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Essays on Systemic Risk in European Banking

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Abstract

This thesis makes a contribution to systemic risk literature in the European banking system. The intimate interdependence between the European banking industries and the fragile GIIPS debt market has jeopardized the banking sector in Europe. The threats of unfavourable financial conditions in European banking sufficiently highlight the importance of the dissertation's distinct focus on systemic risk measurement and on the risk drivers. The outcomes of the three included papers give support to the European authorities to enact comprehensive macroprudential regulation schemes.

The first paper estimates the systemic risk contributions of GIIPS-block banking on 14 major banking systems in Europe. The CoVaR measure further evaluates the magnitude of risk using two methods; quantile regression and DCC. Our results indicate a substantial spillover effect of GIIPS banking on the examined banking systems. In other words, the countries' banking sectors are in part driven by systemic risk in the GIIPS banking system. We also find supporting evidence of amplified spillover effects from the GIIPS-block banking sector during the financial crises.

The second paper firstly quantifies the sovereign debt spillovers based on daily returns of GIIPS and individual banks' CDSs over the period of 2007-2015. Then, it examines banks' financial features and financial markets' circumstances that determine variations in the banks' sovereign risk exposures. We find those banks that hold higher assets in times of crisis or work in markets with unfavorable profiles, i.e. low returns and high idiosyncratic risks tend to be further susceptible to sovereign risk. However, we do not observe that variations in the risk exposures have been driven by dissimilarities in individual fundamentals such as leverage, debt-to-cash, and market-to-book value of equity ratios.

The third paper analyzes the main determinants of systemic contagion from an individual country's banking sector to the whole banking industry of Europe in 1999-2013. The results show that differences in systemic risk contribution are driven by a combination of balance-sheet characteristics and macroeconomic conditions such as the country-level VaR, crisis episodes, size or total asset, bilateral loan, market-to-book ratio, stock market returns, and industry production index (IPI).

Keywords

Systemic Risk, CoVaR, GIIPS, Quantile Regression, DCC, CDS

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To my beloved mother

Contents

Abstract

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Hassan Sabzevari
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INTRODUCTION

Introduction

1 Background and Objectives

Systemic risk, as a permanent threat to worldwide financial systems, has recently drawn the attention of economists and authorities to mitigate its effects. A sequence of financial crashes in the last three decades, i.e. in Asia, Russia, Argentina, the US, and Europe, provides sufficient evidence on the importance of systemic risk. The fact that economies are complicatedly linked produces large and costly consequences to financial markets. That is, the interdependence between financial entities creates sequential failures of other institutions (Huang, Zhou, and Zhu, 2009; Adrian and Brunnermeier, 2016). Such adverse effects or spillovers are principal causes of the systemic risk of financial systems and the intuition behind this research. In contrast to the well-known risks in banking, such as credit, market, liquidity, and operational, there is no unique definition for systemic risk. Simply, this type of risk has been recognized with a low probability of occurrence but significant consequences for the health of economies. Generally, it can be characterized by three common features: (a) affecting a substantial portion of the financial markets; (b) exposing negative externalities; and (c) necessitating public authorities' intervention to deter or mitigate the risk externalities (Borri, Caccavaio, and Di Giorgio, 2012).

The most serious impacts of the global financial crisis of 2007-2009 appeared and extended in Europe immediately after the US market's failure. Two years after the crisis, five of the Eurozone countries (Greece, Ireland, Italy, Portugal, and Spain, denoted as GIIPS) failed to meet their financial commitments without receiving bailout packages. These countries persistently experienced little economic development and large public debt growth (Black et al., 2016). These facts sufficiently highlight the importance of the dissertation's distinct focus on systemic risk measurement at the European level.

Systemic risk studies might be conducted for various financial institutions such as commercial banks, investment banks, insurance companies, and pension funds. We intentionally focus on evaluating risk spillovers among banks. Our main reasoning is that banking systems have special features, meaning: their complex structure, high leverage, low cash-to-asset and low capital-to-asset ratios, high interconnectedness, and large ownership of market capitalization. In this respect, banks appear to be exposed to undesirable externalities more than other financial institutions. As an example, in 2011, after the sovereign risk expansion, some European banks had to write-off the Eurozone sovereign debts in their balance sheets (Kalbaska and Gątkowski, 2012). In a study, Engle et al. (2015) examined their risk measure, SRISK, using a sample of 196 large European financial firms consisting of all banks, insurance companies, financial services, and real-estate firms over 2000-2012. They showed that banks and insurance companies bear approximately 83% and 15%, respectively, of systemic risk exposure. In addition, the malfunctioning of the banking system can be very costly to the stability of the financial sector, economic growth, employment, and social welfare, as was apparent in the last subprime crisis (Huang, Zhou, and Zhu, 2009).

This thesis contributes to the existing studies on systemic risk as it attempts to quantify the systemic risk contributions of the ”GIIPS-block” or country-wide banking industries to other major European banking systems. In this respect, it is the first study that sheds particular light on systemic risk in European banking at the country level, as opposed to related studies that emphasize individual banking levels. The thesis examines all of the distressed countries in a single index such as the GIIPS index, or the country-level banking index. Another notable deviation from the literature is that it incorporates new explanatory variables that better obtain the strength of banking industries' interdependence. Assessing the risk exposure using the new set of influencing variables can contribute to the explanatory power of the models.

Comprehensive macroprudential supervision, which considers the European banking system as a whole, is crucial for achieving financial stability. This type of supervision outperforms the traditional microprudential regulation that unintentionally gives banks strong incentives to pose more of a risk to the system (Black et al., 2016). Therefore, the present study does not intend to illustrate countries or markets that initiate systemic risk but attempts to distinguish the major characteristics of a country's banking industry and macroeconomy that determine its systemic importance. The research outcomes will benefit the European authorities by identifying Systemically Important Banking Industries (SIBIs) while imposing macroprudential policies. The research also provides regulators with basic hints and implications to limit or prevent systemic risk before any likely crisis.

2 Measuring Systemic Risk

Recently, there has been considerable interest in measuring systemic risk due to its importance. A formulated measure must be capable of accounting for the possible systemic nature of a financial institution's risk and the degree of sensitivity of global financial markets to adverse shocks. Having considered various methods for evaluating systemic risk such as Systemic Expected Shortfall (SES), Systemic Risk Index (SRISK), Marginal Expected Shortfall (MES), Shapley Value methodology, and Lehar's approach, we prefer the Conditional Value at Risk (CoVaR) approach.

Banking j's CoVaR relative to the i banking sector is defined as the VaR of banking industry j conditional on the i banking sector being in distress or conditioning on some event $C(X^i)$ of the i banking sector. The difference between the CoVaR conditional on the distress of i and the CoVaR conditional on the normal state of i, which is referred to as $\Delta CoVaR^{j|i}$, captures the marginal contribution of i's banking to the overall systemic risk of the banking industry j. The $CoVaR^{j|i}$ can be explicitly defined as the qth quantile of the conditional probability distribution. $CoVaR^{j|i}$ can be explicitly defined as the qth quantile of the conditional probability distribution.

$$Pr(X_t^j \leq CoVaR^{j|C(X_t^i)} | C(X_t^i)) = q$$

and $\Delta CoVaR^{j|i}$ denoting banking i's contribution to country j's banking, is defined as

$$\Delta CoVaR^{j|i} = CoVaR^{j|X_t^i=VaR_q^i} - CoVaR^{j|X_t^i=Median^i}$$

The conditioning enables us to extract externalities embedded in the fundamental comovement of financial institutions. Other advantages of CoVaR are its straightforward computation, its simplicity, and its beneficial output. As an example, the systemic risk contribution that is measured by CoVaR can be utilized as a basis to tax Systemically Important Financial Institutions (SIFIs) to punish them by requiring an enhanced capital buffer. Through acting on a comprehensive regulatory framework, financial authorities can internalize externalities created by SIFIs. (Adrian and Brunnermeier, 2016; Acharya, Engle, and Richardson, 2012; Acharya et al., 2010). There are different methods for calibrating CoVaR such as quantile regressions, multivariate GARCH, Dynamic Conditional Correlation (DCC), cupola functions, and bootstrapping of returns. In this research we use quantile regressions and DCC, which are appealing for their simplicity and efficient use of data.

3 Data

Unlike Adrian and Brunnermeier (2016), who perform their analysis by focusing on the market value of total assets, we employ banking equity indices, in the first and the third paper, and credit default swap (CDS) spreads, in the second paper. The forward-looking nature and real-time availability of equity market data offers an instantaneous and straightforward assessment of any conceivable events in the banking system. Stock indices proxy for the financial market conditions since banking equities reflect each and every communicated figure in the markets.

Concerning the use of CDSs in the second paper, a key advantage of using CDS data is that it provides a much more direct measure of credit risk of the GIIPS sovereign debt. The sovereign CDSs are insurance-like contracts and the CDS spreads are the cost of insurance to protect investors against losses on sovereign debts. In other words, CDS spreads reveal all information about the underlying debt and serve as a proxy for the counterparty's credit default probability and the economic circumstances (Kalbaska and Gątkowski, 2012; Alter and Beyer, 2014; Ang and Longstaff, 2013).

4 Overview of the Papers

4.1 Paper I

Measuring the Exposure of European Banking to the Risk of the GIIPS Banking Sector

The GIIPS countries, i.e. Greece, Ireland, Italy, Portugal, and Spain, have been particularly vulnerable thanks to the unfavorable financial conditions and the sovereign debt crisis. This paper evaluates the systemic risk contributions of GIIPS-block banking on 14 major banking systems in Europe. In great detail, we evaluate and measure the systemic risk flow of banks in the GIIPS countries to the rest of the major European banking systems. The CoVaR measure further evaluates the magnitude of risk using two methods: quantile regression and DCC. The non-parametric quantile regression delivers unbiased estimates since it does not depend on restrictive distributional assumptions. Additionally, quantile regression estimates, relative to the ordinary least squares regression, are more robust against outliers. This estimator effectively detects the presence of systemic risk in European banking since it does not require stock indices to be symmetric or tail-independent. After computing the risk measures, a Guntay-Kupiec (GK) test has been employed to distinguish between systemic risk and systematic or market risk (Guntay and Kupiec, 2014).

Our results firstly indicate a substantial spillover effect of GIIPS banking on the examined banking systems, which cannot be explained by VaR measures. Second, larger systemic risk was evident during the recent financial crisis due to higher volatility and correlation. Finally, the GK test indicates that the quantile regression method yields larger negative CoVaR values than the DCC method. Under the alternative hypothesis of the GK test, the magnitude of the non-parametric quantile regression estimator reflects tail-dependence in the sample data. That is, we find evidence supporting the existence of significant spillover effects from the GIIPS-block banking sector. To sum up, the countries' banking sectors are in part driven by systemic risk in the GIIPS banking system.

4.2 Paper II

Determinants of Banks' Exposure to the Eurozone Debt Risk

The sovereign debt crisis began in 2009 across Europe and devastatingly impacted the real economy. The intimate interdependencies between the European banks and the fragile GIIPS debt market motivate this paper's focus on investigating the triggers of the European banks' exposure to the GIIPS sovereign debts. More specifically, this paper investigates banks' financial features and financial markets' circumstances that determine variations in the banks' sovereign risk exposures. To this end, the paper firstly quantifies the sovereign debt spillovers based on daily returns of GIIPS and individual banks' CDSs over the period 2007-2015. Then, it examines bank-specific and market condition determinants on the risk exposures by running fixed-effects panel regression.

We find those banks that hold higher assets in times of crisis or work in markets with unfavorable profiles, i.e. low returns and high idiosyncratic risks tend to be further susceptible to sovereign risk. Moreover, sovereign risk is persistently driven by the flows of global markets such as the subprime crisis and the Eurozone debt crisis effects. Finally, we do not observe that variations in the risk exposures have been driven by dissimilarities in individual fundamentals such as leverage, debt-to-cash, and market-to-book value of equity ratios.

4.3 Paper III

Determinants of Systemic Risk in European Banking

This paper analyzes the main determinants of systemic contagion from an individual country's banking sector to the whole banking industry of Europe. Using a dataset of 15 banking industries and stock returns from 1999-2013, the paper initially measures the risk spillover from these banking industries to the European system. To determine the role of different attributes in the risk expansion, we then run dynamic GMM panel regression of the CoVaR measure on idiosyncratic country-level fundamentals and macroeconomic variables. To this end, several banking and macroeconomic factors have been selected to investigate their influence on the risk expansion.

The results show that differences in systemic risk exposure are driven by a combination of balance-sheet characteristics and macroeconomic conditions such as the previous one-year lag of systemic risk, country-level VaR, crisis episodes, size or total asset, bilateral loan, market-to-book ratio, stock market returns, and industry growth index or industry production index (IPI). Large banking industries are closely connected within the European banking system through assets/liabilities, investments, and other connection channels. Supposedly protected banks have less incentives to implement stringent risk measures and disciplines. In other words, the implicit bailout guarantees enhance the risk appetite of those banks. This outcome supports the claim that large and interconnected European banks should be subject to greater regulatory standards by European macroprudential regulation schemes. In addition, the systemic risk indicator for European banks was heightened at the peak of the global and debt crises, in 2008-2011, due to higher correlation and volatility in the market. Finally, other causes of the risk in European banking are the VaR of each single banking industry, the performance of each country's stock market, market-to-book ratio, IPI, and the new variable, introduced by this paper, namely bilateral loans between country pairs.

5 Policy Implications

Systemic risk in banking is one of the main reasons why banks are regulated and supervised since it undesirably induces negative effects in the rest of the economy through transmission or contagion of distress. In addition, the ongoing integration, globalization, and the consolidation process in the banking business render obvious indications for systemic risk expansion in banking. As occurred during the European sovereign debt crisis, banks found themselves severely under-capitalized because they had not accumulated a capital buffer for their risk exposure. The risk measures can be employed to calibrate the systemic risk capital surcharges or capital requirements. A capital requirement based on a forward-looking manner initiates ex-ante motivations for banks to carry out activities that generate less systemic risk. In addition, it must raise the capital reserve of systemically influential banks and thus protect the whole financial system against the risk spillovers (Adrian and Brunnermeier, 2016).

Managing and mitigating systemic risk requires a comprehensively counter-cyclical regulation to be brought into action. Risk management policy is procyclical when it is able to magnify economic or financial fluctuations. As an example, the capital requirement regulations of the Basel II accord have been criticized for their possible procyclicality. In contrast, a risk management policy, e.g. regulations about capital requirement, is called countercyclical if it works against the fluctuations in the economy. For instance, when the economy is in an upswing, the countercyclical policy raises capital requirement and, in contrast, reduces the capital surcharge when it is in a downturn. This in turn requires supervisors to consistently examine the drivers of systemic risk and to recognize systemically important banking industries, or SIBIs. The dissertation's results have implications for shaping such regulatory policies and imposing macroprudential regulations before entering periods of heightened uncertainty.

Interdependence between banks and sovereign risk is extremely important when setting regulatory capital requirements. The findings, in the second and the third papers, suggest that some factors are much more important than others in determining systemic risk contributions. In dealing with or preventing the sovereign crashes, an optimal capital reserve should be used to appropriately weight the different risk suppliers as a function of their relative importance. Regarding the second paper's observations, a possible and effective way of allocating proper weights is to detect sovereign risk zones. The explanatory power of market-based variables in this study lends support to that purpose. In the next step, pricing the CDSs of these risky sovereigns must be emphasized in the future plans. Mispricing, i.e. overpricing or underpricing, of the CDSs not only leads to a misallocation of assets but also disorders the risk-weights for holding adequate capital.

To sum up, regulation based on the risk of financial institutions in isolation can lead other financial entities to take excessive risk. Regulation should reflect the systemic contribution to minimize the adverse effects of possible domino-like collapses once designing capital requirements. Ideally, adjustments in the regulatory capital or capital requirement must be countercyclical. That is, the rise in regulatory capital should take place before the spread of crises and not in the course of crises.

To conclude, the aforementioned financial and macroeconomic factors are the major reference to establish the amount of additional capital requirements for SIBIs and to maintain the stability of the system. During crises, policymakers require adequate responses or remedial policy actions to safeguard the financial market. However, prior to the advent of any distress in the banking markets, the design and implementation of those policies in Europe require careful and comprehensive monitoring of the significant risk drivers. A predictive or forward model that incorporates those risk determinants can be employed to calibrate the capital requirements in a counter-cyclical fashion. That is, the rise in regulatory capital or capital requirement should take place before the spread of a crisis and not at the occurrence of that episode.

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PAPER I

Measuring the Exposure of European Banking to the Risk of the GIIPS Banking Sector

Hassan Sabzevari and Farrukh Javed

Abstract

This paper attempts to evaluate the systemic risk contribution of GIIPS-block (Greece, Ireland, Italy, Portugal, and Spain) banks on banking industries of the rest of major European countries. To quantify systemic risk, the Conditional Value-at-Risk (CoVaR) approach has been employed. In order to empirically calculate the magnitude of risk, the CoVaR measure is further evaluated by quantile regression and Dynamic Conditional Correlation (DCC). Our results firstly indicate a significant spillover effect of GIIPS banking on the examined banking systems. Second, larger systemic risk was evident during the last financial crises. This period was highly volatile and European banking indices were strongly correlated with the GIIPS banking index. Finally, the Guntay-Kupiec test is employed to distinguish between systemic risk and systematic risk. Our findings designate that the non-parametric method, quantile regression, yields larger CoVaR values than the parametric method based on the bivariate Gaussian distribution.

Keywords: Systemic Risk, CoVaR, Quantile Regression, DCC, Correlation
JEL Classification: G01, G10, G21, N24

1 Introduction

Systemic risk demonstrates part of the nature of a financial crisis in which either many financial institutions fail to perform appropriately or one institution's failure contagiously causes the failure of other institutions. Huge losses and failures of banks or financial institutions can cause negative externalities or spillovers in the rest of the financial markets. Systemic risk measures provide a way to quantify the strength of loss and to capture the negative externalities. In other words, the measures estimate the magnitude at which the risk to a financial system increases due to distress in a particular financial firm (Adrian and Brunnermeier, 2016).

Systemic risk analysis and risk measurement are fairly new research topics. The sequence of the financial crashes at the end of the 1990s, such as crises in Mexico in 1994, Asia in 1997, Russia in 1998, Argentina in 1998, and Brazil in 1999, and the recent financial instability of 2007-2008 provides ample evidence of the importance of taking this risk into account. Systemic risk is associated with a low probability of occurrence but severe consequences for the health and well-being of economies (De Bandt and Hartmann, 1998). As a result of that importance, recently, there has been considerable interest in finding alternative risk measures that do not suffer from Value at Risk's (VaR) shortcomings. The measure must be capable of accounting for the possible systemic nature of a financial institution.

