in the cross markets integration level as well as in the dynamic evolution of the DCCs between different portfolios,

[1]Squared arithmetic returns are used as proxy for CDS and bond unconditional volatility.

[2]Results of the ARCH-LM test and the Ljung-Box tests are only presented for the 10^{th} lag order. However, the tests are also conducted up to 5^{th}, 20^{th} and 50^{th} lag orders and the results are the same: all the statistics are significant at 1% statistic level. Besides the R/S (hurst) (Hurst, 1951) test presented in this table, the long-memory behavior is also investigated through the R/S (Lo) (Lo, 1989) and the GPH test (Geweke and Porter-Hudak, 1983). Results are not reported here due to space limitation but can be provided upon request.

which is quite predictable given the notable difference between countries' credit risk levels. The highest average over-time correlation is recorded between the synthetic portfolios of Eastern Europe credit markets (0.3343), while the least important correlation level is obtained between the North American portfolios (0.0099). Focusing particularly on the most meaningful graphs of the PIIGS and the developed countries, we can clearly distinguish two correlation regimes: Before the Global Financial Crisis, correlations were at their lowest levels. With the occurrence of the first turmoil period in the financial markets, CDS and bond markets are becoming more correlated. This relationship is reinforced right after the outbreak of the European debt crisis. The most important fluctuation of cross-market correlation during the first crisis period is recorded in the PIIGS with an increase by 2.5% compared to the tranquil period. The PIIGS have the highest variation of its cross-markets correlation during the sovereign debt crisis, registering an increase by 11.28% compared to the tranquil period and by 8.78% compared to the first crisis period. The same conclusions are drawn for the time-varying countries' average correlation in Figure 4.2. Across all the studied countries, the average correlation during the quiet period is 0.2409. After the outbreak of the financial crisis in 2007, this correlation increased slightly by 0.2% to reach 0.2432. A second wave of contagion caused by the Sovereign debt crisis makes the correlations increase once again by 20.1% to reach 0.4439 this time, which implied that the the risk spillover is becoming more important between credit markets during this period.

The pattern of the time-varying DCC can clearly be divided into four distinct phases. Before the first financial crisis, the level of correlations were low because of the weak demand on sovereign CDS contracts. Governments were still considered as riskless entities and international investors were not risk averse when it comes to sovereigns. By the end of 2007, financial markets in general started to feel some tension and the correlations became following an increasing trend. Some researchers and economists even argued that the increase in the average correlation is explained by the fact that the CDS trading conditions have worsened the crisis, impacting the credit cost. A third phase is detected after the outbreak of the European Debt Crisis characterized by a drastic increase in correlations due to the considerable number of speculative operations on sovereign CDS. The crisis effects are beginning to be felt and credit markets are suffering from a bullish phase because of the governments creditworthiness decline. The consequences of the rescue operations adopted by the International Monetary Fund - among other organizations - are reflected in the decease of the credit markets' interactions during the fourth phase.

Based on the regressions results of Equation 4.7 (Table 4.5), risk spillover is significantly detected in our studied countries. Credit risk markets in worldwide countries seem to interact during crisis periods. A significant increase in correlations are recorded in 21% of the studied countries during the first crisis and in 67% of the sample during the second crisis. This suggests that the European debt crisis's intensity and severity are more important than in the Global Financial Crisis. In fact, many countries around the world, that present a decoupling behavior (no significant interaction) during the credit crisis, become prone to contagion effects during the sovereign debt crisis (Italy, Spain, Austria, Turkey...). Although the CDS markets and the corresponding bond markets of the PIIGS countries are initially not interconnected during the first crisis, this dynamic has changed during the sovereign crisis where reinforced links are observed (except for Ireland). The same observations are made for Newly Industrialized countries and some developed and emerging countries. Meanwhile, whatever the period is, no contagion effects are noticed in credit markets of some countries such as Finland, Netherlands, Norway, Slovakia, the USA, Bulgaria, Czech, Romania and Venezuela, and this is in spite of the economic recession and financial instability of these countries.

Table 4.3: Estimates of the Dynamic conditional correlation model for each country

	Dynamic Conditional Correlation							
	ρ_{21}		α		β		***df***	
Panel A: PIIGS								
Portugal	0.2819	**	0.0148	**	0.9823	***	3.7983	***
	(0.1354)		(0.0071)		(0.0097)		(0.1471)	
Ireland	0.1715	***	0.0118		0.9696	***	3.0570	***
	(0.0342)		(0.0074)		(0.0247)		(0.0599)	
Italy	0.3013	**	0.0176	*	0.9786	***	4.5032	***
	(0.1469)		(0.0106)		(0.0142)		(0.1997)	
Greece	0.0660		0.0403	***	0.9379	***	3.1664	***
	(0.0474)		(0.0053)		(0.0077)		(0.0788)	
Panel B: Developed countries								
Spain	0.0286		0.0081	***	0.9914	***	4.4282	***
	(0.1954)		(0.0024)		(0.0029)		(0.1831)	
Austria	0.1794	***	0.0132	***	0.9822	***	3.3709	***
	(0.0660)		(0.0035)		(0.0042)		(0.1034)	
Belgium	0.0691		0.0057	***	0.9920	***	3.9147	***
	(0.1003)		(0.0018)		(0.0025)		(0.1251)	
Denmark	0.0160		0.0000		0.8584	**	-	
	(0.0229)		(0.0000)		(0.4243)		-	
Finland	0.0561	***	0.0000	***	0.1375		3.8306	***
	(0.0202)		(0.0000)		(0.2919)		(0.1142)	
France	0.2743	***	0.0157	****	0.9810	***	3.7714	***
	(0.1248)		(0.0045)		(0.0068)		(0.1212)	
Germany	0.0632		0.0506	***	0.9044	***	-	
	(0.1244)		(0.0021)		(0.0025)		-	
Japan	0.0588	***	0.0000		0.8349		5.6601	***
	(0.0183)		(0.0000)		(0.8687)		(0.3050)	
Latvia	0.0424	***	0.0064	**	0.9276	***	2.1608	***
	(0.0156)		(0.0026)		(0.0257)		(0.0068)	
Lithuania	0.0622	**	0.0019	***	0.9947	***	3.4016	***
	(0.0309)		(0.0007)		(0.0014)		(0.0793)	
Netherlands	0.1148	*	0.0066	**	0.9907	***	3.9715	***
	(0.0689)		(0.0027)		(0.0044)		(0.1294)	
Norway	0.0314	**	0.0000	***	0.6373		2.5155	***
	(0.0126)		(0.0000)		(0.9267)		(0.0315)	
Slovakia	0.0712	***	0.0057		0.9826	***	3.4942	***
	(0.0266)		(0.0037)		(0.0135)		(0.0975)	
Slovenia	0.5282	***	0.0725	***	0.9201	***	3.0405	***
	(0.0653)		(0.0105)		(0.0113)		(0.0470)	
Sweden	0.0106		0.0148		0.5125		4.0303	***
	(0.0173)		(0.0152)		(0.4987)		(0.1403)	
UK	0.1055	**	0.0119	***	0.9806	***	4.6030	***
	(0.0533)		(0.0036)		(0.0053)		(0.2042)	
USA	0.0099		0.0040		0.4650	*	2.1600	***
	(0.0091)		(0.0029)		(0.2521)		(0.0089)	
Panel D: Newly Industrialized countries								
Brazil	0.1300	***	0.0058	**	0.9794	***	3.6458	***
	(0.0263)		(0.0024)		(0.0070)		(0.1021)	
China	0.1063	***	0.0043		0.9719	***	3.9023	***
	(0.0271)		(0.0057)		(0.0390)		(0.1575)	
Turkey	0.3796	***	0.0263	**	0.8942	***	5.5082	***
	(0.0240)		(0.0111)		(0.0544)		(0.3600)	

Table 4.3: Estimates of the Dynamic conditional correlation model for each country (*Continued*)

	Dynamic Conditional Correlation							
	ρ_{21}		α		β		***df***	
Panel D: Emerging countries								
Bulgaria	0.0458	**	0.0313	**	0.7769	***	4.0352	***
	(0.0220)		(0.0157)		(0.1261)		(0.1508)	
Croatia	0.0550	*	0.0167	***	0.9654	***	4.1853	***
	(0.0331)		(0.0063)		(0.0128)		(0.1438)	
Czech	0.1622	*	0.0107		0.9829	***	3.4589	***
	(0.0836)		(0.0081)		(0.0199)		(0.1080)	
Hungary	0.3671	***	0.0078	**	0.9858	***	4.1746	***
	(0.0379)		(0.0040)		(0.0077)		(0.1714)	
Poland	0.2186	***	0.0215	*	0.9594	***	5.4449	***
	(0.0532)		(0.0126)		(0.0362)		(0.3140)	
Romania	0.1009	***	0.0303	**	0.8818	***	4.5394	***
	(0.0297)		(0.0120)		(0.0436)		(0.1801)	
Russia	0.2393	***	0.0278	*	0.9382	***	4.2543	***
	(0.0367)		(0.0143)		(0.0403)		(0.1549)	
Ukraine	0.0553	***	0.0000		0.0185		2.9884	***
	(0.0179)		(0.0000)		(4.1500)		(0.0478)	
Venezuela	0.0031		0.0007		0.9931	***	2.6038	***
	(0.0239)		(0.0006)		(0.0027)		(0.0373)	

This table reports the results of the AR(1)-FIEGARCH(1,d,1)-DCC model for each studied country. *, ** and *** denote statistical significance at respectively 10%, 5% and 1%.

Table 4.4: Estimates of the Dynamic conditional correlation model for each synthetic portfolio

	Dynamic Conditional Correlation							
	ρ_{21}		α		β		***df***	
Panel E: GDP growth classification								
Developed countries	0.09850	***	0	***	0.62854		3.88330	***
	(0.0182)		1.37E-18		(0.5777)		(0.1289)	
Emerging countries	0.23343	***	0.01806	***	0.96958	***	3.78372	***
	(0.0441)		(0.0043)		(0.0076)		(0.1292)	
PIIGS	0.10637	**	0.00496	**	0.99144	***	3.79914	***
	(0.0542)		(0.0023)		(0.0045)		(0.1133)	
Newly industrialized countries	0.22148	***	0.01926		0.40230	*	4.11583	***
	(0.0201)		(0.0228)		(0.2096)		(0.1840)	
Panel F: Regional poclassification								
Eastern Europe	0.30222	***	0.01218	**	0.97693	***	4.41218	***
	(0.0505)		(0.0059)		(0.0126)		(0.2068)	
Western Europe	0.14443	***	0.01851	*	0.91385	***	2.91002	***
	(0.0203)		(0.0108)		(0.0481)		(0.0584)	
North America	0.00985		0.00405		0.46496	*	2.15999	***
	(0.0091)		(0.0029)		(0.2521)		(0.0089)	
South America	0.11848	***	0.00000		0.52463		4.93062	***
	(0.0191)		5.92E-09		(0.9417)		(0.2497)	
Asia	0.15883	***	0		0.76673		7.10144	***
	(0.0184)		3.83E-07		(0.6166)		(0.4794)	
Panel G: Credit rating classification								

Table 4.4: Estimates of the Dynamic conditional correlation model for each synthetic portfolio (*Continued*)

	Dynamic Conditional Correlation							
	ρ_{21}		α		β		***df***	
Investment-Grade countries	0.07214		0.00785	***	0.99002	***	3.53272	***
	(0.0768)		(0.0025)		(0.0035)		(0.0944)	
Speculative-Grade countries	0.16067	***	0.00482		0.98721	***	2.76522	***
	(0.0267)		(0.0039)		(0.0182)		(0.0472)	

This table reports the results of the AR(1)-FIEGARCH(1,d,1)-DCC model for each synthetic portfolio. *, ** and *** denote statistical significance at respectively 10%, 5% and 1%.

The change in correlations during crisis periods is interpreted as a shift in the comovement between the country's credit markets and denotes thus the occurrence of a financial risk spillover within the same country. The observation of this phenomenon particularly during crisis periods can be explained by several reasons: First, real markets linkages play a role in deepening cross-markets spillovers through strengthening financial relations between these two studied credit markets during crises (Kodres and Pritsker, 2002; Forbes, 2012). As CDS trading becomes more intense in order to manage credit risk, the CDS market becomes more vulnerable to absorb shocks that negatively affect the bond market, leading to weaker CDS performances. Similarly, the bond market can also be adversely affected by financial spillovers following a sharp increase or decrease in the CDS prices, given that market participants normally invest in CDS market not for returns but rather for risk mitigation.

Second, the increase in the correlation during crisis periods can also be explained by trade diversification (Shinagawa, 2014). Cross-market portfolio rebalancing can foster risk spillovers as trade increases volatility and hence exposure to market-specific shocks, which creates implicit linkages. The creation of some initially inexistent cross-market linkages due to portfolio investment makes volatility transfer from one market to another more important during crisis. In fact, investors transmit idiosyncratic risks from the bond market to the CDS market (and vise versa) by rebalancing their portfolios' risk exposures particularly after shocks occurrence. Yet, the rise in financial risk characterizing crisis periods makes contagion occur by the simple fact of withdrawing financial positions from one market, due to the increase in its credit risk, to reinvest in another one, considered as less risky, which is unfavorable for financial stability. Our results show thus, that if a country has a strong cross-market portfolio investment, then it is subject to more spillovers effects and it should enhance more prudential regulations to deal with the rising risk of financial shocks transmission especially during crises.

Synthetic portfolios' analysis show that the risk transmission among credit markets is present during both crises in the PIIGS and Asian countries' portfolios. Developed countries and newly industrialized countries' portfolios only exhibit spillover effects respectively during the sovereign crisis and the Financial crisis. Results of credit ratings classification portfolios are not conclusive.

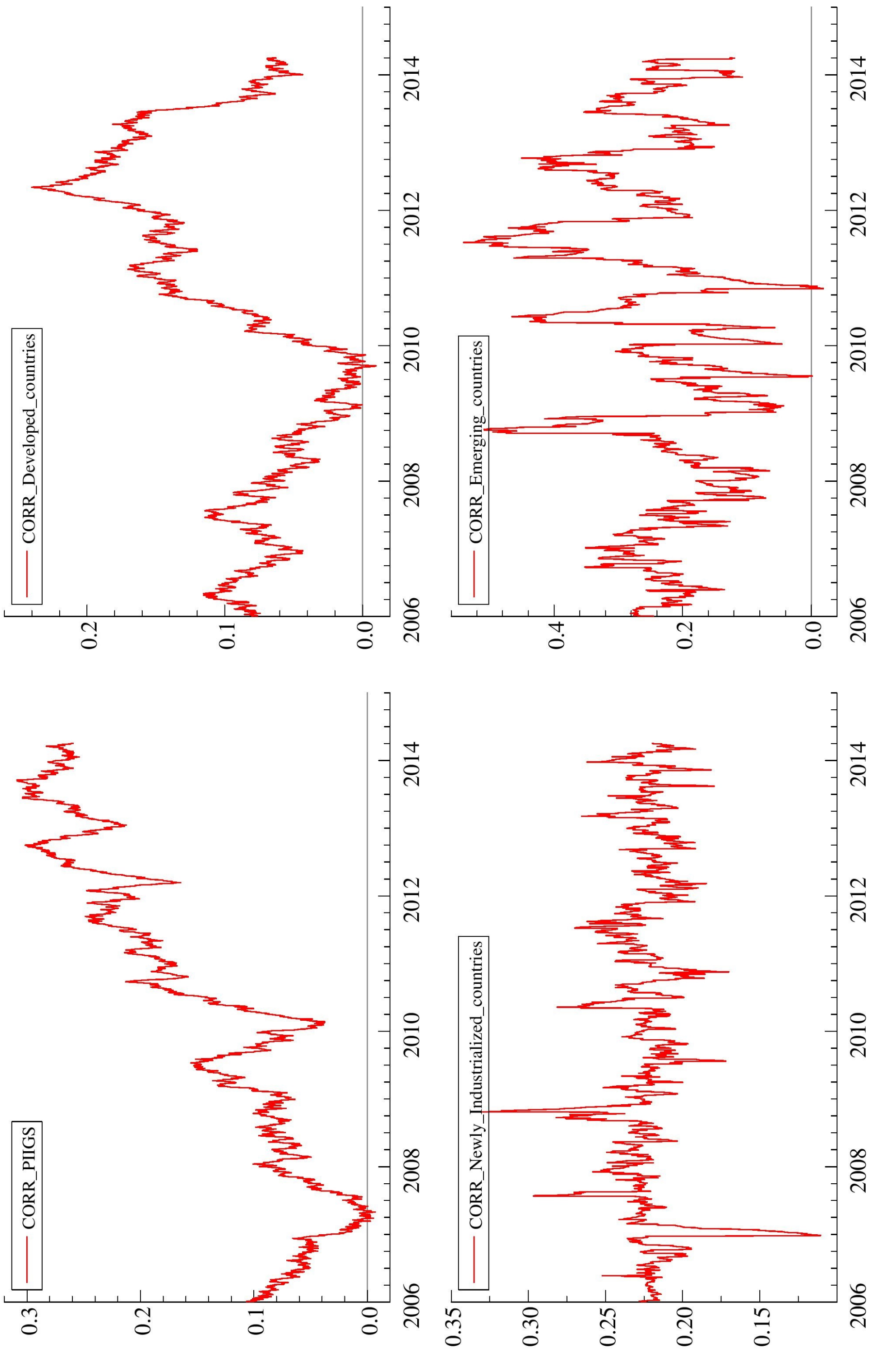

Figure 4.1: Dynamic Conditional correlation between the CDS and the underlying bond markets for each of the four constructed portfolios

Table 4.5: Dynamic Conditional Correlation Regressions Over Time

	μ_0		a_1		b_1		b_2	
Panel A: PIIGS								
Portugal	0.98660	***	0.00016		0.00143		0.00485	***
	(0.00314)		(0.00075)		(0.00092)		(0.00127)	
Ireland	0.99364	***	0.00099		-0.00054		0.00105	
	(0.00244)		(0.00063)		(0.00079)		(0.00078)	
Italy	0.99233	***	0.00008		0.00148		0.00332	**
	(0.00247)		(0.00100)		(0.00110)		(0.00135)	
Greece	0.77180	***	-0.22820	***	1.03E-06		0.00225	***
	(0.01372)		(0.01373)		(0.00069)		(0.00069)	
Spain	0.99225	***	-0.00026		0.00083		0.00292	**
	(0.00249)		(0.00076)		(0.00092)		(0.00114)	
Panel B: Developed countries								
Austria	0.99608	***	0.00023		0.00032		0.00095	**
	(0.00179)		(0.00038)		(0.00046)		(0.00047)	
Belgium	0.99619	***	0.00000	**	0.00027		0.00076	***
	(0.00165)		(0.00017)		(0.00023)		(0.00028)	
Denmark	0.13644	***	0.00763	***	2.19E-08		-3.91E-08	*
	(0.02138)		(0.00019)		(0.00000)		(0.00000)	
Finland	0.99845	***	-0.00003		0.00018		0.00024	
	(0.00128)		(0.00013)		(0.00019)		(0.00018)	
France	0.99643	***	0.00017		0.00049		0.00153	**
	(0.00181)		(0.00058)		(0.00063)		(0.00061)	
Germany	0.96609	***	-0.00019		-0.00016		-0.00056	**
	(0.00177)		(0.00025)		(0.00028)		(0.00029)	
Japan	0.80238	***	0.01156	***	-2.22E-08	*	-1.02E-08	
	(0.01287)		(0.00075)		(1.23E-08)		(1.21E-08)	
Latvia	0.98514	***	-0.00086	***	0.00097	***	0.00062	**
	(0.00349)		(0.00028)		(0.00031)		(0.00026)	
Lithuania	0.99796	***	-0.00034	**	0.00045	*	0.00063	**
	(0.00142)		(0.00016)		(0.00026)		(0.00027)	
Netherlands	0.99676	***	-0.00005		0.00035		0.00027	
	(0.00184)		(0.00029)		(0.00032)		(0.00031)	
Norway	0.99510	***	0.00041		-4.01E-05		8.26E-05	
	(0.00214)		(0.00039)		(0.00030)		(0.00026)	
Slovakia	0.99343	***	0.00034		6.76E-05		7.03E-05	
	(0.00252)		(0.00029)		(0.00028)		(0.00020)	
Slovenia	0.97722	***	0.02248	***	-0.01188	***	-0.00520	**
	(0.00445)		(0.00485)		(0.00356)		(0.00242)	
Sweden	0.80467	***	0.00145	***	-7.29E-09		2.70E-07	**
	(0.01281)		(0.00009)		(21.40E-08)		(14.65E-08)	
UK	0.98485	***	0.00104	**	-0.00064		0.00161	**
	(0.00359)		(0.00044)		(0.00057)		(0.00064)	
USA	0.97858	***	0.00022	***	-5.12E-05		-1.33E-05	
	(0.00446)		(0.00005)		(43.74E-06)		(43.35E-06)	
Panel C: Newly Industrialized Countries								
Brazil	0.98784	***	0.00126	**	0.00101		-0.00087	*
	(0.00355)		(0.00063)		(0.00070)		(0.00052)	
China	0.97906	***	0.00196	***	0.00033	**	0.00028	*
	(0.00432)		(0.00042)		(0.00017)		(0.00016)	
Turkey	0.92741	***	0.02833	***	-0.00036		-0.00240	**
	(0.00811)		(0.00324)		(0.00122)		(0.00124)	
Panel D: Emerging countries								
Bulgaria	0.99393	***	0.00002		0.00026		0.00045	
	(0.00236)		(0.00023)		(0.00035)		(0.00035)	

Table 4.5: Dynamic Conditional Correlation Regressions Over Time(*Continued*)

	μ_0		a_1		b_1		b_2	
Croatia	0.99287	***	-0.00062		0.00131	*	0.00148	*
	(0.00241)		(0.00047)		(0.00076)		(0.00081)	
Czech	0.99819	***	-0.00013		0.00026		0.00017	
	(0.00123)		(0.00015)		(0.00018)		(0.00018)	
Hungary	0.99393	***	0.00173	**	0.00006		0.00093	***
	(0.00225)		(0.00079)		(0.00030)		(0.00029)	
Poland	0.98838	***	0.00163	**	0.00108		0.00249	***
	(0.00299)		(0.00072)		(0.00072)		(0.00083)	
Romania	0.97267	***	0.00203	***	0.00069		0.00062	
	(0.00500)		(0.00063)		(0.00081)		(0.00080)	
Russia	0.99064	***	0.00170	**	0.00011		0.00137	**
	(0.00301)		(0.00077)		(0.00064)		(0.00069)	
Ukraine	0.93130	***	0.00318	***	0.00005		-0.00053	**
	(0.00784)		(0.00046)		(0.00034)		(0.00024)	
Venezuela	0.98420	***	0.00348	***	-0.00292	***	-0.00018	
	(0.00374)		(0.00108)		(0.00109)		(0.00060)	
Panel E: GDP growth classification								
Developed countries	0.99716	***	0.00022		-0.00017		0.00037	**
	(0.00126)		(0.00018)		(0.00018)		(0.00016)	
Emerging countries	0.98252	***	0.00438	***	-0.00102		0.00128	
	(0.00407)		(0.00146)		(0.00127)		(0.00090)	
PIIGS	0.99697	***	-0.00016		0.00049	**	0.00046	**
	(0.00127)		(0.00021)		(0.00023)		(0.00023)	
Newly Industrialized countries	0.94373	***	0.01173	***	1.19E-03	***	-0.00036	
	(0.00710)		(0.00154)		(0.00045)		(0.00030)	
Panel F: Regional classification								
Eastern Europe	0.99407	***	0.00238	**	-0.00045		-0.00009	
	(0.00246)		(0.00103)		(0.00057)		(0.00039)	
Western Europe	0.98364	***	0.00215	***	-0.00039		0.00111	**
	(0.00396)		(0.00071)		(0.00057)		(0.00048)	
North America	0.97858	***	0.00022	***	-0.00005		-0.00001	
	(0.00446)		(0.00005)		(0.00004)		(0.00004)	
South America	0.72857	***	0.03187		3.39E-03	***	-6.68E-04	
	(0.01478)		(0.00200)		(0.00118)		(0.00080)	
Asia	0.47236	***	0.08382	***	0.00000	**	0.00000	*
	(0.01902)		(0.00302)		(10.99E-12)		(7.46E-12)	
Panel G: Credit rating classification								
Investment grade	0.99575	***	-0.00012		0.00021		0.00078	
	(0.00194)		(0.00044)		(0.00052)		(0.00050)	
Speculative grade	0.99143	***	0.00151	***	0.00002		0.00008	
	(0.00286)		(0.00053)		(0.00023)		(0.00015)	

This table reports the regression results of Equation 4.7. μ_0 is a constant.The coefficients a_1, b_1 and b_2 represent respectively the lagged values, the dummy variable of the GFC and the dummy variable of the EDC. Values in parentheses depict standard deviation. *, ** and *** denote statistical significance at respectively 10%, 5% and 1%.

In the second stage, and since risk spillover cannot only be detected by a significant increase in bivariate correlation, a Bayesian cointegrated VAR approach is used to model the interrelationship between the two credit markets. In order to capture small and extreme contagion effects, transformed data are used - instead of in levels or first-difference spreads - allowing to control for heteroscedasticity and serial correlation. Results of the two-order BVECM are available upon request.

Figure 4.2: Average Dynamic Conditional correlation between the CDS and the corresponding bond markets of 33 countries

Transmission of financial shocks from one credit market to another within the same country is identified using the Granger Causality test. Table 4.6 reports the statistics of the Granger Causality test for each hypothesis.

Results of the full sample period show that the CDS market Granger causes the bond market in 16 (49%) countries, while the bond market only impacts the CDS market in nine (27%) countries. Focusing on the constructed portfolio's analysis, the CDS spreads influence the borrowing cost only in Newly Industrialized countries, Eastern Europe and Asia. The bidirectional spillover effect is only detected in few countries, namely Italy, Ireland, Belgium and Romania. These results suggest that long-term equilibrium relationship between credit markets has an impact on the risk spillover.

The same Table presents the spillover results from the CDS markets to the bond markets and vice versa on different sub-periods. Evidences show that, during the tranquil period, there is a risk transmission from the CDS market to the Bond market in 37% of cases while the reverse dynamic is only valid in 27% cases. The changes in investors risk appetite during crises made risk spillover effects occurring in further countries. There is a greater number of Granger Causality interrelationships between credit markets during the financial crisis and the sovereign crisis. In fact, the percentage of countries where the CDS volatility spills over the bond market increased from 37% to 55% during the global Financial Crisis and to 61% during the European debt crisis. The risk spillover percentage from the bond spreads to CDS spreads is, also, accentuated during the turmoil break but does not seem to follow a logical pattern. The bidirectional interaction degree dropped again to 33% during the post-crisis period.

Even though countries level analysis does not seem to perfectly coincide between the AR(1)-FIEGARCH(1,d,1)-DCC and the BVECM, the general interpretation remains the same. Contagion effects and risk spillovers are detected in sovereign credit markets with a reinforced phenomenon during crisis periods.

4.4.3 Financial and economic implications

Results of the Bayesian VECM and the Granger Causality test show that the highest statistically significant risk spillovers are recorded in Spain and Japan. For Spain, a 1% increase in CDS spreads would result in an increase of 9.841 basis points in the bond spreads, whilst a 1% increase in the bond spreads of Japan would increase the CDS spreads by 430.45 basis points. Similarly, the synthetic portfolios analysis show that the CDS spreads of the developed countries portfolio would decrease by 1.661 basis points after a 1% increase in the bond one. For the Newly Industrialized countries portfolios, the only significant volatility spillover is detected from the CDS spreads to the bond spreads, with a fairly small impact magnitude (0.16 basis points). Focusing on the constructed portfolios using the regional classification, the variation in CDS spreads leads to an increase in the bond spreads of Western Europe and Asia, with a respective average increase by 1.67 basis points and 0.04 basis points. The relationship in the other direction only exists for the Western European and North America portfolios. Lastly, a 1% bond spreads variation causes CDS fluctuation by -5.737 basis points of the Investment-grade portfolio, however the opposite relationship does not appear to be significant.