VaR is a broadly accepted risk measure that computes the stand-alone risk of loss on a specific risky asset or portfolio. This measure has been criticized as not conveying any implication of the loss of an institution if an adverse movement occurs for another institution. In other words, the VaR of a financial entity misleadingly under-evaluates the extent of joint covariation in the returns of that entity during extreme events. For that reason, during market crises and disturbances, when the comovement between markets and financial institutions' assets is considerably high, VaR does not reflect the systemic risk properly. This, in turn, can destabilize the financial markets and trigger collapses when they would not occur otherwise. Therefore, imposing financial regulations based only on the risk of a country's banking industry in isolation might not be sufficient to protect that industry against systemic risk (Hong, 2011; Adrian and Brunnermeier, 2016).

In contrast to VaR, there is almost no agreed definition for systemic risk. However, it is acknowledged as the risk of collapse or failure of a chain of financial institutions, resembling a domino effect (Kaufman and Scott, 2003). According to the Bank for International Settlements (BIS) *"the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader financial difficulties"* (cited in Kaufman and Scott, 2003).

In this study, we essentially focus on evaluating the risk spillover among banking industries. The motivation arises due to the fact that banks are one of the most prominent financial intermediaries in the economy. They are connected directly and indirectly through interbank deposits, interbank loans, payment system clearings, and serving similar deposits or loans. The malfunctioning of banking systems can be very costly to the real economy, as been shown in a number of financial distresses and crashes including the recent subprime crisis (Huang et al., 2009). Since the early 19th century (for example, Thornton's paper of 1802), it has been recognized that problems in one bank can spillover or externalize into the rest of the banking systems and other financial institutions. To sum up, the significant role of banks amongst other financial intermediaries, their intense inter-connection, and their large ownership of market capitalization or assets are remarkable enough to convince us to focus distinctly on the systemic risk event in the banking sector.

The GIIPS countries have been particularly vulnerable in the past 10 years thanks to the adverse financial conditions and the sovereign debt crisis. The sovereign debt crisis began in 2009 across Europe following the US subprime crisis and the failure of the banking industries in Iceland and the Middle East. The distress extended largely to Greece, Ireland, and Portugal in 2009. While the debt crisis was most severe in these countries, Italy and Spain were also identified as financially vulnerable countries during the crisis period (Lane, 2012). We investigate, in great detail, the systemic risk flow of banks in the GIIPS countries to the rest of the major European banking systems. Therefore, a total of 14 major European banking systems are considered in this study. In addition, owing to the striking role of the subprime crisis for the functionality of European banks, we also examine the variation in the systemic risk both before and after the crisis.

This paper contributes to the existing studies on systemic risk as it attempts to quantify the systemic risk contribution of the fragile European banking systems, in GIIPS countries, on other major European banking industries. The existing literature on systemic risk does not examine the contagion risk flow from the GIIPS banking sector on the rest of the major banking industries at the country level. For instance, Martin Schüler (2002) evaluated fluctuations in the systemic risk potential in European banking. He shows some evidence of a rise in interdependencies among European banks in 1980-1995. In addition, some of the previous literature suggest that bond spreads or sovereign CDSs are the major drivers of systemic risk in European banking. As an example, Ang and Longstaff (2013) examined the systemic sovereign credit risk in the US and Europe. Reboredo and Ugolini (2015) investigated systemic risk in the European debt market both before and after the arrival of the Greek debt crisis.

The current paper employs the CoVaR methodology, as introduced by Adrian and Brunnermeier (2016). The authors define a banking industry's contribution to systemic risk as the difference between the CoVaR conditional on that industry being under distress and the CoVaR in the median state of that banking industry. According to the authors, CoVaR is a measure used to study tail risk and volatility models. By defining the conditional risk, it is possible to capture the potential risk spillover among banking systems, which was not feasible using the standard VaR method. We evaluate the CoVaR measure by employing two methods: quantile regression and the DCC method of conditional correlation. One can consider involving other possible methods for calibrating CoVaR such as cupola functions or bootstrapping of returns, but these two methods are attractive with respect to their simplicity and efficiency in handling data. The quantile regression framework competently estimates the Co-

VaR measure since it considers only the tail correlation taken from the entire observations. On the other hand, the DCC method delivers time-varying estimates of systemic risk between two banking industries while quantile regression does not generate those kinds of output. Since correlation among banking industries is one of the very features of creating systemic risk, we implement a time-varying correlation structure of the DCC model. In addition, employing the daily DCC-CoVaRs also enables us to observe fluctuations in the risk spillovers during the course of crisis.

In this study, we also empirically test the robustness of the quantile regression CoVaR in measuring systemic risk by newly introduced test statistics. Following the Guntay and Kupiec test (GK)(2014), we compare the non-parametric CoVaR estimator, i.e. quantile regression, with its Gaussian parametric counterpart. Since the quantile regression method does not require the banking indices to be symmetric or tail-independent, it can help us to discover the presence of systemic risk in the returns.

Concerning the use of data, there are two approaches to calculate systemic risk. The first approach is related to firm-specific information and characteristics such as size, leverage, liquidity, etc. The second approach is associated with publicly available market data, such as stock returns, option prices, and CDS spreads, as they are supposed to reveal all information about listed financial firms (Benoit et al., 2013). Adrian and Brunnermeier (2016) conducted their analysis by focusing on the market value of total financial assets. As a deviation from these, we use banking equity indices for the risk evaluation. The forward-looking nature and real-time availability of equity market data offers an instantaneous and clear gauge of systemic risk.

The remainder of this paper is organized as follows: Section 2 reviews the current literature on the topic and the methods; Section 3 describes briefly the data and the sources of data collection; in Section 4 we further explain the CoVaR measure, the applied methods, and the GK test statistics; Section 5 presents the CoVaR and the GK test results; and Section 6 concludes.

2 Literature Review

In recent years, different approaches have been adopted in the existing literature to examine and quantify systemic risk. For instance, De Nicolo and Kwast (2002) estimated systemic risk using a measure of interdependencies of financial institutions. The authors measured total interdependencies by the correlations of stock returns of large banking organizations. They found a significant upward trend in the stock return correlations between large and complex US banking organizations during the period 1988-1999. The authors conclude that the potential systemic risk in the banking sector might have been boosted due to factors other than consolidation activity in banking[1].

By employing the Monte Carlo simulations, Lehar (2005) suggests measuring the systemic risk based on Merton's (1973) model. The author finds the probability of default that a certain fraction of banks with total assets of more than a certain percentage of all banks' total assets will go bankrupt in a short period of time. The probability of default is extracted from the relationship between a bank's asset value and its liabilities. Through applying a structural model, namely Merton's model, Allenspach and Monnin (2009) extend Lehar's approach. The authors studied the development of correlations between large international banks' asset-to-debt ratios over the period 1993-2006 and calculated a systemic risk index for that period. They found that the correlation between banks' asset-to-debt ratios shrinks in the first segment of the sample period and then increases after 2000.

As an alternative to structural models, Bhansali et al. (2008) quantified systemic risk and evaluated the magnitude of the credit risks faced by the financial markets. They implemented a linear three-jump model on the prices of credit derivatives, denoted by CDX for the US and iTraxx for Europe. Moreover, to quantify the relative magnitudes of macroeconomic risks embedded in the prices of tranches of liquid credit indices, three kinds of default event were incorporated into the model:

[1] De Nicolo and Kwast (2002)remark that finding these factors could be a fruitful theme for future research.

firm-specific defaults, industry-wide defaults in a specific sector of the economy, and economy-wide or system defaults. Their findings indicate that a larger fraction of the total credit risk was associated with the systemic credit risk in the last subprime credit crisis.

Huang et al. (2009) suggest a framework for measuring systemic risk by the price of insurance against financial distress. The setup was based on ex-ante measures of default probabilities of individual banks and forecasted asset return correlations. This indicator offers an insight into the market perception of the level of theoretical insurance premium that protects the firm against distressed losses in the banking system. According to the authors, the indicator is higher when the average failure rate increases or when the exposure to common factors rises.

Many studies have also been conducted on the methodologies of measuring the systemic risk contribution of individual banks. Tarashev et al. (2009) propose an approach to estimate the systemic importance of individual financial institutions using the Shapley Value methodology[1]. The authors proved that this methodology can be utilized and extended for the calibration of a macroprudential capital buffer.

Acharya et al. (2010) propose a framework for formalizing and measuring systemic risk that is both model-based and practically relevant. They empirically demonstrated that each financial institution's contribution to the system can be measured through Systemic Expected Shortfall (SES). For an individual institution, SES is its propensity to be undercapitalized when the system as a group is undercapitalized. Similarly, in order to produce a systemic risk index for a firm, Brownlees and Engle (2012) propose an empirical methodology to measure capital shortage of the individual firm given its degree of leverage and Marginal Expected Shortfall (MES).

[1] The Shapley value method originates from cooperative game theory. It designs a way of assigning the collective payoff created by a group to the individual contributors.

3 Data

To accomplish the objectives of this paper, we apply the suggested risk measure to the daily equity indices of the main European banking industries for the period of April 1998-May 2014. The daily observations of the banking equity indices were obtained from the constructed MSCI of the examined countries. MSCI provides comprehensive banking equity indices in many developed and emerging markets. The index aims to deliver a full coverage of the banking industry with emphasis on liquidity, investability, and replicability. The period of study, 1998-2014, covers several major economic recessions such as those of Russia, Argentina, and the last subprime crisis. Therefore, it is interesting to analyze whether or not our chosen models are good enough to capture risk spillover in these periods of turmoil.

The data is composed of 14 big European banking industries, and was obtained from Datastream. It is worth mentioning that we could not find an index for the GIIPS banking system. Therefore, we built a market capitalization-weighted index of banks of each single country's banking industry. The daily market capitalization of GIIPS was collected from Datastream. Table 1 shows the yearly weights of the market capitalization of the GIIPS countries for the period 1998-2014. As can be seen in this table, Spain, with a weight of ranging from 32% to 66%, and Italy, with a weight ranging from 26% to 46%, have the highest market capitalization weights. This means that these two countries have the biggest banking industries within the GIIPS countries.

Simple descriptive statistics of the logarithmic returns are provided in Table 2. The statistics illustrate that banking indices depict very low means of returns; high standard deviations; extreme negative daily returns; rather high skewness (of either sign); and very high kurtosis for some countries' banking indices within 1998-2014. There are two abnormal observations in Table 2 regarding the minimum daily returns of the banking indices. The first abnormality is concerned with the Dutch banking sector related to a daily downturn of 129.9% (of log returns or 72% of ordinary returns), reported on 14 October 2008. The second ob-

Year	Greece	Ireland	Italy	Portugal	Spain
1998	0.039	0.076	0.304	0.055	0.525
1999	0.080	0.090	0.439	0.055	0.335
2000	0.124	0.065	0.418	0.053	0.340
2001	0.087	0.061	0.454	0.057	0.342
2002	0.079	0.081	0.381	0.061	0.397
2003	0.066	0.110	0.407	0.064	0.353
2004	0.077	0.089	0.388	0.052	0.394
2005	0.090	0.089	0.375	0.037	0.409
2006	0.093	0.078	0.418	0.032	0.378
2007	0.102	0.083	0.417	0.040	0.359
2008	0.137	0.063	0.427	0.046	0.327
2009	0.095	0.012	0.469	0.047	0.377
2010	0.094	0.008	0.395	0.040	0.463
2011	0.057	0.010	0.358	0.032	0.543
2012	0.016	0.013	0.291	0.019	0.661
2013	0.018	0.016	0.301	0.032	0.633
2014	0.089	0.025	0.264	0.030	0.591

Table 1: **Market share of the banking industries within GIIPS.** This table presents the market capitalization weights of the GIIPS countries' banking in the period 1998-2014. We built the market capitalization-weighted index of the GIIPS banking system relying on these weights.

servation is noticed for the Irish banking sector with a daily decline of 75.2% (of log returns or 52% of ordinary returns) on 19 January 2009.

The recent financial crisis reached its peak in the Netherlands in the last four months of 2008. In this period, two main financial companies, Fortis NV and ABN AMRO, experienced extreme distress. Prior to its collapse in 2008, Fortis was the greatest financial services company in Belgium, known as Fortis SA/NV, and in the Netherlands, known as Fortis NV. On 13 October 2008, the Belgian government designed and approved a mechanism to compensate certain categories of Fortis shareholders. In the same month, the Dutch state became involved and bailed out the bank. Another Dutch bank that was involved with changes in the

Index	Mean	Std Dev	Min	Max	Skewness	Kurtosis
Austria	0.013	2.027	-13.532	14.323	-0.166	6.320
Belgium	-0.033	2.473	-25.482	18.568	-0.336	10.041
Czech Republic	0.038	2.306	-21.244	14.379	-0.819	10.720
Denmark	0.020	1.701	-14.660	15.312	0.039	7.482
Finland	0.030	2.059	-18.212	19.624	0.113	9.434
France	0.005	2.234	-13.448	18.315	0.223	6.730
Germany	-0.026	1.993	-16.491	15.801	-0.071	8.939
Luxembourg	-0.036	1.209	-19.885	15.923	-0.813	39.932
Netherlands	-0.077	2.941	-129.914	15.116	-20.931	912.489
Norway	0.028	2.178	-19.222	25.487	0.210	15.509
Poland	0.032	1.680	-12.526	8.276	-0.144	3.928
Sweden	0.016	1.916	-10.793	14.655	0.363	5.977
Switzerland	-0.013	1.950	-11.445	17.773	0.150	7.131
UK	-0.015	1.940	-19.471	18.801	-0.061	11.075
GIIPS	-0.026	1.877	-10.322	15.497	-0.085	5.235
Greece	-0.071	2.867	-16.316	22.055	0.315	10.210
Ireland	-0.077	3.794	-75.205	29.759	-1.725	52.641
Italy	-0.029	1.962	-11.963	15.792	-0.108	8.239
Portugal	-0.056	1.723	-11.727	12.788	0.035	10.794
Spain	-0.010	1.955	-14.277	19.058	0.305	10.952

Table 2: **Descriptive statistics of the major European banking indices.** This table reports the basic descriptive statistics of the banking indices' daily log returns such as mean, standard deviation, min, max, all-in percentage, skewness, and kurtosis in the period 1998-2014.

management, ownership, and financial conditions was ABN AMRO. This bank was acquired by a banking consortium consisting of the Royal Bank of Scotland (RBS) Group, Santander Group, and Fortis. On 13 October 2008, the British government declared a bail-out package for the financial system. This resulted in a total state ownership in RBS of 58%. Following the collapse of Fortis and the nationalization of RBS, ABN AMRO was nationalized by the Dutch government. Consequently, the Dutch banking returns declined to the extreme on 14 October 2008 (Fassin and Gosselin, 2011).

As for the fall in the Irish index, Anglo Irish Bank was one of the six main banks in Ireland with an asset size of almost 90 billion euros, approximately 50% of the Irish GDP. On 19 January 2009, the board of directors of this bank resigned to allow the government to appoint a new board of directors. The bank came into state ownership on 21 January 2009, which caused a sharp decline in the Irish stock market. These events describe the seemingly peculiar downturn in the daily returns of the Irish banking index on 19 January 2009 (Eichengreen, 2015).

4 CoVaR Methodology

It has been argued in a number of studies that during non-crisis periods the main drivers of comovement of a financial firm versus the market are the firm's fundamentals, whereas in the times of turmoil or crisis, the comovement tends to increase due to the market's unforeseen turbulences[1]. The CoVaR measure, in contrast to other available measures, not only extracts the comovements or systemic risk embedded in banking but also reflects an individual bank's contribution to it. In risk measurement literature, VaR_q^j is implicitly defined as the qth quantile, i.e.

$$pr(X_t^j \leqslant VaR_q^j) = q \tag{1}$$

where X_t^j is the returns of country j's banking for which VaR_q^j is defined. In contrast to VaR_q^j, the country j's banking CoVaR relative to the GIIPS

[1] See, Acharya et al., 2010 and Bhansali et al., 2008.

banking sector, denoted by $giips$, is defined as the VaR of banking industry j conditional on the GIIPS banking sector being in distress or conditioning on some event $C(X^{giips})$ of the GIIPS banking sector. The difference between the CoVaR conditional on the distress of $giips$ and the CoVaR conditional on the normal state of $giips$, which is referred to as $\Delta CoVaR^{j|giips}$, captures the marginal contribution of $giips$'s banking to the overall systemic risk of the banking industry j. The $CoVaR^{j|giips}$ can be explicitly defined as the qth quantile of the conditional probability distribution.

$$Pr(X_t^j \leq CoVaR^{j|C(X_t^{giips})}|C(X_t^{giips})) = q$$

and $\Delta CoVaR^{j|giips}$, denoting the banking $giips$'s contribution to country j's banking, is defined as

$$\Delta CoVaR^{j|giips} = CoVaR^{j|X_t^{giips}=VaR_q^{giips}} - CoVaR^{j|X_t^{giips}=Median^{giips}}$$

Through use of the $CoVaR$ measure, we can examine risk overflows from the banking sector in $giips$ to another banking industry j throughout the entire financial system. For example, $\Delta CoVaR^{j|giips}$ captures the rise in risk of banking j when the banking sector $giips$ is under financial stress. Several methods have been proposed to evaluate risk within the $CoVaR^{j|giips}$ setting, but in this work we opt to apply two methods, namely quantile regression and the DCC. The latter method is useful in assessing the dynamic and time-varying pattern of risk spillover in crisis periods (Adrian and Brunnermeier, 2016).

4.1 Quantile Regression

The classical OLS regression examines and models the relationship between explanatory variable X and the conditional *mean* of the dependent variable Y given $X = x$, whereas quantile regression aims to model the relationship between X and the conditional *quantiles* of Y given $X = x$ (Koenker and Bassett, 1978). In quantile regression, the parameter estimates the change in a specified quantile of the dependent variable produced by a one-unit change in the explanatory variable. Another distinction between OLS and quantile regression is that the OLS method is established upon minimizing the total sum of squared residuals and is intended to fit models for conditional mean functions. While quantile regression is built on the basis of minimizing asymmetrically weighted absolute errors and aimed to fit conditional quantile functions (Buhai, 2004).

Quantile regression is also more useful when it is important to incorporate extreme events into the model, such as studies on the financial crisis, in which the lower quantiles of the banking institution's returns are critical from an economic point of view. It also provides a better understanding of the conditional distribution of the response variable Y given $X = x$ when both lower and upper or all quantiles are intended. Mathematically, quantile regression minimizes the following equation for the q-th quantile where $e_t = y_t - \alpha_q - \beta_q X_t$ is the error term, i.e.

$$Q(\beta_q) = \sum_{t:y_t \geq \alpha_q + \beta_q X_t}^{N} q \mid y_t - \alpha_q - \beta_q X_t \mid + \sum_{t:y_t < \alpha_q + \beta_q X_t}^{N} (1-q) \mid y_t - \alpha_q - \beta_q X_t \mid \tag{2}$$

Similar to OLS, which fits a linear model to y_t by minimizing the sum of the squared error, quantile regression fits a linear model to y_t using the asymmetric loss function $Q(\beta_q)$. More specifically, quantile regression minimizes a sum that gives asymmetric penalties $q\ |e_t|$ for underprediction and $(1-q)\ |e_t|$ for overprediction. Although the estimation of equation 2 entails linear programming techniques, such as the simplex method, and does not assume any distributional form, the quantile regression estimator is asymptotically normally distributed.

To define the quantile regression estimation of CoVaR, consider the following quantile regression, which is estimated for each country j's banking index:

$$\hat{X}_{t,q}^{j,giips} = \hat{\alpha_q}^{j,giips} + \hat{\beta}_q^{j,giips} X_t^{giips}$$

where $\hat{X}_{t,q}^{j,giips}$ denotes the predicted value of returns of country j conditional on the GIIPS banking index return. The quantile regression coefficient, $\hat{\beta}_q^{j,giips}$, estimates the change in a specified q-th quantile of

$CoVaR^{j|X_t^{giips}}$ produced by a one-unit change in VaR_q^{giips}. If we use VaR_q^{giips} as a predictor, it gives the $CoVaR_q^{j,giips}$ measure for the conditioning event $C(X^{giips})$ in which $X_t^{giips} = VaR_q^{giips}$. However, $\Delta CoVaR_q^{j|giips}$ is presented by the following relations:

$$CoVaR_q^{j|X_t^{giips}=VaR_q^{giips}} = \hat{\alpha_q}^{j,giips} + \hat{\beta}_q^{j,giips} VaR_q^{giips} \tag{3}$$

$$CoVaR_q^{j|X_t^{giips}=VaR_{50\%}^{giips}} = \hat{\alpha_q}^{j,giips} + \hat{\beta}_q^{j,giips} VaR_{50\%}^{giips}$$

therefore, $\Delta CoVaR_q^{j|giips}$ is given by:

$$\Delta CoVaR_q^{j|giips} = \hat{\beta}_q^{j,giips}(VaR_q^{giips} - VaR_{50\%}^{giips}) \tag{4}$$

Note that the unconditional VaR_q^{giips} and $VaR_{50\%}^{giips}$ are estimated by the Gumbel distribution VaR and $\beta_q^{j,giips}$ is estimated by the q-th quantile of quantile regression. We demonstrate the estimation results of 1%-CoVaR, evaluated by equation 3, in Table 3. Common quantiles for computing (unconditional) VaR and CoVaR are the 1% and 5% levels. However, in this study, we intentionally mark the 1% quantile since it better represents severe events, i.e. crisis episodes, in the financial markets (Adrian and Brunnermeier, 2016).

4.2 Dynamic Conditional Correlation (DCC)

One potential shortcoming of the quantile regression procedure is that it does not allow us to accommodate for the time-varying and dynamic nature of systemic exposure to GIIPS's banking risk. Among the choices, a multivariate GARCH model can be employed to account for time-varying covariance structure between assets/returns. Engle (2002) introduced a model, famously known as the *Dynamic Conditional Correlation* (DCC), which is based on the decomposition of the conditional covariance matrix into conditional standard deviations and correlations.

The DCC model parameterizes the conditional correlations in two steps: estimation of univariate GARCH process and the standardized residuals, and then the estimation of correlation through the use of the standardized residuals obtained in the first step. Therefore, to account for the time-varying structure of risk exposure between different countries' banking indices and the GIIPS banking index, we employ the DCC model in this study. The CoVaR measure is then estimated for each banking industry j paired with the GIIPS index.

4.2.1 Construction of DCC Model

In order to estimate the time-varying conditional correlation through the DCC model, the two-step procedure of Engle (2002) is usually followed. In the first step of this procedure, the parameters of univariate conditional volatility models are estimated. In the second step, the standardized residuals from the estimated models are then evaluated to estimate the dynamic correlation structure. The purpose of the univariate step is to construct zero mean residuals. In order to choose a suitable univariate conditional volatility model, we fit several models to each return series, such as the AR and MA processes together with the GARCH(1,1) process to capture the time-varying volatility component. The assessment for the final model, from among those chosen, is conducted using Akaike Information Criterion (AIC). We finally select an AR(1)-GARCH(1,1) model, presented in the following equations. Consider the returns X_t^j for banking equity index j, defined by an AR process with ρ_j as the autoregressive parameter.

$$X_t^j = \rho_j X_{t-1}^j + \epsilon_t^j \tag{5}$$

with

$$\epsilon_t^j = \xi_t^j \sigma_t^j$$

where ξ_t^j is standard normal with mean 0 and variance 1. The residuals are conditionally normally distributed with a time-varying variance structure defined through the following GARCH(1,1) process:

$$\sigma_t^{2,j} = \alpha_0^j + \alpha_1^j \epsilon_{t-1}^{2,j} + \beta_{j,1} \sigma_{t-1}^{2,j} \tag{6}$$

where α_1^j and β_1^j are the parameters of the GARCH(1,1) process.

Having obtained the series for standardized residuals (ξ_t^j=ϵ_t^j/σ_t^j) for the banking industry j from the univariate step, we move on to the DCC setup. We construct the time-varying conditional correlation structure as suggested in Engle (2002). In a very general setting and for a set of n assets, the vector of returns $X_t = [X_{1,t}, X_{2,t}, \ldots X_{n,t}]$ can be denoted as

$$X_t \sim N(\mu, H_t),$$

$$H_t \equiv D_t R_t D_t \tag{7}$$

where μ is the vector of unconditional means, H_t is the variance covariance matrix and D_t is a diagonal matrix with standard deviations on the diagonal. R_t is the time-varying conditional correlation matrix, which is defined as:

$$R_t = E_{t-1}[\xi_t \xi'_t]$$

where,

$$\xi_t = D_t^{-1}(X_t - \mu) \quad \text{and} \quad \xi_t \underset{i.i.d}{\sim} N(0, I_n) \tag{8}$$

Using the standardized residuals ξ_t, extracted from the univariate setup, the component of the correlation matrix of the standardized residuals Q_t can easily be estimated.

$$Q_t = (1 - a - b)\bar{Q} + a\xi_{t-1}\xi'_{t-1} + bQ_{t-1} \tag{9}$$

$$R_t = Q^{*^{-1}}_{t-1} Q_t Q^{*^{-1}}_{t-1} \tag{10}$$

where Q_t^* is a diagonal matrix composed of the square root of the diagonal elements of Q_t. In equation 9, $\bar{Q}$ is the unconditional covariance of the standardized residuals obtained from the first stage of estimation and a and b are the scaler parameters such that $a + b < 1$.

4.2.2 DCC-CoVaR

We assume that each country's banking index and the GIIPS index follow a bivariate normal distribution.

$$(X_t^{giips}, X_t^j) \sim N\left(0, \begin{pmatrix} (\sigma_t^{giips})^2 & \rho_t \sigma_t^j \sigma_t^{giips} \\ \rho_t \sigma_t^j \sigma_t^{giips} & (\sigma_t^j)^2 \end{pmatrix}\right) \tag{11}$$

Where ρ_t and σ_t are the time-varying correlation and standard deviation, respectively, estimated by the DCC setup. Since the returns are assumed to be normally distributed, the returns distribution of banking j conditional on $giips$ banking is also normal,

$$X_t^j \mid X_t^{giips} \sim N\left(\frac{X_t^{giips} \sigma_t^j \rho_t}{\sigma_t^{giips}}, \left(1-\rho_t^2\right)\left(\sigma_t^j\right)^2\right) \tag{12}$$

The $CoVaR(q,p)$ as the q%-VaR of the banking system j given the $giips$ banking at its p%-VaR level is defined implicitly as:

$$Pr(X_t^j < CoVaR_t^{giips}(p,q) | X_t^{giips} = VaR_t^{giips}(p)) = q \tag{13}$$

Having obtained the conditional distributions, we move on to evaluating the conditional probabilities as:

$$Pr\left(Z_t < \frac{CoVaR_t^{giips}(p,q) - X_t^{giips} \rho_t \sigma_t^j / \sigma_t^{giips}}{\sqrt{\left(1-\rho_t^2\right)}\left(\sigma_t^j\right)} \mid X_t^{giips} = VaR_t^{giips}(p)\right) = q$$

where $Z_t = \left[\frac{X_t^j - X_t^{giips} \rho_t \sigma_t^j / \sigma_t^{giips}}{\sqrt{\left(1-\rho_t^2\right)}\left(\sigma_t^j\right)}\right] \sim N(0,1)$. The $giips$' VaR is given by $VaR_t^{giips}(p) = \Phi^{-1}(p)\sigma_t^{giips}$. Combining these relations, we get:

$$CoVaR_t^{j|giips}(p,q) = \Phi^{-1}(q)\sigma_t^j \sqrt{1-\rho_t^2} + \Phi^{-1}(p)\rho_t \sigma_t^j \tag{14}$$

And since for a standard normal distribution the $\Phi^{-1}(50\%) = 0$, we can estimate $\Delta CoVaR^{j|giips}(q,q)$ using the following equation (Adrian and Brunnermeier, 2016).

$$\Delta CoVaR^{j|giips}(q,q) = \Phi^{-1}(q)\rho_t \sigma_t^j \tag{15}$$

If we plug in the unconditional estimates of correlation and standard deviation in the equation above, instead of the time-varying ones, we obtain a new simplified fashion of the DCC-CoVaR model. We call this method Unconditional Correlation CoVaR (UC-CoVaR), which is formulated by the following equation:

$$\Delta CoVaR^{j|giips}(q) = \Phi^{-1}(q)\rho\sigma^{j} \tag{16}$$

In this equation, Φ^{-1} is the inverse of the normal cumulative distribution function, q is the chosen quantile, ρ is the sample correlation between country j and the GIIPS banking index, and σ^{j} is the standard deviation of j's banking index.

4.3 Guntay-Kupiec (GK) Test Statistics

In the systemic risk measurement literature, tail-dependence measures such as CoVaR can be employed as a basis to penalize Systemically Important Banking Industries (SIBIs). This can be done, directly, by imposing higher tax on such banking, or indirectly, by obliging them to enhance their regulatory capital and liquidity requirements. A disadvantage of the CoVaR measure, when it is evaluated by the quantile regression, is that CoVaR is often confounded by *"systematic risk"*. In other words, banking industries that have higher systematic risk will have a tendency to create larger (negative) CoVaR even though there is no indication of SIBI (Guntay and Kupiec, 2014).

In the newly proposed GK test (2014), such weakness is tackled by presenting a null hypothesis based on the assumption that returns of banking indices are normally distributed. This test offers the possibility to evidently differentiate systemic risk from systematic risk. Under the null hypothesis, the bivariate returns follow a parametric design with a Gaussian distribution. Having considered this distributional assumption, i.e. symmetric and tail-independent, the probability of an extreme realization in one return series is not driven by an extreme realization in another series. Therefore, we employ the GK test statistics to investigate whether the risk being considered is, in nature, systemic or systematic.

The following equation, a time-invariant version of equation 15, characterizes the closed form expression for the $\Delta CoVaR$ measurement approach under the null hypothesis of no systemic risk (Guntay and Kupiec, 2014).

$$\Delta CoVaR_{param}^{j|giips}(q) = \Phi^{-1}(q)\rho\sigma^{j} \tag{17}$$

In this equation, Φ^{-1} is the inverse of the normal cumulative distribution function, q is the chosen quantile, ρ is the sample correlation between country j and the GIIPS banking index, and σ^{j} is the standard deviation of j's banking index.

To build a statistical test for systemic risk, we compare the quantile regression $\Delta CoVaR$ estimator with the bivariate Gaussian parametric counterpart. Since the bivariate distribution is symmetric and tail-independent under the null hypothesis of no systemic risk, and no correlation, the parametric $\Delta CoVaR$ does not accommodate systemic risk. On the other hand, as the non-parametric estimator does not require returns to be symmetric or tail-independent, it might be utilized to examine the presence of systemic risk in the banking returns. The non-parametric estimation of $\Delta CoVaR$, similar to equation 4, is represented by the following relation:

$$\Delta CoVaR_{nonparam}^{j|giips}(q) = \hat{\beta}_{q}^{j,giips}(VaR_{q}^{giips} - VaR_{50\%}^{giips}) \tag{18}$$

By taking the difference between the non-parametric estimate of $\Delta CoVaR$ and the parametric estimate, the test statistics eliminate the effect of systematic or idiosyncratic risk under the null hypothesis. Under the same hypothesis, this difference, with an expected value equal to 0, has a sampling error that varies with respect to a chosen sample. This error depends on both the correlation of banking indices returns with the GIIPS banking index and the idiosyncratic risk of the individual banking index of each country. However, normalizing the difference can further control the idiosyncratic part of the error, but the returns correlation is still left as a *"nuisance"* parameter. Hence, this parameter must be controlled while constructing the Monte Carlo Simulation (MCS) test statistics. Therefore, the critical values for the test statistics are evaluated corresponding to the magnitude of correlations between the returns. The GK test statistics are then defined as:

$$GK^{j}_{CoVaR}(q) = -\frac{\Delta CoVaR^{j|giips}_{nonparam}(q) - \Delta CoVaR^{j|giips}_{param}(q)}{\sigma^{j}_{param}} \tag{19}$$

In this equation, $\Delta CoVaR^{j|giips}_{nonparam}(q)$ and $\Delta CoVaR^{j|giips}_{param}(q)$ are the non-parametric and parametric estimations of $\Delta CoVaR$, respectively. σ^{j}_{param} is the standard deviation of the returns for country j's banking. Since under the alternative hypothesis, banking indices returns are in part determined by systemic risk, the non-parametric estimators should create larger $\Delta CoVaR$. The null hypothesis cannot be accepted when there is evidence of a large systemic risk element existing in the banking indices. An MCS determines the critical values needed to reject the null hypothesis in favor of the alternative hypothesis (Guntay and Kupiec, 2014).

5 $\Delta CoVaR$ Estimation Results

This section reports our findings in this study. We obtain the $\Delta CoVaR$ estimates through the quantile regression and the DCC structure. In the following subsections, we describe the estimation procedure and the results obtained from each method.

5.1 $\Delta CoVaR$ Estimation Using Quantile Regression

The VaR of a banking equity index is proportional to the variance of that index, but the CoVaR exposure of that equity index conditioned on distress in the GIIPS banking sector is proportional to the covariance of the banking equity index and the GIIPS index. As a result, we need to assess the VaR of the GIIPS index to examine the $\Delta CoVaR$ exposure of each banking industry (see equation 4). The VaR is evaluated using the Gumbel distribution method. Gumbel distribution belongs to the class of extreme value distributions and successfully captures extreme events in our sample[1]. A method based on quantile regression, which requires this VaR estimation, is then applied to estimate the $\Delta CoVaR$ measure. In contrast to the ordinary least square regression, which approximates the conditional mean of the dependent variable given certain values of the predictor variables, quantile regression attempts to estimate either the conditional median or other quantiles of the dependent variable given certain values of the predictor variables.

In Table 3, the coefficient of the 1%-$\Delta CoVaR$ indicates the marginal effect of change in the 1%-quantile returns of each European country's banking index due to variations in the GIIPS banking index when GIIPS is at its stress state, 1%-VaR. It can be seen from the table that there is a fairly wide range of marginal effects of distress in GIIPS banking on the selected European countries' banking systems, ranging from 0.26 for Luxembourg to 1.25 for Belgium. The intercept indicates the 1%-quantile of the country's banking return. The GIIPS coefficient represents the change in the 1%-quantile of the country's return produced by a unit change in the GIIPS' banking index. For instance, the estimate for Belgium describes that a one-unit rise in the GIIPS' banking return raises the 1%-quantile of the Belgian banking industry's return by 1.25 units. From Table 3, it can be seen that the coefficient of GIIPS is significant for all countries at a 1% significance level. Therefore, there is no concern about the significance of the relation between the banking indices and the GIIPS index.

Table 4 describes the results of the CoVaR analysis using different methods. The table, in column $\Delta CoVaR$ (QR), presents the one-day $\Delta CoVaR$ estimates, using the quantile regression approach. For example, the $\triangle CoVaR$ measure for Belgium is more than 7%, which indicates that when the GIIPS banking industry goes to distress, from its median state, the returns of the Belgian banking sector decline by 7%.

Figure 1 depicts that the marginal effects of a one-unit change in the GIIPS's index returns in the 1% and 50%-quantile (or median) of the countries' indices (see columns of 1%-Coef and 50%-Coef in Table 4).

[1] For details on this VaR measurement method, see Kevin Dowd (2007).

	Austria	**Belgium**	**Czech Republic**	**Denmark**	**Finland**	**France**	**Germany**
Cons.	-4.44^{***}	-5.71^{***}	-5.92^{***}	-3.82^{***}	-5.05^{***}	-4.16^{***}	-4.37^{***}
	(0.27)	(0.19)	(0.73)	(0.20)	(0.24)	(0.18)	(0.25)
GIIPS	0.89^{***}	1.25^{***}	0.80^{**}	0.61^{***}	0.54^{***}	0.98^{***}	0.89^{***}
	(0.14)	(0.09)	(0.37)	(0.10)	(0.13)	(0.10)	(0.12)
	Luxemburg	**Netherlands**	**Norway**	**Poland**	**Sweden**	**Switzerland**	**UK**
Cons.	-3.58^{***}	-5.42^{***}	-5.19^{***}	-4.16^{***}	-4.12^{***}	-4.20^{***}	-4.11^{***}
	(0.17)	(0.38)	(0.27)	(0.15)	(0.19)	(0.21)	(0.21)
GIIPS	0.26^{***}	0.71^{***}	0.72^{***}	0.56^{***}	0.65^{***}	0.74^{***}	0.75^{***}
	(0.09)	(0.20)	(0.12)	(0.08)	(0.09)	(0.11)	(0.08)

Table 3: **Estimation results of the 1%-quantile regression.** This table reports the 1%-quantile regression outputs, based on equation 3, of the 14 European countries' banking indices on the GIIPS's banking index. The regression coefficients of GIIPS characterize the marginal effects. Standard errors are in parentheses. ***, **, and * denote the significance levels at 1%, 5%, and 10%, respectively.

Countries	Corr	VaR	1%-Coef	50%-Coef	$\Delta CoVaR$ (QR)	$\Delta CoVaR$ (DCC)	$\Delta CoVaR$ (UC)	GK-Stat
Austria	0.605	-6.051	0.893	0.552	-5.017	-2.277	-2.851	1.069
Belgium	0.667	-7.093	1.247	0.819	-7.009	-3.133	-3.835	1.284
Czech Republic	0.381	-7.033	0.796	0.329	-4.476	-1.592	-2.046	1.054
Denmark	0.552	-4.753	0.610	0.447	-3.427	-1.713	-2.182	0.732
Finland	0.501	-5.886	0.537	0.441	-3.018	-1.779	-2.401	0.300
France	0.765	-6.566	0.982	0.841	-5.522	-3.261	-3.976	0.692
Germany	0.684	-5.642	0.894	0.648	-5.025	-2.629	-3.172	0.930
Luxemburg	0.143	-3.824	0.265	0.000	-1.488	-0.236	-0.404	0.897
Netherlands	0.270	-6.239	0.707	0.326	-3.976	-1.995	-1.845	0.724
Norway	0.522	-6.110	0.717	0.480	-4.030	-1.898	-2.646	0.635
Poland	0.433	-4.500	0.560	0.306	-3.149	-1.415	-1.695	0.865
Sweden	0.617	-5.289	0.651	0.574	-3.659	-2.338	-2.752	0.474
Switzerland	0.654	-5.810	0.744	0.601	-4.180	-2.556	-2.966	0.623
UK	0.659	-5.246	0.745	0.607	-4.188	-2.605	-2.976	0.625

Table 4: **Estimation outputs of** $1\% - \Delta CoVaR$**.** This table presents the correlation between the banking indices and the GIIPS index, the 1%-Gumbel distribution VaR, on a daily basis, the 1% and 50% of quantile regressions coefficients, the one-day estimates of $\Delta CoVaR$, evaluated by quantile regression (QR), the average of DCC over the whole sample and the Unconditional Correlation (UC), and finally the GK test statistics for the banking industries.