Table 4.6: Results of the Granger Causality test for each country

Period	Full sample period (2151 observations)		Reference period (387 observations)		1^{st} crisis period (FGC) (608 observations)		$2nd$ crisis period (EDC) (628 observations)		2^{nd} tranquil period (523 observations)	
Null hypothesis	CDS spreads don't Granger Cause BOND spreads	Bond spreads Granger Cause CDS spreads	CDS spreads don't Granger Cause BOND spreads	Bond spreads Granger Cause CDS spreads	CDS spreads don't Granger Cause BOND spreads	Bond spreads Granger Cause CDS spreads	CDS spreads don't Granger Cause BOND spreads	Bond spreads Granger Cause CDS spreads	CDS spreads don't Granger Cause BOND spreads	Bond spreads Granger Cause CDS spreads
Panel A: PIIGS										
Portugal	0.97089	0.01231	0.75965	3.16713 **	0.44391	0.12999	6.54555 ***	14.0039 ***	9.76194 ***	6.60284 ***
Ireland	1.551	0.79542	1.74805	6.34902 ***	0.03791	0.55862	4.8356 ***	0.59372	4.20851 **	4.58866 **
Italy	6.73729 ***	22.2601 ***	5.93823 ***	0.80102	5.81745 ***	15.4976 ***	0.61787	4.9548 ***	4.87172 ***	3.23148 **
Greece	4.35929 **	5.28345 ***	2.20999	2.06649	2.8953 *	4.44856 **	6.97264 ***	18.4997 ***	-	-
Spain	4.65146 ***	0.27772	40.2035 ***	0.99867	0.78467	1.18757	3.36181 **	24.403 ***	33.2779 ***	25.9784 ***
Panel B: Developed countries										
Austria	3.32727 **	0.32438	3.24986 **	0.22516	0.50675	0.6889	0.22538	0.01474	0.68436	0.11823
Belgium	5.93388 ***	4.32858 **	2.59163 *	10.3955 ***	2.76186 *	0.08631	20.8007 ***	5.92412 ***	1.85094	0.03326
Denmark	1.05934	3.53201 **	-	-	0.30739	3.33429 **	3.50565 **	0.08537	2.26609	3.99965 **
Finland	12.9256 ***	0.66562	3.01728 *	6.67105 ***	10.8908 ***	0.42257	4.10476 **	0.29582	0.6022	0.90781
France	12.9256 ***	0.66562	3.01728 *	6.67105 ***	10.8908 ***	0.42257	4.10476 **	0.29582	0.6022	0.90781
Germany	1.71439	0.68117	0.47397	0.01251	8.00111 ***	0.98048	0.00122	0.43237	0.1458	0.45493
Japan	15.4939 ***	1.2969	0.24696	0.88068	2.87537 *	1.65835	5.00961 ***	1.04354	1.13924	0.92788
Latvia	10.5022 ***	0.25408	21.337 ***	132.1 ***	0.27912	0.3983	5.26676 ***	1.743	1.64341	3.88558 **
Lithuania	6.94523 ***	0.99595	2.09828	0.04463	3.07909 **	0.42995	1.31624	0.35578	0.53585	0.8368
Netherlands	66.2509 ***	1.63376	3.57812 **	12.9999 ***	37.879 ***	0.74233	5.8141 ***	3.93974 **	0.9679	2.00851
Norway	0.08919	4.57649 **	1.93617	46.7836 ***	0.44392	7.19414 ***	0.47693	0.05064	0.18438	3.95162 **
Slovakia	0.28043	0.77317	0.0912	1.95748	5.31209 ***	1.00143	0.72627	1.51162	3.0637 **	0.27193
Slovenia	0.0042	0.48615	0.60742	0.26269	0.04812	0.11492	3.86482 **	0.79021	2.50702 *	2.50946 *
Sweden	1.88723	0.77317	12.1706 ***	1.95748	0.33081	1.00143	2.50807 *	1.51162	0.10519	0.27193
UK	5.33281 ***	0.32845	1.47072	1.4756	2.52803 *	0.7362	0.56786	0.3329	2.46622 *	2.33642 *
USA	0.11638	17.432 ***	0.6057	0.27316	0.26028	1.29493	2.89187 *	0.39957	4.43082 **	0.21421
Panel C: Newly Industrialized Countries										
Brazil	1.27598	0.00828	0.04288	0.02768	0.71842	1.36148	0.63197	0.11805	0.20753	0.0884
China	13.9125 ***	0.59263	0.25619	0.34172	3.99163 **	1.25542	6.20479 ***	0.28945	0.56544	0.45439
Turkey	1.57768	2.9129 *	3.00488 *	3.7778 **	3.32688 **	49.4579 ***	4.21516 **	3.18001 **	3.82213 **	10.569 ***
Panel D: Emerging countries										
Bulgaria	0.68957	0.59668	0.30657	0.43672	0.20086	0.24738	0.78856	0.54504	1.98584	0.21249
Croatia	-	-	-	-	-	-	-	-	-	-
Czech	1.30284	1.3048	0.43851	0.42536	0.20616	2.95223 *	0.0923	2.41742 *	3.01996 **	0.03396
Hungary	44.3501 ***	0.61389	78.2871 ***	0.26735	8.59453 ***	0.93751	6.31387 ***	2.02756	0.45115	0.09483
Poland	0.03111	2.97687 *	0.2657	0.62461	0.73554	0.20415	1.22211	4.08668 **	0.18798	1.5589
Romania	11.518 ***	7.64142 ***	2.03056	0.06478	7.7554 ***	0.53047	2.0129	0.5768	1.4335	0.52753
Russia	0.02352	0.97677	9.2725 ***	1.37809	0.87043	0.5129	2.00966	1.76747	0.66975	3.87435 **
Ukraine	0.04767	0.59157	0.75976	0.65707	-	-	0.93397	6.30671 ***	1.60477	1.51399
Venezuela	3.66454 **	0.5089	1.6443	1.20849	13.4502 ***	0.24526	0.40176	4.46504 **	6.23033 ***	7.29161 ***
Panel E: GDP growth classification										
PIIGS	0.16674	0.07674	1.34132	17.2019 ***	0.30259	2.85923 *	9.14149 ***	6.58324 ***	0.02592	0.05305
Developed countries	0.96329	71.7662 ***	0.95915	4.35237 **	3.07506 **	0.57885	1.90718	2.23617	2.29671	7.46553 ***
Newly Industrialized countries	3.74875 **	0.92384	0.36224	0.04038	0.45623	2.09834	0.74996	0.41804	1.58869	1.74315
Emerging countries	1.93398	0.34881	0.30935	0.85784	15.3693 ***	4.1319 **	1.6811	1.07932	0.03835	0.07006
Panel F: Regional classification										
Eastern Europe	35.9775 ***	0.46051	4.86121 ***	1.51667	1.52183	0.52169	0.72894	2.03497	0.58404	0.13701
Western Europe	0.2766	3.75303 **	6.41154 ***	0.32401	0.03068	4.61965 **	1.38787	4.97559 ***	0.59312	0.69213
North America	0.11638	17.432 ***	0.6057	0.27316	0.26028	1.29493	2.89187 *	0.39957	4.43082 **	0.21421

Table 4.6: Results of the Granger Causality test for each country (*Continued*)

Period	**Full sample period** (2151 observations)		**Reference period** (387 observations)		**1^{st} crisis period (FGC)** (608 observations)		**$2nd$ crisis period (EDC)** (628 observations)		**2^{nd} tranquil period** (523 observations)	
Null hypothesis	CDS spreads don't Granger Cause BOND spreads	Bond spreads Granger Cause CDS spreads	CDS spreads don't Granger Cause BOND spreads	Bond spreads Granger Cause CDS spreads	CDS spreads don't Granger Cause BOND spreads	Bond spreads Granger Cause CDS spreads	CDS spreads don't Granger Cause BOND spreads	Bond spreads Granger Cause CDS spreads	CDS spreads don't Granger Cause BOND spreads	Bond spreads Granger Cause CDS spreads
South America	0.21714	0.00111	0.06636	0.00728	2.12927	7.50716 ***	3.00935 *	2.49166 *	0.02294	0.12494
Asia	3.32727 **	0.32438	3.24986 **	0.22516	0.50675	0.6889	0.22538	0.01474	0.68436	0.11823
Panel G: Credit rating classification										
Investment-grade Countries	0.39275	6.05944 ***	0.69625	4.73122 ***	1.08101	30.9774 ***	1.15912	1.17675	0.24494	1.56402
Speculative-grade countries	0.80026	1.05019	0.15979	0.40512	0.05856	0.07877	0.06829	0.065	0.0188	0.03252

This Table presents the statistics of the classic Granger Causality test based on the VECM equations. For each ECM model. two hypothesis are tested: CDS spreads don't granger cause Bond spreads and Bond spreads don't granger cause CDS spreads. *. ** and *** denote statistical significance at levels 10%. 5% and 1%.

Our results are relevant to both portfolio managers and policymakers. On the one hand, the time-varying cross-market behavior is an accurate indicator of financial stability. We show that after the outbreak of the Financial Global Crisis and the European Debt crisis, credit markets exhibit contagion effects and risk spillovers between CDS market and the corresponding bond market in a unidirectional or bidirectional depending on the country. National policymakers should, thus, put in place regulatory economic policies for countries presenting systemic risk. Furthermore, in some countries, crises in the bond market should be anticipated right after the occurrence of a financial shock in the CDS market and vice versa, if ever the shock shows up in one market and yet doesn't show up in the other one. Consequently, appropriate regulative solutions should be taken at the right moment to stop the propagation of such phenomenon.

On the other hand, credit markets' participants could, as well, take advantages of our findings. They could potentially adjust their trading operations depending on the co-movement dynamics of the CDS and the bond market. First, since credit assets' prices are highly correlated in some countries, portfolio managers could speculate on the predictability of the borrowing cost by following the evolution of the CDS spreads over time. Second, our results reveal that the studied credit markets present heterogeneous characteristics that could benefit to financial traders by investing in a diversified portfolio of worldwide countries combinations. Third, our findings show that the risk spillover mechanism is changing overtime and across countries. This should be taken into consideration by credit risk managers while elaborating their constantly evolving hedging positions. Yet, arbitrage opportunities could be detected by focusing on whether the country is prone to contagion phenomena or not.

4.5 Conclusion

This essay gives further evidences of risk spillover on credit markets in an international context. The time-varying interactions between the Sovereign CDS markets and the corresponding government bond markets of 33 worldwide countries are studied using both AR(1)-FIEGARCH(1,d,1)-DCC and Bayesian VECM frameworks. The first approach allows us to define countries that are prone to contagion effects during crisis periods and to estimate the conditional means and volatility used to treat the heteroscedastic properties of our data. The transformed data are used to model a dynamic financial system, in the second approach, so we can quantify and ascertain the direction of the credit risk spillover.

Our findings reveal that some of the studied countries are prone to contagion phenomenon with a significant fluctuation of the dynamic conditional correlation in 21% (67%) of the credit markets during the sovereign debt crisis. Contagion effects are, thus, occurring in more countries during the second crisis period which implies that the European Debt crisis's intensity and severity are more important than in the Global Financial Crisis. Results at the aggregate geographical area level show that only Asian countries are hit by waves of contagion between credit markets during both crises while South America and Western Europe are only subjects to credit contagion respectively during the second crisis and the first crisis.

The directions of the risk spillovers, as given by the second approach, are changing over time and across countries. The CDS market seems to incite crises transmission more that the bond market since 16 financial shock transmissions are detected from the CDS markets versus nine to the CDS markets. Sub-periods analysis affirms, once again, that crises increase the percentage of co-movements between credit markets and that the Sovereign Debt Crisis is more intense and affects more countries all over the world than the Financial Crisis.

The results of both econometric approaches show, globally, that worldwide countries exhibit different credit markets characteristics and present some reactions' divergences to crises. The findings highlight the importance of putting in place different economic and regulatory policies depending on the country's characteristics to control for credit risk propagation. A particular focus should be given by policymakers to credit markets' dynamic comovements during crisis periods. Markets' participants are also concerned by our findings so they can anticipate financial turmoil and appropriately balance risk against profitability in investment mix.

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Appendices

4.6 Appendix: Univariate AR(1)-FIEGARCH model

Table 4.7: Estimates of the univariate AR(1)-FIEGARCH process for each country

		Mean Equation		Variance Equation									
		Cst(M)	*AR(1)*	*Cst(V)*	*d-Figarch*	*ARCH (ϕ)*	*GARCH (δ)*	*EGARCH (θ_1)*	*EGARCH (θ_2)*	*Student*	*GED*	*Asymmetry*	*Tail*
Panel A: PIIGS													
Portugal	Bond	7.7600 ***	0.2357 ***	6.2583 ***	0.5559 ***	-1.0030 ***	0.9526 ***	-0.3423 ***	0.1457 ***	5.3506 ***	-	-	-
		(0.8132)	(0.0430)	(0.1327)	(0.0014)	(0.0000)	(0.0004)	(0.0330)	(0.0033)	(0.0334)	-	-	-
	CDS	0.0000	0.0944 ***	0.0210	0.2881 ***	-0.1760	0.9773 ***	-0.0271	0.3473 ***	-	0.4225 ***	-	-
		(0.0001)	(0.0023)	(3.0014)	(0.0860)	(0.1844)	(0.0243)	(0.0478)	(0.0438)	-	(0.0540)	-	-
Ireland	Bond	0.0012	0.1912 ***	0.2300	0.5715 ***	-0.0711 *	0.2414 ***	-0.0565 ***	0.0554 ***	5.1129 ***	-	-	-
		(0.0064)	(0.0298)	(0.9678)	(0.0104)	(0.0366)	(0.0287)	(0.0018)	(0.0013)	(0.2364)	-	-	-
	CDS	0.0001 ***	0.1401 ***	0.0000	0.9133 ***	0.5195 *	0.3796 ***	-0.6708 ***	0.9761 ***	-	-	0.0574 ***	2.0054 ***
		(7.44E-07)	(0.0247)	(3.1046)	(0.0183)	(0.3049)	(0.1112)	(0.1257)	(0.1286)	-	-	(0.0149)	(0.0006)
Italy	Bond	1.7944 ***	-0.1028 ***	0.0900	0.2245 ***	-0.8893 ***	1.0233 ***	-0.2064 ***	0.1902 ***	3.4704 ***	-	-	-
		(0.1622)	(0.0302)	(0.4788)	(0.0234)	(0.0014)	(0.0021)	(0.0085)	(0.0046)	(0.0344)	-	-	-
	CDS	-0.0124	0.0967 ***	8.0533 ***	0.0000	-0.4057	0.9936 ***	0.1114 ***	0.4791 ***	-	-	-	-
		(0.0124)	(0.0353)	(2.5807)	(0.2177)	(0.3926)	(0.0042)	(0.0304)	(0.0824)	-	-	-	-
Greece	Bond	0.0000	0.0288	0.0432	0.4390 ***	0.1064 ***	0.4127 ***	-0.1655 ***	0.1958 ***	5.9779 ***	-	-	-
		(3.58E-05)	(0.0832)	(1.4710)	(0.0303)	(0.0269)	(0.0102)	(0.0431)	(0.0262)	(0.3319)	-	-	-
	CDS	0.0000	0.0095	0.0401	0.4512 ***	0.1009	0.4015 ***	-0.0943	0.1987 ***	5.9989 ***	-		
		(0.0001)	(0.1610)	(5.5253)	(0.0371)	(0.3491)	(0.1372)	(0.1084)	(0.0272)	(0.9455)	-		
Panel B: Developed countries													
Spain	Bond	-0.0156	-0.1081 ***	3.9701 ***	0.6284 ***	-0.9254 ***	0.9602 ***	0.0895 ***	0.3320 ***	-	-	0.0088	4.4842 ***
		(0.0971)	(0.0243)	(0.7658)	(0.1110)	(0.0385)	(0.0175)	(0.0252)	(0.0744)	-	-	(0.0135)	(0.4407)
	CDS	-0.0042 **	0.0562 **	0.0000	0.7349 ***	0.3367	0.0200	-0.1020	1.0000 ***	-	-	-0.0591 ***	2.0647 ***
		(0.0018)	(0.0269)	(2.1096)	(0.0500)	(0.4372)	(0.5033)	(0.1433)	(0.0441)	-	-	(0.0157)	(0.0405)
Austria	Bond	-0.0779 ***	-0.2418 ***	2.7891 ***	0.8013 ***	0.0956	-0.0847	0.0704 ***	0.2739 ***	-	1.0710 ***	-	-
		(0.0027)	(0.0058)	(0.5617)	(0.0520)	(0.2478)	(0.2080)	(0.0218)	(0.0511)	-	(0.0611)	-	-
	CDS	0.0000	0.0225	0.0000	0.9144 ***	5.1682 ***	-0.3004	-0.9810 ***	1.0000 ***	-	-	0.0495 ***	2.0004 ***
		(3.2E-06)	(0.0206)	(2.8862)	(0.0191)	(0.6202)	(0.2781)	(0.0865)	(0.0912)	-	-	(0.0129)	(0.0000)
Belgium	Bond	0.0657 ***	-0.1673 ***	4.2525 ***	0.6195 ***	0.1226	0.7119 ***	0.7889 **	0.0304	2.0353 ***	-	-	-
		(0.0230)	(0.3690)	(0.8754)	(0.0321)	(0.3418)	(0.0965)	(0.3082)	(0.0253)	(0.0272)	-	-	-
	CDS	-0.0002	0.0260	0.0508	0.9232 ***	2.0550 **	-0.9964 ***	0.6089 *	0.8160 ***	-	-	0.0392	2.0031 ***
		(0.0003)	(0.2279)	(3.1368)	(0.1079)	(0.8680)	(0.0215)	(0.3591)	(0.1433)	-	-	(0.0242)	(0.0019)
Denmark	Bond	-0.0289	-0.2866 ***	24.6965 **	0.0678 ***	-0.7200 ***	0.9893 ***	-0.1948 ***	0.3301 ***	3.2265 ***	-	-	-
		(0.0315)	(0.0221)	(12.485)	(0.0249)	(0.0476)	(0.0072)	(0.0314)	(0.0434)	(0.3241)	-	-	-
	CDS	0.0002 ***	0.0494 *	0.0000	0.7298 ***	0.4208 *	-0.9279 ***	0.1235 ***	0.1257 ***	2.5866 ***	-	-	-
		(0.0000)	(0.0272)	(2.9757)	(0.0247)	(0.2202)	(0.0212)	(0.0035)	(0.0035)	(0.1047)	-	-	-
Finland	Bond	-0.0656 *	-0.2818 ***	24.2394 **	0.0545 ***	-0.7628 ***	0.9872 ***	-0.0551 *	0.4731 ***	3.2873 ***	-	-	-
		(0.0395)	(0.0226)	(10.981)	(0.0191)	(0.0386)	(0.0072)	(0.0327)	(0.0459)	(0.2976)	-	-	-
	CDS	0.0010 ***	-0.1012 ***	0.4212	0.3655 ***	-0.8007 ***	0.9440 ***	-0.1442 ***	0.2719 ***	3.2901 ***	-	-	-
		(0.0002)	(0.0361)	(0.6024)	(0.0197)	(0.0069)	(0.0034)	(0.0317)	(0.0251)	(0.0642)	-	-	-
France	Bond	0.0223	-0.1688 ***	1.9949 ***	0.7169 ***	-0.3851 **	0.0646	0.0882 ***	0.5760 ***	-	-	0.0028	2.9117 ***
		(0.0307)	(0.0224)	(0.7677)	(0.0509)	(0.1806)	(0.2347)	(0.0338)	(0.0687)	-	-	(0.0137)	(0.1956)
	CDS	0.3345 ***	0.0619	0.3133	0.8278 ***	1.2721 ***	-0.8984 ***	-0.0367 *	0.2733 ***	-	-	-	-
		(0.1141)	(0.0611)	(0.4545)	(0.0455)	(0.2426)	(0.0828)	(0.0200)	(0.0416)	-	-	-	-
Germany	Bond	-0.0170	-0.3369 ***	3.7406 ***	0.4791 ***	-0.9207 ***	0.9706 ***	-0.0026	0.4117 ***	-	-	0.0275	5.4535 ***
		(0.0472)	(0.0213)	(0.7309)	(0.0828)	(0.0291)	(0.0140)	(0.0325)	(0.0467)	-	-	(0.0187)	(0.6419)
	CDS	0.0000	-0.2262 ***	0.4490 ***	0.5882 ***	1.1354 ***	-0.9955 ***	0.0915	0.3412 ***	-	0.3247 ***	-	-
Japan		(0.0001)	(0.0031)	(0.5054)	(0.0624)	(0.0948)	(0.0028)	(0.1586)	(0.0354)	-	(0.0513)	-	-
Japan	Bond	0.2189 ***	-0.1590 ***	0.0000	0.5064 ***	-0.9650 ***	1.0021 ***	-0.1006 ***	0.0034 **	5.1627 ***	-	-	-
		(0.0299)	(0.0294)	(2.5666)	(0.0994)	(0.0096)	(0.0007)	(0.0158)	(0.0016)	(1.5616)	-	-	-
	CDS	0.0000	-0.0018	0.0000	0.6648 ***	-0.4910 ***	0.7938 ***	0.0749 *	0.2195 ***	-	0.3782 **	-	-
		(0.0002)	(0.0027)	(2.7626)	(0.0528)	(0.0216)	(0.0108)	(0.0451)	(0.0113)	-	(0.1474)	-	-
Latvia	Bond	0.0182 ***	0.2342 **	3.8119 ***	0.3605 ***	0.3477 ***	0.9612 ***	-0.0053 **	0.0230 ***	3.1869 ***	-	-	-
		(0.0048)	(0.1189)	(0.8157)	(0.0110)	(0.0548)	(0.0022)	(0.0024)	(0.0007)	(0.0768)	-	-	-
	CDS	0.0003 ***	0.1541 ***	0.1216	0.7659 ***	0.7534 ***	-0.9865 ***	-0.9699 ***	0.9887 ***	2.0091 ***	-	-	-
		(9.71E-06)	(0.0411)	(1.2852)	(0.0186)	(0.0148)	(0.0018)	(0.2513)	(0.2425)	(0.0036)	-	-	-
Lithuania	Bond	0.9973 ***	-0.0089	1.0239 *	0.4724 ***	-0.5506 ***	0.7862 ***	-0.1540 ***	0.1442 ***	5.9128 ***	-	-	-
		(0.2508)	(0.0149)	(0.5450)	(0.0482)	(0.1421)	(0.0471)	(0.0129)	(0.0169)	(0.3875)	-	-	-
	CDS	0.0974 ***	0.4995 ***	0.0668	0.6397 ***	1.0582 ***	-0.9711 ***	-0.3183 ***	0.2991 ***	2.1858 ***	-	-	-
		(0.0091)	(0.0007)	(0.2986)	(0.0591)	(0.3945)	(0.0517)	(0.0461)	(0.0406)	(0.0325)	-	-	-
Netherlands	Bond	-0.0540	-0.2738 ***	13.0711 ***	0.5851 ***	-0.9969 ***	0.9903 ***	-0.0529	0.5440 ***	2.6190 ***	-	-	-
		(0.0400)	(0.0238)	(3.5749)	(0.0438)	(0.0003)	(0.0050)	(0.0380)	(0.0549)	(0.1304)	-	-	-
	CDS	0.0000	-0.1902 ***	0.6221 **	0.6185 ***	0.0859 ***	0.7062 ***	0.1179 ***	0.1186 ***	0.2468 ***	-	-	-
		(1.59E-05)	(0.0007)	(0.2749)	(0.0060)	(0.0103)	(0.0022)	(0.0135)	(0.0033)	(0.0052)	-	-	-
Norway	Bond	-0.0501	-0.0914	3.0169 ***	0.7209 ***	-0.3349 **	-0.0381	-0.0888 **	0.3041 ***	-	1.0868 ***	-	-
		(0.0607)	(0.0573)	(0.3532)	(0.0582)	(0.1308)	(0.2160)	(0.0345)	(0.0553)	-	(0.0745)	-	-

Table 4.7: Estimates of the univariate AR(1)-FIEGARCH process for each country (*Continued*)