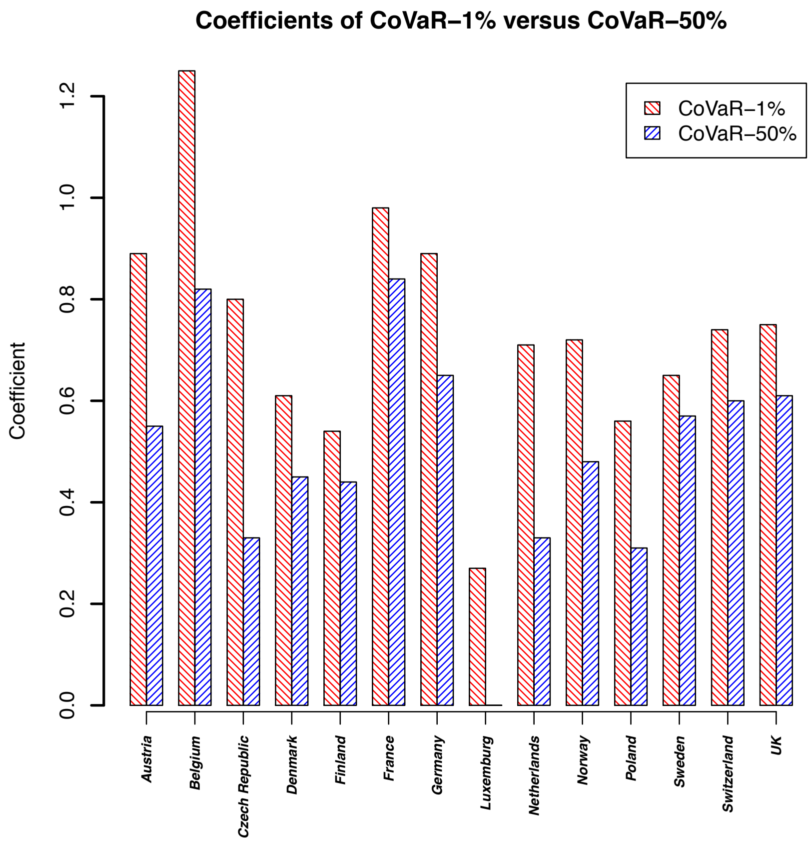

Figure 1: **Marginal effects of GIIPS banking on the European banking industries.** This figure contrasts the magnitude of the 1% with the 50% CoVaR coefficients of different European countries. These coefficients are extracted from Table 4.

For all banking indices, the 1%-quantile marginal effect (of a one-unit change in the GIIPS's return) is larger than the 50%-quantile marginal effect of the corresponding change in the GIIPS's index return. That is to say, when the GIIPS's banking industry is at its 1%-tail, a one-unit rise in the returns has a higher effect on the European countries' banking systems. This stylized fact is quite reasonable and rational. It shows that, as the GIIPS's banking system deviates one unit from its 1%-tail, in its worst condition, the other European countries' banking systems respond higher than when it deviates one unit from its 50% state, or its median.

5.2 $\Delta CoVaR$ Estimation Using DCC

We follow a four-step procedure to estimate $DCC - \Delta CoVaR$s. In the first step, we check whether or not each index is stationary. An ADF test has been employed to evaluate the stationarity of the banking indices, and it has been observed that the candidate data is stationary[1]. In the next step, we fit a set of ARMA-GARCH(1,1) models to each index. Based on the AIC, the AR(1)-GARCH(1,1) process comes out to be the best possible model for the chosen data. In the third step, we estimate a bivariate DCC(1,1) for the fitted standardized residuals of each series obtained from the AR(1)-GARCH(1,1). The motivation behind the choice of this model is that it is parsimonious in structure and captures and incorporates the time-varying volatility and correlation structure. In the final step, we plug-in the estimated time-varying correlation and standard deviation of each country's banking index in equation 15. It gives us time-varying estimates of $\Delta CoVaR$. This is important in order to analyze the behavior of $\Delta CoVaR$ throughout the period of study.

To contrast DCC-$\Delta CoVaR$ with quantile regression-$\Delta CoVaR$, we compute the mean of these time-varying estimates over the whole sample as an indicator of the $\Delta CoVaR$ estimate. Therefore, the main distinction between DCC and QR-$\triangle CoVaR$ is the time-varying structure in that measure, otherwise the interpretations are alike. The estimation results of $DCC - \Delta CoVaR$ are presented in Table 4, column $\Delta CoVaR$ (DCC).

[1]The results of the ADF test can be provided upon request.

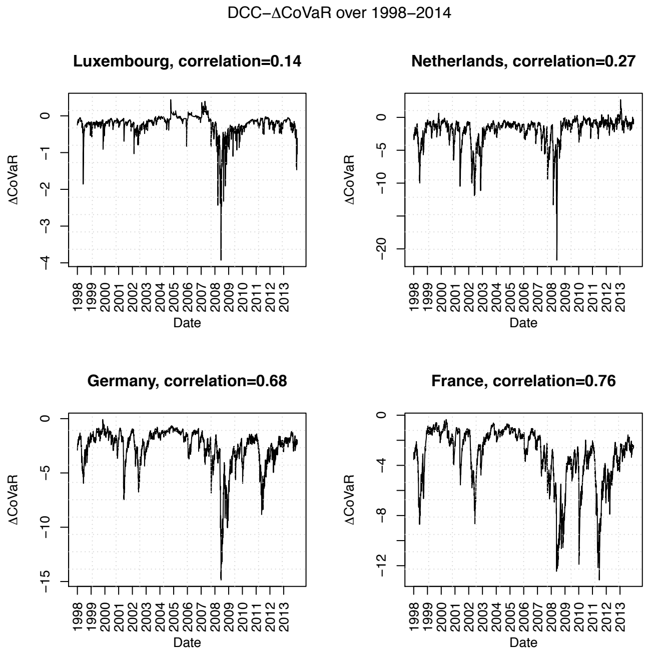

Figure 2: **Variations of daily** $DCC-\Delta CoVaR$**.** This figure shows the time-varying behavior of $DCC-\Delta CoVaR$ for the four selected countries, Luxembourg, the Netherlands, Germany, and France. These countries' indices have the lowest and the highest correlation with the GIIPS banking index, respectively, during 1998-2014.

Figure 2 demonstrates the daily DCC-$\Delta CoVaR$ of four countries. Two have the lowest correlation with the GIIPS banking index, i.e. Luxembourg with a correlation of 0.14 and the Netherlands with a correlation of 0.27, and other two have the highest correlation, i.e. Germany, 0.68, and France, 0.76. We might notice that the maximum value of systemic risk measure, the DCC-$\Delta CoVaR$, for Luxembourg and the Netherlands is around 4% and 21%, respectively, during the current financial crisis. While this value for Germany and France for the same period is in a range of 12-15%.

The spike in the Dutch DCC-$\Delta CoVaR$ banking relates to the crisis events for the Fortis group and other affiliated banks such as RBS and ABN AMRO (Fassin and Gosselin, 2011). These sharp downturns in the indices returns occurred at the end of 2008 when the financial markets faced severe distress and some of the large banks were rescued through the states' bailout plans. In that year, there was an extraordinary spike in the markets when Lehman Brothers collapsed. As a result, the financial crisis went into its most agitated state and created an excessive level of volatility in the market[1]. Therefore, the fluctuations of the four countries' banking indices are distinctly higher during the recent financial crisis period, 2008-2010.

So far, in the previous section, we discussed the findings obtained after evaluation of DCC-$\Delta CoVaR$ through equation 15. In order to see how this conditionality matters in the evaluation of risk, we evaluate $\Delta CoVaR$ by plugging in the unconditional cross-sectional correlation (of each banking index with the GIIPS banking index) and the simple standard deviation (of each European country's banking index) into equation 16. We name the new measure Unconditional Correlation-$\Delta CoVaR$, denoted by UC-$\Delta CoVaR$. The result of this measure is presented in Table 4. Since both UC-$\Delta CoVaR$ and DCC-$\Delta CoVaR$ measures are obtained from a similar formulation in equation 15, the cross-sectional correlation between UC-$\Delta CoVaR$ and the mean of DCC-$\Delta CoVaR$s is 0.97, which is very sig-

[1] It is somewhat remarkable that the ΔCoVaR measure, as an advantage, does not categorize the risk contribution as a causal effect of GIIPS or a common factor's risk (see Adrian and Brunnermeier, 2016).

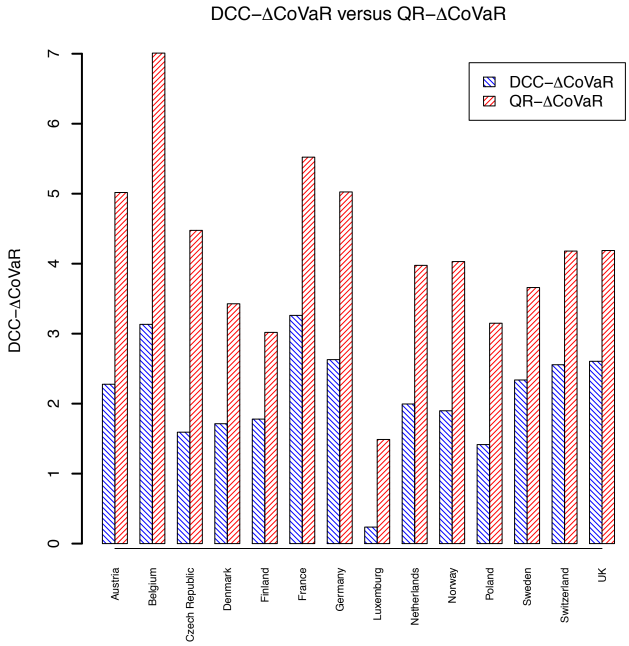

Figure 3: $QR - \Delta CoVaR$ **measure versus** $DCC - \Delta CoVaR$**.** The figure plots the quantile regression-$\Delta CoVaR$, denoted by $QR - \Delta CoVaR$, and the mean of the daily $DCC - \Delta CoVaRs$ in absolute terms.

nificant. The nearly perfect cross-sectional correlation of the UC and DCC-$\Delta CoVaR$ for the 14 countries is reasonably in line with the statistical and economic insight. The UC-$\Delta CoVaR$ represents rather close results to the DCC result, although it does not reflect the likely time-varying correlation between the countries' indices and the GIIPS index. However, the method's simplicity and straightforwardness is encouraging enough to rely on it when we lack adequate data for measuring $\Delta CoVaR$[1].

[1] For instance, in the continuation of this research we are supposed to estimate $\Delta CoVaR$ on a yearly basis, which would give us, at most, 260 observations. Therefore, based on our analysis we believe that in these cases we can rely on such unconditional models. Of course, applying this method implies considering constant variance and correlation, which seems rather unrealistic during turbulent times and for longer time-spans, but quite realistic for tranquil times and for shorter time-spans.

5.3 Quantile Regression (QR) versus DCC and UC-$\Delta CoVaR$

We estimate a time-invariant fashion of $\Delta CoVaR$ by quantile regression and a time-variant fashion by DCC. Regarding the fact that the estimation methods differ severely, the disparity between the estimations of quantile regression and the mean of DCC-$\Delta CoVaR$ is more remarkable and illustrative in Figure 3. In other words, it can be seen that the two methods produce very dissimilar patterns of systemic risk contribution[1]. The main benefit of the DCC specification is that it inherently incorporates an estimation of dynamic and contemporaneous correlation with GIIPS to estimate the magnitude of any potential tail spillover effects. Taking into consideration the existence of the heteroskedastic nature of correlation, it offers a powerful tool for cross-sectional forecasting since it absorbs tails more strongly (Adrian and Brunnermeier, 2016). The two methods, quantile regression and DCC, show a high positive correlation, 0.84, with each other. This suggests that these methods are capturing, but not perfectly, the same aspects of the state of the GIIPS and the main European countries' banking systems.

The scatter plots in Figure 4 better illustrate the relation between the correlation of the banking indices with the GIIPS index and the absolute value of $\Delta CoVaR$. The left scatter plot highlights the relationship between correlation and the absolute value of $QR - \Delta CoVaR$. The right scatter plot presents a positive relation between the correlation and $DCC - \Delta CoVaR$. This means that the positive relation between correlation and $\Delta CoVaR$ is even more evident for the $DCC - \Delta CoVaR$. We must notice that daily correlation, by construction, is an influential factor in the DCC method (see equation 15).

We observe that the $\Delta CoVaR$ measures move connectedly with correlation so must increase as the correlation of the European banking indices with the GIIPS index increases. The main reasoning for this conjecture is that countries with a higher correlation, or interdependence, must have been extremely affected by the spillovers of distressful events

[1] The next step for extending this research is to fit a time-varying quantile regression estimation by introducing some state variables in the model.

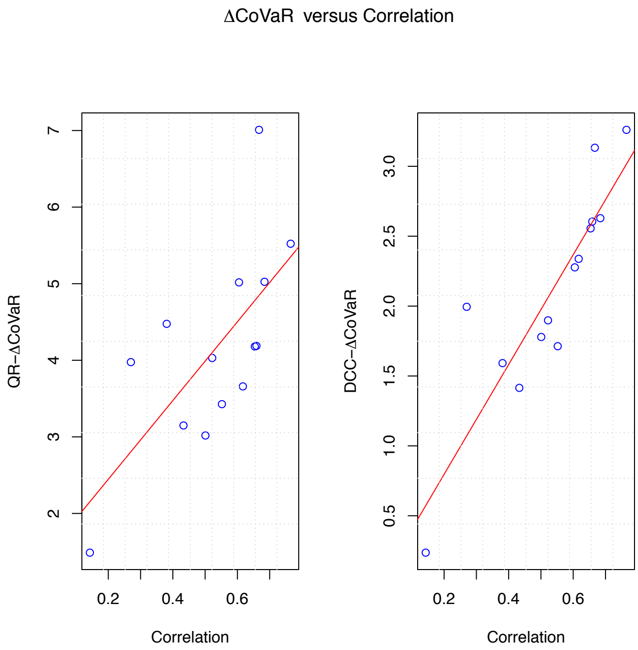

Figure 4: $\Delta CoVaR$ **against correlation.** These scatter plots demonstrate the relation between the correlation of European countries' banking indices with the GIIPS index and the absolute value of $QR-\Delta CoVaR$ and $DCC-\Delta CoVaR$, i.e. the mean of time-varying $DCC-\Delta CoVaR$s over the entire history of observations. The solid line on each scatter plot is a linear regression line of the correlations and the $\Delta CoVaR$s.

in the banking sector of GIIPS. Therefore, one can assume that an observed increase in correlation between a banking index and the GIIPS index signals a climb in the systemic risk potential (see De Nicolo and Kwast, 2002 and Schüler and Schröder, 2003).

5.4 $\Delta CoVaR$ Estimations in Pre-crisis and Post-crisis

So far in our analysis, we have considered a full range of data that involves both crisis and tranquil periods. However, it is also worth knowing the performance of the risk quantification methods in these periods

	Pre-crisis, 1998-2007				Post-crisis, 2008-2014			
Countries	**Mean**	**Std Dev**	**Min**	**Max**	**Mean**	**Std Dev**	**Min**	**Max**
Austria	0.054	1.409	-8.108	7.258	-0.051	2.710	-13.532	14.323
Belgium	0.004	1.584	-7.599	12.509	-0.089	3.409	-25.482	18.568
Czech Republic	0.061	2.226	-21.244	14.379	0.003	2.425	-18.984	14.222
Denmark	0.043	1.300	-6.407	15.312	-0.016	2.175	-14.660	11.339
Finland	0.035	1.643	-11.265	12.117	0.023	2.568	-18.212	19.624
France	0.029	1.706	-9.991	10.620	-0.031	2.857	-13.448	18.315
Germany	-0.001	1.544	-10.034	8.298	-0.064	2.529	-16.491	15.801
Luxembourg	0.022	0.984	-9.516	15.923	-0.124	1.485	-19.885	14.419
Netherlands	0.000	1.869	-10.791	13.485	-0.194	4.063	-129.914	15.116
Norway	0.038	1.511	-9.887	10.845	0.013	2.915	-19.222	25.487
Poland	0.056	1.578	-10.202	8.034	-0.004	1.825	-12.526	8.276
Sweden	0.018	1.611	-8.249	9.734	0.013	2.306	-10.793	14.655
Switzerland	0.006	1.716	-11.445	10.111	-0.043	2.260	-10.834	17.773
UK	0.003	1.534	-10.165	7.312	-0.042	2.433	-19.471	18.801
GIIPS	0.015	1.253	-6.920	7.815	-0.088	2.549	-10.322	15.497

Table 5: **Pre-crisis and post-crisis descriptive statistics of the daily indices.** This table presents the summary statistics, including mean, standard deviation, minimum, and maximum of the banking indices, in percentage, before and after the last financial crisis. As it illustrates, the post-crisis period, 2008-2014, is characterized by lower means, larger (negative) minimums, lower maximums, and larger daily standard deviations.

separately. In this section, we compare the $\Delta CoVaR$ estimation for two different time spans, before and after the 2007-2008 crisis. The first period ranges from April 1998 to the end of 2007, which involves several small crises, and the second period is from January 2008 to May 2014, which contains more stressful and volatile episodes due to the US subprime crisis (see Table 5).

Table 6 summaries the result for the estimates of $\Delta CoVaRs$ measured by both quantile regression and DCC for the pre-crisis and post-crisis periods. Here, we notice two interesting observations. The first remark is that it shows a rise in the correlation of banking indices with GIIPS after the crisis. The average of sample correlations before the crisis is 0.45, while it is 0.58 after the crisis. The second important observation is that the absolute value of QR-$\Delta CoVaR$ and DCC-$\Delta CoVaR$ escalate from a mean of 2.65% and 1.43% in the pre-crisis period to 5.87% and 3.13% in the post-crisis period, indicating more than 100% growth in the systemic risk evaluated by quantile regression and DCC, respectively. The change in the correlation and systemic risk, as a measure of volatility, could be an indicator of instability in the correlation and standard deviation for the entire period of study, 1998-2014.

5.5 Guntay-Kupiec (GK) Test Results

In Table 7 we report the 1%, 5% and 10% critical value estimates for 8 different empirical correlations of countries and GIIPS indices[1]. The critical values are evaluated using the MCS of the bivariate normal distribution of returns. 25,000 simulations are done for a sample size of 4,200 daily observations of zero means and unit variances[2].

Contrasting the GK test statistics, represented in Table 4, with the critical values of the corresponding correlation, reported in Table 7, shows that for all countries we cannot accept the null hypothesis at the significance levels of 1%, 5%, and 10%. This acknowledges the existence of

[1] There are 14 banking indices in the sample of which a few indices have the same or very close correlation with the GIIPS banking index.

[2] We have almost 4,200 daily observations for the period April 1998-May 2014; therefore, the sample size of each simulation, 4,200 observations, is chosen accordingly.

	Pre-crisis, 1998-2007			Post-crisis, 2008-2014		
Countries	**Corr**	**QR**	**DCC**	**Corr**	**QR**	**DCC**
Austria	0.380	-2.369	-1.124	0.692	-6.520	-4.076
Belgium	0.553	-2.434	-1.758	0.706	-9.209	-5.272
Czech Republic	0.344	-4.470	-1.353	0.438	-4.726	-1.977
Denmark	0.404	-1.719	-1.029	0.621	-4.976	-2.747
Finland	0.275	-1.531	-0.784	0.616	-6.539	-3.505
France	0.625	-3.501	-2.067	0.832	-7.686	-5.248
Germany	0.594	-2.608	-1.843	0.731	-7.017	-3.791
Luxemburg	0.108	-1.024	-0.109	0.161	-2.342	-0.485
Netherlands	0.607	-4.164	-2.197	0.153	-6.075	-1.366
Norway	0.409	-2.783	-1.092	0.567	-5.919	-3.233
Poland	0.319	-1.879	-0.987	0.535	-4.027	-2.084
Sweden	0.523	-2.398	-1.720	0.680	-5.692	-3.241
Switzerland	0.601	-3.461	-2.064	0.707	-5.663	-3.325
UK	0.622	-2.976	-1.944	0.683	-5.843	-3.500

Table 6: **Estimation outputs of the risk measure in the pre-crisis and post-crisis periods.** This table illustrates the cross-sectional correlation of the European banking indices with GIIPS and the $\Delta CoVaR$ evaluated by quantile regression (QR) and DCC before and after the 2007/2008 financial crisis.

Level/Corr	0.14	0.24	0.30	0.50	0.55	0.60	0.66	0.76
1%	-0.31	-0.30	-0.30	-0.28	-0.28	-0.27	-0.25	-0.22
5%	-0.21	-0.21	-0.21	-0.20	-0.19	-0.19	-0.18	-0.16
10%	-0.16	-0.17	-0.16	-0.16	-0.15	-0.15	-0.14	-0.13

Table 7: **Critical values of the GK test for various correlations.** This table presents the critical values estimates at 1%, 5%, and 10% significance levels obtained from the MCS of the GK test statistics.

tail-dependence and systemic risk. In other words, under the alternative hypothesis of the GK test, the magnitude of the non-parametric estimator, i.e. quantile regression, reflects tail-dependence in the examined data. To sum up, any crisis or tail event in the GIIPS banking sector significantly spillovers onto the European banking industry, which can be computed by employing the quantile regression method.

6 Conclusion

$\Delta CoVaR$ aims to extract externalities embedded in the fundamental comovement of financial institutions or spillover effects. In the current study, we calibrate the $\Delta CoVaR$ measure by applying two methods consisting of quantile regression, as a time-invariant approach, and DCC, as a time-varying approach. The findings indicate a significant spillover effect of GIIPS banking on the examined banking systems, especially during the recent financial crisis. The systemic risk of European banks reached its height in the recent financial crisis. Finally, the GK test indicates that the non-parametric method, such as quantile regression, yields larger negative $\Delta CoVaR$ values than the parametric method based on the Gaussian distribution. This acknowledges that the quantile regression method can capture the tail risk existing in the interconnection of the European banking systems and the banking sector in GIIPS.

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Paper II

Determinants of European Banks' Exposure to the Eurozone Debt Risk

Hassan Sabzevari

Abstract

This paper examines the financial fundamentals and market circumstances that determine variations in the sovereign risk exposure of large European banks. Employing the well-known CoVaR approach, it firstly quantifies the sovereign debt spillovers. Then, it attempts to find drivers of exposure to the Eurozone debt crisis. The results acknowledge the role of size, or total asset, during the phase of the 2008-2011 crises as a central determinant of risk exposure. In addition, stock market returns and volatility are key determinants of systemic risk exposure. We also show that variations in the risk exposures have not been driven by dissimilarities in individual financial features such as debt-to-equity, short-term debt-to-cash, and market-to-book value of equity ratios. It can be concluded that a mix of market-based factors, such as local/global market conditions, and bank size play a major part in driving the systemic risk exposure.

Keywords: Systemic Risk, CoVaR, Sovereign Debt, GIIPS, CDS
JEL Classification: C58, G01, G20, G23, C30, G32, E43, F30, H63

1 Introduction

The most severe impacts of the global financial crisis of 2007/2008 arose and extended into Europe immediately after the collapse of Lehman Brothers in the US. Since early 2009, five of the Eurozone countries, i.e. Greece, Ireland, Italy, Portugal, and Spain, the so-called GIIPS, failed to generate enough economic growth to meet their financial commitments. The concerns were highlighted in November 2009 when the Greek government disclosed that its fiscal deficit was twice as large as previously expected[1] (Bolton and Jeanne, 2011). The rapid widening of the debt distress generated a financial tragedy such that a few states such as Greece, Ireland, Portugal, Spain, and Cyprus defaulted on their government debts (Kalotychou and Remolona, 2013). The reasons leading to the GIIPS crisis are a mixture of joint and country-specific factors. Some of the factors are as follows: inappropriate risk assessment of the countries; too low borrowing costs for fragile economies; trade imbalances; small productivity levels in the GIIPS economies, and a decline in the competitiveness of those economies generous public sector benefits and, therefore, high government debt; chronic tax evasion; weak competitiveness or declining competitiveness; and finally granting huge amounts of risky credit to the property bubble, see Figure 6 in the Appendix (Desai, 2013).

Due to the fragility of the debt markets and the devastating impacts of any debt crisis on the real economy, this paper aims to investigate the determinants of the European banks' exposure to the sovereign debt crisis in the GIIPS countries. Banks are more vulnerable to negative externalities than other financial institutions. Several special features of banking systems give rise to concerns about systemic risk in this industry: their complex structure, high leverage, low cash-to-asset and low capital-to-asset ratios, and high interconnectedness. In addition, government debts have historically played an important part in the banking system. For example, European banks possess a substantial amount of sovereign debts[2] that enables them not only to earn interest income but also to

[1]The revision of the 2009 Greek budget deficit was 12.7% of GDP while the previous estimate was 6.0% (Lane, 2012).

[2]Figure 7 in the Appendix presents the outstanding credits of different countries to the

hold less regulatory capital compared to other types of asset (Barth et al., 2012). In 2011, and after the spike in sovereign risk, European banks, unlike the banking systems of the US and other countries, had to write-off the Greek debts[1]. This distress continued due to the increasing indebtedness of the GIIPS countries (Manzo and Picca, 2014; Black et al., 2016). Therefore, indebted banks demanded assistance packages from third parties such as other Eurozone countries, the ECB[2], or the IMF[3]. To sum up, the intimate interdependencies between the European banks and the GIIPS sovereign debts convey that the banking industry and debt crises are intertwined.

Even though there is no universally concise definition of systemic risk, its concept is a particularly strong propagation of failures from one institution, market, or asset to another. Mishkin defines systemic risk as *"the likelihood of a sudden, usually unexpected, event that disrupts information in financial markets, making them unable to effectively channel funds to those parties with the most productive investment opportunities"* (Mishkin, 1995, cited in Kaufman and Scott, 2003). Among the various methods used to evaluate systemic risk[4] our preferred measure of systemic risk is the CoVaR approach, introduced by Adrian and Brunnermeier for the first time in 2008. By computing this measure we mean exactly the so-called *"exposure CoVaR"* because it measures the extent to which an individual institution is affected by financial events in the GIIPS-block (see Adrian and Brunnermeier, 2016). This method is attractive with respect to its simplicity and also its beneficial output, i.e. presenting the risk contribution of an individual sovereign. In addition, the measure is not explicitly sensitive to size or leverage ratio, different from Acharya et al.'s (2012) model. In their method, Acharya and others comprise these features, i.e. market capitalization and financial leverage,

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GIIPS-block sovereigns. As an example, two large economies in the Eurozone, France and Germany, hold around 60% of the Greek and Italian debts.

[1] For instance, the American CDS market did not significantly react to the problems of Greece (see Kalbaska and Gątkowski, 2012).

[2] European Central Bank

[3] International Monetary Fund

[4] Systemic Expected Shortfall (SES), Systemic Risk Index (SRISK), Marginal Expected Shortfall (MES), Shapley Value methodology, and Lehar's approach.

into the measure.

We fit the CoVaR measure based on the daily returns of five-year sovereign CDSs and banks senior CDSs over the period 2007-2015. The sovereign CDSs are insurance-like contracts and the spreads are the cost of insurance to protect investors against losses on sovereign debts. The use of CDS data is encouraged by its growing importance in the global financial markets. In addition, CDS spreads reveal all information about the underlying debt and serve as a proxy for the counterparty's credit default probability (Kalbaska and Gątkowski, 2012; Alter and Beyer, 2014). In other words, sovereign CDS spreads represent credit risk in the global markets and the local economic forces. The spreads will rapidly adjust to reflect the latest financial conditions information on both direct and indirect linkages across economies. As an example, in 2008-2009, and after the outbreak of the global financial crisis, CDS spreads for private and public debt rose particularly in most developed countries.

To determine the drivers of systemic risk exposure, we run a fixed-effects panel regression of yearly CoVaRs on current-year market financials and also one-year lagged of individual bank qualities. We document economically significant observations of spillovers from public debts on the reviewed banks within financial crashes. We also find that those banks that hold higher assets in times of crisis or those that work in markets with unfavorable profiles, i.e. low returns and high idiosyncratic risks, tend to be further vulnerable to sovereign risk. Therefore, the results provide strong detail to suggest that systemic risk has deep roots in the flows of financial markets instead of bank-specific financial ratios. The flows are the local or global market indicators such as stock market returns and volatility and crisis-period effects. The results have implications for shaping regulatory policies before entering periods of heightened uncertainty.

There is an extensive body of literature on sovereign CDS spreads, in general, and on the Eurozone sovereign CDS spreads, in particular. One strand of this literature focuses on major drivers in sovereign CDS spreads and sovereign credit risk. For instance, Ang and Longsta (2013) and Longsta et al. (2011) examined the systemic sovereign credit risk in the US and Europe. They provide considerable evidence that the CDS spreads are related to common global and financial market factors rather than macroeconomic factors. Another strand of the literature investigates the drivers of either systemic risk in Europe or the Eurozone debt crisis independently. However, there is less evidence relating the contagion effects of sovereign debt crisis to individual European banks through the analysis of their CDSs. The first contribution of this study is that we shed more light on the relation between exposure of individual banks to the Eurozone sovereign debts. Moreover, we incorporate all the Eurozone distressed countries in a single index, denoted by GIIPS CDS index. Then, we try to determine the drivers of the individual banks' exposure to the GIIPS sovereign CDS spreads.

The remainder of this paper is organized as follows: Section 2 reviews the related literature on the sovereign debt crisis and its drivers; Section 3 discusses the data used in this study; the description of the considered risk measure, CoVaR, and the potential determinants of systemic risk are documented in Section 4; Section 5 presents our empirical results; finally, concluding remarks are given in Section 6.

2 Literature Review

Kalbaska and Gątkowski (2012) studied the long-term dynamics of CDSs after the "credit crunch" in August 2007. They carried out an analysis of fluctuations in correlations between CDS spreads of GIIPS along with some of the "core countries", France, Germany, and the UK. The core countries hold a large share of the GIIPS-block debts. The EWMA[1] correlation analysis in the period of August 2005-September 2010 indicates that sovereign risk mainly hit the EU countries and those "core countries". They found that there were several waves of contagion after the credit crunch and the global crisis. Furthermore, among the GIIPS-block, the CDS markets of Spain and Ireland had the biggest impact on the European CDS market.

[1] Exponential Weighted Moving Average

Barth and Yun (2012) analyzed the interdependency between banks and sovereign risk. In addition, the authors surveyed the relationship between sovereign risk and the size of a bank, as well as the extent of a bank's diversification abroad. They found supporting indications of different patterns existing in that relationship across countries and even across banks within the same country. Likewise, higher correlations between bank and sovereign risk were found in countries in which the ratio of the assets of banks relative to their home country's GDP was relatively high. They also found that the bailout of individual banks contributed to an increase in sovereign CDS spreads, while bank CDS spreads declined only among those banks that were bailed out.

Using sovereign CDSs for the US Treasury, individual US states, and major Eurozone countries, Ang and Longstaff (2013) contrasted the systemic credit risk of sovereign CDS spreads. The authors found that there was a strong heterogeneity across US and European issuers. That is, systemic risk among US sovereigns is much less than that among Eurozone sovereigns. In addition, most of the sovereign CDS spreads variations can be explained by US equity, volatility, and bond market risk premia. In other words, systemic sovereign risks in both markets are strongly linked to financial market variables rather than macroeconomic fundamentals.

Aizenman, Hutchison, and Jinjarak (2013) used a model to explain CDS prices of the 2009-2010 sovereign debt crisis. The authors aimed to identify the role of "fiscal space"[1] and other macro factors in accounting for the risk. They assert the large prediction errors of the GIIPS pricing models. They argue that "fiscal space" has been an important determinant of market-based sovereign risk. In addition, they found rigorous proof of mispricing, i.e. overpricing, in the GIIPS countries given the current "fiscal space" and other existing fundamentals. A possible interpretation of this finding is that the market is more considerate to non-economic factors or expectations of deteriorating future instead of existing fundamentals. In other words, the market players do not consider

[1] The paper defines "fiscal space" as financial wellbeing and flexibility of a government or, specifically, debt (deficit) relative to tax revenues. In their paper, "fiscal space" is measured as outstanding public debt relative to the de facto tax base.

current conditions or current fundamentals but the future expectations. The authors conclude that highly unpredicted errors in CDS pricing of GIIPS might be attributable to excessive pessimism and an overreaction to the current fiscal deterioration and fundamentals.

Manzo and Picca (2014) aimed to classify systemic shocks into sovereign and banking categories. The authors point out that sovereign shocks have a significant and persistent impact on banking systemic failures, but not vice versa. That is, a systemic risk in the banking industry has a smaller transitory influence on systemic sovereign risk. This result suggests that the sovereign exposure of banks is through asset/liability. Furthermore, they found a significant impact of sovereign shocks on foreign banks, but lower in magnitude than their impact on domestic banks.

Reboredo and Ugolini (2015) investigated systemic risk in the European debt market before and after the arrival of the Greek debt crisis. The authors employed sovereign bond benchmark indices and the Copula-CoVaR measure. Their results provide verification of systemic risk expansion for the distressed countries, especially for the Portuguese market. Also, the findings show strong comovement between the European debt market and the EMU[1] index before the debt crisis. For those non-distressed and decoupled countries from Greece, the systemic impact of the Greek debt crisis was less.

3 Data

We measure sovereign risk using daily quotes of five-year senior CDSs, as the most actively traded and the most liquid ones, and five-year sovereign CDS index for GIIPS over the period 2007-2015. We collect all five-year CDSs of banks based in European countries consisting of Austria, Belgium, the Czech Republic, Cyprus, Denmark, Finland, France, Germany, Hungary, Iceland, Luxembourg, Norway, Poland, Romania, Russia, Switzerland, Sweden, and the United Kingdom. The first set of data includes 100 CDSs for different banks in those 18 countries. However, 61 of those banks are subsidiary of another larger bank or holding, that is, it remains

[1] European Economic and Monetary Union

only 39 CDSs. Moreover, several CDSs, out of the 39 remaining CDSs, have not been traded during the years of analysis, 2007-2015. As a result, the final data set covers 25 banks/CDSs in 10 different countries. These banks have issued loans in Austria, Belgium, Denmark, France, Germany, Iceland, Norway, Russia, Sweden, and the UK. The banks are listed in Table 7 in the Appendix.

Unlike for bank CDSs, we cannot obtain the GIIPS CDS index from Capital IQ or other databases. Hence, we construct a GDP-weighted index of the five comprising countries within the GIIPS-block. The yearly GDPs of the constituent list are collected from the Eurostat database. Table 1 reports summary statistics for the five-year CDS spreads[1] of the distressed sovereign sources. According to this table, the average/mean of the Greek sovereign is 12 times more than the Spanish/Italian and six times more than the Portuguese one. Greece declared its official request for financial assistance in May 2010, followed by Ireland in November 2010, and Portugal in May 2011 (see Figure 1). In addition to the 2010 bailout package, a public offer for the exchange of privately owned Greek debt, as a debt exchange, was concluded on 8 March 2012. Accordingly, the settlement date for the securities was deferred to 11 April 2012. On this date, the Greek CDS spreads began to plunge from beyond 25,000 to 9,000 bps, a 65% drop.

A description of the selected explanatory variables can be found in Table 2. This table reports the mean values of the considered explanatories in 2007-2015. The mean for all of the explanatory variables alternates during the crisis period compared to the non-crisis periods. More precisely, the mean of the individual market's risk (standard deviation: *SD*), European volatility index (VSTOXX: *V*), correlation of stock markets (*C*), leverage ratio (debt-to-equity: *DE*), and short-term debt-to-cash ratio (*DC*) substantially increases, while the mean for stock market returns (*R*) and market-to-book ratio (*MB*) decreases significantly in the crisis period. The summary statistics point to the main argument of this paper that there is indeed a disparity between the two periods of "non-crisis"

[1] The five-year contracts are the most traded CDS in the market since they are traded and initiated at a low cost (see Liu, 2015).

CDS	**Mean**	**Std Dev**	**Min**	**Max**
GIIPS	318.48	380.76	4.35	2098.38
Greece	2270.91	4145.19	4.40	25960.76
Ireland	229.16	247.60	1.80	1286.91
Italy	170.12	132.71	5.30	595.67
Portugal	328.00	349.88	3.40	1762.10
Spain	169.97	139.69	2.40	636.67

Table 1: **Descriptive statistics of the sovereign CDS spreads.** The table reports the descriptive statistics, i.e. mean, standard deviation, minimum, and maximum, of the CDS spreads level in basis points of the six sovereign risk sources (of the GIIPS index and the five sovereigns) over the entire sample period of 2007-2015.

and "crisis". All of the explanatory variables, i.e. individual market characteristics and bank-specific data, are collected from Capital IQ.