		Mean Equation		Variance Equation									
		Cst(M)	*AR(1)*	*Cst(V)*	*d-Figarch*	*ARCH* (ϕ)	*GARCH* (δ)	*EGARCH* (θ_1)	*EGARCH* (θ_2)	*Student*	*GED*	*Asymmetry*	*Tail*
	CDS	-0.0003***	0.8175***	0.4281	0.3150***	-0.2365***	0.9364***	0.0937***	0.4323***	-	0.1760***	-	-
		(1.36E-05)	(0.0030)	(0.2840)	(0.0166)	(0.0071)	(0.0015)	(0.0272)	(0.0103)	-	(0.0085)	-	-
Slovakia	Bond	0.0016***	-0.2490**	0.8148***	0.9999***	0.9282***	-0.9965***	-0.5435***	0.6117***	2.0018***	-	-	-
		(0.0004)	(0.1189)	(0.2752)	(0.0228)	(0.0298)	(0.0016)	(0.0604)	(0.0778)	(0.0008)	-	-	-
	CDS	-0.0668**	-0.1191***	5.4226***	0.8035***	-0.4865***	0.9880***	0.2049***	0.5786***	-	-	-	-
		(0.0288)	(0.0182)	(1.4856)	(0.2630)	(0.1247)	(0.0074)	(0.0537)	(0.1142)	-	-	-	-
Slovenia	Bond	0.0044***	0.0715**	0.0581	0.5168***	-0.1364***	0.6020***	-0.0923***	0.0979***	5.1420***	-	-	-
		(0.0008)	(0.0282)	(3.0993)	(0.0236)	(0.0420)	(0.0177)	(0.0057)	(0.0052)	(0.9658)	-	-	-
	CDS	0.0000	0.2802***	3.0352**	0.6164***	2.3753***	-0.8950***	-0.1393***	0.2001***	-	0.3197***	-	-
		(1.48E-05)	(0.0005)	(1.3671)	(0.0113)	(0.0797)	(0.0774)	(0.0314)	(0.0118)	-	(0.0281)	-	-
Sweden	Bond	0.0473	-0.1475***	2.7978***	0.6845***	-0.2389	0.0373	-0.0373	0.2744***	-	1.1664***	-	-
		(0.0913)	(0.0123)	(0.2916)	(0.0627)	(0.1795)	(0.1442)	(0.0340)	(0.0620)	-	(0.0736)	-	-
	CDS	0.0000	0.0004***	0.0000	0.4437***	-0.8536***	0.9684***	-0.0718	0.2755***	-	0.4034***	-	-
		(3.21E-05)	(0.0001)	(1.4813)	(0.0338)	(0.0034)	(0.0029)	(0.0574)	(0.0109)	-	(0.0168)	-	-
UK	Bond	0.1458*	-0.0642***	3.3684***	0.5105***	1.4904**	-0.5054**	-0.0720**	0.2541***	-	-	-	-
		(0.0841)	(0.0107)	(0.2930)	(0.0791)	(0.6891)	(0.2397)	(0.0303)	(0.0827)	-	-	-	-
	CDS	0.0011***	-0.1393*	0.0000	0.5601***	-0.1599***	0.9496***	0.1510***	0.2467***	-	-	0.0237**	2.0032***
		(0.0001)	(0.0729)	(0.3464)	(0.0233)	(0.0291)	(0.0017)	(0.0284)	(0.0120)	-	-	(0.0119)	(0.0002)
USA	Bond	0.0367***	-0.2895***	4.6413***	0.7415***	-0.7610**	0.9874***	0.0742	0.2948***	-	-	-	-
		(0.0047)	(0.0044)	(0.6196)	(0.0941)	(0.3362)	(0.0146)	(0.0960)	(0.0935)	-	-	-	-
	CDS	-0.0004***	0.1755***	0.0559	0.6790***	3.3278***	-0.8820***	0.2100***	0.2776***	-	-	0.0959***	4.1426***
		(1.06E-05)	(0.0579)	(3.9518)	(0.0123)	(0.3343)	(0.0390)	(0.0317)	(0.0356)	-	-	(0.0232)	(0.1980)
Panel D: Newly Industrialized countries													
Brazil	Bond	0.0000***	-0.1712***	0.0800	0.4973***	-0.5948***	0.9415***	-0.1906***	0.1912***	-	-	-0.1029***	2.6819***
		(0.0000)	(0.0329)	(0.3843)	(0.0043)	(0.0045)	(0.0004)	(0.0006)	(0.0006)	-	-	(0.0148)	(0.0093)
	CDS	0.0000	0.1275***	0.0000	0.8061***	0.6964***	-0.8102	0.3783***	0.3803***	-	0.5049***	-	-
		(0.0002)	(0.0004)	(1.8448)	(0.0746)	(0.1142)	(0.9426)	(0.0261)	(0.0261)	-	(0.0576)	-	-
China	Bond	0.0000	-0.1915**	3.3515***	0.9064***	-0.8650***	0.4678*	-0.0090	0.4189***	-	1.0861***	-	-
		(0.0001)	(0.0782)	(0.4573)	(0.0580)	(0.0857)	(0.2491)	(0.0334)	(0.0704)	-	(0.0894)	-	-
	CDS	0.0002***	-0.0171	0.0004	0.8667***	0.3318	0.2095**	-0.2582***	0.2604***	-	-	-0.0044	2.2447***
		(6.82E-08)	(0.0722)	(1.3588)	(0.0119)	(0.2334)	(0.0997)	(0.0088)	(0.0088)	-	-	(0.0105)	(0.0323)
Turkey	Bond	0.1529	-0.0894***	8.0787***	0.5623***	-0.9462***	0.9659***	0.1235***	0.3298***	-	-	-	-
		(0.2022)	(0.0274)	(0.6184)	(0.0655)	(0.0336)	(0.0127)	(0.0286)	(0.0609)	-	-	-	-
	CDS	-0.0235	0.1271***	3.2014***	0.6707***	0.0540	0.4514**	0.1287***	0.2096***	-	1.2335***	-	-
		(0.0829)	(0.0207)	(0.4726)	(0.0490)	(0.3233)	(0.2277)	(0.0295)	(0.0460)	-	(0.0617)	-	-
Panel D: Emerging countries													
Bulgaria	Bond	-0.4130***	-0.2623***	6.0109***	0.4359***	0.0197	0.3269	-0.2339***	1.0000***	-	-	-0.0441***	2.2141***
		(0.0203)	(0.0256)	(0.5152)	(0.0817)	(0.2703)	(0.2473)	(0.0760)	(0.1546)	-	-	(0.0150)	(0.0706)
	CDS	0.1573	0.1112	0.5931**	0.3932***	-0.4082**	-0.1202	-0.0157	0.2209***	5.0210***	-	-	-
		(0.2378)	(0.0704)	(0.2554)	(0.0367)	(0.1815)	(0.1591)	(0.2207)	(0.0327)	(0.8241)	-	-	-
Croatia	Bond	0.0002***	0.1512***	0.3903*	0.4983***	1.6892***	0.5722***	0.1365***	0.1384***	-	-	0.0782***	2.9342***
		(0.0001)	(0.0385)	(0.2152)	(0.0040)	(0.0248)	(0.0031)	(0.0031)	(0.0030)	-	-	(0.0096)	(0.0094)
	CDS	-0.0444**	0.0512**	0.6472	0.6601***	-0.7882***	0.8179***	0.1213**	0.6441***	-	-	-0.0297***	2.4496***
		(0.0197)	(0.0219)	(0.6993)	(0.0422)	(0.1712)	(0.1412)	(0.0479)	(0.1284)	-	-	(0.0108)	(0.1388)
Czech	Bond	-0.1023	-0.1907***	3.3285***	0.6879***	-0.5407***	0.3518	0.0900***	0.3009***	-	1.1684***	-	-
		(0.1126)	(0.0339)	(0.3493)	(0.0790)	(0.1679)	(0.2544)	(0.0322)	(0.0578)	-	(0.0590)	-	-
	CDS	0.0000	-0.0187	0.0000	0.7007***	-0.5648***	0.9238***	0.7781***	1.0000***	-	-	0.0184*	2.0033***
		(0.0001)	(0.0152)	(1.4698)	(0.0612)	(0.0602)	(0.0286)	(0.1448)	(0.1099)	-	-	(0.0102)	(0.0012)
Hungary	Bond	-0.4581**	0.0486**	4.6328***	0.5986***	-0.4131**	0.6709***	0.1324***	0.2182***	-	-	0.0012	3.5631***
		(0.1834)	(0.0222)	(0.5112)	(0.0764)	(0.2002)	(0.1330)	(0.0326)	(0.0558)	-	-	(0.0146)	(0.2903)
	CDS	0.0030	0.1240***	0.8032	0.5912***	-0.9081***	0.9624***	0.1221***	0.6366***	-	-	-0.0167	2.6584***
		(0.0223)	(0.0216)	(1.5513)	(0.0645)	(0.0531)	(0.0213)	(0.0385)	(0.0923)	-	-	(0.0134)	(0.1651)
Poland	Bond	-0.0910***	-0.0260*	4.1651***	0.6494***	0.1220	0.1896	0.0618**	0.2233***	-	1.3093***	-	-
		(0.0320)	(0.0152)	(0.3934)	(0.0733)	(0.3270)	(0.2490)	(0.0253)	(0.0573)	-	(0.0664)	-	-
	CDS	-0.0159	0.0255	0.0000	0.6333***	-0.7539***	0.8565***	0.1112***	0.5230***	-	-	-0.0123	3.0747***
		(0.0145)	(0.0216)	(0.8252)	(0.0575)	(0.2329)	(0.1671)	(0.0272)	(0.0758)	-	-	(0.0114)	(0.2282)
Romania	Bond	0.0000	0.1087***	2.5158***	0.4527***	0.5309***	0.6784***	-0.3201***	0.3369***	-	0.2158***	-	-
		(0.0001)	(0.0010)	(0.6993)	(0.0214)	(0.0318)	(0.0071)	(0.0061)	(0.0059)	-	(0.0108)	-	-
	CDS	-0.0219	0.1081***	0.0000	0.6761***	-0.4885	0.6747*	0.1050***	0.5614***	-	-	-0.0265**	2.6752***
		(0.0185)	(0.0206)	(1.0093)	(0.0510)	(0.5453)	(0.3893)	(0.0306)	(0.0983)	-	-	(0.0126)	(0.1585)
Russia	Bond	0.0003***	-0.1152***	7.2254***	0.4792***	0.2799***	0.9133***	-0.2233***	0.2320***	-	0.2266***	-	-
		(0.0001)	(0.0006)	(2.3140)	(0.0898)	(0.0538)	(0.0072)	(0.0203)	(0.0190)	-	(0.0770)	-	-
	CDS	-	-	-	-	-	-	-	-	-	-	-	-
										-	-	-	-

Table 4.7: Estimates of the univariate AR(1)-FIEGARCH process for each country (*Continued*)

		Mean Equation		Variance Equation									
		Cst(M)	*AR(1)*	*Cst(V)*	*d-Figarch*	*ARCH* (ϕ)	*GARCH* (δ)	*EGARCH* (θ_1)	*EGARCH* (θ_2)	*Student*	*GED*	*Asymmetry*	*Tail*
Ukraine	Bond	0.0002 ***	-0.0939	0.0001 ***	0.9653 ***	0.0961 ***	-0.4089 ***	0.0461 ***	0.1100 ***	2.0040 ***	-	-	-
		(4.11E-05)	(0.0728)	2.281.5	(0.0056)	(0.0275)	(0.0382)	(0.0043)	(0.0020)	(0.0003)	-	-	-
	CDS	-0.1257	0.1207 ***	3.7019 ***	0.7533 ***	0.5272 *	-0.5383 *	0.1793 ***	0.5647 ***	-	-	-0.0160	2.9146 ***
		(0.1192)	(0.0220)	(0.6556)	(0.0324)	(0.2949)	(0.3239)	(0.0345)	(0.0839)	-	-	(0.0117)	(0.1919)
Venezuela	Bond	0.0369 ***	0.8231 ***	0.6914 ***	0.3224 ***	0.0419 ***	0.5472 ***	-0.0337 ***	0.1808 ***	2.6454	-	-	-
		(0.0051)	(0.0243)	(0.2663)	(0.0023)	(0.0096)	(0.0048)	(0.0072)	(0.0031)	(0.0082)	-	-	-
	CDS	0.0000 ***	0.2603 ***	0.0000	0.4700 ***	-0.6510 ***	0.9617 ***	0.4498 ***	0.4675 ***	-	-	-0.0900 ***	2.1977 ***
		(1.41E-06)	(0.0147)	(0.2166)	(0.0040)	(0.0020)	(0.0002)	(0.0044)	(0.0037)	-	-	(0.0088)	(0.0011)

This table reports the results of the AR(1)-FIEGARCH(1,d,1)-DCC model for each studied country. *, ** and *** denote statistical significance at respectively 10%, 5% and 1%.

Table 4.8: Estimates of the Univariate AR(1)-FIEGARCH process for each synthetic portfolio

		Mean Equation		Variance Equation									
		Cst(M)	*AR(1)*	*Cst(V)*	*d-Figarch*	*ARCH* (ϕ)	*GARCH* (δ)	*EGARCH* (θ_1)	*EGARCH* (θ_2)	*Student*	*GED*	*Asymmetry*	*Tail*
Panel E: GDP growth classification													
Developed	Bond	0.0234	-0.2377 ***	-0.1671	0.7809 ***	-0.3858 ***	-0.1752	-0.0107	0.4122 ***	-	-	-0.0194 *	4.0269 ***
countries		(0.0208)	(0.0223)	(0.5008)	(0.0612)	(0.1375)	(0.1442)	(0.0358)	(0.0582)	-	-	(0.0116)	(0.3734)
	CDS	0.0001	0.0376	0.0000	0.7766 ***	0.0235	0.1142	0.0410	0.7106 ***	-	-	-0.0083	2.6714 ***
		(0.0007)	(0.0233)	(1.5651)	(0.0318)	(0.4402)	(0.4356)	(0.0313)	(0.1156)	-	-	(0.0128)	(0.2864)
Emerging	Bond	-0.2774 **	-0.0171	4.8020 ***	0.5149 ***	-0.2027	0.5345 ***	0.0692	0.4505 ***	-	-	-0.0163	2.2194 ***
countries		(0.1142)	(0.0172)	(0.5888)	(0.0563)	(0.2959)	(0.1887)	(0.0496)	(0.1261)	-	-	(0.0154)	(0.1125)
	CDS	-0.0516	0.2335 ***	0.2464	0.6987 ***	-0.0624	0.4166 ***	0.1044 ***	0.3285 ***	-	1.2166 ***	-	-
		(0.0543)	(0.0265)	(0.5406)	(0.0373)	(0.2294)	(0.1329)	(0.0205)	(0.0553)	-	(0.0516)	-	-
PIIGS	Bond	0.0554	-0.0633 **	4.7019 ***	0.6549 ***	0.0051	0.4424 ***	0.1017 ***	0.2649 ***	-	-	-	-
		(0.1062)	(0.0312)	(0.7584)	(0.0910)	(0.2649)	(0.1514)	(0.0262)	(0.0853)	-	-	-	-
	CDS	0.0006	0.1059 ***	0.0000	0.6885 ***	-0.9984 ***	1.0011 ***	0.0870	1.0000	-	-	-0.0067	2.3109 ***
		(0.0225)	(0.0243)	(5.0840)	(0.0772)	(0.0147)	(0.0048)	(0.1747)	(0.9625)	-	-	(0.2342)	(0.7630)
Newly	Bond	-0.0602	-0.1465 ***	4.1025 ***	0.4354 ***	0.8349 **	-0.1546	-0.0773 **	0.3325 ***	-	-	-0.0100	3.3387 ***
Industrialized		(0.1287)	(0.0242)	(0.3822)	(0.0683)	(0.4033)	(0.2727)	(0.0373)	(0.0578)	-	-	(0.0203)	(0.3768)
countries	CDS	-0.0179	0.2004 ***	0.0000	0.7220 ***	0.5125	0.0835	0.1068 ***	0.2985 ***	-	1.1551 ***	-	-
		(0.0417)	(0.0320)	(0.5273)	(0.0404)	(0.6475)	(0.4716)	(0.0274)	(0.0520)	-	(0.0558)	-	-
Panel F: Regional poclassification													
Eastern	Bond	-0.1801 ***	-0.0907 ***	4.0282 ***	0.4939 ***	-0.1700	0.2792	0.0819 **	0.4759 ***	-	-	0.0182	3.2801 ***
Europe		(0.0207)	(0.0134)	(0.3795)	(0.0720)	(0.2893)	(0.2712)	(0.0387)	(0.0889)	-	-	(0.0162)	(0.2678)
	CDS	-0.0300	0.1386 ***	0.1566	0.6053 ***	-0.6498 **	0.8080 ***	0.1329 ***	0.4032 ***	-	-	-0.0269 **	5.0042 ***
		(0.0377)	(0.0231)	(0.6596)	(0.0598)	(0.2644)	(0.1724)	(0.2506)	(0.0698)	-	-	(0.0132)	(0.5269)
Western	Bond	-0.0766	-0.0659 **	2.5829 ***	0.8239 ***	-0.1913	0.0620	0.1138 ***	0.2949 ***	-	-	-	-
Europe		(0.0641)	(0.0301)	(0.5569)	(0.1390)	(0.1483)	(0.2025)	(0.0339)	(0.0728)	-	-	-	-
	CDS	-0.0029	0.1318 ***	7.7504 **	-	-0.3835	0.9948 ***	0.1318 ***	0.5990 ***	-	-	-	-
		(0.0044)	(0.0303)	(3.4023)	-	(0.2600)	(0.0050)	(0.0458)	(0.0980)	-	-	-	-
North	Bond	0.0367 ***	-0.2895 ***	4.6413 ***	0.7415 ***	-0.7610 **	0.9874 ***	0.0742	0.2948 ***	-	-	-	-
America		(0.0047)	(0.0044)	(0.6196)	(0.0941)	(0.3362)	(0.0146)	(0.0960)	(0.0935)	-	-	-	-
	CDS	-0.0004 ***	0.1755 ***	0.0559	0.6790 ***	3.3278 ***	-0.8820 ***	0.2100 ***	0.2776 ***	-	-	0.0959 ***	4.1426 ***
		(0.0000)	(0.0579)	(3.9518)	(0.0123)	(0.3343)	(0.0390)	(0.0317)	(0.0356)	-	-	(0.0232)	(0.1980)
South	Bond	0.0317 ***	0.0442 ***	0.1489	0.5354 ***	0.0245	0.2640 **	-0.0994	0.0908 ***	5.1386 ***	-	-	-
America		(0.0038)	(0.0164)	(0.8798)	(0.0151)	(0.1807)	(0.1285)	(0.0038)	(0.0044)	(0.1782)	-	-	-
	CDS	-0.0001 ***	0.3198 ***	0.0001	0.6206 ***	-0.1636 ***	0.8275 ***	0.2073 *	0.2083 *	-	-	0.0270	3.5270 ***
		(0.0000)	(0.0401)	(8.3897)	(0.0142)	(0.0381)	(0.0306)	(0.1073)	(0.1070)	-	-	(0.0594)	(0.4106)
Asia	Bond	0.0079	-0.1286 ***	1.5875 ***	0.7441 ***	-0.2696	0.6725 ***	0.2105 *	0.0750	-	1.5593 ***	-	-
		(0.0541)	(0.0229)	(0.3734)	(0.1060)	(0.7316)	(0.1216)	(0.0122)		-	(0.0702)	-	-
	CDS	-0.0081	0.1005 ***	0.0000	0.7052 ***	0.4349	0.0005	0.0924 ***	0.4510 ***	-	-	0.0028	3.2224 ***
		(0.0078)	(0.0229)	(1.1222)	(0.0536)	(1.0635)	(0.9443)	(0.0321)	(0.0744)	-	-	(0.0123)	(0.2459)
Panel G: Credit rating classification													
Investment-	Bond	0.0193	-0.1632 ***	3.2958	0.4217	-0.9589 ***	0.9944 ***	0.0629 *	0.2986 ***	-	-	-	-
Grade		(0.0342)	(0.0287)	(2.7291)	(0.8852)	(0.2291)	(0.0100)	(0.0371)	(0.0560)	-	-	-	-
countries	CDS	0.0013	0.0999 ***	0.0000	0.6993 ***	-0.9553 ***	0.9784 ***	0.0543 *	0.5909 ***	-	1.1812 ***	-	-
		(0.0030)	(0.0270)	(0.8653)	(0.0651)	(0.0173)	(0.0071)	(0.0290)	(0.0557)	-	(0.0552)	-	-
Speculative-	Bond	-0.1522	0.3905 ***	0.0000	0.1613 **	-0.4625 ***	0.9985 ***	0.4808 ***	0.2380 ***	-	-	-	-
Grade		(0.2250)	(0.0293)	(19.243)	(0.0752)	(0.1207)	(0.0029)	(0.0525)	(0.0501)	-	-	-	-
Countries	CDS	-0.0392 **	0.2272 ***	0.8631	0.6405 ***	0.1397	0.5502 ***	0.0837 ***	0.2868 ***	-	1.0300 ***	-	-
		(0.0191)	(0.0063)	(0.5634)	(0.0558)	(0.3119)	(0.1573)	(0.0154)	(0.0366)	-	(0.0644)	-	-

This table reports the results of the AR(1)-FIEGARCH(1,d,1)-DCC model for each synthetic country. *, ** and *** denote statistical significance at respectively 10%, 5% and 1%.

Chapter 5

The Credit Default Swap market contagion during recent crises: International evidence

This essay, published ***in Review of Quantitative Finance and Accounting***, analyzes Credit Default Swap spread dynamics to determine whether the sovereign Credit Default Swap market is subject to contagion effects. Analysis is performed on credit spreads data from 35 worldwide countries belonging to four different economic categories over a period from 2006 until 2014, covering the subprime crisis and the European sovereign debt crisis.

A novel approach is proposed to estimate the Dynamic Conditional Correlations between CDS spreads using the AR(1)-FIEGARCH(1,d,1)-DCC model. Based on our findings, we put a slant on the financial market vulnerability, reinforced by contagion effects during the different phases of the crises. Furthermore, analysis of each country solely shows that contagion effects are sterner during the Eurozone crisis compared to the global financial crisis and that the level of exposure to crises differs across global markets and regions. Yet our approach provides evidences that crises spread to countries across the world regardless their economic status or geographical positions.

Keywords : Sovereign risk spillover, Credit Default Swaps, Contagion phenomenon, Dynamic Conditional Correlation.

5.1 Introduction

Several episodes of financial crises have occurred recursively since the globalization and the creation of the financial sphere. An accentuation of this recurring phenomenon is observed during the last two decades with the occurrence of more and more financial crises characterized not only by their persistence but especially by their severity and their magnitude. From the Great Depression of 1929 in the USA, other crises have followed, such as the European Monetary System (EMS) crisis in 1992-1993, the Latin American crisis in 1994, the Asian financial crisis in 1997-1998, the Russian crisis in 1998 and the Brazilian crisis in 1999. The most recent crises are the bursting of the technology bubble in the USA in 2001, the subprime crisis of 2007 and the crisis of European sovereign debt of 2010 (see Reinhart and Rogoff (2008); Reinhart (2010); D'Apice and Ferri (2016)). Since crises have been constantly emerging for years, it is crucial to note they are changing nature over time. Indeed, the crises seem to last longer, since 9 years after the crisis of 2007, the financial market continues to feel its effects (see Dron and Pillet (2016); Pentecôte et al. (2016)). This feature is in addition to the development of a contagious nature throughout markets, whereby the occurrence of a crisis in a country can have effects on international financial markets and spreads to other countries. Financial researchers have always used the word contagion to talk about such phenomena.

In light of these observations, economists have begun to develop empirical models to anticipate crises and to study factors likely to accentuate this kind of phenomenon in order to understand if these crises constitute independent events or rather symptoms of contagion episodes. Answering this question appears particularly important for analyzing the both crises: the Credit Crisis (2007-2009) and the European Sovereign Debt Crisis (2010-2012). Yet, the defining of how shocks spread across countries is of particular interest. As a result, economists and policymakers can reduce the extend of instability and contagion effects. The study of financial contagion is also relevant for fund managers and investors so that they can revise upward spillover risk and take into account the limits of portfolio diversification.

Since derivatives markets play an important role in the price discovery process of financial assets, we try in this essay to study contagion phenomena in the credit derivatives market. Using a new class of model based on the AR(1)-FIEGARCH-DCC model, this essay aims to study the contagion effects within the sovereign Credit Default Swap (CDS, hereafter) markets in order to investigate the vulnerability of these markets to such a phenomenon. This question seems to be intriguing, since during the recent financial crises, a joint and common rise in CDS spreads has been observed. We study the dynamics of CDS markets during the two recent financial turmoils, namely the Global Financial Crisis, which began with the collapse of the subprime market in 2007, and the European Sovereign Debt crisis. The ultimate goal is to verify the presence of a shock spillover across sovereign CDS markets and to quantify market interactions. To address this problematic, the Dynamic Conditional Correlations of CDS spreads between the crises generators and the other 34 countries are analyzed. To provide a representative sample of the international sovereign credit market, a large set of countries belonging to different geographical regions (Eastern Europe, Western Europe, North America, South America and Asia) and economic levels (low economic growth countries, developed countries, newly industrialized countries and emerging countries) is used. This analysis is carried out through the Exponentially Weighted Moving Average (EWMA) model (Coudert and Gex, 2010; Kalbaska and Gatkowski, 2012) and the AR(1)-FIEGARCH(1,d,1)-DCC models (Christensen et al., 2010). These approaches are used to determine the existence of significant links between the recent financial crises' originators and different markets during different sub-periods, and then compare the strengths of each country's response to contagion effects.

This essay contributes to the existing literature on several prospects: Firstly, we extend the field of study and go beyond the abundantly studied context: countries are chosen as to represent a benchmark of international CDS markets and thus provide international evidence of sovereign contagion from a global rather than a local or regional perspective as it has been done in the literature. Second, contrary to other studies of sovereign CDS markets, we examine two recent crises: the global financial crisis 2007-2009 (GFC, hereafter) and the European debt crisis, since distress transmission depends on crisis magnitude and severity. Third, the approaches used in our essay are more accurate since they allow for taking into account more CDS market properties (such as long-memory range, information asymmetries...). Yet, we do not limit our investigation to country-by-country analysis. Indeed, the analysis of regional and economic aggregate contagion can provide different results because the level of crisis exposure is different across global markets and regions.

Our results allow us to draw three major conclusions: The sovereign CDS market is prone to contagion effects, especially during turmoil episodes. The level of crisis exposure differs across global markets and regions. And crises spread to countries across the world regardless their economic status or geographical positions.

The rest of this chapter is organized as follows: section 5.2 gives necessary background information on financial contagion and related works. section 5.3 and section 5.4 are dedicated respectively to sample description and our proposed methodology for contagion detection. Empirical results are covered in section 5.5. section 5.6 depicts an economic and financial discussion and section 5.7 concludes the chapter and outlines possible economic and financial implications.

5.2 Crises and contagion: Literature review

5.2.1 Contagion definition

The identification, measurement and prediction of the contagion phenomenon depend on the definition of this concept. The term "contagion" remains controversial and has always stirred widespread discord among economists as to its exact definition and measurement. Indeed, whether theoretically or empirically speaking, too many ambiguities arise as to the exact definition of contagion and no method of its quantifying wins unanimous support of researchers. However, by taking stock of previous studies, we find a summary definition commonly used in the theoretical literature and its corresponding measure adopted in empirical works. Generally, contagion is defined as a transmission of financial shocks through countries. It corresponds to a scenario in which financial shocks, affecting at first only a few financial institutions or some parts of the economy, spread to the rest of the financial sector and other countries of the global economy resulting in a simultaneous increase in asset prices' co-movements (Kalbaska and Gatkowski, 2012)[1].

A first category of researchers think that there are some reasons related to countries' idiosyncratic features (trade linkages and free-trade area, financial agreements and cooperation, markets' characteristics . . .) and therefore make them vulnerable to contagion effects (Forbes and Chinn, 2004; Borio, 2008). Another strand of the literature defines this phenomenon as a pure contagion that cannot be explained by changes in the fundamentals of countries (Wu, 2000; Pericoli and Sbracia, 2003; Caporale et al., 2005). Pure contagion occurs when a significant increase in correlations between financial markets is due to a shock relative to a change in investor appetite towards risk: when risk aversion of investors increases, they reduce their exposure to risky assets resulting in a fall in these assets' prices. Contrary, when the risk appetite of investors increases, they increase their demand for risky assets, which simultaneously increases their values (Forbes and Rigobon, 2002; Coudert and Gex, 2010; Broto and Perez-Quiros, 2015). Thus, the pure contagion operates in the same direction as the level of

[1]For a complete survey on different contagion definitions, see Missio and Watzka (2011) whom summarize all the existing definitions in the literature and draw up a report of the four most used ones: (i) There is a financial contagion when the probability of a crisis's appearance in one country increases considerably after the occurrence of a crisis in another country; (ii) Contagion phenomenon is observed when several financial assets' volatility across markets of one country simultaneous rise; (iii) Contagion is defined as a sudden modification in financial assets' prices without any economic explanations related to fundamentals and (iv) the significant increase in prices' co-movements across international markets implies a contagion phenomenon.

risk aversion and is in no way related to fundamentals, exchange regime or exchange rates (Kumar and Persaud, 2002). This essay only focuses on pure contagion phenomena between crises generators (the USA, Greece and Ireland) and the remaining 32 countries worldwide.

5.2.2 Related works

The state of the art of financial contagion phenomena can be divided into three groups according to the study aim: First, the empirical studies list several transmission channels of financial distress that can explain the contagion on financial markets. Several researchers investigate on pathways through which crises can be transmitted and highlight various factors that could make a market prone to contagion effects. Taking stock of this literature, a summary of four transmission channels can be drawn: the correlated information channel, also known as the wake-up call hypothesis, the liquidity channel, the cross-market hedging channel and the counterparty risk (Pritsker, 2001; Kodres and Pritsker, 2002; Chiang et al., 2007). Extensive studies of the last channel exist, whether theoretical or empirical. Jarrow and Yu (2001) develop a theoretical model including default probabilities of the counterparty to explain the negative impact of defaulter companies on the whole economy observed during the Asian crisis in 1997. The results show a correlation between default probability of financial companies, that does not only depend on common risk factors but also on specific factors called counterparty risk. An empirical measurement of this counterparty risk has been integrated in pricing models for bonds and credit derivatives (Packer and Wooldridge, 2005; Jorion and Zhang, 2007; Markose et al., 2010; Blinder, 2013; Fink and Scherr, 2014; Jenkins et al., 2016; Xiang et al., 2017; Hu et al., 2018).