4 Methodology and Variables

We follow the systemic risk literature to relate the GIIPS debt crisis to financial fundamentals. We conduct the analysis by employing a fixed-effects (FE) panel regression. The final specification of the FE-panel regression takes the form of the model in equation 1.

$$\begin{aligned} \triangle CoVaR_{i,t}^{i|giips} = \; & \alpha_i + \beta_1 CDA_{i,t-1} + \beta_2 A_{i,t-1} + \beta_3 R_{i,t} + \beta_4 SD_{i,t} + \\ & \beta_5 V_t + \beta_6 RSD_{i,t} + \beta_7 C_{i,t} + \beta_8 MB_{i,t-1} + \\ & \beta_9 DC_{i,t-1} + \beta_{10} DE_{i,t-1} + \epsilon_{i,t} \end{aligned} \quad (1)$$

In this equation, yearly $\triangle CoVaR_{i,t}^{i|giips}$ is regressed on the main potential explanatory factors. Therefore, the right-hand side of equation 1 includes the supposed risk drivers/determinants, which are computed on a yearly basis. These variables are the product of crisis dummy (*CD*)

Selected Variables and the Indication for Systemic Risk		Mean		
Variables	**Indication**	**Non-crisis**	**Crisis**	**Total**
Mean of Returns (*R*)	Economic Condition	0.02	-0.05	-0.01
Standard Deviation (*SD*)	Market Systematic Risk	1.12	2.08	1.55
VSTOXX (*V*)	European Market Volatility	3.66	9.63	6.31
Return/Std Dev (*RSD*)	Market Adjusted Return	0.02	-0.01	0.00
Correlation (*C*)	Stock Market Interconnection	0.71	0.82	0.76
Total Asset (*A*)	Size	2.97	3.49	3.15
Market/Book (*MB*)	Growth Expectation	0.31	0.00	0.15
Debt/Cash (*DC*)	Banking Run Issues	0.47	0.80	0.63
Debt/Equity (*DE*)	Leverage or Solvency	1.31	1.88	1.61

Table 2: **Description of explanatory variables.** This table lists the selected variables, their indication for systemic risk, and also their sample mean in non-crisis, crisis, and total period of 2007-2015. Mean and standard deviation of returns are in percentage. Total asset (A), market-to-book (MB), debt-to-equity (DE), and short-term debt-to-cash (DC) ratios, are in logarithmic format.

and total asset (*A*), denoted by CDA, the mean of stock market returns (*R*), the individual market's risk or standard deviation (*SD*), the European volatility index or VSTOXX (*V*), the ratio of *R* to *SD*, denoted by *RSD*, correlation of stock markets (*C*), short-term debt-to-cash ratio (*DC*), market-to-book ratio (*MB*), and, finally, the debt-to-equity ratio (*DE*). Amongst the explanatory variables, the financial characteristics such as total asset, market-to-book, short-term debt-to-cash, and debt-to-equity ratios are lagged by one-year.

4.1 $\triangle CoVaR$ Method

Based on a mixture of Value at Risk (VaR) and comovement concepts, Adrian and Brunnermeier (2016) estimate the marginal contribution of each single institution to the overall systemic risk. The so-called $\triangle CoVaR$ approach proposes an analytical framework for measuring spillover effects and inter-linkages between the GIIPS sovereign debt and European banks. More specifically, $\triangle CoVaR$ captures the VaR of a banking institution conditional on the fact that the GIIPS countries are under distress.

This measure can be computed using different methods, such as quantile regression, Multivariate GARCH, DCC[1], and Cupola. Under some simplifying assumptions on the DCC method, we obtain the $\triangle CoVaR$ estimates through the Unconditional Correlation structure, denoted by UC-CoVaR. Making very minor manipulations to Adrian and Brunnermeier's (2016) setup[2], the UC-CoVaR is assessed by plugging in unconditional or time-invariant estimates of correlation and standard deviation in Equation 2. With regard to this current study, UC-CoVaR reflects the risk spillover from the GIIPS's sovereign debts to individual European banks. We estimate the risk measure on a yearly basis from daily observations in that year meaning that we have, at most, 260 daily observations in hand. Therefore, we lack adequate observations to run other sophisticated or data-centered models such as quantile regression[3]. Another rea-

[1] Dynamic Conditional Correlation

[2] Adrian and Brunnermeier (2016) evaluated the conditional estimations of correlation and standard deviation utilizing multivariate GARCH.

[3] Quantile regression estimates the comovement in the tail/quantile observations using

son for using UC-CoVaR is that the estimates of correlation and standard deviation (on a yearly basis of daily observations) make this specification simple enough and, at the same time, allow us to update the estimation for each year.

$$\triangle CoVaR^{i|giips}(q) = \Phi^{-1}(q)\rho_{(i,giips)}\sigma^{i} \tag{2}$$

Equation 2 measures the exposure of bank i to the risk caused by sovereign debts in GIIPS. The expression depends on the correlation between bank i's CDS spreads and the CDS spreads of the GIIPS countries, denoted by $\rho_{(i,giips)}$, and the standard deviation of the bank's CDS spreads, denoted by σ^{i}. In this equation, $\Phi^{-1}(q)$ represents the CDF inverse of normal distribution at q-percent quantile, 1% and 5% in this study. The estimates of correlation and standard deviation are constant or time-invariant for each year. The $\triangle CoVaR$ estimation is conducted for six risk sources including the GIIPS-block and the five countries within GIIPS. The GIIPS-block sovereign CDS is a GDP-weighted index of the five sovereign CDSs.

4.2 Variables

The set of variables to detect the drivers of sovereign risk includes standard idiosyncratic bank financial profiles and market conditions. The core explanatory variables are the mean and standard deviation of stock market returns, correlation, VSTOXX, total asset, market-to-book, debt-to-equity or leverage, and short-term debt-to-cash ratios, and the crisis dummy. These variables have been frequently mentioned as the potential determinants of systemic risk.

A few studies deliver evidence of stock market indications for the state of the economy. For instance, Levine and Zervos (1996) demonstrate a positive relationship between stock market development and long-term economic growth (cited in Manzo and Picca, 2014). In another study, Ang et al. (2013) provide empirical support that sovereign credit spreads are related to financial market variables. Stock market prices re-

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the entire history of data

flect the evaluation of all market players on different listed firms' future prospects. They also contain the impact of the firms' interdependencies with other institutions or overseas economies. To wrap up, economists believe that embedded systemic risk in the financial system is less when the stock market is growing (Ang and Longstaff, 2013).

The correlation of stock markets designates the degree to which the markets tend to move together. Therefore, it generally proxies for the development of interdependencies or potential contagion risk[1] among markets though it does not give an indication of the direction of the spillover (see De Nicolo and Kwast 2002). In other words, correlation by itself can be used to explain the contagion effect by investigating the relationship between stock index and both bank and country characteristics.

The VSTOXX index is based on the Euro STOXX 50[2] real-time option prices and is designed to reflect market expectations of the European market-wide volatility. This index is meant to be forward looking and is calculated from both call and put options (De Bruyckere et al., 2013). In the literature, a strong relation between sovereign credit risk and the implied volatility index has been observed[3]. Higher VSTOXX values signal predictable fluctuations of short-term volatility in the market. In other words, upsurges in the VSTOXX index indicate uncertainty regarding the strength of economic fundamentals. Therefore, we expect a positive relation between the VSTOXX index and the risk measure (Black et al., 2016).

Total asset is one of the main bank-specific variables that are considered in this paper. We use the natural logarithm of a bank's total asset to proxy for the bank's size. The positive (or negative) contribution of size-variable on systemic risk is not theoretically determined and is primarily linked to the outcomes of various contrasting channels. There are three main channels in which size affects systemic risk: "guarantee", "diversification", and "monopoly". For that reason, the degree of importance

[1] In the literature, contagion is broadly defined as excess correlation that is a significantly unexpected deviation from the correlation induced by economic fundamentals (see Poirson and Schmittmann, 2013).

[2] The Euro STOXX 50 index was introduced in 1998 and is composed of 50 stocks from 12 Eurozone countries.

[3] See Pan and Singleton, 2007.

and the sign of size have to be determined empirically for any specific research.

The "guarantee channel" can describe the rationale behind the amplifying effects of size on negative spillovers. In the case of financial distress, large banks are more likely to be rescued by state bailouts. The bailout packages are intended to rebuild confidence in the financial markets and public view. Optimism for state bailouts might encourage managers to engage in risky projects or investments (see De Bruyckere et al., 2013 and Gandhi and Lustig, 2015). The "diversification channel", on the one hand, implies that well-diversified banks suffer less individual risks. That is, to diversify and manage stand-alone risks, large banks are inclined to participate in more banking activities. Therefore, diversified portfolios of assets and liabilities are more systemically interconnected to other banks or financial institutions and are of higher systemic importance. In other words, although diversification provides ex-ante benefits, it also causes ex-post contagion (see Zhou, 2010; Moore and Zhou, 2014; Korte and Steffen, 2014). In terms of the "monopoly channel", it is worth mentioning that large and monopolistic banks can raise their profits and accordingly lessen their systemic risk externalities to the system. As a supportive argument, more profitable banks are less vulnerable to macroeconomic or liquidity shocks due to holding higher capital buffers (Bostandzic and Weiß, 2013).

The market-to-book ratio (*MB*), i.e. the market value divided by the book value of common equity, shows optimistic expectations for the banking system and proxies for growth opportunities. The ratio contains some additional information about the relationship between financial risk and capital structure. Because of the growth opportunities or competitive advantages, a higher *MB* ratio should reflect greater expected future gains. Those glamour banks, i.e. those with high *MB* ratios, hypothetically augment more to systemic risk and destabilization of the financial system. Therefore, this must imply a positive relationship with the CoVaR measure (Liu, 2015).

Leverage ratio, or the ratio of debt-to-common equity, discloses the solvency of banks. A greater proportion of equity provides a cushion regarding the strength of a bank or financial institution. A few studies confirm the hypothesis that highly leveraged banks contribute more to systemic risk and perform worse than their competitors during the financial crisis. In other words, leveraged banks not only have lower capacity to resist shocks but also contribute undesirably to economic volatility. The more a bank is vulnerable to downturns and business cycles, the greater the likelihood of credit default. Thus, we expect a positive relation between leverage ratio and systemic risk indicators (see Adrian and Brunnermeier, 2016; Bostandzic and Weiß, 2013, López-Espinosa et al., 2012).

The specialty of banks and their vulnerability to runs is widely recognized in the economic literature. A bank run occurs when a large number of a bank's customers simultaneously withdraw cash from their deposit accounts. It is a systematic response to the perception of the bank's solvency risk. The critical financial ratio to analyze "banking run" is the ratio of cash reserves to demand deposits, the so-called fractional-reserve ratio. If this ratio is low, the bank's reserves will not be sufficient to cover the withdrawals. As a result, the panic response might turn into a true default situation for the bank. In this survey, we consider the short-term debt-to-cash ratio (*DC*) as a hint for the fractional-reserve strength of a bank.

It is repeatedly claimed that, in the course of any crisis, there is an escalation in the systemic risk factors, i.e. correlation and standard deviation. For instance, relying on the EWMA correlation analysis and the Granger-causality test, Kalbaska and Gątkowski (2012) demonstrate that correlations and cross-county interdependencies increased after 2007. In other studies, the researchers document an intimate joint movement of financial markets during times of crisis (De Bruyckere et al., 2013). The crisis dummy in our research is a factor classifying two periods: "non-crisis", 2007 and 2012-2015, and "crisis", 2008-2011. As a result, we assign values of zero to the "non-crisis" and one to the "crisis" period in the years of examination. The time horizon of 2008-2011 is chosen to indicate the persistent shocks to the financial markets and the real economy following those two crises. This means that, from theoretical aspects, there must be a one-to-one relationship between this dummy and the

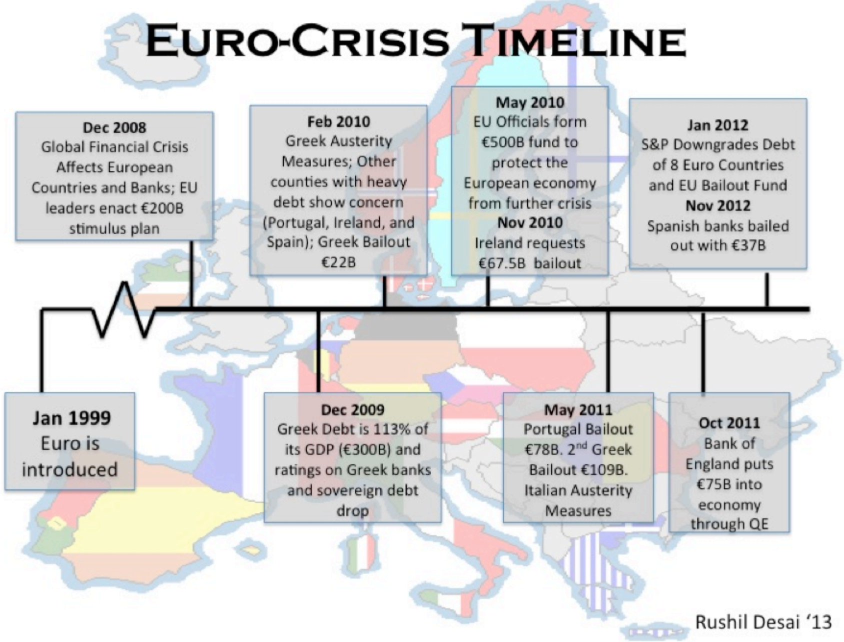

Figure 1: **European debt crisis timeline.** This figure elaborates the chronology of the sovereign debt crisis of December 2009-November 2012 (Desai, 2013).

systemic risk measure.

5 Estimation Results

The objective of our empirical analysis in this section is to explore the determinants of European banks' exposure to the sovereign debt crisis. In the first phase, we evaluate the UC-CoVaR measure of systemic contagion from the sovereign debt in GIIPS to the European banks. In the second step, we attempt to uncover the main determinants of systemic risk by investigating the relationship between sovereign debt risk spillovers and bank/country financials. This section also examines the systemic risk exposure from the decomposed sovereigns within GIIPS, i.e. Greece, Ireland, Italy, Portugal, and Spain, on the individual banks.

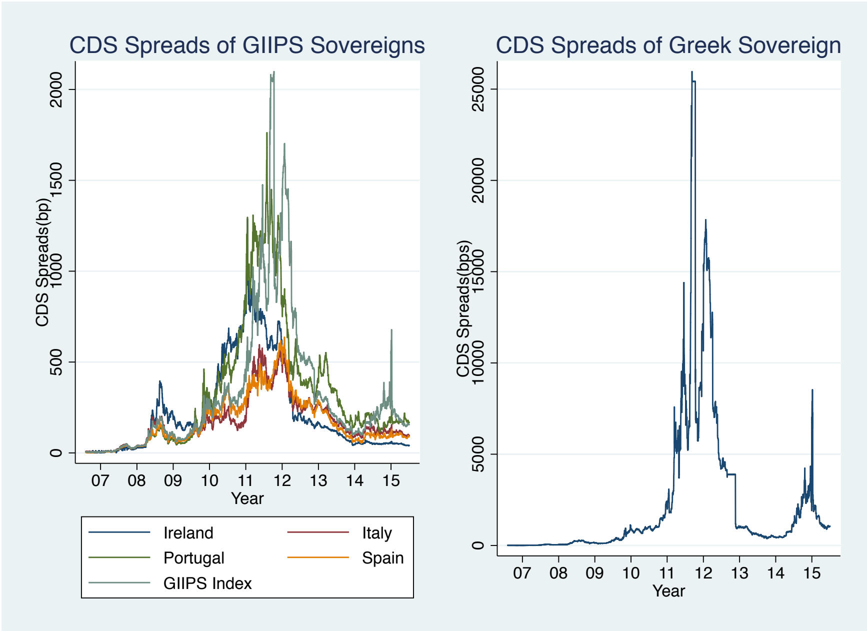

Figure 2: **CDS spreads of GIIPS sovereigns and GIIPS index.** These plots display the CDS spreads, in basis points, of six different risk sources during 2007-2015. The CDS spreads of the Greek sovereign is plotted separately due to the higher level of spreads compared to other CDSs.

5.1 Sovereign CDSs and Crisis Chronology

As mentioned before, we apply the measure to CDS spreads. A CDS contract is an agreement that allows the transfer of credit risk between two parties, the buyer and the seller. The buyer pays a predetermined amount of periodic premium (or spread) to hedge the underlying loan against the default of the issuer. As soon as the issuer defaults, the insurance seller pays the loan's outstanding amount to the buyer. Therefore, the CDS spreads implicitly reveal forward-looking information about the creditworthiness of the loan issuer (Manzo and Picca, 2014). In a couple of studies, it is empirically verified that sovereign CDS spreads encompass principal credit risk information on a country's banking system (see Avino and Cotter, 2014).

Figure 1 illustrates the chronology of events in the "Eurozone crisis" and the economic breakdown of the five risky countries in Europe (see Desai, 2013). For instance, from 2007 to 2010, the Irish public debt-to-GDP ratio rose roughly 20% annually. Irish banks and sovereign debt were increasingly vulnerable in the autumn of 2008 and co-moved strongly after the Eurozone crisis[1]. The Irish CDS spreads reached a peak of over 600 basis points by the start of 2011. These countries were seen even as the main source of cross-country spillovers in the Eurozone since early 2009. During the crisis, Euro-area countries were most strongly affected by cross-country spillovers from the countries within GIIPS. In October 2011, Sir Mervyn King, Governor of the Bank of England, signified the crisis as *"the most serious financial crisis at least since the 1930s, if not ever"*. As a result, CDS spreads of sovereign debt swiftly rose immediately after November 2009 and in the course of crisis. The five-year senior CDS spreads for the five countries within the GIIPS-block and also the GIIPS index are plotted in Figure 2.

As of 2010, the spreads of the GIIPS-block started to trend upwards dramatically due to the imminent crisis expectations. In this year, the GIIPS's CDS spreads ranged from 153 bps for the Italian debt to 562 bps for the Greek sovereign debt. Looking at the evolution of the CDS spreads, we notice that the volatility of sovereigns was the highest during 2011. For most CDSs, the volatility expanded sharply when the markets tumbled and it touched the highest level within a nine-year window in 2011.

However, the Greek CDS spreads continued surging even in 2012, exceeding 25,000 bps due to the market pessimism on the Greek default or debt restructuring (see Figure 2). The distinguished behavior of the Greek sovereign CDS spreads might imitate a distinct perspective of the debt sustainability in Greece compared with the sovereign debts in Spain and Italy. The Spanish and Italian economies are larger in size than the Greek economy and are tied more strongly to Eurozone with respect to their fiscal fundamentals. As a result, the market outlook for Italy and Spain is compared with the general outlook for the Euro area. In contrast, the Greek CDS spreads considerably broadened following the first

[1] For more information on the debt crisis in the Eurozone, see Heinz and Sun, 2014.