Second, Alter and Schüler (2012) examine the co-movement relationship between sovereign CDS of seven European countries (France, Germany, Italy, Ireland, the Netherlands, Portugal and Spain) and the corresponding CDS of their domestic banks from 2007 to 2010. Using cointegration analysis, Granger causality and Impulse Responses Functions[1], Alter and Schüler (2012) show that the rescue operations, engaged by the International Monetary Fund and the European Union, have an impact on the relationship between these two CDS markets. They note that for the period prior to government interventions, banks CDS exert a contagion effect on sovereign CDS, while during the second period, the sovereign CDS market takes the lead. This relational direction is only valid and significant in the short term. In this sens, Acharya et al. (2014) find an empirical evidence of a direct feedback relationship between the sovereign CDS market and the private sector (Banks CDS). Wang and Moore (2012) also show the spread of Lehman Brothers financial distress to the sovereign markets. In the same context, several economists have focused on the interdependence between the 2007 credit crisis and the European sovereign debt crisis (Ejsing and Lemke, 2011; Acharya et al., 2014; k et al., 2016). Results of these studies point to that the implementation of bank bailout programs by the European government leads to an increase in sovereign credit risk because of the costs generated. The various rescue operations induce a degradation of balance sheets and governments guarantees and thus cause a crisis spread from the private sector to the public finances. Moreover, the authors show that these financial rescue cost increases the sensitivity of government credit risk to potential financial shocks.

Third, much of the literature focuses on the study of contagion existing on the financial markets. Indeed, many researchers are reconsidering the 2007 financial crisis in order to

[1]The impulse response function (IRF) provides information on the current and future evolution (range and duration) of time series, following a financial shock on an innovation.

understand the reaction of the entire CDS market with regard to the turmoil phases. Using an EWMA model, empirical evidence of contagion phenomena is found on the USA and European CDS markets following the financial distress of General Motors and Ford in March 2005 (Packer and Wooldridge, 2005; Coudert and Gex, 2010). The financial troubles of these two firms have effects on the credit market because of their huge amounts of issued debts. This contagion phenomenon is reinforced by the fact that a large number of Collateralized Debt Obligations (CDO) have for collateral the debts of these two companies. Similarly, using the standard event study, Jorion and Zhang (2007) empirically examine the effect of a credit event (bankruptcy) on the information transfer between companies. The main conclusions drawn are the following: a positive correlation between the CDS spreads of several companies implies a contagion effect, whereas a negative correlation assumes the predominance of competition effects. Yet the study of financial contagion during the European debt crisis is still expanding. Grammatikos and Vermeulen (2012) show that the European sovereign CDS market is subject to a contagion effect mainly caused by the Greece inability to repay its debts. Through an EWMA framework analysis, Kalbaska and Gatkowski (2012) provide evidence of financial contagion in sovereign CDS markets (PIIGS[1], the UK, France and Germany) based on data spanning the period 2005 to 2010. Our essay contribution is built on this last strand of the literature.

5.2.3 Limits of the literature

Most of these previous studies focus on homogeneous samples by studying contagion between countries linked either by their economies or by their geographical positions. Indeed, all research based on crisis transmission between PIIGS[2] - for example - are somewhat predictable and obvious because these countries are financially very unstable making them logically very vulnerable to financial distress; and are closely linked commercially, which is undoubtedly a transmission channel of the financial turmoil (Pan and Singleton, 2008; Longstaff et al., 2011). However, studies focusing especially on international datasets remain infrequent. For example, Caramazza et al. (2004) study the Mexican, Asian and Russian crises spread around the world during the 1990s. Yet, using an error correction model, Srivastava et al. (2016) give evidence of risk spillover from the equity markets to the sovereign CDS markets of 56 sovereigns studied (see Lee et al. (2015) for a similar study).

Unlike most of these studies, our empirical analysis provides international evidence of crises spread in sovereign CDS markets, which is important given the international diversification of portfolio investment and the shift to a single global economic and financial policy. Indeed, our sample consists of a reference pool (PIIGS), i.e. countries with low economic growth, around which we choose to study countries with no economic and / or geographic correlation. First, if contagion spreads from one country to another, countries geographical diversification seems to be very interesting. Second, it is important to test the contagion effects on countries in which crises are likely to have quite different impact[3](developed countries, newly industrialized

[1]Portugal, Ireland, Italy, Greece and Spain.

[2]The PIIGS denotes the 5 European countries that suffer the most from indebtedness and represent a weak growth prospects with high unemployment rates. They are called, somewhat disdainfully, the "*Club Med*" countries for their fiscal laxity and the fragility of their economies.

[3]Some empirical studies show that developed countries are more likely to constitute a transmission channel of crises and suggest that reasons of the propagation of turmoil in industrial countries differ from those in emerging countries (Caramazza et al., 2004).

countries[1] and emerging countries[2])[3].

On the other hand, many of these studies base their work on the adjusted correlation coefficients, which are none other than the corrected unconditional Pearson correlation coefficients. Several critics have been developed against the use of this method. First, the method results only inform us about the degree of correlation of each sub-period without considering the underlying dynamics between the different sub-periods. Second, another disadvantage of this method is that it only perform with the latest information. It further ignores information about the series dynamic behavior contained in the earliest observations. This technique is therefore inefficient to detect weak correlations. Third, this method does not take into account ARCH effects, which characterize financial time series, leading to suboptimal estimates. And fourth, unconditional correlation assumes that the relationship between time series is always linear, which is clearly not the case for non-linear dependent financial assets. To overcome these shortcomings, our work is based on a time varying dynamic conditional correlations (EWMA and AR(1)-FIEGARCH-DCC) that allow us to make a common interest into past and present observations and take into account more CDS market specifications (volatility clustering, information asymmetry, long-memory behavior...). Yet, by allowing the correlations to be time-dependent, possible changes in the interconnection behavior in the same sub-period can be identified over time.

5.3 Sample description

This section presents one of our essay contributions: the sample under study, composed by countries around the world, allowing us to provide international evidence of the global financial contagion on sovereign CDS markets.

5.3.1 Data and sample description

The sample studied is composed of sovereign CDS issued on the bonds of 35 countries of different economic status (weak economic growth, developed countries, newly industrialized countries and emerging countries) and belonging to 5 different geographical regions (Eastern Europe, South and Central America, Asia and Western Europe) (see Table 5.1). The advantage of choosing these (apparently) uncorrelated economies is to check the international context. For each country, 5-year daily CDS spreads denominated in USD are collected from The data comes from Thomson Reuters ®and Bloomberg ®.Although CDS contracts exist for other maturities (1 year, 2 years, 3 years, 4 years, 10 years...) and other currencies (EUR, JPY, pound sterling...), our sample only contains the 5-year maturity and the US denomination since this market segment is the most liquid one. In order to improve CDS spreads reliability and maintain a high quality database, we first extract the observed CDS contracts following aforementioned criteria, which represent the major part of our dataset. Then, we fill the gaps with contracts denominated in other currency and / or other maturities.

[1]These are all economies which, by their development strategies, have experienced a major industrial take-off over the last 20 to 40 years.

[2]These countries are characterized by a fast economic growth but still have not reached the level of GDP per capital of developed countries. Unlike the newly industrialized countries, emerging countries have already had a significant industrial sector or a development in sectors other than industry.

[3]We use different criteria of countries' economic classification (the NU, the CIA World Factbook, the IMF and the World Bank criteria) as to have a sample of sufficient size in each category.

Table 5.1: Countries classification according to their economic status and geographical positions

Economy	Country	Continent
	Portugal	Western Europe
	Ireland	Western Europe
PIIGS low economic growth countries (5)	Italy	Western Europe
	Greece	Western Europe
	Spain	Western Europe
	Austria	Western Europe
	Belgium	Western Europe
	Denmark	Western Europe
	Estonia	Eastern Europe
	Finland	Western Europe
	France	Western Europe
	Germany	Western Europe
	Japan	Asia
Developed countries (17)	Latvia	Eastern Europe
	Lithuania	Eastern Europe
	Netherlands	Western Europe
	Norway	Western Europe
	Slovakia	Eastern Europe
	Slovenia	Eastern Europe
	Sweden	Western Europe
	UK	Western Europe
	USA	North America
	Brazil	South America
Newly industrialized countries (4)	China	Asia
	Qatar	Asia
	Turkey	Asia
	Bulgaria	Eastern Europe
	Croatia	Eastern Europe
	Czech	Eastern Europe
	Hungary	Western Europe
Emerging countries (9)	Poland	Eastern Europe
	Romania	Eastern Europe
	Russia	Asia
	Ukraine	Eastern Europe
	Venezuela	South America

These 35 countries are classified according to the NU, the CIA World Factbook, the IMF and the World Bank criteria.

The data collected from January 2^{nd}, 2006 until April 3^{rd}, 2014, provide a sample of 2154 observations per series. Prior to 2006, the sovereign CDS market was relatively illiquid, particularly for developed countries, which is why our analysis began at that date. Almost all time-series for our selected countries are available for the entire period studied, with the exception of Greece where data only extend to September 12^{th}, 2013 when spreads has reached unreasonable levels and the credit market has become completely illiquid. Our sampling period covers the Global Financial Crisis as well as the Sovereign Debt Crisis.

5.3.2 Crisis timeline

Previous research defines the length, the breadth and the crisis chronology using either an economic or an econometric approach. On the one hand, the studies determining the crisis timeline based on economic and financial events, such as Kalbaska and Gatkowski (2012), seems arbitrary in a certain way since the definition and timing of crises are chosen subjectively.

On the other hand, the statistical approach may also present some flexibility problems since it avoids linking the crisis period to economic events (Kenourgios and Dimitriou, 2015). In order to correctly determine the crises chronology, we use a methodology that takes into account both economic and econometric approaches following Dimitriou et al. (2013). Dimitriou et al. (2013) only use this technique to define the recent international credit crisis while we use it to determine the GFC as well as the European debt crisis.

We start by defining a relatively long period covering both the international financial crisis and the European Debt Crisis. Given the interdependence and the coupling between these two crises, it seems interesting to study the CDS market behavior during these different turmoil phases in order to distinguish between market reactions to different crises. Among several studies, we choose to refer to the official timeline provided by the BIS (2009)[1] to define different phases of the GFC: (i) A pre-crisis period, in which the global banking system was, in a way, healthy, strengthened and sound coupled with a globally favorable economic climate. This period, called the "quiet period", is prior to the third quarter of 2007. (ii) A 1st crisis period, characterized by an increase in the inability of market actors to correctly price some risky structured credit products (namely the subprime). This phase is known as the "initial financial turmoil" and spans from July 2007 to mid-September 2008. It has been triggered by the beginning of Bear Sterns problems and by the BNP Paribas announcement of the financial crisis and the credit crunch. (iii) A 2nd turmoil phase, defined by the BIS as a "Sharp financial market deterioration", starting up from mid-September 2008 until late 2008. At this stage of the financial crisis, the whole world perspectives sharply changed (abruptly decrease in risk appetites with a big loss of market confidence) due to Lehman Brothers Bankruptcy[2]. The 3rd crisis phase is defined as a “macroeconomic deterioration” because of the role played by the drastic policy measures in the financial system, the market stabilization and the counterparty risk reduction. It extends from late 2008 to the end of the first quarter of 2009. The last phase described by the BIS (2009) is called "stabilization and tentative signs of recovery" (from the second quarter of 2009 to October 2009) during which some hope signs appeared, the financial indicator returned to normal thresholds and investors readjusted upwards their risk appetite.

Referring to the Thomson Reuters official publications, the European debt crisis goes through four phases: (i) From October 2009 to April 2010, "Greek accounting unravels" phase when the world figured out that the Greek budget deficit was much higher than what the country announced. (ii) The 2nd phase started after the adoption of EU and IMF bailout measures following the increase in sovereign credit risk. This phase is called "the crisis spreads" and runs from May 2010 to June 2011. (iii) From July 2011 to March 2012, the crisis deepened and the sovereign risk rose to new high levels since the Eurozone finance ministers put off any decision on the sovereign debt program. (iv) Starting in April 2012, the Euro area experienced a phase of "containing the crisis" with the adoption of a permanent rescue fund whose role is to obtain countries and banks' balance sheets under control. (For a more detailed sovereign debt crisis timeline, see the survey by Pisani-Ferry et al. (2013) entitled "EU-IMF assistance to Eurozone countries: an early assessment".) Thus, the Global Financial crisis could be defined from August 2007 to March 2009 and the European debt crisis could be defined from October 2009 to March 2012.

Next, since financial crises are characterized by a sharp increase in financial assets volatil-

[1]See also the Federal Reserve Bank of ST. Louis's report entitled "The Financial crisis: a time-line of events and policy actions" (2009).

[2]Lehman Brothers, the 4th biggest investment bank in the USA, has been declared Bankrupt in September 15th, 2008.

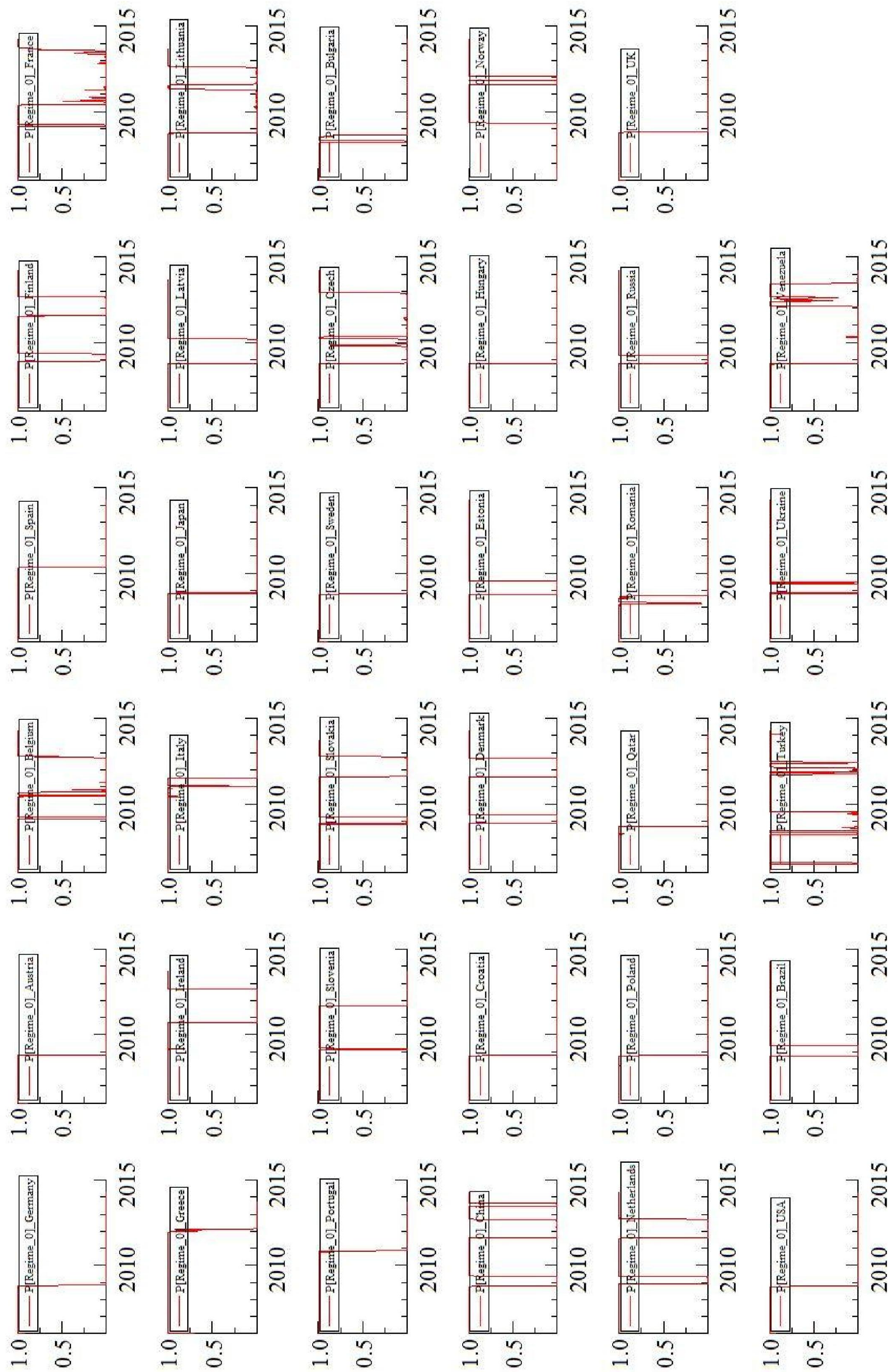

Figure 5.1: Regime Switching classification

ity, we check the phases of excessive volatility for each of the CDS markets using Markov's switching ARMA model. As explained by Dimitriou et al. (2013), this model class takes into account structural breaks with two regimes: stable and volatile, where 0 corresponds to a low conditional volatility and 1 to a high conditional volatility. Thus, this model allows us to define different sub-periods of the crises. Results of the filtered regime probabilities are presented in Figure 5.1.

By taking stock of the results of these two previous methods, the period studied can be divided into 4 sub-periods:

- From January 2006 to June 2007: a reference period (quiet period);
- From July 2007 to March 2009: 1^{st} crisis period (credit crunch);
- From March 2009 to October 2009: Post-crisis period (quiet period);
- From November 2009 to March 2012: 2^{nd} crisis period (European Debt crisis);
- From March 2012 to April 2014: Post-crisis period (quiet period).

5.4 Methodology: A Dynamic Conditional Correlation approach

As mentioned above, to investigate the existence of a pure contagion in the sovereign CDS market, we rely on the contagion detection method suggested by Pericoli and Sbracia (2003) and Caporale et al. (2005): the contagion is defined as a significant increase in the degree of co-movements between countries during crises compared to normal periods. We begin our econometric analysis by estimating conditional correlations between CDS spreads of the crises sources (The USA, Greece and / or Ireland) and the remaining 34 countries in the sample. To do so, two econometric approaches are presented in the following subsections to estimate dynamic conditional correlations: a reference method based on an EWMA model - used to compare our findings with the previous literature results - and a more complex method, which has a high computational complexity based on an AR(1)-FIEGARCH(1,d,1)-DCC model.

Since most of financial times series are modeled by an autoregressive process (Goudarzi and Ramanarayanan, 2010; Conrad et al., 2011) and because of the supposed market efficiency, the mean equation of time series is generated by an AR(1) as follows:

$$x_{i,t} = ln(S_{i,t}) - ln(S_{i,t-1}) = \alpha_{i,0} + \alpha_{i,1}x_{i,t-1} + \varepsilon_{i,t}, \tag{5.1}$$

with $S_{i,t}$ denotes the time series of a country i at time t. This AR(1) representation can be written as:

$$(1 - \alpha_{i,1}L)x_{i,t} = \alpha_{i,0} + \varepsilon_{i,t}, \tag{5.2}$$

where L corresponds to the lag operator, i denotes a given country from the sample, $\alpha_{i,0}$ is a constant, $|\alpha_{i,1}| < 1$ and $\varepsilon_{i,t} = e_{i,t}\sigma_{i,t}$ with $e_{i,t}$ constitutes a weak white noise with variance 1. $\sigma^2_{i,t}$ is a positive parameter representing the conditional variance of $x_{i,t}$ such as $\sigma^2_{i,t} = Var(x_{i,t}|\mathcal{F}_{t-1})$ with $\mathcal{F}_t$ is the market information set at a given moment t. Thus, the AR(1) quantifies the speed of the information integration in CDS spreads returns.

5.4.1 EWMA model

The use of the EWMA method in the literature to quantify contagion is justified by several reasons: (i) it makes it possible to analyze the underlying dynamics of the correlations in each period while other methods only allow correlations to be calculated for a number of sub-periods (Coudert and Gex, 2010). (ii) This method is of common interest to past and present observations in such a way it can detect small changes more easily and quickly, when other methods take into account only the most recent data, forgetting the past ones (Ferreira and Lopez, 2005; Raza et al., 2015). (iii) Yet, since time series are characterized by greater impact of recent observations on second moments than on the first, the EWMA model gives more weight to recent data compared to past data using a constant weighting parameter. Thereby, researchers claim that the use of the EWMA model is preferable to other complicated models in estimating dynamic conditional correlations (Ferreira and Lopez, 2005; Coudert and Gex, 2010; Kalbaska and Gatkowski, 2012; Raza et al., 2015).

The EWMA volatility is defined as a moving average of the quadratic returns of a time series $(x_{i,t})$ weighted by a sequence of smoothing parameters:

$$\sigma_{i,t}^2 = \frac{1}{n}\sum_{k=1}^{n} \alpha_{i,k} x_{i,t-k}^2. \tag{5.3}$$

The weights α_k decrease as we go back in time. Each quadratic return is weighted by a ad hoc structure defined by a lambda parameter in the following way: $\alpha_{k+1} = \lambda\alpha_{i,k} = \lambda^2\alpha_{i,k-1} = \cdots = \lambda^{n+1}\alpha_{k-n}$, with λ is the smoothing parameter also known as the decay factor such as $0 < \lambda < 1$.

According to Morgan (1996), the optimal smoothing parameter is given by finding the smallest root mean square error of the variance forecast[1] over different values of λ. The use of the RMSE criterion on 480 financial time series for the daily data set leads to λ equal to 0.94, and for the monthly data set λ equals 0.97. In a sample composed by CDS of 226 European and American firms, Coudert and Gex (2010) find $\lambda = 0.94$, while Kalbaska and Gatkowski (2012) find $\lambda = 0.939$ in a sample composed by European sovereign CDS. Furthermore, other strand of the literature finds a value for λ mostly equal to 0.5, which seems to be underestimated, probably due to the very small sample. In this essay, following the literature, λ is assumed to be equal to 0.939.

Variance can, also, be rewritten as a function of λ as follows:

$$\sigma_{i,t}^2 = \frac{\sum_{k=1}^{n} \lambda^{k-1} x_{i,t-k}^2}{\sum_{k=1}^{n} \lambda^{k-1}}. \tag{5.4}$$

When the dataset contains an infinite number of observations, which is close to our case with a large number of data, the EWMA variance is equivalent to an IGARCH(1,1):

$$\sigma_{i,t}^2 = (1-\lambda)x_{i,t-1}^2 + \lambda\sigma_{i,t-1}^2. \tag{5.5}$$

By analogy to the variance expression, the EWMA covariance between two series (i and j) can also be defined as an autoregressive form as follows:

$$\sigma_{ij,t} = Cov(x_{i,t}, x_{j,t}) = (1-\lambda)x_{i,t-1}x_{j,t-1} + \lambda Cov(x_{i,t-1}, x_{j,t-1}). \tag{5.6}$$

[1] $RMSE_v = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{i+1}^2 - \sigma_{i+1}^2(\lambda))^2}$.

Since the correlation is the covariance between both the returns ($x_{i,t}$, $x_{j,t}$) divided by their respective standard deviations, the correlation equation can be written as:

$$\rho_{ij,t} = \frac{Cov(x_i, x_j)_t}{\sigma_{i,t}\sigma_{j,t}} = (1-\lambda)\frac{x_{i,t-1}x_{j,t-1}}{\sigma_{i,t-1}\sigma_{j,t-1}} + \lambda\rho_{ij,t-1}, \tag{5.7}$$

with i is a country where the crisis initially triggers and j is a given country from the sample. $x_{i,t}$ and $x_{j,t}$ denote financial time series of respective countries i and j.

5.4.2 A bivariate FIEGARCH-DCC model

The second approach used for investigating the contagion phenomena is based on a multivariate Fractionally Integrated Exponential GARCH (FIEGARCH) dynamic conditional correlation (DCC) framework introduced by Bollerslev and Mikkelsen (1996). This method has already been used to identify volatility spillover effects between oil prices and different stock markets indexes by Youssef and Belkacem (2015).

Baillie et al. (1996) argue that financial assets' conditional volatility may be more persistent than what is captured by ordinary ARCH and GARCH models and suggested the use of a new class of Fractionally Integrated Generalized AutoRegressive Conditionally Heteroskedastic model instead of a standard GARCH model. Bollerslev and Mikkelsen (1996) extend this new class of Fractionally Integrated process and suggest that financial market volatility is best estimated by a mean-reverting fractionally integrated model. The relevance and the reliability of FIEGARCH specifications for characterizing financial assets' volatility are illustrated by empirical findings based on the US stock market. The same conclusion could be relevant in the case of correlations.

Moreover, Conrad et al. (2011) recommend the use of this class of models because it increases flexibility in the conditional variance and includes several GARCH specifications in the volatility process. Indeed, the FIEGARCH model allows (i) an asymmetric response of volatility to positive and negative news, (ii) a long-range volatility dependence (Surgailis and Viano, 2002; Christensen et al., 2010; Günay et al., 2016) and (iii) it allows the data to determine the power of the returns for which the predictable structure in the volatility pattern is the strongest (Ruiz and Veiga, 2008; Conrad et al., 2011). Fantazzini (2011) discuss empirical examples and show that FIEGARCH outperforms other fractional models for volatility. This model is the one that fits the best in terms of convergence, computational time and diagnostic tests[1].

The dynamic conditional correlation estimation of the FIEGARCH model must go through a two-steps process:

The first step: a univariate process

A univariate FIEGARCH(1,d,1) model is estimated for each of the time series in order to obtain the estimations of $\sigma_{ii,t}$ following the same process used by Youssef and Belkacem (2015), Goudarzi and Ramanarayanan (2010), Ruiz and Veiga (2008) and Bollerslev and Mikkelsen (1996).

[1]The Ljung-Box tests (Q-statistics), the Residual-Based Diagnostic, the Nyblom test for stability and the Adjusted Pearson Godness-of-fit test. See the Review-Empirical Appendix of Fantazzini (2011) for detailed description of theses diagnostic tests.

According to Bollerslev and Mikkelsen (1996), a FIEGARCH(1,d,1) model is written as follows:

$$ln(\sigma_t^2) = c_0 + \phi(L)^{-1}(1-L)^{-d}[1+\psi(L)]g(e_{t-1}), \tag{5.8}$$

with $(1-L)^{-d}$ denotes the fractional differencing operator[1], $\phi(L)$ and $\psi(L)$ corresponds to lag polynomials, and $g(e_t)$ is a quantization function of information flows such as $g(e_t) = \theta e_t + \gamma[\mid e_t \mid - E(\mid e_t \mid)]$ where γ is the leverage coefficient. When $\gamma > 0$, the impact of bad news (negative shocks) on volatility is greater than the impact of good news (positive shocks with the same absolute magnitude), leading to an increase of the conditional variance in a more proportional way and vice versa:

$$\begin{cases} g(e_t) & = (\theta+\gamma)e_t - \gamma E[|e_t|], \text{ if } e_t \geq 0, \\ g(e_t) & = (\theta-\gamma)e_t - \gamma E[|e_t|], \text{ otherwise.} \end{cases} \tag{5.9}$$

Unlike the FIGARCH model, the FIEGARCH is automatically well-defined and does not need any non-negativity restrictions.

The second step: a multivariate process

In the second step, we draw on the work proposed in Tse and Tsui (2002)[2],[3] and we introduce the multivariate FIEGARCH specification to estimate the conditional correlation. To do this, we use the standardized residuals defined in the first step of our methodology by their standard deviation.