Sample Mean	$\Delta CoVaR - 1\%$			Stock Market Correlation		
Risk Source	**Non-crisis**	**Crisis**	**Total**	**Non-crisis**	**Crisis**	**Total**
GIIPS	1.40	3.64	2.34	0.71	0.82	0.76
Greece	0.73	3.09	1.73	0.35	0.59	0.46
Ireland	1.53	2.94	2.12	0.63	0.70	0.66
Italy	2.25	3.60	2.82	0.69	0.81	0.74
Portugal	1.86	3.53	2.57	0.60	0.75	0.67
Spain	1.99	3.53	2.64	0.67	0.79	0.72

Table 3: **Sample mean of $\Delta CoVaR - 1\%$ and correlation.** The first part of this table shows the sample mean of sovereign risk exposure ($\Delta CoVaR - 1\%$) of all examined banks during the non-crisis, the crisis, and the entire period of 2007-2015. The second part displays the yearly mean of correlation of the stock markets, which have at least one representative bank amongst the 25 examined banks, with the five countries within GIIPS and also the GIIPS stock index.

state restructuring in mid-2011, persistently well above 1,000 bps.

5.2 Estimation of $UC - \triangle CoVaR$

We estimate the $\triangle CoVaR$ measure by the UC method of equation 2. The invariant estimates of correlation and standard deviation are plugged in this equation. The correlation between bank i's CDS spreads and the CDS spreads of the GIIPS is denoted by $\rho_{(i,giips)}$ and the standard deviation of bank i's CDS spreads is denoted by σ^i. It is obvious that $\triangle CoVaR$ is a negative number if the correlation is non-negative. In order to make the interpretations more straightforward, we multiply the $\triangle CoVaR$ values by minus one. The $\triangle CoVaR$ estimation is done for six risk sources including the GIIPS-block and the five countries within GIIPS. The GIIPS-block sovereign CDS is a GDP-weighted index of the five sovereigns.

Table 3 presents the means of $\triangle CoVaR - 1\%$ and stock market correlation over three subsamples: the "non-crisis period", 2007 and 2012-2015, the "crisis period", 2008-2011, and the "total sample", 2007-2015.

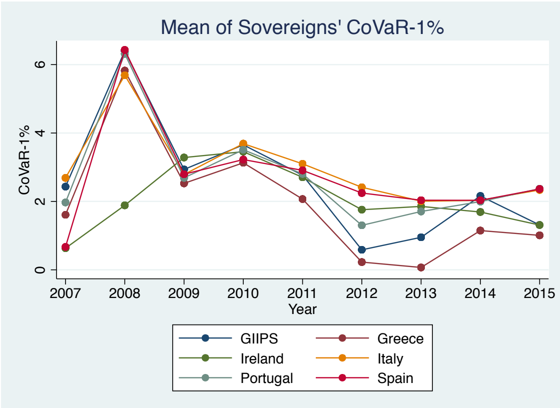

Figure 3: **Mean of yearly** $\triangle CoVaR - 1\%$ **from different sources.** The graph depicts the yearly cross-sectional mean of $\triangle CoVaRs - 1\%$ for all 25 banks in 2007 to 2015. The exposure is decomposed into six different sources, i.e. five sources amongst the GIIPS countries and also the GIIPS index itself.

The non-crisis period is considered as a period of stability for the European banking system. In contrast, in the financial/debt crisis period, the risk elements of correlation and standard deviation are quite unstable and volatile. Based on the $\triangle CoVaR$ measure, three observations are noteworthy. First, the yearly mean of $\triangle CoVaR$ heightens in the crisis for different sovereigns. Specifically, the mean of $\triangle CoVaR$, caused by the Greek sovereign debt, is roughly three times larger during the crisis compared to the non-crisis period. Second, the mean of stock market correlation rises for all of the distressed countries during the crisis but not as notably as the rise in the $\triangle CoVaR$. Third, the Italian sovereign debt has the highest externalities of the reviewed banks. That is to say that the European banks are, on average, more vulnerable to sovereign distress in Italy than other sovereign debts in the GIIPS countries[1]. However, this evidence seems largely unsurprising due to the size and importance of the Italian economy in the Eurozone and also in Europe as a whole.

[1]For more details on this observation, see Kalotychou and Remolona, 2013.

5.3 $\triangle CoVaR$ and Time-effect

The global financial crisis broke out in the autumn of 2008, whereas the GIIPS debt crisis adversely emerged right after the gradual indications of global economy recovery in 2010. Nevertheless, Europe continued to remain systemically fragile subsequent to the extension of the debt crisis. The risk level was still large until the end of 2011 due to deteriorations in sovereign fundamentals and rising government debt levels. Figure 3 shows the yearly cross-sectional mean of $\triangle CoVaR$, sourcing from the GIIPS sovereigns, on the examined banks over 2007-2015.

We run OLS regressions to explain the fluctuations in the $\triangle CoVaR$s of GIIPS on the selected banks during the evaluation period. Table 4 reports the regressions of the dependent variable ($\triangle CoVaR-1\%$) of different risk sources such as the GIIPS-block, Greece, Ireland, Italy, Portugal, and Spain, on eight different year dummies. Concerning the primary risk source, GIIPS, we find some statistical significance for the coefficients of the year dummies. The substantially positive and significant coefficient of the constant term determines the dummy of 2007 (as a base year) where the coefficients of the remaining years (2008-2015) are all zero. As an initial reaction to the subprime crisis, there is an additional 3.97% increase in the risk exposure (driven by the GIIPS-block) in 2008 plus the 2007 constant exposure of 2.43%. In 2009, there are no significant extra spillovers more than that of 2007, but still no decrease is detected. Similarly, there is neither statistically significant reduction nor expansion in the risk externalities in 2010 and 2011 extra to the (base year) effect of 2007. In spite of that, from 2012, there is a substantial drop in the risk spillovers compared to those of 2007.

As relating to other sovereigns, the magnitude and statistical significance of coefficients differ from the results of the GIIPS sovereign debt but still the signs remain positive or zero for the years 2008-2011. As an example, the risk exposure of the Greek sovereign debt considerably increases in 2008 and 2010, compared to the base year of 2007. However, the risk exposure does not change in 2009 and 2011 more than that of 2007. Therefore, these observations statistically motivate the corresponding values of "crisis dummy" in our study, namely zero for 2007,

Year	GIIPS	Greece	Ireland	Italy	Portugal	Spain
2008	3.97***	4.22***	1.25	3.00***	4.34***	5.76***
	(0.89)	(0.76)	(0.78)	(0.91)	(0.87)	(0.95)
2009	0.51	0.92	2.65***	0.10	0.72	2.12**
	(0.79)	(0.68)	(0.70)	(0.81)	(0.78)	(0.85)
2010	1.22	1.52**	2.82***	1.01	1.54**	2.55***
	(0.79)	(0.68)	(0.69)	(0.81)	(0.77)	(0.84)
2011	0.34	0.46	2.07***	0.41	0.83	2.24***
	(0.78)	(0.67)	(0.69)	(0.80)	(0.77)	(0.83)
2012	-1.85**	-1.38**	1.13	-0.27	-0.67	1.57*
	(0.78)	(0.67)	(0.69)	(0.80)	(0.77)	(0.83)
2013	-1.48*	-1.54**	1.22*	-0.68	-0.27	1.36
	(0.77)	(0.66)	(0.68)	(0.79)	(0.76)	(0.83)
2014	-0.27	-0.46	1.06	-0.66	0.02	1.36
	(0.77)	(0.66)	(0.68)	(0.79)	(0.76)	(0.83)
2015	-1.12	-0.61	0.68	-0.35	0.40	1.69**
	(0.77)	(0.66)	(0.68)	(0.79)	(0.76)	(0.83)
(2007)	2.43***	1.61***	0.63	2.69***	1.97***	0.67
	(0.63)	(0.54)	(0.55)	(0.64)	(0.62)	(0.67)
Obs.	178	178	178	178	178	178
$\boldsymbol{R^2}$	0.32	0.4	0.17	0.16	0.25	0.22

Table 4: **Time-effect regressions.** The OLS regressions of the risk measure, $\triangle CoVaR - 1\%$, originating from various sovereigns in nine years, 2007-2015, are presented in this table. The constant term indicates the coefficient of the base year, 2007. ***, **, and * denote the significance levels at 1%, 5%, and 10%, respectively.

and 2012-2015, and one for 2008-2011.

5.4 Univariate Regression Estimation

So far we have measured systemic risk, $\triangle CoVaR{-}1\%$, and have shown that the comovement of the individual banks with debts in GIIPS is quite substantial. In this section, we attempt to discover the main factors that can significantly explain variations in banks' exposure to the GIIPS debt crisis in the examined years. Table 5 displays the univariate FE-panel regressions of $\triangle CoVaR - 1\%$ from six different origins of sovereign debt risk on a few financial market variables and bank fundamentals.

The sign of most variables is the same as the hypothetical one in the literature (see 4.2). Consistent with earlier studies, the role of the subprime and sovereign debt crisis period of 2008-2011 is reflected in the positively significant and large coefficient of the crisis dummy (*CD*). The positive sign of size variable (*A*) means that large banks are closely connected with the GIIPS-block through interbank investments and other exposures[1]. Similar to the observations above, the coefficient of the interaction term of *CD* and *A*, CDA, is also positive and significant at 1% level. The interaction term (CDA) has a larger contribution and explanatory power, a higher R^2, at explaining exposure to the GIIPS sovereign risk.

Furthermore, systemic risk is positively related to changes in the standard deviation of local stock market returns (*SD*), the volatility index in Europe (*V*) and correlation of stock markets (*C*) for most of the risk origins. In contrast to those market-related variables, mean of yearly returns (*R*), and the ratio of mean to standard deviation of returns (*RSD*) are negatively related to the variations in $\triangle CoVaR - 1\%$. The outputs also show that bank-specific profiles, market-to-book (*MB*), debt-to-equity (*DE*), and short-term debt-to-cash (*DC*) ratios do not significantly drive the systemic risk exposure of the sampled banks, that is, either the coefficients are insignificant or the R^2s are very low.

[1] This is similar to various related studies, from different perspectives, that give approval to the "Too Big To Fail (TBTF)" hypothesis.

Risk Source	**GIIPS**		**Greece**		**Ireland**		**Italy**		**Portugal**		**Spain**	
Variables	**Coef**	R^2	**Coef**	R^2	**Coef**	R^2	**Coef**	R^2	**Coef**	R^2	**Coef**	R^2
Crisis Dummy (*CD*)	2.16*** (0.29)	0.27	2.31* (0.28)	0.31	1.33*** (0.23)	0.19	1.23*** (0.25)	0.14	1.57*** (0.26)	0.19	1.44*** (0.29)	0.14
Asset (*A*)	0.37** (0.17)	0.03	0.26 (0.17)	0.02	0.31** (0.12)	0.04	0.13 (0.13)	0.01	0.02 (0.14)	0	0.07 (0.16)	0
Crisis*Asset (CDA)	3.66*** (0.50)	0.26	3.74*** (0.49)	0.28	2.23*** (0.39)	0.18	2.01*** (0.42)	0.13	2.77*** (0.45)	0.2	2.59*** (0.50)	0.15
Mean of Returns (*R*)	-1.02*** (0.18)	0.18	-1.03*** (0.18)	0.18	0.36** (0.14)	0.04	-0.64*** (0.14)	0.11	-0.91*** (0.15)	0.19	-0.86*** (0.17)	0.15
Standard Deviation (*SD*)	1.13*** (0.18)	0.22	1.33*** (0.17)	0.30	-0.22 (0.17)	0.01	0.55*** (0.14)	0.1	0.83*** (0.15)	0.18	0.76*** (0.17)	0.12
Return/Stdev (*RSD*)	-1.99*** (0.47)	0.1	-1.95*** (0.47)	0.1	0.76** (0.36)	0.02	-0.96** (0.38)	0.04	-1.57*** (0.41)	0.09	-1.27*** (0.45)	0.05
VSTOXX (*V*)	0.76*** (0.10)	0.27	0.84*** (0.10)	0.34	0.17** (0.09)	0.03	0.48*** (0.08)	0.18	0.62*** (0.09)	0.24	0.62*** (0.10)	0.21
Correlation (*C*)	1.20*** (0.32)	0.08	1.19*** (0.17)	0.25	0.38* (0.20)	0.02	0.60** (0.24)	0.04	0.84*** (0.24)	0.08	0.41 (0.32)	0.01
Market/Book (*MB*)	-0.34** (0.17)	0.03	-0.25 (0.17)	0.01	-0.29** (0.12)	0.03	-0.11 (0.13)	0	-0.01 (0.15)	0	-0.07 (0.16)	0
Debt/Equity (*DE*)	0.41* (0.22)	0.02	0.32 (0.22)	0.01	0.22 (0.17)	0.01	0.15 (0.18)	0	0 (0.19)	0	0.02 (0.21)	0
Debt/Cash (*DC*)	-0.14 (0.29)	0	-0.19 (0.29)	0	0.063 (0.21)	0	-0.01 (0.23)	0	-0.12 (0.25)	0	-0.04 (0.27)	0

Table 5: **Univariate FE-panel regressions.** This table investigates how individual financial characteristics of banks contribute to their risk exposure caused by six different origins, meaning the GIIPS-block, Greece, Ireland, Italy, Portugal, and Spain.***,**, and * denote the significance levels at 1%, 5%, and 10%, respectively.

5.5 $\triangle CoVaR$ and Correlation

Figure 4 plots the yearly mean of sample correlation between stock markets in the 10 examined European countries and the five Eurozone distressed countries over a nine-year horizon. The correlation lines illustrate that homogeneity is present in both the level and the strength of comovement between different GIIPS stock markets and other markets except for the Greek market. There is some evidence that interdependencies, i.e. yearly mean of correlations, among European stock markets have increased over the last two decades after the introduction of the euro. During these years, there has been a substantial temporary rise in correlation following the integration of markets (see Schröder and Schüler, 2003). The strengthened interdependence between stock markets in the European countries and the GIIPS sovereigns, excluding for Greece, is particularly evident in 2007-2011, as seen in Figure 4.

To investigate the relation between stock market correlation and "systemic risk" measure, we plug in the correlation variable between a country's stock market and the GIIPS countries or the GIIPS-block stock index in univariate FE regressions. The FE regression of $\triangle CoVaR{-}1\%$ on stock market correlation (C) is represented in Table 5. The correlation variable corresponds to the covariate of each of the 10 stock markets in which the CDS is issued with the stock indices of different GIIPS sovereigns, i.e. Greece, Ireland, Italy, Portugal, Spain, and the GIIPS stock index[1]. Successively, the analogous $\triangle CoVaR$s are the negative spillovers of debts in the five sovereigns or the GIIPS index on the sampled individual banks. As an example, Spain-$\triangle CoVaR$ represents the risk contagion from the Spanish sovereign debt to the 25 reviews. This correlation of Spain characterizes the co-variation of the 10 stock markets with the Spanish market index.

According to the positive and significant coefficient of correlation (C), one can assume that an observed increase in correlation between a stock market and the GIIPS index returns signals a climb in the systemic

[1] As mentioned before, the index is a GDP-weighted index of the five constituent countries within GIIPS.

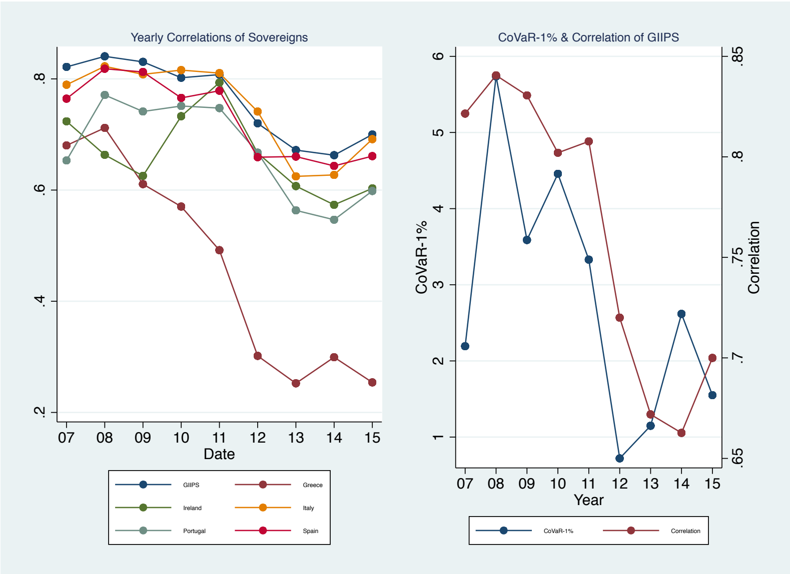

Figure 4: **Comovement of stock market correlation and** $\triangle CoVaR - 1\%$**.** The left-plot depicts the yearly cross-sectional mean of stock markets correlations, of the GIIPS-block, and also the constituent countries in GIIPS (Greece, Ireland, Italy, Portugal, and Spain) with the 10 representative European countries. The right plot demonstrates the change in the sample yearly means of GIIPS-$\triangle CoVaR - 1\%$ and the GIIPS stock index correlation, i.e. of the GIIPS-block index with the 10 European ones.

risk exposure. The regression outputs show that, for most of the cases, the higher the correlation, the higher the systemic risk, except for Spain, for which the coefficient is not significant. For instance, the univariate regression of Greece-$\triangle CoVaR$ on correlation explains 25% of the variations in risk exposures of the banks on the Greek sovereign debt risk, R^2 amounts to 0.25.

5.6 Multivariate Regression Model

The regression model in equation 1 relates $\triangle CoVaR$ to market financials, i.e. mean and standard deviation of market returns, stock market correlation, crisis dummy, and European market volatility, also cor-

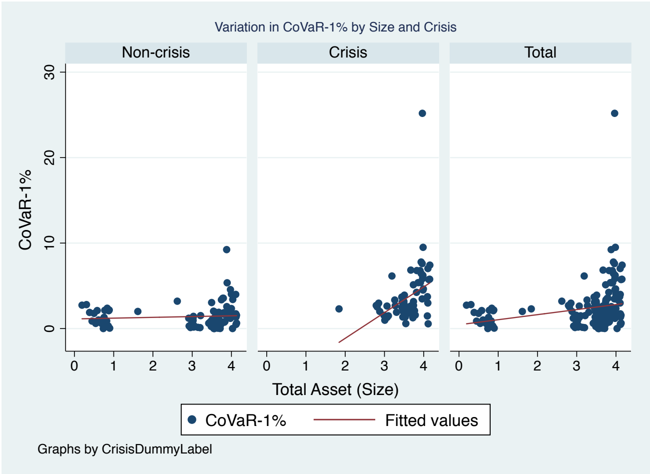

Figure 5: **Variation in $\triangle CoVaR - 1\%$ by crisis dummy and total asset.** This graph shows the change in $\triangle CoVaR - 1\%$ for different sizes (or total asset) in three different categories, i.e. the non-crisis, the crisis, and the whole period, respectively.

responding to individual bank qualities, i.e. total asset, market-to-book, leverage, and short-term debt-to-cash ratios. Table 6 shows some of the empirically interesting results of the (unbalanced) panel regression model.