The Dynamic Conditional Correlation model is defined as a time-varying variance-covariance matrix:

$$\Omega_t = D_t H_t D_t, \tag{5.10}$$

with D_t denotes a diagonal matrix $N\times N$ such as $D_t = diag(\sigma_{11,t}\dots\sigma_{NN,t})$, $\sigma_{NN,t}$ denotes the conditional standard deviation obtained from the univariate model AR(1)-FIEGARCH(1,d,1). Then, H_t corresponds to the correlation matrix of the standardized residuals $\varepsilon_{i,t}$ such as $H_t = \{\rho_{ij,t}\}$. H_t is obtained from the recursion of

$$H_t = (1-\theta_1-\theta_2)H + \theta_1 H_{t-1} + \theta_2 \Xi_{t-1}. \tag{5.11}$$

where the parameters θ_1 and θ_2 are supposed to satisfy the non-negativity constraint and the inequality $\theta_1 + \theta_2 <= 1$. H is a time invariant matrix $(\rho_{ij} > 0)$ with a unit diagonal element $(\rho_{ii} = 1)$ and Ξ_{t-1} is the correlation matrix of the lagged estimations of $\varepsilon_{i,t}$. Tse and Tsui (2002) require Ξ_{t-1} to depend on the lagged residuals so, analogously to the $x_{i,t-1}^2$ in the GARCH(1,1) representation, they let Ξ_{t-1} to be specified by the following formula:

$$\Xi_{ij,t-1} = \frac{\sum_{s=1}^{S} e_{i,t-s}e_{j,t-s}}{\sqrt{(\sum_{s=1}^{S} e_{i,t-s}^2)(\sum_{s=1}^{S} e_{j,t-s}^2)}}, 1 \leq i < j \leq M. \tag{5.12}$$

[1]The differencing operator is defined by its Maclaurin series expansion. In the branch of mathematical analysis, a Taylor series of a function f (at a single point a) is a representation of power series calculated from the successive values of f and its derivatives at the point a. If $a = 0$ then the series is so-called Maclaurin series expansion. $(1-L)^d = (1-d)\sum_{h=1}^{\infty}\Gamma(h-d)\Gamma(1-d)^{-1}\Gamma(h+1)^{-1}L^h = 1-\delta_d(L)$ with Γ is the gamma function (it is a special function extending the factorial function to the whole set of complex numbers, hence the name of function of complex variables.).

[2]See also Engle (2002) and Engle and Kelly (2012) for further DCC estimation methods. They propose another class of multivariate model allowing some new specifications on the correlation matrix calculation.

[3]Conrad et al. (2011) present a different formulation of the multivariate DCC model and apply it to study the contagion effect on the national stock market.

Furthermore, $S \leq M$ is a necessary condition to make ψ_{t-1} positive definite and so for Γ_{t-1}. So, in our bivariate case, the conditional correlation coefficient is defined as:

$$\rho_{12,t} = (1-\theta_1-\theta_2)\rho_{12} + \theta_1\rho_{12,t-1} + \theta_2 \frac{\sum_{s=1}^{S} e_{1,t-s}e_{2,t-s}}{\sqrt{(\sum_{s=1}^{S} e_{1,t-s}^2)(\sum_{s=1}^{S} e_{2,t-s}^2)}}. \tag{5.13}$$

5.4.3 DCC behavior over time

One of the most common methods of detecting contagion is to check whether there is a significant increase in correlations between different countries from one period to another. To do this, Coudert and Gex (2010), Kalbaska and Gatkowski (2012), Dimitriou et al. (2013) and Kenourgios and Dimitriou (2015) estimate the regressions putting in relation the conditional correlations ($\rho_{ij,t}$), their lagged values ($\rho_{ij,t-1}$) and dummy variables representing different crisis periods (D_k). We follow this approach and consider the following equation:

$$\rho_{ij,t} = a_{ij,0} + a_{ij,1}\rho_{ij,t-1} + b_{ij,k}D_k + \eta_{ij,t}. \tag{5.14}$$

where a_0 is a constant $\in [0,\infty)$, η_t represents the innovations, $\rho_{ij,t}$ is the pairwise conditional correlation at time t where i indicates the crisis generator (the USA, Greece or Ireland) and j refers to another country in the sample. k corresponds to the crisis index: equal to 1 for the first financial crisis and equal to 2 for the European Debt Crisis.

We consider these OLS regressions on the pairs of each country since the estimates in time series are more reliable than the panel analysis (Chiang et al., 2007).

5.5 Empirical results

5.5.1 Summary statistics and data analysis

Table 5.3 provides descriptive statistics of CDS spreads (in level and log returns) during the period running from January 2^{nd}, 2006 to April 3^{rd}, 2014 for a total of 2154 daily observations. Panels A, B, C and D correspond to the summary statistics of respective PIIGS, developed countries, newly industrialized countries and emerging countries. The average CDS spreads ranges from 28,124 bp (Finland) to 876.060 (Venezuela), regardless of Greece. In general, CDS markets are highly volatile with the lowest standard deviation recorded in Norway (18.123%). Greece is obviously the riskiest market with the greater volatility (which is not very surprising given the nature of indebtedness in this country[1]). Moreover, the minimums and maximums are not of the same magnitude and vary a lot from one country to another, which obviously highlights the heterogeneity of the 35 countries in our sample.

The ADF test (Table 5.3) confirms the existence of a unit root in all CDS spread series. We cannot reject the null hypothesis of the presence of a unit root. CDS spreads are integrated of order 1. Thus, the logarithmic returns of CDS spreads are used rather than CDS spreads in levels in order to get stationary time series:

$$x_{i,t} = log(S_{i,t}) - log(S_{i,t-1}), \tag{5.15}$$

[1] According to Eurostat data, Greece has recorded the largest public indebtedness increase in the European Union countries during the sample period. Greek public debt has increased by 65% from 106.1% of GDP in 2006 to 175.1% of GDP in early 2014.

where $S_{i,t}$ is the CDS spread of country i at the instant t.

The use of logarithmic returns instead of raw data is frequently used in similar articles dealing with corporate or sovereign CDS spreads (see among others, Koy (2017), Hacioğlu and Dinçer (2017), Puliga et al. (2014), Kaya and Manac (2013) and Coudert and Gex (2010)). Several reasons exist in the financial literature explaining the need for this CDS logarithmic transformation: first, it makes the data stationary, which is required for GARCH modeling. Second, it reduces the asymmetry of the data probability distribution, which facilitates random sampling (randomization) and thus provides a better estimate of t-statistics, p-values and confidence intervals. More specifically, Das et al. (2006) argue that the first difference of the natural logarithm (of CDS spreads) may be better fitted than spread levels and this transformation does not induce any information loss.

Furthermore, the ARCH-LM tests (Table 5.4) reveal the time series heteroscedasticity and confirm the existence of an ARCH effect in all CDS spreads log returns (except for Greece, Lithuania and Slovenia). Moreover, several tests are applied to check the volatility long-memory path. Absolute returns and squared returns are used as proxies for unconditional volatility. The results of the Gaussian semi-parametric (Robinson and Henry, 1999) estimates and log periodogram (Geweke and Porter-Hudak, 1983) estimates show a long memory path observed for all CDS spreads studied.[1]

This preliminary analysis clearly suggests the implementation of a GARCH family model taking into consideration several properties: volatility clustering, long-memory behavior, asymmetry and leverage effects. Cross market correlations are estimated using a FIEGARCH-DCC approach.

Table 5.3: Descriptive statistics, normality and non-stationary tests for the CDS spreads

	CDS spreads in level						CDS spreads log returns					
	Obs.	***Min.***	***Mean***	***Max.***	***Std. Dev.***	***ADF statistics***	***Skewness***		***Excess Kurtosis***		***Jarque-Bera***	
Panel A: PIIGS												
Portugal	2154	4.02	311.23	1527.00	356.15	-0.994	0.36	***	14.02	***	17671	***
Ireland	2154	1.75	232.90	1191.50	249.26	-0.991	-0.48	***	84.33	***	60000	***
Italy	2154	5.58	161.93	591.54	148.52	-0.967	0.19	***	16.22	***	23617	***
Greece	2009	5.20	8068.60	37081.00	14532.00	-1.512	-21.78	***	769.29	***	400001	***
Spain	2154	2.55	165.66	641.98	153.97	-0.988	0.0021		46.92	***	10001	***
Panel B: Developed countries												
Austria	2154	1.75	61.13	268.98	58.57	-1.282	0.60	***	18.42	***	30567	***
Belgium	2154	2.05	83.61	406.12	85.62	-1.086	0.06		78.57	***	50001	***
Denmark	2154	9.00	42.71	158.23	37.26	-1.063	0.76	***	24.43	***	53766	***
Estonia	2154	9.25	127.30	725.00	142.52	-1.056	-0.17	***	51.38	***	20000	***
Finland	2154	2.69	28.12	90.84	22.55	-0.977	1.85	***	28.37	***	73433	***
France	2154	1.50	60.58	249.63	59.07	-0.993	0.44	***	49.14	***	20000	***
Germany	2154	1.40	32.95	119.17	28.02	-1.060	-0.27	***	53.22	***	20001	***
Japan	2154	2.13	52.63	157.21	38.33	-0.842	0.19	***	15.41	***	21325	***
Latvia	2154	5.50	258.32	1163.00	236.02	-1.103	5.18	***	546.91	***	2.0E+06	***
Lithuania	2154	6.00	203.03	847.50	171.73	-0.939	28.38	***	1127.9	***	1.0E+07	***
Netherlands	2154	7.67	42.61	139.84	33.41	-0.950	1.11	***	13.20	***	16071	***
Norway	2154	11.94	37.11	62.16	18.12	-1.491	-0.04		11	***	10847	***
Slovakia	2154	5.33	87.73	328.25	74.34	-0.962	0.63	***	28.47	***	72859	***
Slovenia	2154	4.25	138.52	511.07	136.61	-0.646	10.14	***	273.64	***	600001	***
Sweden	2154	1.63	29.15	156.36	26.48	-1.247	2.72	***	47.76	***	20000	***
UK	2154	16.50	49.04	164.79	30.52	-0.955	0.25	***	10.88	***	10635	***
USA	2154	15.00	32.82	95.00	14.57	-0.937	0.12	**	21.48	***	41412	***
Panel C: Newly Industrialized Countries												
Brazil	2154	61.50	145.15	586.86	65.13	-1.480	0.47	***	16.45	***	24348	***
China	2154	10.00	75.87	276.30	48.68	-1.395	0.69	***	25.65	***	59175	***
Qatar	2154	7.80	96.91	390.00	64.47	-0.507	1.50	***	32.29	***	94319	***
Turkey	2154	110.95	214.85	831.31	82.51	-1.310	0.31	***	5.83	***	3084	***
Panel D: Emerging countries												
Bulgaria	2154	13.22	198.11	699.39	140.48	-1.002	0.07		14.7	***	19397	***
Croatia	2154	24.88	247.41	636.36	153.87	-0.550	-0.18	***	22.05	***	43617	***
Czech	2154	3.41	73.94	350.00	55.81	-1.186	-0.13	**	27.93	***	69984	***
Hungary	2154	17.34	255.41	738.60	171.24	-0.913	0.61	***	8.74	***	6991	***
Poland	2154	7.67	119.28	415.00	84.84	-1.031	0.98	***	14.58	***	19399	***

[1] According to Robinson and Henry (1999) and Geweke and Porter-Hudak (1983), the use of an autoregressive fractionally integrated moving average for the volatility model is suitable when time series exhibit long memory behavior.

Romania	2154	17.00	236.50	764.75	158.49	-1.009	0.51	***	7.2	***	4747	***
Russia	2154	36.88	191.78	1113.40	154.53	-1.833	0.87	***	49.34	***	20000	***
Ukraine	2154	126.13	767.11	5304.90	760.94	-1.286	-0.18	***	9.99	***	8963	***
Venezuela	2154	124.62	876.06	3239.30	560.93	-0.627	0.90	***	6.71	***	4332	***

The table reports descriptive statistics for the daily CDS spreads expressed in basis points. Min., Max. and Std. Dev. refer respectively to the minimum, the maximum and the standard deviation. The Augmented Dickey-Fuller (ADF) is a unit root test that informs about the time-series stationarity. The null hypothesis is defined as the presence of a unit root in the process (non-stationary time series).

Table 5.4: Long memory and LM-ARCH tests for CDS spreads log-returns

	Long-memory tests (Absolute returns)		**Long-memory test (Squared returns x^2)**		**LM ARCH test**		
	GSP test (m=1076)	***GPH test (m=1076)***	***GSP test (m=1076)***	***GPH test (m=1076)***	***Test statistics (2 lags)***	***Test statistics (5 lags)***	***Test statistics (10 lags)***
Panel A: PIIGS							
Portugal	0.3023 ***	0.2692 ***	0.2288 ***	0.1407 ***	58.044 ***	39.140 ***	22.137 ***
Ireland	0.2474 ***	0.1907 ***	0.2444 ***	0.2074 ***	157.970 ***	74.344 ***	45.639 ***
Italy	0.2589 ***	0.2219 ***	0.1711 ***	0.1537 ***	57.377 ***	29.944 ***	17.445 ***
Greece	0.0961 ***	0.0821 ***	-0.0003	-0.0023	0.230	0.096	0.052
Spain	0.2619 ***	0.2377 ***	0.1439 ***	0.2093 ***	182.290 ***	72.903 ***	36.542 ***
Panel B: Developed countries							
Austria	0.3371 ***	0.3287 ***	0.3404 ***	0.3281 ***	283.350 ***	140.370 ***	71.482 ***
Belgium	0.2118 ***	0.1732 ***	0.1015 ***	0.3420 ***	328.330 ***	140.370 ***	71.482 ***
Denmark	0.2815 ***	0.2555 ***	0.1744 ***	0.1378 ***	42.821 ***	17.306 ***	11.212 ***
Estonia	0.2760 ***	0.2645 ***	0.3420 ***	0.1851 ***	27.871 ***	14.242 ***	7.630 ***
Finland	0.2430 ***	0.2217 ***	0.1159 ***	0.1150 ***	27.871 ***	14.242 ***	7.630 ***
France	0.2463 ***	0.2197 ***	0.1480 ***	0.2840 ***	201.260 ***	87.366 ***	45.379 ***
Germany	0.2814 ***	0.2978 ***	0.7146 ***	0.6846 ***	181.530 ***	92.406 ***	52.784 ***
Japan	0.2780 ***	0.2107 ***	0.1918 ***	0.1611 ***	62.116 ***	28.032 ***	17.629 ***
Latvia	0.1338 ***	0.1080 ***	0.0856 ***	0.3969 ***	412.230 ***	196.580 ***	99.564 ***
Lithuania	0.1446 ***	0.1022 ***	0.0077	0.0128	0.430	0.172	0.086
Netherlands	0.3032 ***	0.2932 ***	0.2256 ***	0.1829 ***	71.434 ***	32.203 ***	16.961 ***
Norway	0.2928 ***	0.2462 ***	0.2087 ***	0.1903 ***	86.182 ***	49.087 ***	26.112 ***
Slovakia	0.2355 ***	0.1851 ***	0.1169 ***	0.0846 ***	12.236 ***	8.376 ***	8.355 ***
Slovenia	0.2123 ***	0.1989 ***	0.0309 **	0.0321	2.559 *	1.038	0.544
Sweden	0.2247 ***	0.1703 ***	0.0905 ***	0.2072 ***	98.155 ***	39.406 ***	19.678 ***
U.K.	0.2860 ***	0.2804 ***	0.1925 ***	0.1704 ***	55.721 ***	32.002 ***	18.265 ***
U.S.	0.2135 ***	0.1290 ***	0.1905 ***	0.2681 ***	60.620 ***	37.354 ***	20.959 ***
Panel C: Newly Industrialized Countries							
Brazil	0.2877 ***	0.2287 ***	0.1886 ***	0.1344 ***	33.131 ***	36.350 ***	55.198 ***
China	0.2724 ***	0.2476 ***	0.1845 ***	0.1979 ***	85.575 ***	44.817 ***	27.653 ***
Qatar	0.2490 ***	0.2355 ***	0.1271 ***	0.0865 ***	26.582 ***	12.185 ***	6.751 ***
Turkey	0.3074 ***	0.2684 ***	0.2538 ***	0.1648 ***	82.601 ***	62.644 ***	33.245 ***
Panel D: Emerging countries							
Bulgaria	0.2877 ***	0.2691 ***	0.2283 ***	0.2124 ***	106.770 ***	47.920 ***	43.067 ***
Croatia	0.2601 ***	0.2146 ***	0.1940 ***	0.1858 ***	83.689 ***	35.955 ***	29.893 ***
Czech	0.1995 ***	0.1730 ***	0.1400 ***	0.1278 ***	38.443 ***	30.459 ***	19.986 ***
Hungary	0.2971 ***	0.2574 ***	0.2343 ***	0.2351 ***	115.270 ***	49.075 ***	29.141 ***
Poland	0.2664 ***	0.2055 ***	0.1722 ***	0.2138 ***	127.710 ***	54.292 ***	30.817 ***
Romania	0.2963 ***	0.2674 ***	0.2503 ***	0.1791 ***	97.933 ***	45.899 ***	26.632 ***
Russia	0.2882 ***	0.2726 ***	0.1282 ***	0.1654 ***	305.760 ***	130.670 ***	65.718 ***
Ukraine	0.3056 ***	0.2747 ***	0.2239 ***	0.1627 ***	66.588 ***	40.325 ***	25.063 ***
Venezuela	0.3100 ***	0.2862 ***	0.2360 ***	0.2186 ***	116.970 ***	55.489 ***	31.445 ***

*,** and *** imply statistical significance at respectively 10%, 5% and 1%. GSP and GPH denote respectively the Gaussian semi parametric test of Robinson (1995) and the Log Periodogram Regression of Geweke and Porter-Hudak (1983). LM-ARCH is the Lagrange Multiplier test for auto-regressive conditional heteroscedasticity, with a null hypothesis corresponds to homoscedastic innovations.

Focusing on the CDS spread paths of PIIGS (Figure 5.2), we find that spreads were low until the end of 2007, indicating that the market is not expecting any credit event and that the default risk on the underlying debt is very weak: the CDS market is so far underdeveloped. The first change in the path of the credit derivative market took place around August 2007 and the first CDS spread increases were recorded around December 2007. These spreads increased sharply after the outbreak of the European debt crisis between October 2009 and April 2010,

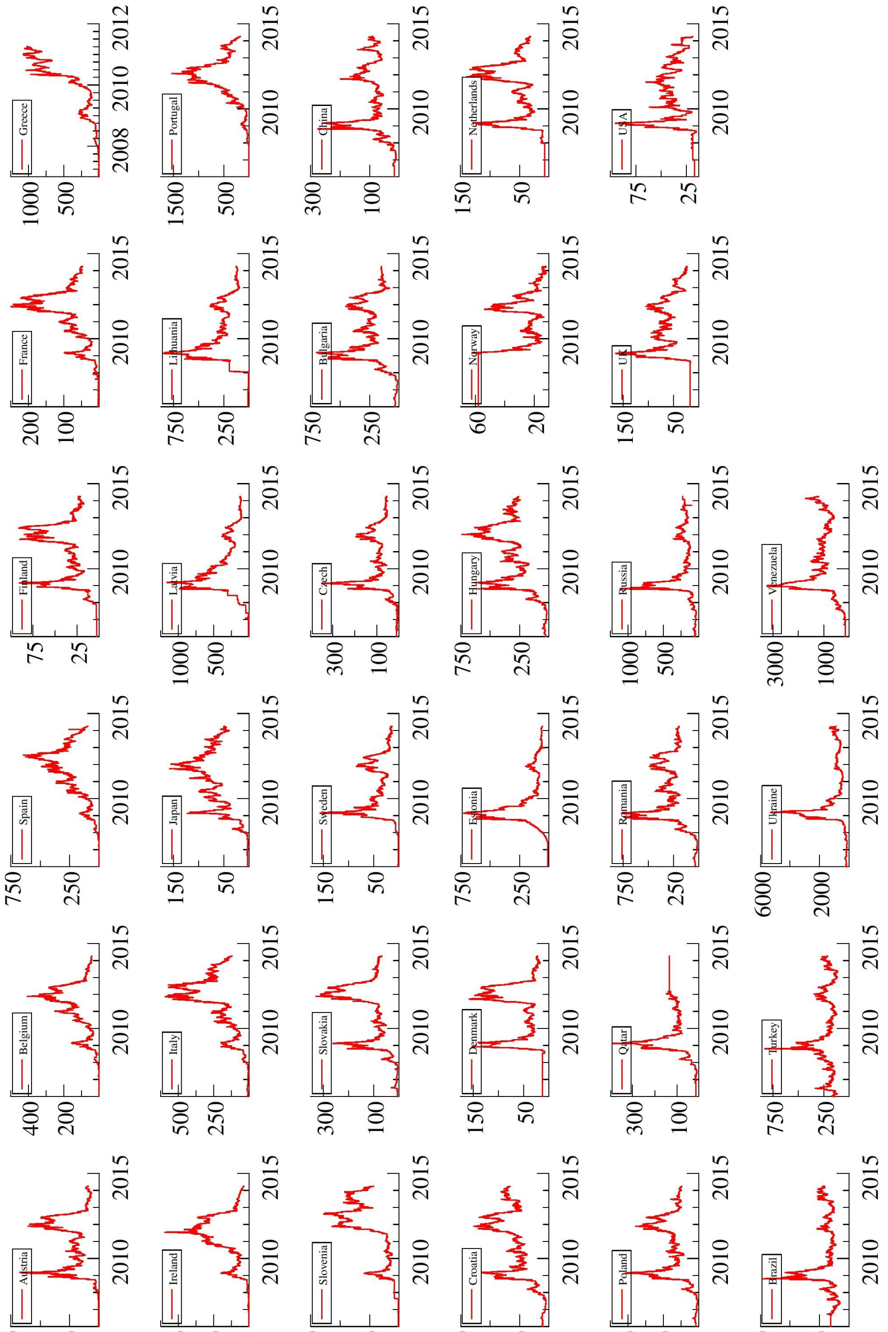

Figure 5.2: Time-varying CDS spreads of 35 countries from January 2006

with increasing investor uncertainty about the Greece ability to repay its debts. Greek CDS spreads continue to rise, even after the adoption of the EU and IMF bailout measures in May 2010, recording peaks at very high levels as investors continue to reevaluate upwards the credit risk from Greece. CDS spreads in Portugal, Ireland, Italy and Spain follow the same movements as Greek CDS spreads, but in a lesser magnitude. With the exception of a few small declines in response to rescue operations, spreads have steadily increased through mid-2012. As of that date, there has been a downward trend in the CDS markets of these countries.

For developed countries, no uniform behavior is observed in the CDS markets. In almost all countries (except Slovenia, Estonia, Latvia and the USA.), the pattern of CDS spreads seems to be trending upwards with two major peaks in 2009 and 2012. We can clearly see a return to previous values after 2012. For emerging and newly industrialized countries CDS spreads were already high before the first crisis period. The CDS prices in these countries have risen sharply after the credit crunch and the triggering of the European debt crisis, suggesting that investors are worried about the impact of Greece's solvency problems.

As a result, it can be seen that crisis periods sparked a contagion surge in the CDS market behavior of almost all the countries studied. Nevertheless, differences in behavior are recorded between the PIIGS, the developed countries, the emerging countries and the newly industrialized countries. This suggests that the level of crises exposure differs from country to country. The previous findings suggest an international transmission of crises since (i) the exposure of European markets to American banking system crisis is relatively high and (ii) the American CDS market reacts to Greek problems.

5.5.2 Unconditional correlation analysis

Table 5.5 presents unconditional correlations of CDS spreads in level between crises' generators and other countries in the sample. Throughout the full period studied, the correlation coefficients are almost always highly positive, which implies that the CDS spreads evolve in the same direction. The average correlation coefficients of the 34 countries and the USA, Greece and Ireland equal respectively 0.68, 0.22 and 0.55. This suggests, at first sight, that the studied CDS markets share a common behavior with the crises' generators that could eventually boost the occurrence of financial contagion. Ostensibly, comparing unconditional correlations during quiet period and crisis periods show an increase in the coefficients, though, this is not conclusive. In fact, this rise is not necessarily statistically significant and does not necessarily refer to an increase in the underlying interconnection's intensity between CDS spreads (this may simply be due to a change in volatility)[1].

Table 5.5: Sample unconditional correlation between the crises' generators and other countries

	Crisis generator: USA			**Crisis generator: Greece**			**Crisis generator: Ireland**		
	Full period	***Tranquil period***	***1st crisis period***	***Full period***	***Tranquil period***	***2nd crisis period***	***Full period***	***Tranquil period***	***2nd crisis period***
Panel A: PIIGS									
Portugal	0,50	-0,75	0,92	0,50	0,92	0,60	0,89	-0,60	0,85
Ireland	0,69	0,69	0,98	0,23	-0,63	0,29	-	-	-

[1]Moreover, these results do not really make sense, especially for Denmark, the Netherlands and Norway during the pre-crisis period probably due to a statistical artefact.

Italy	0,59	-0,76	0,94	0,64	0,84	0,50	0,79	-0,56	0,68
Greece	0,69	-0,80	0,95	-	-	-	0,23	-0,63	0,29
Spain	0,58	-0,02	0,93	0,66	0,06	0,53	0,83	-0,02	0,83
Panel B: Developed countries									
Austria	0,81	-0,09	0,97	0,21	-0,08	0,58	0,76	-0,16	0,50
Belgium	0,68	-0,38	0,97	0,32	0,51	0,44	0,94	-0,23	0,82
Denmark	0,74	0,00	0,95	0,27	0,00	0,59	0,73	0,00	0,58
Estonia	0,62	-0,37	0,90	-0,16	0,23	0,11	0,14	-0,47	-0,21
Finland	0,81	0,85	0,96	0,36	-0,72	0,54	0,80	0,59	0,65
France	0,62	-0,53	0,96	0,52	0,58	0,56	0,86	-0,33	0,71
Germany	0,77	0,01	0,97	0,39	0,04	0,48	0,87	-0,10	0,68
Japan	0,74	-0,85	0,89	0,42	0,75	0,46	0,83	-0,56	0,57
Latvia	0,65	0,30	0,88	-0,19	-0,29	-0,21	0,24	0,06	-0,73
Lithuania	0,76	-0,78	0,90	-0,10	0,68	0,10	0,41	-0,66	-0,09
Netherlands	0,77	0,00	0,99	0,46	0,00	0,60	0,75	0,00	0,57
Norway	-0,31	0,00	-0,08	-0,50	0,00	0,31	-0,39	0,00	0,56
Slovakia	0,71	-0,32	0,92	0,43	0,15	0,61	0,75	-0,17	0,53
Slovenia	0,41	-0,82	0,97	0,81	0,77	0,65	0,51	-0,61	0,52
Sweden	0,84	-0,63	0,97	0,08	0,48	0,33	0,57	-0,42	0,15
UK	0,91	0,00	0,99	0,03	0,00	0,04	0,63	0,00	0,01
USA	-	-	-	0,11	-0,80	-0,16	0,69	0,69	0,60
Panel D: Newly Industrialized countries									
Brazil	0,52	-0,88	0,83	-0,04	0,84	0,22	0,06	-0,58	0,22
China	0,78	-0,88	0,90	0,22	0,77	0,45	0,53	-0,72	0,50
Qatar	0,78	-0,63	0,94	0,33	0,58	0,66	0,39	-0,29	0,38
Turkey	0,37	-0,31	0,70	-0,19	0,22	0,43	0,06	-0,18	0,37
Panel D: Emerging countries									
Bulgaria	0,83	-0,78	0,88	0,04	0,92	0,32	0,58	-0,62	0,33
Croatia	0,75	-0,85	0,91	0,43	0,92	0,46	0,73	-0,67	0,65
Czech	0,88	-0,53	0,95	0,13	0,60	0,43	0,61	-0,45	0,45
Hungary	0,77	-0,74	0,89	0,44	0,71	0,57	0,75	-0,57	0,59
Poland	0,87	-0,72	0,95	0,26	0,84	0,44	0,74	-0,52	0,62
Romania	0,84	-0,77	0,88	0,15	0,90	0,29	0,57	-0,65	0,29
Russia	0,67	-0,63	0,85	0,06	0,75	0,40	0,24	-0,41	0,26
Ukraine	0,65	-0,68	0,95	-0,02	0,73	0,14	0,14	-0,49	-0,39
Venezuela	0,76	0,69	0,90	-0,03	-0,67	-0,53	0,35	0,35	-0,19

The tranquil period refers to the pre-crisis phase spanning from 01/02/2006 to 06/30/2007. The first crisis period and the second crisis period match with the Global Financial crisis from 07/01/2007 to 03/31/2009 and and the European Debt crisis from 11/01/2009 to 03/31/2012.

5.5.3 EWMA Conditional Correlation analysis

The EWMA dynamic correlations are estimated between the sample countries and the crises originators - namely the USA for the first crisis and Greece and Ireland for the second crisis. Then, these correlations are tested over several sub-periods in order to detect any significant variation between the crisis periods and the reference period.

Figure 5.3 shows the evolution of the average EWMA correlation of the 35 countries studied, with regard to the crises' sources. This evolution pattern confirms once again that our studied period can be divided into 4 sub-periods. The lowest average correlation values are recorded during the pre-crisis period. During the crises phases, global correlations tend to increase, depicting the occurrence of contagion phenomena in the sovereign CDS market. Interestingly, we see that, as a first step, the countries' behavior towards Greece and Ireland is close. After 2010, countries' CDS markets broke away from Greece but continued to be correlated with Ireland, probably because of its banking-based economy. The markets behavior towards the USA is different, obviously because of the different crisis nature (although the two are of course related).

The curves of Figure 5.4, Figure 5.5 and Figure 5.6 describes the evolution of correlations between crises' originators and the other countries at a country level. Before the credit crunch

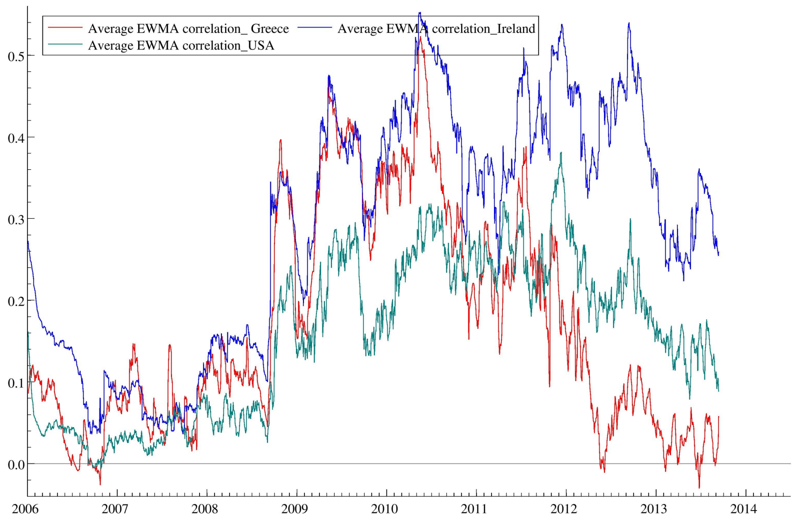

Figure 5.3: Average EWMA correlations between all the countries and the crises' generator countries.

in July 2007, correlations between the USA and all countries around the world were at their lowest levels, whereas after the exit of the crisis, correlations recorded significant increases. Correlation levels continue to rise after the triggering of the European debt crisis at the end of 2009. These same curves show a stabilization of correlations by the end of 2009 mainly for weak economic growth countries (PIIGS). Although it is very brief and poorly significant, this stabilization may be justified by the fact that European Central Bank set up some rescue plans for most of the countries affected by the financial distress allowing them to come through the credit crunch. However, this quiet phase is brief because the transfer of private debt to the sovereign sector has worsened the financial situation and made the correlations between Greece, Ireland and the countries in the sample recorded drastic increases in 2010. Despite the incessant rescue operations to save the financial situation, the correlations pursue a bullish behavior reflecting a contagion phenomenon that affects more and more European and worldwide countries.

Referring to results of the OLS regressions[1], the approach seems to detect more contagion spillovers during the second crisis period (respectively 23 and 27 significant correlation increases when Greece and Ireland are crisis's generators) compared to the first crisis period (only 14 significant increases). This implies, at first sight, that the European debt crisis is greater than during the global financial crisis. In fact, many countries around the world, showing a decoupling behavior during the credit crisis, become subject to contagion during the sovereign debt crisis (Finland, Latvia, Hungary, China. . .). Aggregate results show that developed and emerging countries are prone to several contagion waves during the study period. More detailed results are exposed in the next subsection.

[1]Results are not reported here, however, they can be provided upon request to the corresponding author.

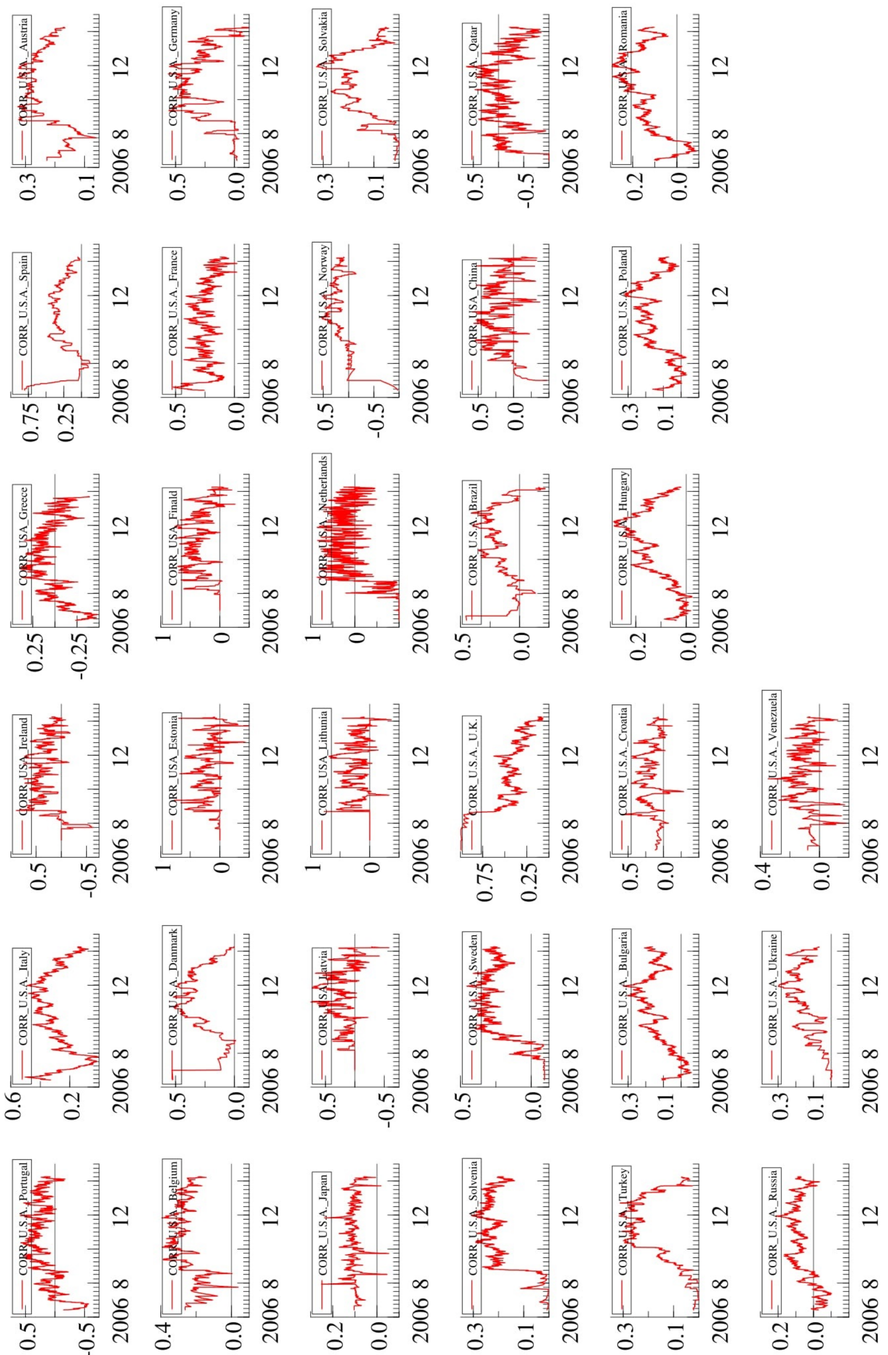

Figure 5.4: Sample EWMA correlations between crisis originator (USA) and other countries

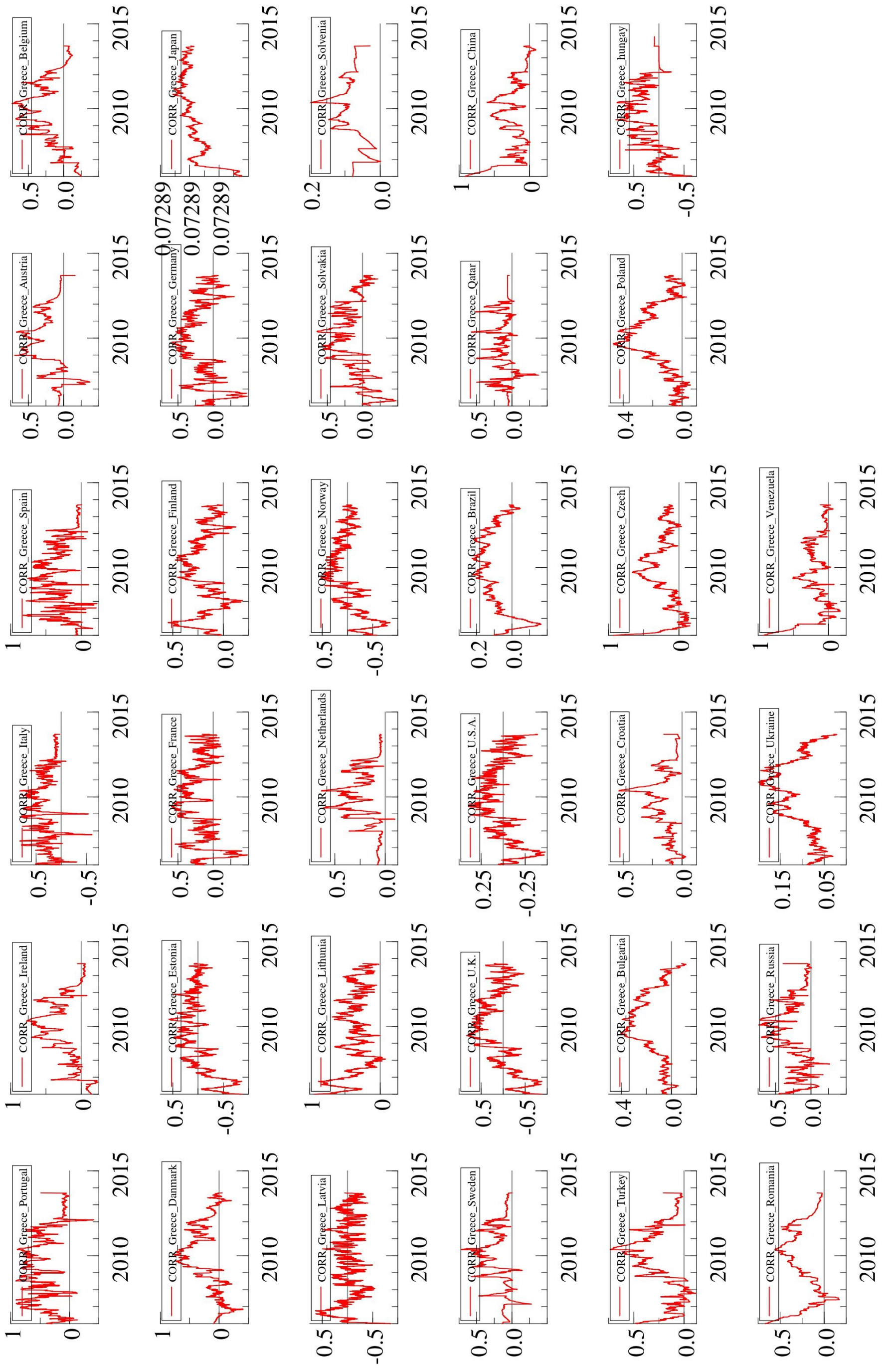

Figure 5.5: Sample EWMA correlations between Greece and other countries

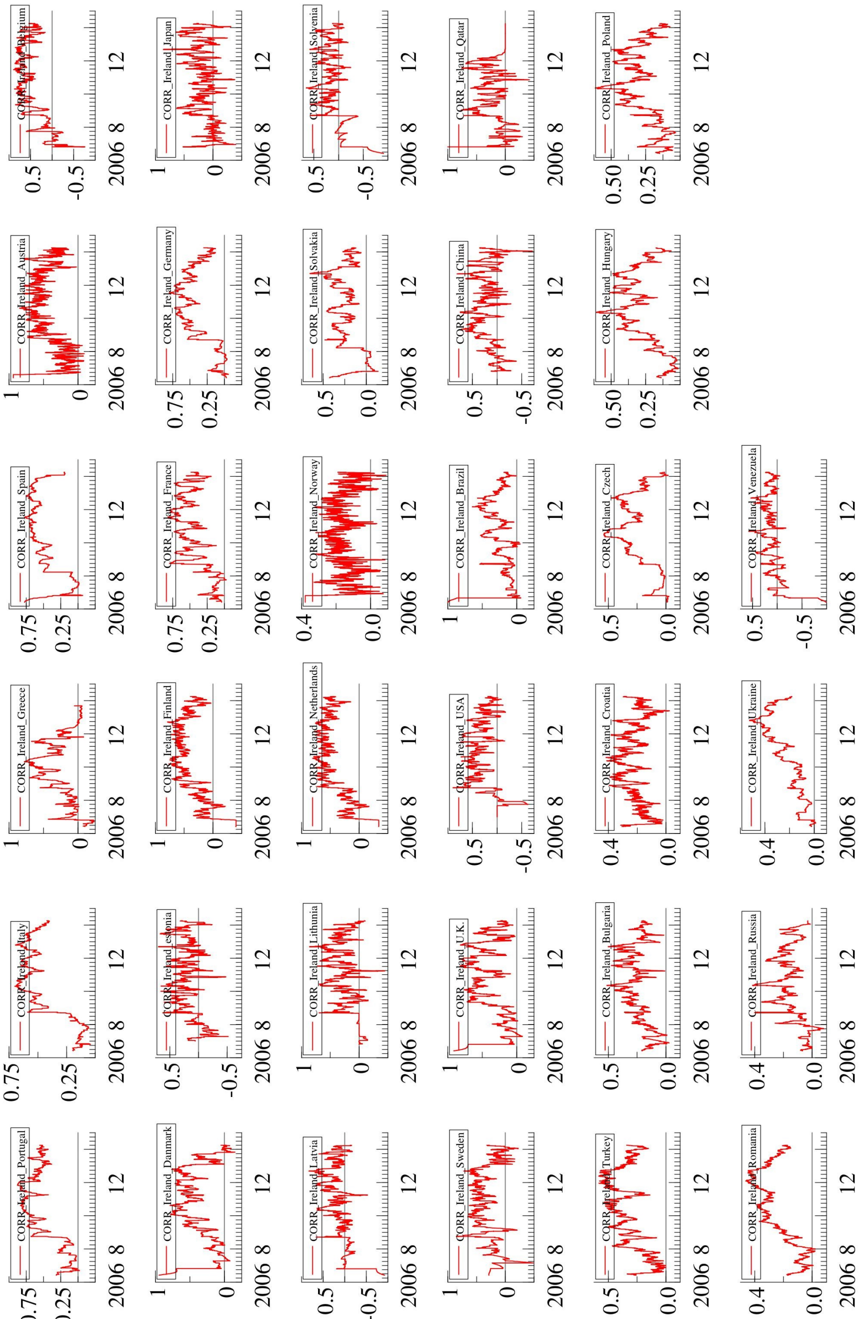

Figure 5.6: Sample EWMA correlations between Ireland and other countries

5.5.4 The bivariate AR(1)-FIEGARCH-DCC model analysis

We present in this section the estimation results of the univariate AR(1)-FIEGARCH(1,d,1) model (Table 5.6) and the multivariate FIEGARCH-DCC model (Table 5.7) for the 35 countries studied.

As supposed in the previous section, the results of the univariate process show that most time series follow a statistically positive and significant autoregressive AR(1) term, which means that relevant information is automatically and instantly integrated with CDS market prices (except for Slovakia, Sweden, China, Croatia and the Czech Republic). The Table 5.6 also shows that the CDS markets mainly present a fractional differencing motion represented by the significant parameter d[1]. Yet, the statistical significance of the model parameters confirms the relevance of using FIEGARCH(1,d,1).

The results of the multivariate model are presented in Table 5.7. They show that the t-student degrees of freedom (represented by the *df* parameter) are highly significant at the 1% level regardless of the crisis generator. This confirms once again the Jarque-Bera results and the adequacy of the student distributed innovations hypothesis instead of a Gaussian distribution. Furthermore, the average conditional correlation ρ_{12} is mostly significant among the full sample countries. Indeed, the USA - as the subprime crisis generator - is the most correlated with developed countries and Western Europe, while it is the least correlated with emerging countries and Eastern Europe. Besides, it is higher in Greece (or Ireland [2]) and PIIGS and Greece (or Ireland) and Eastern Europe, and lower in Greece (or Ireland) and NIC and emerging countries.

As mentioned earlier,the statistical significance of these dummy variables implies structural changes in the conditional correlation model over time due to financial shocks. Specifically, when b_k (of the Equation 5.14) is significant and positive, it means that the correlation level has increased during the period k compared to the quiet period, justifying thus the presence of a contagion on the CDS market. Conversely, a negative and / or insignificant dummy variable confirms a decoupling hypothesis between sovereign CDS markets. The results are reported in Table 5.8.

During the first crisis period - namely the global financial crisis - b_1 is significantly positive in 12 times series and significantly negative in 4 of the 34 studied pairwise. This statistical significance is mainly recorded among developed countries. The contagion phenomenon exists on the Italian, Spanish, Australian, Danish, Norwegian, Slovak, Slovenian, British, Qatari, Turkish, Russian and Ukrainian markets, while the other markets in the sample are decoupled from the global financial crisis. And no crisis transmission between the USA and these countries is observed. According to the consolidated results, growing dependence is observed between the USA and developed countries, emerging and newly industrialized countries, on the one hand, and between the USA and Eastern Europe and Asia on the other hand. The EWMA model presents, more or less, the same results except that the AR(1)-FIEGARCH-DCC model captures more significant relationships during the first financial crisis.

During the second crisis period (the European Debt crisis), there is no big difference between EWMA and AR(1)-FIEGARCH-DCC results. Based on the assumption that the crisis started in Greece, the emerging countries and PIIGS are strongly affected by contagion

[1]According to Dimitriou et al. (2013), when d parameter is greater than 0.5 and highly significant, which means a high degree of persistence of behavior on the financial markets, this indicates that the persistence of the shock on the conditional volatility of financial assets returns follows a hyperbolic rate of decay.

[2]Greece and Ireland since the European debt crisis generators show mainly the same results.

Table 5.6: Univariate AR(1)-FIEGARCH(1,d,1) estimates

	Mean Equation			Variance Equation				
	***Cst* (α_0)**	***AR(1)* (α_1)**	***Cst* * 10^4 (c_0)**	***d-Figarch***	***ARCH* (ϕ)**	***GARCH* (ψ)**	***EGARCH* (θ)**	***EGARCH* (γ)**
Panel A: PIIGS								
Portugal	-0,0022 **	0,2022 ***	0,0000	0,3033 ***	-0,3951 ***	0,9374 ***	-0,0566	0,4448 ***
	(0,0009)	(0,0066)	(32,63)	(0,0505)	(0,1216)	(0,0196)	(0,0356)	(0,0937)
Ireland	0,0002 ***	0,0310	0,0299	0,5676 ***	-0,3734 ***	0,9158 ***	0,0207	0,3351 ***
	(4,9E-07)	(0,0219)	(17,94)	(0,0754)	(0,0238)	(0,0153)	(0,0179)	(0,0406)
Italy	0,1242 ***	-	-48503,0 ***	0,4284 ***	0,0026	0,3833	0,0640	0,4903 ***
	(0,0007)	(0,0147)	(3886,4)	(0,1377)	(0,1082)	(0,0213)	(0,0394)	(0,0606)
Greece	0,0000	0,0102	0,0400	0,4484 ***	0,0995	0,3991 ***	-0,1011	0,1969 ***
	(3,9E-05)	(0,2249)	(331,7)	(0,0348)	(0,1257)	(0,0534)	(0,9572)	(0,0441)
Spain	0,0027	0,3067 ***	0,0000	0,6023 ***	0,6469 ***	0,9172 ***	-0,1165 *	0,7325 ***
	(0,0031)	(0,1067)	(7,860)	(0,0927)	(0,1279)	(0,0183)	(0,0648)	(0,1295)
Panel B: Developed countries								
Austria	0,0056 ***	0,1567 ***	-43309,0 ***	0,1364 **	-0,4010 ***	0,9255 ***	0,1308 ***	0,3799 ***
	(0,0018)	(0,0061)	(28,48)	(0,0559)	(0,0881)	(0,0141)	(0,0411)	(0,0746)
Belgium	-0,0117 ***	0,3062 ***	0,0000	0,1306 ***	-0,6521 ***	0,9814 ***	-0,1591	0,3909 ***
	(0,0030)	(0,1076)	(1634,2)	(0,0380)	(0,0895)	(0,0058)	(0,0975)	(0,0640)
Denmark	0,0010 ***	0,0128	0,0400	0,4350 ***	0,0978	0,3971 ***	-0,1031 ***	0,1809 ***
	(0,0002)	(0,0337)	(104,28)	(0,0099)	(0,0669)	(0,0296)	(0,0288)	(0,0151)
Estonia	5,0E-06	-0,0021	0,0061	0,3300	0,0637	0,8084 ***	-0,1832	0,1856 ***
	(4,9E-05)	(0,0040)	(17,258)	(0,0279)	(0,0556)	(0,0099)	(0,0240)	(0,0265)
Finland	0,0006 ***	0,0360	0,0400	0,4446 **	0,1465	0,5075 ***	-0,0935 ***	0,1150 ***
	(2,4E-05)	(0,0243)	(8438,0)	(0,0276)	(0,1434)	(0,0689)	(0,0206)	(0,0200)
France	-0,0015	0,1243 **	0,0000	0,5847 ***	0,5999 ***	-0,6835 ***	0,1547 **	0,6018 **
	(0,0010)	(0,0533)	(2613,1)	(0,0320)	(0,2040)	(0,1698)	(0,0709)	(0,0980)
Germany	-0,0053 **	0,1676 ***	100,0	0,2954 ***	-0,6266 ***	0,9763 ***	0,1061	0,2720 ***
	(0,0022)	(0,0497)	(13185,0)	(0,0727)	(0,1789)	(0,0129)	(0,0910)	(0,1818)
Japan	0,0035 ***	0,0476	0,0000	0,6488 ***	0,7921	0,0986	0,0080	0,3857 ***
	(0,0012)	(0,0426)	(31,649)	(0,1727)	(1,0844)	(0,8379)	(0,0402)	(0,0802)
Latvia	-0,0112 ***	0,1012 ***	0,0000	0,5914 **	-0,6983	0,1771	0,4097 ***	0,5422 ***
	(0,0009)	(0,0025)	(11,542)	(0,2063)	(0,4576)	(0,3086)	(0,0723)	(0,1088)
Lithuania	4,0E-06	0,0114	0,0400	0,3773 ***	0,1190	0,5059 ***	-0,1589 ***	0,1660 ***
	(0,0002)	(0,1024)	(36845,0)	(0,0327)	(0,2176)	(0,1091)	(0,0249)	(0,0261)
Netherlands	0,0002	0,0251	0,0400	0,0466 ***	0,1136	0,4273 ***	-0,1011 *	0,1349 ***
	(2,5E-06)	(0,0914)	(64,053)	(0,0345)	(0,1645)	(0,0847)	(0,0546)	(0,0514)
Norway	0,0005	0,0101	0,0400	0,4494 ***	0,0999	0,3997 ***	-0,1011 ***	0,1986 ***
	(2,0E-06)	(0,0361)	(3,1849)	(0,0187)	(0,0650)	(0,0270)	(0,0076)	(0,0125)
Slovakia	-0,0025 **	-0,1570 ***	-40243,4 ***	0,4331 ***	-0,4353 **	0,6822 ***	0,1359 **	0,4315 ***
	(0,0010)	(0,0514)	(3006,5)	(0,0674)	(0,2012)	(0,1897)	(0,0555)	(0,1217)
Slovenia	0,0007 *	0,1680 ***	0,0331	0,0012	0,6018 **	0,7967 ***	-0,1647 ***	0,2723 ***
	(0,0004)	(0,0381)	(20,732)	(0,0237)	(0,2515)	(0,0374)	(0,0208)	(0,0462)
Sweden	-0,0061 ***	-0,0356	0,0000	0,0000	-0,3359	0,9917 ***	0,1156 ***	0,4635 ***
	(0,0016)	(0,0563)	(1293,7)	(0,0992)	(0,2850)	(0,0025)	(0,0369)	(0,0998)
UK	0,0002 ***	0,0919	0,0000	0,4201 ***	-0,0282	0,7196 ***	0,1386 **	0,4243 ***
	(5,9E-07)	(0,0827)	(4128,3)	(0,0641)	(0,3535)	(0,0650)	(0,0669)	(0,1279)
USA	0,0002 **	0,0021	0,0000	0,5341 ***	-0,3177 ***	0,9592 ***	-0,3835 ***	0,9595 ***
	(0,0001)	(0,0054)	(2022,2)	(0,0301)	(0,0225)	(0,0017)	(0,1346)	(0,0325)
Panel C: Newly Industrialized countries								
Brazil	0,0024 **	0,1529 ***	0,0000	0,1306 **	0,4793	0,9839 ***	0,0169	0,2390 ***
	(0,0010)	(0,0260)	(5,474)	(0,0555)	(0,3993)	(0,0050)	(0,0129)	(0,0538)
China	0,0073 ***	-0,0547	0,0000	0,3698 ***	-0,3988 ***	0,8756 ***	0,0087	0,5201 ***
	(0,0020)	(0,0551)	(2496,9)	(0,0481)	(0,1416)	(0,0291)	(0,0344)	(0,0761)
Qatar	1,1E-05	0,0101	0,0400	0,4495 ***	0,0999 ***	0,3998 ***	-0,1006 **	0,1991 ***
	(0,0001)	(0,0173)	(119,9)	(0,0040)	(0,0175)	(0,0090)	(0,0487)	(0,0095)
Turkey	-0,0005	0,1483 ***	-64905,0 ***	0,4012 ***	0,0062	0,7530 ***	0,0668 **	0,1768 ***
	(0,0009)	(0,0246)	(3751,3)	(0,1474)	(0,3723)	(0,1340)	(0,0293)	(0,0624)
Panel D: Emerging countries								
Bulgaria	-0,0005	0,2205 ***	0,0000	0,4928 ***	-0,5425	0,8447 ***	0,0132	0,5028 ***

Table 5.6: Univariate AR(1)-FIEGARCH(1,d,1) estimates (*Continued*)

	Mean Equation						Variance Equation									
	Cst (α_0)		***AR(1)*** (α_1)		***Cst **** 10^4 (c_0)		***d-Figarch***		***ARCH*** (ϕ)		***GARCH*** (ψ)		***EGARCH*** (θ)		***EGARCH*** (γ)	
Panel A: PIIGS																
	(0,0006)		(0,0309)		(8663,0)		(0,1171)		(0,5623)		(0,2432)		(0,0481)		(0,1027)	
Croatia	-0,0030	***	-0,0633		0,0000		0,5126	***	-0,4206		0,7869	***	0,1250	***	0,5499	***
	(0,0005)		(0,0457)		(4696,0)		(0,0887)		(0,3135)		(0,0994)		(0,0378)		(0,0794)	
Czech	-0,0047	***	-0,1228	***	0,0000		0,5521	***	-0,4131		0,6228		-0,0848	**	0,3102	***
	(0,0009)		(0,0312)		(2720,5)		(0,0524)		(0,4940)		(0,3818)		(0,0384)		(0,0732)	
Hungary	-0,0017	**	0,1459	***	0,0000		0,4133	***	-0,6548	***	0,9381	***	-0,0120		0,4558	***
	(0,0009)		(0,0019)		(17,5390)		(0,1407)		(0,1330)		(0,0413)		(0,0323)		(0,0751)	
Poland	-0,0027	***	0,1023	**	0,0000		0,4478	***	-0,5921	***	0,9149		0,0247		0,4849	***
	(0,0009)		(0,0406)		(25,4530)		(0,0854)		(0,1325)		(0,0363)		(0,0339)		(0,0587)	
Romania	-0,0017	**	0,1780	***	-64055,2	***	0,2982	***	-0,3546	**	0,8010	***	0,0644	**	0,4189	***
	(0,0007)		(0,0324)		(11,3710)		(0,1002)		(0,0860)		(0,0156)		(0,0356)		(0,0706)	
Russia	-0,0014	**	0,1207	***	-63710,5	***	0,4577	***	0,5469		0,5932	***	0,0658	***	0,1807	***
	(0,0001)		(0,0251)		(84945,0)		(1,0041)		(0,4137)		(0,3922)		(0,0254)		(0,0386)	
Ukraine	-0,0001		-0,0218		-63150,2	***	0,3884	***	0,0225		0,5559	***	0,0739	**	0,3882	***
	(0,0014)		(0,0374)		(6,2086)		(0,0563)		(0,2392)		(0,1346)		(0,0325)		(0,0733)	
Venezuela	0,0001	***	0,2573	***	0,0000		0,0710		-0,1871		0,9833	***	-0,0235		0,6324	***
	(2,0E-08)		(0,0553)		(10,7510)		(0,0488)		(0,1192)		(0,0031)		(0,0741)		(0,0655)	
Panel E: GDP growth classification																
Developed coun- tries	0,0001		0,2330	***	-74719,5	***	-0,0796		0,2101		0,8333	***	-0,0243		0,3599	***
	(0,0002)		(0,0353)		(1205,2)		(0,0893)		(0,2266)		(0,0309)		(0,0356)		(0,0611)	
Emerging coun- tries	-0,0001		0,2982	***	-73878,4	***	0,5117	***	0,2799		0,5208	***	0,0664	***	0,2397	***
	(0,0006)		(0,0240)		(1173,4)		(0,1088)		(0,3549)		(0,2005)		(0,0215)		(0,0604)	
PIIGS	0,0003		0,0672		-31603,0		0,1526		-0,3547		0,9561		-0,0395		0,4246	
	(465,83)		(0,0472)		(465,8)		(0,0807)		(0,2740)		(0,0157)		(0,0485)		(0,1000)	
NIC	-0,0005		0,2741		-74533,1	***	0,5913	***	0,7682		0,2766		0,0870	**	0,1758	***
	(0,0009)		(0,0256)		(8060,0)		(0,0658)		(0,7001)		(0,4052)		(0,0342)		(0,0510)	
Panel F: Regional classification																
Eastern Europe	0,0006		0,2189	***	-70400,7	***	0,2359	**	-0,2265		0,7556	***	0,0284		0,4849	***
	(0,0005)		(0,0349)		(1609,0)		(0,1086)		(0,1493)		(0,0702)		(0,0386)		(0,1067)	
Western Europe	0,0010	*	0,2127	***	-67669,0	***	0,3569		-0,3829	**	0,8213	***	0,0300		0,3957	
	(0,0006)		(0,0278)		(7864,1)		(0,2326)		(0,1952)		(0,1195)		(0,0268)		(0,0703)	
North America	0,0002	**	0,0021		0,0000		0,5341	***	-0,3177	***	0,9592	***	-0,3835	***	0,9595	***
	(0,0001)		(0,0054)		(2022,2)		(0,0301)		(0,0225)		(0,0017)		(0,1346)		(0,0325)	
South America	0,0012	**	0,2389	***	0,0000		0,1399	*	-0,2613		0,9831	***	0,0073		0,4678	***
	(0,0005)		(0,0063)		(5,2405)		(0,0760)		(0,2080)		(0,0048)		(0,0232)		(0,0752)	
Asia	-2,4E-05		0,2410	***	-69710,0	***	0,5140	***	0,2972		0,5413	***	0,0934	***	0,2077	***
	(0,0006)		(0,0237)		(1030,9)		(0,0720)		(0,3780)		(0,1760)		(0,0295)		(0,0503)	

*,** and *** imply statistical significance at respectively 10%, 5% and 1%. Numbers in parentheses represent standard errors.

Table 5.7: Bivariate AR(1)-FIEGARCH estimates

	Crisis generator: USA				Crisis generator: Greece				Crisis generator: Ireland			
	ρ_{12}	θ_1	θ_2	*df*	ρ_{12}	θ_1	θ_2	*df*	ρ_{12}	θ_1	θ_2	*df*
Panel A: PIIGS												
Portugal	0,1976***	0,0170***	0,9541***	2,2779***	0,2783***	0,0479***	0,8938***	2,4179***	0,9966***	0,2424**	0,9743***	2,6618***
	(0,0258)	(0,0063)	(0,0149)	(0,0232)	(0,0342)	(0,1618)	(0,0444)	(0,0221)	(0,0039)	(0,0098)	(0,0095)	(0,0451)
Ireland	0,1498***	0,0355***	0,9296***	2,3151***	0,9835***	0,0509***	0,9488***	2,9253***	-	-	-	-
	(0,0445)	(0,0080)	(0,0133)	(0,0171)	(0,0130)	(0,0094)	(0,0095)	(0,0486)				
Italy	0,1055	0,0072***	0,9901***	2,3761	0,3650***	0,0149***	0,9758***	3,1802***	0,3670***	0,0152***	0,9786***	2,8356***
	(0,0889)	(0,0017)	(0,0031)	(0,0290)	(0,0866)	(0,0068)	(0,0139)	(0,0742)	(0,0644)	(0,0054)	(0,0081)	(0,0592)
Greece	0,0622	0,0737***	0,9124***	2,7699***	-	-	-	-	0,9835***	0,0509***	0,9488***	2,9253***
	(0,0276)	(0,0331)	(0,0605)	(0,0230)					(0,0130)	(0,0094)	(0,0095)	(0,0486)
Spain	0,2250***	0,0014***	0,9957***	2,3129***	0,3092***	0,1087***	0,8186***	2,4574***	0,9992***	0,0071***	0,9928***	2,7061***
	(0,0331)	(0,0003)	(0,0012)	(0,0245)	(0,0276)	(0,0331)	(0,0605)	(0,0230)	(0,0003)	(0,0011)	(0,0012)	(0,0478)
Panel B: Developed countries												
Austria	0,2669***	0,0034***	0,9888***	2,2374***	0,4467***	0,0080***	0,9896***	2,3617***	0,0769	0,0562***	0,9344***	2,6144***
	(0,0303)	(0,0012)	(0,0038)	(0,0170)	(0,0416)	(0,0011)	(0,0015)	(0,0182)	(0,1120)	(0,0086)	(0,0101)	(0,0405)
Belgium	0,2646***	0,0112**	0,9599***	2,4889***	0,4238***	0,0153***	0,9805***	2,3130***	0,4790***	0,0606***	0,8828***	2,5585***
	(0,0278)	(0,0056)	(0,0219)	(0,0274)	(0,0336)	(0,0152)	(0,0046)	(0,0136)	(0,0339)	(0,0225)	(0,0471)	(0,0323)
Denmark	0,1887***	0,0072***	0,9569***	2,3919***	0,1565***	0,0000	0,8110***	2,1507***	0,1041***	0,0053***	0,9062***	2,0296***
	(0,0237)	(0,0022)	(0,0126)	(0,0136)	(0,0157)	(4,0E-08)	(0,1523)	(0,0060)	(0,0000)	(0,0000)	(0,0000)	(0,0021)
Estonia	0,4232***	0,0295***	0,9620***	2,5863***	0,4022***	0,0271***	0,9713***	2,2522***	0,0521	0,0502***	0,9260***	2,3475***
	(0,1274)	(0,0026)	(0,0027)	(0,0248)	(0,1043)	(0,0085)	(0,0094)	(0,0112)	(0,0628)	(0,0095)	(0,0126)	(0,0206)
Finland	0,2598***	0,0134***	0,9351***	2,5957***	0,0570	0,0337***	0,9610***	2,2744***	0,3998***	0,0312	0,8962***	2,5065***
	(0,0285)	(0,0050)	(0,0234)	(0,0238)	(0,0385)	(0,0095)	(0,0115)	(0,0126)	(0,0273)	(0,0236)	(0,0981)	(0,0261)
France	0,2372***	0,0127	0,9692***	2,2700***	0,2607***	0,0489***	0,8561***	2,4116***	0,2705***	0,0241*	0,9619***	2,6153***
	(0,0301)	(0,0077)	(0,0176)	(0,0227)	(0,0269)	(0,0133)	(0,0447)	(0,0209)	(0,0580)	(0,0128)	(0,0233)	(0,0425)
Germany	0,2137***	0,0049	0,8295	2,2365***	0,2875**	0,0483***	0,9369***	2,8158***	0,3432***	0,0197***	0,9629***	2,5235***
	(0,0267)	(0,0056)	(0,9834)	(0,0173)	(0,1407)	(0,0092)	(0,0137)	(0,0437)	(0,0417)	(0,0110)	(0,0230)	(0,0327)
Japan	0,1943**	0,0270***	0,9652***	2,9935***	0,0932**	0,0168***	0,9659***	2,4479***	0,1698***	0,0022**	0,9926***	3,1198***
	(0,0864)	(0,0032)	(0,0041)	(0,0532)	(0,0378)	(0,0060)	(0,0141)	(0,0234)	(0,0271)	(0,0011)	(0,0030)	(0,0707)
Latvia	0,0356	0,0471***	0,9447***	2,1408***	-0,0986***	0,0873***	0,7854***	2,7648***	0,9999***	0,0139***	0,9861***	2,4352***
	(0,1545)	(0,0043)	(0,0045)	(0,0140)	(0,0342)	(0,0215)	(0,0591)	(0,0366)	(0,0000)	(0,0012)	(0,0014)	(0,0221)
Lithuania	0,0351	0,0106***	0,9812***	2,1950***	0,0129	0,0466***	0,8564***	2,8418***	0,9994***	0,0576***	0,9370***	2,3825***
	(0,0519)	(0,0029)	(0,0058)	(0,0110)	(0,0281)	(0,0165)	(0,0581)	(0,0464)	(0,0008)	(0,0074)	(0,0081)	(0,0265)
Netherlands	0,1925***	0,0073	0,0019	2,5805***	0,2231***	0,0225***	0,9187***	2,4163***	0,2852***	0,0607***	0,9036***	2,6938***
	(0,0177)	(0,0094)	(0,6416)	(0,0236)	(0,0282)	(0,0072)	(0,0259)	(0,0190)	(0,0629)	(0,0213)	(0,0357)	(0,0338)
Norway	0,1391***	0,0064*	0,9724***	2,4359***	0,2773	0,0610***	0,9347***	2,7472***	0,1917***	0,0144***	0,9678***	2,1912***
	(0,0254)	(0,0032)	(0,0143)	(0,0196)	(0,1839)	(0,0110)	(0,0117)	(0,0335)	(0,0315)	(0,0049)	(0,0119)	(0,0130)
Slovakia	0,1283***	0,0040	0,9748***	2,2825***	0,2085***	0,0645***	0,7398***	2,9633***	0,9999***	0,0121***	0,9879***	2,6403***
	(0,0237)	(0,0043)	(0,0260)	(0,0221)	(0,0275)	(0,0236)	(0,1415)	(0,0566)	(0,0000)	(0,0043)	(0,0051)	(0,0408)
Slovenia	0,1520***	0,0075**	0,9630***	2,2225***	0,1199***	0,0000***	0,9977***	2,1827***	0,0982***	0,0151	0,8765***	2,2135***
	(0,0281)	(0,0032)	(0,0158)	(0,0093)	(0,0149)	(0,0000)	(0,0008)	(0,0078)	(0,0234)	(0,0092)	(0,0581)	(0,0146)
Sweden	0,1981***	0,0114**	0,9417***	2,1864***	0,1315**	0,0417***	0,9477***	2,6177***	0,2918***	0,0098*	0,9758***	2,2943***
	(0,0221)	(0,0045)	(0,0188)	(0,0104)	(0,0522)	(0,0114)	(0,0159)	(0,0328)	(0,0414)	(0,0055)	(0,0162)	(0,0221)
UK	0,0106	0,0111*	0,9857***	2,5924***	0,2149	0,0522***	0,9423***	2,7192***	0,2941***	0,0431***	0,9321***	2,8317***
	(0,0303)	(0,0067)	(0,0100)	(0,0304)	(0,2415)	(0,0081)	(0,0095)	(0,0362)	(0,0500)	(0,0077)	(0,0107)	(0,0486)
USA	-	-	-	-	0,0622	0,0737***	0,9124***	2,7699***	0,1498***	0,0355***	0,9296***	2,3151***
					(0,2847)	(0,0258)	(0,0371)	(0,0363)	(0,0445)	(0,0080)	(0,0133)	(0,0171)
Panel C: Newly Industrialized Countries												
Brazil	0,1194***	0,0263***	0,9491***	2,7932***	0,1214***	0,0025	0,9912***	3,5231***	0,9742***	0,0508***	0,9425***	3,3910***
	(0,0426)	(0,0078)	(0,0103)	(0,0514)	(0,0430)	(0,0033)	(0,0121)	(0,1069)	(0,0043)	(0,0079)	(0,0086)	(0,1094)
China	0,1539***	0,0130	0,9772***	2,9241***	0,2000***	0,0223*	0,9432***	2,4279***	0,0814	0,0408***	0,9408***	2,7233***
	(0,0546)	(0,0111)	(0,0227)	(0,0459)	(0,0251)	(0,0132)	(0,0432)	(0,0218)	(0,0669)	(0,0098)	(0,0145)	(0,0426)
Qatar	0,0351	0,0129***	0,9769***	2,5090***	0,0638***	0,0193	0,6019***	2,1757***	-0,8529***	0,0564***	0,9395***	2,4667***
	(0,0314)	(0,0049)	(0,0089)	(0,0240)	(0,0151)	(0,0209)	(0,1682)	(0,0092)	(0,0249)	(0,0095)	(0,0100)	(0,0329)
Turkey	0,0202	0,0052***	0,9946***	2,7959***	0,1251**	0,0099***	0,98699***	4,1951***	0,2186**	0,0104**	0,9833***	3,4825***
	(0,0710)	(0,0010)	(0,0012)	(0,0561)	(0,0809)	(0,0037)	(0,0051)	(0,1796)	(0,0569)	(0,0042)	(0,0079)	(0,1127)
Panel D: Emerging countries												
Bulgaria	0,0403	0,0056***	0,9935***	2,4561***	0,1371***	0,0640*	0,8223***	2,5659***	0,2296***	0,0141*	0,9702***	2,8909***

Table 5.7: Bivariate AR(1)-FIEGARCH estimates (*Continued*)

	Crisis generator: USA				Crisis generator: Greece				Crisis generator: Ireland			
	ρ_{12}	θ_1	θ_2	*df*	ρ_{12}	θ_1	θ_2	*df*	ρ_{12}	θ_1	θ_2	*df*
	(0,0537)	(0,0015)	(0,0019)	(0,0308)	(0,0284)	(0,0342)	(0,1423)	(0,0304)	(0,0334)	(0,0076)	(0,0181)	(0,0567)
Croatia	0,0738 **	0,0177 ***	0,9561 ***	2,4591 ***	0,1029 **	0,0307	0,9446 ***	3,3106 ***	0,2667 ***	0,0053 **	0,9921 ***	2,7357 ***
	(0,0287)	(0,0055)	(0,0146)	(0,0328)	(0,0517)	(0,0189)	(0,0475)	(0,0861)	(0,0739)	(0,0024)	(0,0043)	(0,0458)
Czech	0,2323 ***	0,0056	0,9751 ***	2,7355 ***	0,1079 ***	0,0242 ***	0,9475 ***	2,3367 ***	0,2700 ***	0,0101 **	0,9814 ***	2,4720 ***
	(0,0237)	(0,0038)	(0,0157)	(0,0313)	(0,0411)	(0,0068)	(0,0166)	(0,0156)	(0,0587)	(0,0041)	(0,0085)	(0,0294)
Hungary	0,1152 ***	0,0055 ***	0,9921 ***	2,4744 ***	0,1080	0,0087 ***	0,9893 ***	2,5778 ***	0,2369 ***	0,0116 ***	0,9839 ***	2,8947 ***
	(0,0390)	(0,0016)	(0,0024)	(0,0339)	(0,1981)	(0,0023)	(0,0047)	(0,0328)	(0,0628)	(0,0036)	(0,0057)	(0,0602)
Poland	0,2031 ***	0,0101 *	0,9843 ***	3,3043 ***	0,0372	0,0065 ***	0,9920 ***	3,5584 ***	0,2232 ***	0,0118 ***	0,9801 ***	3,0755 ***
	(0,0557)	(0,0060)	(0,0114)	(0,0705)	(0,1943)	(0,0020)	(0,0026)	(0,1077)	(0,0446)	(0,0042)	(0,0076)	(0,0732)
Romania	0,2240 ***	0,0236 ***	0,9541 ***	3,2516 ***	0,1077 ***	0,0555	0,8436 ***	2,6396 ***	0,1727 ***	0,0201 ***	0,9687 ***	2,8174 ***
	(0,0405)	(0,0079)	(0,0211)	(0,0672)	(0,0281)	(0,0343)	(0,1489)	0,035209)	(0,0527)	(0,0051)	(0,0083)	(0,0521)
Russia	0,0494 **	0,0050 ***	0,9934 ***	2,7209 ***	0,1443 ***	0,0142 **	0.977159 ***	2,8197 ***	0,2170 ***	0,0163 *	0,9757 ***	2,9222
	(0,0232)	(0,0013)	(0,0020)	(0,0526)	(0,0458)	(0,0064)	(0,0128)	(0,0519)	(0,0560)	(0,0093)	(0,0170)	(0,0604)
Ukraine	0,0259	0,0066 ***	0,9913 ***	2,5592 ***	0,1177 ***	0,0098	0,9709 ***	3,9972 ***	0,1859 ***	0,0131 *	0,9736 ***	3,0199 ***
	(0,0327)	(0,0025)	(0,0037)	(0,0380)	(0,0321)	(0,0064)	(0,0217)	(0,1390)	(0,0355)	(0,0067)	(0,0175)	(0,0659)
Venezuela	0,0671	0,0263 ***	0,9645 ***	3,1469 ***	0,2193 **	0,0382 ***	0,9505 ***	2,5523 ***	0,1609 **	0,0280 ***	0,9462 ***	2,9027 ***
	(0,0141)	(0,0000)	(0,8150)	(0,0587)	(0,0968)	(0,0078)	(0,0112)	(0,0281)	(0,0425)	(0,0085)	(0,0135)	(0,0609)
Panel E: GDP growth classification												
Developed countries	0,2025 ***	0,0071 **	0,9844 ***	2,3376 ***	0,2292 ***	0,0198 **	0,9701 ***	2,9522 ***	0,3230 ***	0,0108	0,9753 ***	2,5908 ***
	(0,0356)	(0,0034)	(0,0068)	(0,0203)	(0,0627)	(0,0084)	(0,0130)	(0,0547)	(0,0361)	(0,0076)	(0,0196)	(0,0387)
Emerging countries	0,0743 **	0,0073 ***	0,9919 ***	2,7430 ***	0,1381 **	0,0079 ***	0,9879 ***	4,1478 ***	0,2107 ***	0,0110 ***	0,9846 ***	3,4152 ***
	(0,0328)	(0,0023)	(0,0027)	(0,0523)	(0,0611)	(0,0030)	(0,0042)	(0,1693)	(0,0726)	(0,0041)	(0,0073)	(0,1053)
PIIGS	0,1877 ***	0,0204 **	0,9016 ***	2,2136 ***	0,3048 ***	0,0394 **	0,9285 ***	2,4491 ***	0,2002 ***	0,0701 ***	0,8977 **	2,4017 ***
	(0,0281)	(0,0101)	(0,0498)	(0,0108)	(0,0396)	(0,0155)	(0,0375)	(0,0223)	(0,0621)	(0,0234)	(0,0450)	(0,0228)
NIC	0,1250 *	0,0065 ***	0,9913 ***	2,9622 ***	0,1141 *	0,0145 ***	0,9791 ***	2,9586 ***	0,2271 ***	0,0145 **	0,9759 ***	3,6420 ***
	(0,0656)	(0,0018)	(0,0020)	(0,0636)	(0,0611)	(0,0053)	(0,0100)	(0,0634)	(0,0512)	(0,0072)	(0,0143)	(0,1302)
Panel F: Regional classification												
Eastern Europe	0,2156 ***	0,0063 ***	0,9920 ***	2,5775 ***	0,1857 ***	0,0096 *	0,9841 ***	3,5436 ***	0,1984 ***	0,0148 **	0,9709 ***	3,0977 ***
	(0,0542)	(0,0015)	(0,0019)	(0,0389)	(0,0570)	(0,0052)	(0,0098)	(0,1052)	(0,0398)	(0,0072)	(0,0168)	(0,0736)
Western Europe	0,2153 ***	0,0173 *	0,9259 ***	2,2006 ***	0,2744 ***	0,0115 ***	0,9824 ***	4,2854 ***	0,2588 ***	0,0098 ***	0,9847 ***	2,5054 ***
	(0,0287)	(0,0099)	(0,0435)	(0,0114)	(0,0586)	(0,0039)	(0,0065)	(0,1801)	(0,0491)	(0,0016)	(0,0028)	(0,0279)
North America	-	-	-	-	0,0622	0,0737 ***	0,9124 ***	2,7699 ***	0,1498 ***	0,0355 ***	0,9296 ***	2,3151 ***
					(0,2847)	(0,0258)	(0,0371)	(0,0363)	(0,0445)	(0,0080)	(0,0133)	(0,0171)
South America	0,0465	0,0230 **	0,9599 ***	2,5753 ***	0,0704	0,0042 *	0,9925 ***	3,8552 ***	0,1226 **	0,0185	0,8706 ***	3,1553 ***
	(0,0466)	(0,0102)	(0,0118)	(0,0400)	(0,0540)	(0,0022)	(0,0034)	(0,1377)	(0,0561)	(0,0157)	(0,0547)	(0,0854)
Asia	0,0470	0,0076 ***	0,9921 ***	2,7324 ***	0,0962	0,0183 *	0,9772 ***	2,9388 ***	0,0607	0,0070 ***	0,9930 ***	3,4243 ***
	(0,0515)	(0,0014)	(0,0014)	(0,0558)	(0,0752)	(0,0108)	(0,0153)	(0,0606)	(0,2690)	(0,0015)	(0,0019)	(0,0992)

*,** and *** imply statistical significance at respectively 10%, 5% and 1%. Numbers in parentheses represent standard errors.

Table 5.8: Regression results of DCC series (AR(1)-FIEGARCH(1,d,1)-DCC model)

	Crisis generator: USA			Crisis generator: Greece			Crisis generator: Ireland		
	Cst (a_0)	**Lagged values L** (a_1)	1^{st} **crisis dummy** (b_1)	**Cst)** (a_0)	**Lagged values L** (a_1)	2^{nd} **crisis dummy** (b_1)	**Cst** (a_0)	**Lagged values L** (a_1)	2^{nd} **crisis dummy** (b_1)
Panel A: PIIGS									
Portugal	0,99674 ***	-0,00012	0,00079	0,99472 ***	0,00133 *	-0,00031	0,99529 ***	0,00019	0,00264
	(0,0009)	(0,0003)	(0,0005)	(0,0017)	(0,0007)	(0,0007)	(0,0014)	(0,0047)	(0,0096)
Ireland	0,98781 ***	0,00051 ***	-0,00061	0,99351 ***	-0,00135 ***	0,00266 ***	-	-	-
	(0,0034)	(0,0018)	(0,0022)	(0,0007)	(0,0002)	(0,0004)	-	-	-
Italy	0,99654 ***	0,00005	0,00129 ***	0,99157 ***	0,00204 ***	0,00032	0,99266 ***	0,00282 ***	0,00116 **
	(0,0009)	(0,0003)	(0,0004)	(0,0020)	(0,0007)	(0,0007)	(0,0009)	(0,0003)	(0,0005)
Greece	0,98996	-0,00351 **	0,00352	-	-	-	0,99351 ***	-0,00135 ***	0,00266 ***
	(0,0032)	(0,0015)	(0,0021)	-	-	-	(0,0007)	(0,0002)	(0,0004)
Spain	1,00061 ***	-0,00018 **	0,00029 ***	0,99047 ***	0,00232 **	0,00049 **	0,99733 ***	0,00059	0,00118 **
	(0,0003)	(0,0001)	(0,0001)	(0,0027)	(0,0011)	(0,0013)	(0,0010)	(0,0005)	(0,0005)
Panel B: Developed countries									
Austria	1,00061 ***	-0,00028 **	0,00064 ***	0,99498 ***	0,00119	0,00033	0,99442 ***	0,00031 **	0,00228 ***
	(0,0005)	(0,0001)	(0,0001)	(0,0021)	(0,0009)	(0,0012)	(0,0006)	(0,0002)	(0,0003)
Belgium	0,99861 ***	0,00005	0,00053	0,97971 ***	0,01144 ***	-0,00281	0,98390 ***	0,00608 ***	0,00486 **
	(0,0013)	(0,0003)	(0,0004)	(0,0041)	(0,0024)	(0,0021)	(0,0037)	(0,0061)	(0,0049)
Denmark	1,00010 ***	-0,00015	0,00059 **	0,98323 ***	-0,00519 **	0,00695 *	0,99655 ***	0,00023	0,00141 *
	(0,0011)	(0,0002)	(0,0002)	(0,0040)	(0,0023)	(0,0038)	(0,0014)	(0,0006)	(0,0008)
Estonia	0,99757 ***	0,00032 ***	-0,00019 ***	0,99870 ***	-0,00011	0,00043 **	0,99133 ***	-0,00115	0,00125
	(0,0001)	(0,0000)	(0,0000)	(0,0007)	(0,0002)	(0,0002)	(0,0029)	(0,0009)	(0,0016)
Finland	0,99799 ***	0,00018	0,00066	0,99289 ***	0,00075	0,00078	0,97231 ***	0,01182 ***	0,00026
	(0,0018)	(0,0004)	(0,0005)	(0,0029)	(0,0005)	(0,0009)	(0,0051)	(0,0022)	(0,0009)
France	0,99828 ***	-0,00001	0,00068	0,96880 ***	0,00562 ***	0,00238 **	0,98195 ***	0,00452 ***	0,00199 *
	(0,0016)	(0,0003)	(0,0005)	(0,0055)	(0,0014)	(0,0016)	(0,0041)	(0,0012)	(0,0011)
Germany	0,98861 ***	0,00278 ***	-0,00015	0,97759 ***	0,00340 ***	0,00205 **	0,99676 ***	0,00069	0,00091 *
	(0,0034)	(0,0009)	(0,0006)	(0,0047)	(0,0010)	(0,0014)	(0,0015)	(0,0004)	(0,0005)
Japan	0,99641 ***	-0,00029	0,00122	0,99149 ***	0,00128 **	-0,00029	0,99820 ***	0,00030	0,00008
	(0,0018)	(0,0005)	(0,0010)	(0,0029)	(0,0005)	(0,0006)	(0,0013)	(0,0002)	(0,0002)
Latvia	0,99578 ***	0,00183 *	-0,00067	0,95361 ***	-0,01057 ***	0,00638 **	0,99719 ***	0,00013	0,00163 **
	(0,0023)	(0,0010)	(0,0017)	(0,0068)	(0,0021)	(0,0028)	(0,0011)	(0,0005)	(0,0007)
Lithuania	1,00093 ***	0,00005	-0,00119 ***	0,97047 ***	-0,00259 ***	0,00334 **	0,99828 ***	0,00033	0,00027 *
	(0,0011)	(0,0003)	(0,0004)	(0,0055)	(0,0009)	(0,0016)	(0,0004)	(0,0002)	(0,0002)
Netherlands	0,95082 ***	0,02958 ***	-0,00852 *	0,97688 ***	-0,00720 ***	0,01011 ***	0,98015 ***	-0,00022	0,00633 *
	(0,0068)	(0,0046)	(0,0047)	(0,0047)	(0,0026)	(0,0042)	(0,0041)	(0,0018)	(0,0036)
Norway	1,00093 ***	-0,00022 *	0,00076 ***	0,98481 ***	0,00621 ***	-0,00278	0,98484 ***	0,00240 ***	0,00119 **
	(0,0008)	(0,0001)	(0,0002)	(0,0039)	(0,0021)	(0,0024)	(0,0038)	(0,0006)	(0,0005)
Slovakia	0,99745 ***	0,00017	0,00036 **	0,94072 ***	0,00223	0,00386	0,99393 ***	0,00108 ***	0,01046 ***
	(0,0018)	(0,0002)	(0,0002)	(0,0076)	(0,0017)	(0,0029)	(0,0011)	(0,0004)	(0,0004)
Slovenia	1,00004 ***	-0,00144 ***	0,00418 ***	0,94740 ***	0,02824 ***	-0,00721 **	0,97111 ***	-0,00742 ***	0,01250 ***
	(0,0009)	(0,0005)	(0,0012)	(0,0072)	(0,0043)	(0,0034)	(0,0049)	(0,0026)	(0,0047)
Sweden	0,99829 ***	0,00011	0,00053	0,98194 ***	0,00172 *	0,00268	0,99417 ***	-0,00022 *	0,00240 ***
	(0,0016)	(0,0003)	(0,0004)	(0,0044)	(0,0009)	(0,0016)	(0,0005)	(0,0001)	(0,0003)
U.K.	0,99976 ***	-0,00057 ***	0,00123 ***	0,98328 ***	0,00759 ***	-0,00333	0,98875 ***	0,00405 ***	0,00048
	(0,0003)	(0,0001)	(0,0003)	(0,0038)	(0,0021)	(0,0021)	(0,0034)	(0,0014)	(0,0005)
USA	-	-	-	0,98627 ***	-0,00557 ***	0,00622 **	0,98358 ***	0,00299 **	0,00278
	-	-	-	(0,0032)	(0,0010)	(0,0016)	(0,0035)	(0,0014)	(0,0024)
Panel C: Newly Industrialized Countries									
Brazil	0,90773 ***	0,02013 ***	-0,01497 *	0,99206 ***	0,00035 ***	0,00152 ***	0,99786 ***	0,00011	0,00066 *
	(0,0092)	(0,0045)	(0,0085)	(0,0006)	(0,0001)	(0,0002)	(0,0007)	(0,0003)	(0,0004)
China	0,99869 ***	-0,00025	0,00064	0,99818 ***	0,00034 ***	0,00000 ***	0,99828 ***	0,00073 **	-0,00099 *
	(0,0012)	(0,0002)	(0,0005)	(0,0007)	(0,0001)	(3,8E-09)	(0,0007)	(0,0003)	(0,0005)
Qatar	0,99936 ***	-0,00009	0,00025 *	1,00069 ***	0,00018 ***	-0,00023 ***	0,99559 ***	-0,00133	0,00157
	(0,0008)	(0,0001)	(0,0002)	(0,0001)	(0,0000)	(0,0000)	(0,0017)	(0,0008)	(0,0015)
Turkey	0,99999 ***	0,00001	0,00037 *	0,99584 ***	0,00018	0,00059 ***	0,99672 ***	0,00051	0,00080 **
	(0,0009)	(0,0002)	(0,0002)	(0,0021)	(0,0002)	(0,0004)	(0,0014)	(0,0003)	(0,0003)
Panel D: Emerging countries									

Table 5.8: Regression results of DCC series (AR(1)-FIEGARCH(1,d,1)-DCC model)(*Continued*)

	Crisis generator: USA			Crisis generator: Greece			Crisis generator: Ireland		
	Cst (a_0)	**Lagged values L (a_1)**	**1^{st} crisis dummy (b_1)**	**Cst) (a_0)**	**Lagged values L (a_1)**	**2^{nd} crisis dummy (b_1)**	**Cst (a_0)**	**Lagged values L (a_1)**	**2^{nd} crisis dummy (b_1)**
Bulgaria	0,99949 ***	0,00003	0,00033	0,99027 ***	-0,00070 *	0,00214 ***	0,98826 ***	0,00222 ***	0,00137 **
	(0,0010)	(0,0002)	(0,0002)	(0,0019)	(0,0004)	(0,0008)	(0,0033)	(0,0007)	(0,0007)
Croatia	0,99294 ***	0,00125 **	0,00056	0,98812 ***	0,00013	0,00123	0,99328 ***	0,00167 ***	0,00041
	(0,0018)	(0,0006) **	(0,0006)	(0,0035)	(0,0006)	(0,0011)	(0,0016)	(0,0005)	(0,0004)
Czech	0,98757 ***	0,00276 ***	-0,00021	0,99033 ***	-0,00046 **	0,00218 ***	0,99739 ***	0,00055 *	0,00052 **
	(0,0036)	(0,0008)	(0,0003)	(0,0010)	(0,0002)	(0,0004)	(0,0006)	(0,0003)	(0,0003)
Hungary	0,99980 ***	-0,00005	0,00035	0,98766 ***	0,00116 **	0,00141 ***	0,99055 ***	0,00192 ***	0,00152 **
	(0,0013)	(0,0002)	(0,0002)	(0,0022)	(0,0005)	(0,0008)	(0,0014)	(0,0004)	(0,0007)
Poland	0,99710 ***	0,00041	0,00039	0,98863 ***	0,00094 **	0,00160 **	0,99164 ***	0,00147 ***	0,00137 **
	(0,0020)	(0,0004)	(0,0004)	(0,0021)	(0,0005)	(0,0007)	(0,0017)	(0,0005)	(0,0006)
Romania	0,98484 ***	0,00285 ***	0,00073	0,98767 ***	-0,00028	0,00250 ***	0,99191 ***	0,00122 **	0,00157 ***
	(0,0040)	(0,0009)	(0,0009)	(0,0022)	(0,0004)	(0,0009)	(0,0016)	(0,0005)	(0,0006)
Russia	0,99966 ***	0,00001	0,00038 *	0,99152 ***	-0,00002	0,00171 **	0,99252 ***	0,00093 ***	0,00152 ***
	(0,0010)	(0,0002)	(0,0002)	(0,0019)	(0,0005)	(0,0009)	(0,0011)	(0,0003)	(0,0004)
Ukraine	0,99964 ***	0,00006	0,00028 *	0,98720 ***	0,00117 ***	0,00065 *	0,99840 ***	0,00023	0,00032 *
	(0,0007)	(0,0001)	(0,0001)	(0,0036)	(0,0004)	(0,0003)	(0,0011)	(0,0002)	(0,0002)
Venezuela	0,99423 ***	-0,00006	0,00028	0,98816 ***	-0,00029	0,00163	0,97675 ***	0,00304 ***	0,00022
	(0,0201)	(0,0015)	(8,0E-12)	(0,0031)	(0,0010)	(0,0019)	(0,0046)	(0,0007)	(0,0005)
Panel E: GDP growth classification									
Developed countries	0,99393 ***	0,00135 ***	0,00018	0,98688 ***	0,00128	0,00340 **	0,99367 ***	0,00170 **	0,00105 **
	(0,0006) ***	(0,0002) ***	(0,0002)	(0,0033)	(0,0010)	(0,0017)	(0,0022)	(0,0007)	(0,0005)
Emerging countries	0,99898 ***	0,00004	0,00056 **	0,99397 ***	0,00053 *	0,00074	0,99350 ***	0,00121 **	0,00119 **
	(0,0011)	(0,0002)	(0,0003)	(0,0027)	(0,0003)	(0,0005)	(0,0023)	(0,0005)	(0,0006)
PIIGS	0,99277 ***	-0,00170 *	0,00130	0,94823 ***	0,01439 ***	0,00144	0,98599 ***	-0,00099	0,00528 **
	(0,0025) ***	(0,0010) *	(0,0017)	(0,0071)	(0,0024)	(0,0026)	(0,0038)	(0,0012)	(0,0025)
NIC	0,99829 ***	0,00017	0,00026	0,99366 ***	0,00045	0,00078	0,99032 ***	0,00206 ***	0,00143 **
	(0,0015) ***	(0,0003)	(0,0004)	(0,0028)	(0,0003)	(0,0006)	(0,0029)	(0,0007)	(0,0007)
Panel F: Regional classification									
Eastern Europe	0,99243 ***	0,00061 **	0,00087 **	0,98859 ***	0,00111 **	0,00182 ***	0,98587 ***	0,00290 ***	0,00180 **
	(0,0011)	(0,0003)	(0,0004)	(0,0020)	(0,0004)	(0,0007)	(0,0036)	(0,0009)	(0,0008)
Western Europe	0,99881 ***	-0,00077 *	0,00176 **	0,99030 ***	0,00217 ***	0,00094	0,99516 ***	-0,00086 ***	0,00264 ***
	(0,0015)	(0,0004)	(0,0008)	(0,0022)	(0,0007)	(0,0007)	(0,0006)	(0,0002)	(0,0004)
North America	-	-	-	0,98627 ***	-0,00557 ***	0,00622 **	0,98358 ***	0,00299 **	0,00278
	-	-	-	(0,0032)	(0,0010)	(0,0016)	(0,0035)	(0,0014)	(0,0024)
South America	0,95529 ***	0,00977 ***	-0,00845 *	0,99199 ***	0,00039 ***	0,00137 ***	0,98874 ***	0,00274 **	0,00067
	(0,0063)	(0,0027)	(0,0051)	(0,0007)	(0,0001)	(0,0002)	(0,0030)	(0,0014)	(0,0017)
Asia	0,99980 ***	-0,00010	0,00072 **	0,98820 ***	0,00050	0,00194 ***	0,98687 ***	0,00315 ***	0,00169 **
	(0,0011)	(0,0002)	(0,0003)	(0,0020)	(0,0004)	(0,0007)	(0,0034)	(0,0009)	(0,0008)

*,** and *** imply statistical significance at respectively 10%, 5% and 1%. Numbers in parentheses represent standard deviations.

effects. This seems to be obvious since (i) PIIGS and Greece have always had stable economic and geographical dependencies and (ii) emerging countries are facing a complicated period of economic slowdown that makes them more sustainably vulnerable than other countries. However, the sovereign CDS markets in Eastern Europe and America have been the most affected by this financial turmoil. Of the 34 countries studied, 23 display significant dummy coefficients (b_2), which implies their recoupling with the crisis.

Assuming that the European debt crisis has emerged from Ireland, all the economically aggregate markets in the world are showing signs of contagion. In addition, by focusing on the regional aggregation of CDS markets, we note that Eastern and Western Europe as well as Asia exhibit contagion effects. The crisis, initially affecting Ireland, has spread to PIIGS (as expected), most emerging countries and newly industrialized economies. This crisis has even reached several developed countries, namely Austria, Belgium, France and Germany. (2^{nd} crisis dummies display positive significance in 12 of the 17 developed countries studied.)

5.6 Discussion

The regression of dynamic conditional correlations on crisis dummy variables approach shows a general contagion effect for most of the studied countries in both crises. Whether according to the EWMA or AR(1)-FIEGARCH-DCC results, strong evidence confirms the occurrence of contagion waves in both developed and emerging markets after the outbreak of the subprime crisis. Countries around the world (Western Europe, Asia...) are recoupling with the USA from September 2007 onwards.

These findings are consistent and can be economically explained. First, before and during the onset of the subprime crisis, international investors have not correctly assessed the banks solvency risk, and considered the USA is considered the least risky reference in the credit market. An underestimation of this crisis signal coupled with an unsustainable and drastic increase in investors risk appetite for household mortgage debt and small significant decisions have been taken to stop the threats. Thus, they led to the worsening of the initially single-country crisis, and then spread around the world and turned into a global financial depression similar to the great recession of 1929 (Rampell, 2009, 2010; Evans-Pritchard, 2010). Developed countries entered into a recession phase following the USA stock market crash at the end of 2008, namely most European countries (France, Germany...) and even Asian countries (Japan...).

Second, according to the Global Financial Centers Index [1], Wall Street is the world's leading financial center. This advantage may explain the fact that all countries of the world invest in the USA stock market making then, naturally, vulnerable to any changes. Indeed, as the global financial crisis intensifies - especially after the Lehman Brothers bankruptcy - investors flee unsafe investments and reduce their exposure to the USA stock market - considered as increasingly risky - by simultaneously selling their financial assets and preferring liquidity that becomes increasingly scarce. This sell-off leads therefore to a global fall in international stock markets values and drives thus to the occurrence of contagion effects, notably on the sovereign CDS markets.

[1] The GFCI is a financial report published twice a year. The aim of this index is to examine countries' financial competitiveness. It rates and ranks more than 87 major financial centers in terms of their reactions to episodes of economic instability. Over the last several years, New York and London remain the main occupiers of the first place as the world's most economically powerful platform.

Third, the USA has always favored the process of globalization. The expansion of global economic integration has led the USA to develop external demand, to accumulate a consequent volume of transactions and exchanges with the outside world and to extend their relative dependence on foreign markets [1]. These facts may explain the repercussion of the subprime crisis on several foreign countries - belonging to different regions and different categories of economic growth - and its transformation into a global financial crisis. These explanations are highly coherent with the DCC pattern represented in Figure 5.4.

Furthermore, the number of countries affected by contagion effects is greater during the second crisis than in the first crisis period. In fact, these findings suggest that the financial crisis played a role in the credit risk transfer from banks to sovereign states, even if the PIIGS and three other main European countries survived the credit crunch and the Lehman Brothers' failure. Secondly, the cost of repurchasing private sector debts by the sovereign governments increased the sovereign credit risk and so caused further waves of contagion in November 2009. Finally, the worsening of the Greek situation in March-April 2010 (4^{th} period) have made the financial markets, in general, even more nervous, thus favoring the transmission of financial distress in almost all the studied countries. Correlations increased in a significant way between Greece and low economic growth countries, between Greece and 10 developed countries (France, Germany, the Netherlands...), between Greece and the emerging countries (except Croatia and Venezuela) and between Greece and all newly industrialized countries.

Ostensibly and contrary to some previous researches, we do not believe that contagion phenomenon detected during the recent crises is only attributed to fundamental reasons since the sample countries present very heterogeneous trade and financial characteristics: the economic profile of our countries differs from country to country. The developed countries, technically the most advanced, base their sustainable development on the technological progress, while the integration of the emerging countries into the world economy is justified by the large volume of their exports (commodity exports for Russia or Bulgaria for example and manufactured exports for Croatia or Hungary...). On the other hand, the newly industrialized countries (especially China and Turkey) are characterized by a high level of economic openness, which represents 33% in China and 12% in the USA according to the latest WTO report. Thus, our main conclusion is that contagion evidence based on our econometric approaches is not only related to common trade profiles.

Indeed, besides the economic factors, extensively studied in the banking literature, the propagation of credit risk on world markets can be explained by two other reasons: First, these countries present a strong external dependence between their financial markets. In crises generators, a significant part of the local projects financing is made by foreign direct investment, whether through governments or banks, which creates implicit linkages. Second, crisis periods are characterized by competition in the global credit market, which is unfavorable to financial stability. For example, the contagion spillovers may result from the simple withdrawal of financial portfolios from the USA, Greece or Ireland, because of the increase in their credit risks, to reinvest in another country considered less risky. These theoretical reasons merit in-depth study in future work.

[1]According to the OECD report (2016), the USA external demand for exports and imports exceeded $12 million.

5.7 Conclusion

The aim of this chapter is to analyze sovereign risk as well as the financial contagion effect in the CDS markets of countries with weak economic growth (PIIGS), developed countries, emerging countries and newly industrialized countries. To detect the occurrence of a long-term contagion phenomenon, analyses were carried out over a long period from January 2006 to April 2014. The studied period is long enough to cover both the global financial crisis and the European debt crisis.

Since contagion is characterized by an increase in cross-country correlations, an analysis of sovereign CDS spreads conditional correlations between different countries was made using both EWMA and AR(1)-FIEGARCH(1,d,1)-DCC approaches. The first approach is used to compare our results with those of the literature, while the second takes into account more CDS market specifications such as long memory behavior, volatility clustering, information asymmetries, and speed that information is reflected in CDS prices. An econometric study of these correlations is made over several sub-periods - during a calm phase, after the credit crunch and during the European sovereign debt crisis - in order to detect significant level changes.

We find that sovereign CDS markets have experienced several contagion phases. Conditional correlations increased considerably during both crisis periods, confirming the insulating behavior in CDS markets during the quiet period. Most countries around the world recouple during the GFC, especially after the credit crunch, and during the Sovereign crisis, which confirms the role played by crises in transmitting financial distress across countries. That said, the increase in market linkages after the occurrence of a financial shock does not appear to be due solely to common characteristics, as the countries in out sample present very different financial and economic profiles. This is further explained by the fact that globalization makes financial markets implicitly linked by foreign investment and that the global credit market is subject to the phenomenon of competition, which favors the transfer of risk.

All countries were affected by the phenomenon of financial contagion at different levels: countries with weak economic growth strongly reacted to financial shocks, while developed and newly industrialized countries were affected in lesser intensity. Similar countries' responses to financial shocks - arisen on the CDS markets - underline the importance of the credit markets' international integration. We also show that financial distress propagation between markets does not only concern countries in the same geographical area: some Asian countries have been affected by the European debt crisis, which confirms the transmission of financial shocks from Europe to Asia.

Our findings reveal an increase of the number of significant interdependencies between various pairs of countries during the crisis phases compared to calm periods. The results actually show the existence of crisis transmission in the CDS markets during the credit crunch. The contagion phenomenon is stressed with the beginning of the European debt crisis. Thus, we think, undoubtedly, that the 2007-2009 credit crisis played a major role in spreading the crisis through the CDS markets and in transmitting sovereign credit risk.

These findings discredit the appropriate use of portfolio diversification since the counterparty risk considerably increases in this case. Traders should not simultaneously invest in several vulnerable markets that subject to contagion effects. In fact, since most sovereign CDS markets are highly correlated and fluctuate in the same direction, a shift in investor appetite for risk in a single country may result in lower returns in the entire portfolio. On the other hand, these results help policy makers, especially when it comes to protecting countries from future crises. First, politicians should put in place an isolating procedures for contagion-prone countries, namely countries with low economic growth, newly industrialized and emerging countries. Second, a long period of high risk-taking in a given market should be interpreted as a signal for creating financial bubbles and consequent measures must be taken to stabilize the crisis-generating country. Joint decisions between countries such as increasing liquidity and / or reducing interest rates could be good solutions to reduce the likelihood of a financial crash and thus the crisis transmission between countries.

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Conclusion

During the last decades, credit default swaps are regularly traded on the financial markets and their transaction volume is increasingly considerable, reaching their highest values during the credit crisis. Initially created to enable market participants to mitigate, redistribute et transfer credit risk, the usage of CDS instruments has evolved over time and has gained a major place in the over-the-counter market as an "trading-for-profit" instrument. CDS trading is gradually taken over by speculators betting against the creditworthiness of reference entities rather than by investors managing their credit-risk exposures. This purpose mutation combined with the structural opacity, the strikingly complex interconnectedness and the lack of relevant legal infrastructure have put these derivatives in the spotlight of criticisms and have led to awaken the concerns of academics, policy makers and market participants about the real impact of CDS in the economic and financial stability.

This thesis contributed to answering uncertainties about the market functioning and its role in the stability of the economic sphere and the financial activity.Throughout this thesis, we have paid particular attention to issues related to the identification, the measurement and the analysis of the dynamic behaviors of the worldwide sovereign credit default swap markets during the Global Financial Crisis (2007-2009) and the European Sovereign Debt Crisis (2010-2012).

1 Proposals

The five interconnected studies proposed composing the thesis extend the growing CDS studies in several ways: First, our investigations expand the field of study and go beyond the abundantly studied context: countries are chosen as to represent a benchmark of international CDS markets and thus provide international evidences from a global rather than a local or regional perspective as it has mainly been done in the literature. Yet, our data sample allows us to draw more robust conclusions, as it is composed by countries with different credit-risk exposures. Second, the dataset ranges on a relatively long interval from January 2^{nd}, 2006 to March 31^{st}, 2017, As far as we are concerned, our database is the largest dataset ever used in studying sovereign CDS dynamics in terms of size and time-period. The studied time period covers thus the Global Financial Crisis as well as the Sovereign Crisis during which trading CDS contracts is altered by several ISDA regulatory amendments. It also allows us to examine the impact of crises magnitude and severity on the dynamic evolution of several CDS spreads. Third, we mainly use sophisticated and accurate econometric methodologies (Bayesian VAR, FIGARCH, FIEGARCH, FIAPARCH and SETAR), which allows us to take into account more CDS market properties (such as long-memory range, information asymmetries. . .), to provide more robust estimates and to draw new conclusions.

2 Contributions

The thesis is started by assessing the financial statistical features of the sovereign CDS market. Preliminary analyses showed that, volatility clustering, asymmetrical leverage effects and long-memory behavior are observed during the studied period. Results of 9 model estimations indicated that the fractionally-integrated class of models (FIGARCH, FIEGARCH, FIAPARCH and HYGARCH) allow a better forecastability of CDS volatility of the majority of the countries under study. The improvement of the predictability power of the studied models depends, thus, on their ability to capture a maximum of financial stylized facts while estimating the CDS volatility of future days.

Our thesis also fills some literature gaps by empirically investigating, in a second essay, the efficiency of sovereign CDS spreads during periods of strong and weak financial tensions. To do so, we used a particularly suitable and relevant methodological framework by taking into account most of CDS markets' stylized facts detected in the first part. Overall, our results were not in line with what it is commonly found and showed that CDS markets of developed countries, newly industrialized countries and emerging countries do not respect the random walk hypothesis and that their sovereign spreads can actually be predicted. Surprisingly, the current CDS spreads randomness is impacted by financial tensions. However, the structural breaks in the efficiency behavior did not seem to depend on the countries' credit risk level.

The international financial markets have been subject to multiple high fluctuations in the oil prices, which challenged us to investigate the impact of oil prices uncertainty on sovereign credit risk measured by CDS volatility. After controlling for local and global economy-wide factors, we detected some divergences in the role played by the energy market in changing the market perception of governments' creditworthiness. While during the low-risk period no interconnection is found between these two markets, the high-risk period is characterized by improvements of the oil related and no-oil related public finances following the increase in oil price.

The fourth essay showed that crises have indeed altered the time-varying interactions of CDS markets with the corresponding government bond markets and that market participants used CDS spreads in risk perception during periods of strong financial tensions. Results indicated that crises increase the percentage of co-movements between credit markets and that the Sovereign Debt Crisis is more intense and affects more countries all over the world than the Financial Crisis. In most cases, financial shock transmissions are detected from the CDS to the underlying market rather than the opposite direction.

We also showed, in the last part, that the modification in the CDS spreads does not only impact the price of the underlying asset, but it provokes, as well, volatility rising in the other international CDS markets. Globally, sovereign CDS markets have found to be prone to contagion effects. The CDS prices of most countries were more correlated during the both recent crises, emphasizing the role played by these markets in transmitting financial distress all over the world. This increased linkages in price formation did not appear to be due solely to common characteristics but maybe rather to the growth of foreign investments and competition phenomenon.

3 Implications of our findings

In this constantly evolving worldwide credit market, the study of the CDS spreads dynamics needs to keep pace with this change. Since studying the time-varying behavior of sovereign CDS markets is of a paramount in assessing diversifiable risk, in dynamic asset pricing theory and in optimization of portfolio allocation, the economic implication of our findings concerns particularly policymakers, financial practitioners and financial market participants generally. First, we detected some GARCH models that seem accurate and robust in detecting the future volatility of CDS markets. Thus, after taking into account the transaction costs, investors can eventually take advantage of the predictability of sovereign CDS volatility and generate extra-profits by putting in place a simple trading strategy. Second, the relative market inefficiency detected in the second chapter should be taken into account by finance practitioners in upgrading trading strategies, readapting portfolio management techniques and implementing beneficial speculative and arbitrage operations. Regulators should examine the reasons behind these market anomalies observed in some countries during crisis periods. Yet, policy makers should put in place a regulatory framework to make the market more liquid or to increase transaction costs, so to reduce the arbitrage possibilities and the speculation opportunities.

Third, by investigating the key drivers of worldwide CDS volatility, we help regulators to better implement crisis exit solutions. Policymakers may, henceforth, be able to settle some rescue packages with respect to the anticipated fluctuations in oil market conditions. The detected interconnection between the sovereign credit market and the international may deter market participants from investing simultaneously in both markets during periods of high volatility.

Fourth, the fact that worldwide countries present some reactions' divergences to crises should incite authorities to put in place different economic and regulatory policies depending on country characteristics to control for credit risk propagation. Our results on the volatility spillover between the CDS market and its underlying bond market should be used by investors so they can anticipate financial turmoil and appropriately balance risk against profitability in investment mix.

Fifth, our last findings suggest to not simultaneously invest in several vulnerable markets that are subject to contagion effects, since a shift in investor appetite for risk in a single country may result in lower returns in the entire portfolio. Politicians should put in place an isolating procedures for the detected contagion-prone countries to stop crises propagation. Lastly, a long period of high risk-taking in a given market should be interpreted as a signal for creating financial bubbles and consequent measures must be taken to stabilize the crisis-generating country. Joint decisions between countries such as increasing liquidity and/or reducing interest rates could be good solutions to reduce the likelihood of a financial crash and thus the crisis transmission between countries.

4 Future works avenues

Although we have conducted a comprehensive study regarding the global sovereign CDS markets' main behaviors, much interesting avenues are still left for future works. First, since there is a dynamic segmentation in financial markets, it can be interesting to check the robustness of our findings using a different sample from other regions and/or a CDS term structure with different maturities. This might reveal more details about the markets' dynamics and could be beneficial for CDS portfolio construction.

Second, the daily dataset used in this thesis includes many missing values and outliers, which required special treatment that may have caused an unintended loss of information. Using monthly or quarterly data in future work might show more interesting findings. Finally, combining artificial intelligence and machine learning techniques with econometric tools to investigate relational associations and similar patterns among international CDS markets may be a fruitful idea.

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