In this table, the combination of a bank's size (*A*) and crisis dummy (*CD*), denoted by CDA, mean and standard deviation of market returns (*R* and *SD*, respectively) are statistically significant. In contrast to the function played by these variables, we find no evidence that leverage ratio (*DE*), short-term debt-to-cash ratio (*DC*), total asset or size (*A*), by itself, and correlation (*C*) considerably drive countries' risk exposure to the GIIPS debts.

The positive and statistically significant coefficient of CDA provides sound evidence that the interaction term of size and crisis episodes partially explains 26% of variations in the systemic risk exposure on banks. The impact of size and crisis dummy on risk exposure is more illustrative in Figure 5. It depicts the movement in $\triangle CoVaR - 1\%$ with respect to the different sizes of banks in the three different categories, i.e. the non-crisis period, the crisis period, and the whole sample, respectively. In other words, it can be seen as a three-dimensional plot. The dimensions are total asset (or size), $\triangle CoVaR$, and crisis dummy. The fitted line of upward sloping, in the middle plot, signifies the positive role of asset and the crisis period in raising the risk measure, $\triangle CoVaR - 1\%$. As can be seen in Table 6, the interaction of size and crisis dummy, CDA, remains robust at explaining $\triangle CoVaR - 1\%$ (but in different magnitudes) for different sovereigns within GIIPS.

Table 6 also underlies the importance of stock market performance, i.e. mean, standard deviation, and correlation with other stock markets for risk exposure to the GIIPS sovereign debts. Stock market payoff is a prominent indicator of economic climate and is widely used among players in the financial market. Unlike those variables mentioned above, the bank-specific fundamentals such as short-term debt-to-cash, market-to-book, and leverage ratios cannot explain variations of the risk measure in an economically meaningful way. We also examine the robustness of the main regression model of GIIPS-$\triangle CoVaR - 1\%$. This model estimates a similar FE-panel model but with $\triangle CoVaR - 5\%$ as the dependent covariate, instead of $\triangle CoVaR - 1\%$. The robustness check verifies the primary model in terms of the significance of the coefficients and also signs of the coefficients.

The risk spillover from the countries within the GIIPS-block to the same European banks is examined by running separate FE-panel regression models of $\triangle CoVaR - 1\%$. As for the Greek case, the significant explanatories and the magnitude of coefficients are analogous to the regression model for the GIIPS regression, meaning that the interaction of size and crisis dummy (CDA) and also mean and standard deviation of market returns can partially describe variations of exposure to the Greek sovereign debt. For other cases, i.e. the Irish, Italian, Portuguese and Spanish risk measures, interaction of size and crisis dummy (CDA) and average market returns (R) still illustrate variations in the measure. However, the explanatory power of the regressions and also the magnitude of relevant coefficients are different, to some extent, from the GIIPS and Greek cases.

Risk Source	GIIPS	GIIPS	Greece	Ireland	Italy	Portugal	Spain
Variables	$\triangle CoVaR-1\%$	$\triangle CoVaR-5\%$	**-1%**	**-1%**	**-1%**	**-1%**	**-1%**
Crisis*Asset (CDA)	0.46***	0.32***	0.44***	0.38***	0.30***	0.42***	0.34***
	(0.10)	(0.07)	(0.09)	(0.06)	(0.07)	(0.07)	(0.07)
Return to Std Dev (*RSD*)	-1.03**	-0.73**	-0.79*				
	(0.44)	(0.31)	(0.42)				
Standard Deviation (*SD*)	0.37*	0.26*	0.59***				
	(0.20)	(0.14)	(0.19)				
Mean of Returns (*R*)					-0.48***	-0.70***	-0.68***
					(0.14)	(0.14)	(0.15)
Market to Book (*MB*)						0.26**	
						(0.13)	
Constant	1.04***	0.73***	0.03	1.54***	2.38***	2.64***	2.14***
	(0.36)	(0.26)	(0.35)	(0.14)	(0.15)	(0.34)	(0.18)
Obs.	178	178	178	178	178	178	178
R^2	0.34	0.34	0.40	0.20	0.22	0.34	0.24

Table 6: **Multivariate FE-panel regressions.** The table demonstrates the final FE-(unbalanced) panel regressions of all risk sources. $\triangle CoVaR-1\%$ evaluates the risk spillovers that stem from sovereign debt in GIIPS, Greece, Ireland, Italy, Portugal, and Spain. The model with $\triangle CoVaR-5\%$ as the dependent variable checks the robustness of the primary model of $\triangle CoVaR-1\%$.***,**, and * denote the significance levels at 1%, 5%, and 10%, respectively.

6 Conclusion

Recognizing the function of different attributes in the GIIPS sovereign debt risk, we engage key fundamentals and market conditions to detect the risk measure variations. We find some empirical evidence that a mix of market indicators and size (or total asset) drives sovereign risk exposure. In addition, the systemic risk indicator for European banks is heightened in the peak of the global and debt crises, in 2008-2011, due to higher correlation and larger volatility in the CDS spreads. Larger banks are by nature more interconnected, complex, and susceptible to take on systemic risk, especially when markets are distressed by a financial crisis. Local market indicators such as the mean and standard deviation of stock returns can also influence the risk exposure. Each and every communicated figure in the markets is embodied in the stock returns. Therefore, stock market returns proxy for the financial market conditions of the country in which CDSs are issued. Unlike these variables, the included bank-specific variables, i.e. leverage, market-to-book, and short-term debt-to-cash ratios, do not drive changes in the risk exposure between the investigated European banks. To sum up, amongst various factors, a bank's exposure to the GIIPS sovereign debt crisis is more attributed to market returns and volatility, the global economy situation, and total asset.

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A Appendix

Figure 6: **Debt-to-GDP ratio of GIIPS countries**. This figure displays the ratio of debt-to-GDP for the five countries within the GIIPS-block in 2010. It also reports the British banks' exposure to the sovereign debts in GIIPS in the same year.

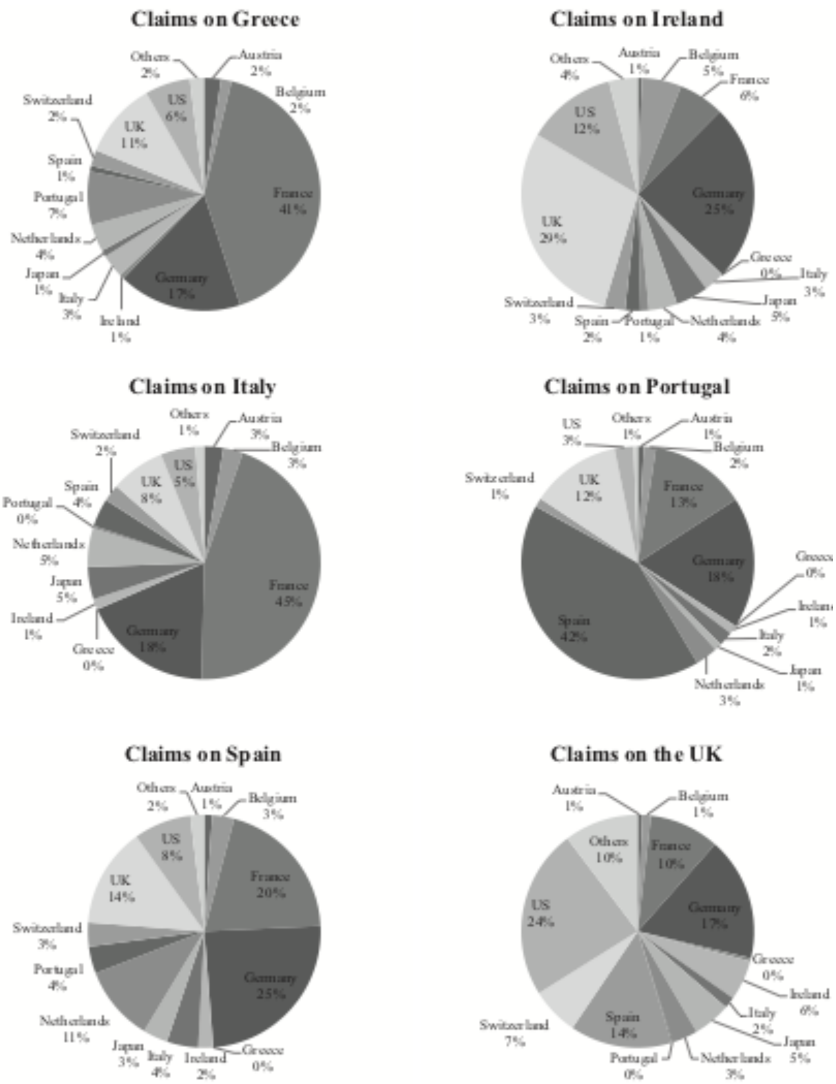

Figure 7: **Claims on the GIIPS countries.** The pie-plots give an overview of different large economies' claims on the five GIIPS countries and the UK in Mach 2011 (Kalbaska and Gątkowski, 2012).

Country	**Name of the Sampled Banks**				
Austria	Erste Group Bank AG	BAWAG P.S.K.			
Belgium	KBC Group NV				
Denmark	Danske Bank A/S				
France	Societe Generale Group	BNP Paribas SA			
Germany	IKB Deutsche Industriebank	Commerzbank AG	DZ Bank AG	Landesbank Baden	
Iceland	Kaupthing (Arion)	LBI hf.			
Norway	DNB ASA				
Russia	Sberbank of Russia OJSC	Russian Agricultural Bank	JSC VTB Bank	VEB Russia	
Sweden	Svenska Handelsbanken	Nordea Bank	Swedbank	SEB	
UK	Co-operative Bank plc	Barclays PLC	HSBC	RBS N.V.	

Table 7: **List of banks.**This table lists 25 European banks that have been reviewed in this study.

PAPER III

Determinants of Systemic Risk in European Banking

Hassan Sabzevari

Abstract

As the main focus of this study, we empirically investigate the important determinants of systemic risk in the European banking system. To achieve this purpose, this paper firstly examines the systemic risk influence of each European country's banking industry on the European banking system, i.e. the whole banking industry of Europe. Conditional Value-at-Risk, or CoVaR, is used to evaluate the risk contagion of each single country's banking to the European banking system. We then run a GMM dynamic panel regression of the CoVaR measure on idiosyncratic country-level banking characteristics and macroeconomic variables. The results show that size is an important determinant of the risk. Interestingly, the contagion significantly expands in the subprime and sovereign debt crisis period of 2008-2012. In addition, individual country-level factors such as *VaR*, stock market returns, market-to-book ratio, bilateral loan, and the industrial growth index are other significant determinants of systemic risk expansion.

Keywords: Systemic Risk, VaR, CoVaR, European Banking System, Crisis
JEL Classification: C30, G01, G20, G21, G28

1 Introduction

Any financial crisis that follows a domino-like failure is systemic by nature and has overwhelming burdens and consequences on the real economy[1]. Kaufman and Scott (2003) define "systemic risk" as *"the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, and is evidenced by comovements (correlation) among most or all the parts"*. After the global subprime crisis of 2007/2008, a few Eurozone states faced negative growth outlooks and accelerating public debts in 2010-12. Financial markets anticipated the Greek default and, subsequently, the risk spread to other large economies such as Italy, Spain, and Ireland. These countries were financially incapable of repaying their debts without receiving assistance through bailout agreements or liquidity injections by the ECB[2] and/or other authorities (Black et al., 2016). During the European debt crisis, physical default probabilities[3] led to insolvency issues as a major source of contagiously negative spillovers. Black et al. (2016) show that the systemic risk of the European banking system reached its peak in November 2011 after the elevation of the Eurozone debt crisis. The European and the worldwide crises of 2007/2008 have drawn the attention of economists and authorities. Therefore, economists and risk analysis practitioners endeavor to mitigate the effects of systemic risk. Realizing this objective would provide regulators with operational policies aimed at limiting systemic risk before any likely crisis (Weiß, Bostandzic, and Neumann, 2014).

The present research aims to address a central question: what are the major characteristics of a country's banking and macroeconomy that determine its systemic importance? In other words, what are the major attributes of Systemically Important Banking Industries (SIBIs) for imposing macroprudential regulations or integrated banking policies? A traditional microprudential regulation regime unintentionally gives banks

[1] Acharya (2009) further explains this observation.
[2] European Central Bank
[3] The physical default probabilities are extracted from the historical data, whereas the risk neutral probabilities are obtained from CDS spreads or bond prices.

strong incentives to burden the system with more of the risk (Black et al., 2016). Comprehensive macroprudential supervision, which considers the European banking system as a whole, is crucial for achieving financial stability. The research outcomes benefit the European authorities while imposing macroprudential policies and identifying SIBIs.

The main incentive of this article for the particular emphasis on banks arises from a variety of evidence concerning banks' substantial functionality in the economy and also the broad extent of any contagion risk in the banking sector[1]. The reliability of banking systems is central for financial sector stability, economic growth, employment, and social welfare (Huang, Zhou, and Zhu, 2012). For instance, Billio et al. (2010) find that shocks to banks propagate to other financial institutions; however, shocks to other financial institutions do not affect banks. In this respect, banks appear to be the most contagious types of financial institution. The ongoing integration, globalization, and consolidation process in the banking business render obvious indications for systemic risk expansion in banking. Furthermore, banking businesses have a high leverage ratio, i.e. a low capital-to-asset ratio, and low cash-to-asset ratio to meet deposit obligations (Schröder and Schüler, 2003). The distinct focus on the European continent is motivated by the fact that the last financial crises sufficiently highlighted the importance of discerning systemic risk sources at the European level to comfort stabilization initiatives in this market (see De Bandt and Hartmann, 1998).

By employing the CoVaR approach, this paper empirically investigates the degree of cross-border interconnectedness in the European banking sector. The advantages of CoVaR are its straightforward computation and also its ability to present the risk contribution of an individual banking industry. By means of the measure, this paper firstly surveys the contribution of each country's banking industry to the European system. Then, it examines the determinants of systemic risk by running a GMM panel regression. The results show that systemic risk is determined by a number of balance-sheet characteristics and macroeconomic conditions such as country-level *VaR* of banking industry, crisis episodes, size

[1] See Kaufman and Scott (2003) for further explanation.

or total asset, bilateral loan, market-to-book ratio, stock market returns, and industry growth index. The degree of importance and also the direction, positive/negative, of these risk drivers are noticeably distinctive (Adrian and Brunnermeier, 2016).

Before the advent of the subprime crisis, there was no substantial literature on the distinguishing drivers of systemic risk in Europe. After the 2007/2008 crisis, there were a few studies on systemic risk determinants either among European individual banks or only among large economies/banking industries in Europe. However, none of the current studies examine the drivers of systemic risk flow from country-level banking industries on the whole banking system in Europe. As an example, Herwartza and Siegel (2009) claim that the advent of the euro has initiated a slight spike in systemic risk. In another study, which conducted a cross-country comparison, Karimalis et al. (2014) show that Spanish and French banks on average contribute more to systemic risk in Europe. Therefore, this paper can contribute to the current literature in two respects. It is the first study that attempts to determine the contributors of contagion risk in the European banking system, meaning that it develops all analysis at the European country-level, as opposed to related studies that emphasize individual banking level. Another notable deviation is that we incorporate a new control, the "bilateral loan", which can obtain the strength of banking industries' interdependence. The bilateral loan is not only one of the chains of interconnection and comovement inside banking systems but also a representative for credit/default risk. Assessing the impact of the bilateral loan can contribute to the explanatory power of our model.

In terms of data type, the analysis centers on banking stock indices rather than historical balance sheet data, e.g. market value of assets. The market value of banking equities reflects forward-looking estimates of any conceivable events in banking. Stock returns reveal common variations in the European banking system related to each country's banking industry[1]. The sample of banking equity indices consists of 15 European countries plus the entire European banking sector. These countries are

[1] See Brownlees and Engle (2012) for the reasoning behind employing equity indices.

attributed by their large capitalization, global activity, cross-border exposures, and/or large size.

The paper proceeds as follows: it reviews the leading studies on the determinants of systemic risk in Section 2; Section 3 describes the data and reports the descriptive statistics; the detailed description of the CoVaR measure and also the contemplated determinants of systemic risk are documented in Section 4; Section 5 presents the final results and robustness checks; Section 6 concludes the paper.

2 Literature Review

Regarding studies on systemic risk determinants, there are mainly three strands of literature. One thread of the literature solely covers European banks or US banks. The second thread addresses the contagion risk between US banks and European banks and their mutual externalities on each other. Finally, other papers target systemic risk drivers among large financial institutions such as banks, insurance companies, and real-estate firms in the US, Europe, and other developed economies. These threads of studies are respectively reviewed as follows.

Herwartza and Siegel (2009) analyzed a cross-sectional set of data that covers nine economies, namely Belgium, Denmark, Finland, France, Germany, Ireland, the Netherlands, Switzerland, and the United Kingdom. The authors investigate the probable influence of exogenous factors on determining the comovements in European banking. The paper claims that the advent of the euro has initiated a slight spike in systemic risk following a short period of transitory dynamics. The introduction of the euro and financial market integration goes along with the convergence of interest rates. Therefore, systemic risk is found to rise in states in which financial market integration/liberalization is continuing or in which markets are experiencing relatively high uncertainty at the national level.

Engle et al. (2015) applied the Marginal Expected Shortfall (MES) methodology to a sample of 196 large European financial firms consisting of all banks, insurance companies, financial services, and real-estate firms over 2000-2012. Of the 1,219 billion euros of systemic risk exposure in Europe, banks and insurance companies bear approximately 83% and 15%, respectively. In terms of countries' share over the recent period, France and the UK have contributed approximately 52% to the risk build-up. With regard to individual firms, the five riskiest financial institutions in that period have been Deutsche Bank, Credit Agricole, Barclays, Royal Bank of Scotland, and BNP Paribas.

In a cross-country comparison, Karimalis and Nomikos (2014) investigated the hypothetical contribution of common market factors and bank-specific characteristics (e.g. balance sheet variables) on systemic risk. For a portfolio of large European banks, lagged values of the implied market volatility, funding liquidity, credit spread, and the change in the three-month Euribor rate are statistically significant in describing CoVaR. The authors show that liquidity risk was a principal determinant of systemic risk contribution at the onset of the 2007/2008 crisis. Furthermore, size and leverage appear to be the most robust sources of systemic risk spillovers.

Black et al. (2016) examined the systemic risk of European banks during crises. The authors introduce the Distress Insurance Premium (DIP) indicator, which combines the characteristics of bank size, default probability, and interconnectedness. The measure indicates that size and leverage raise systemic risk, while adequate short-term liquidity and a satisfactory book-to-market ratio shrink systemic risk. Certain "small banks" can be systemically risky if their credit quality deteriorates or their default probability and/or correlation rises. The authors signify that sovereign default spreads as the cause of the deepened risk in the banking sector during the European debt crisis.

Zhou (2010) applied three systemic importance measures to a constructed dataset consisting of 28 US banks. They demonstrate that a large bank is not essentially systemically important unless it is engaged in diversified banking activities. For instance, the crisis of a large but isolated bank having no diversification or interconnection with other banking counterparts cannot jeopardize the financial system. In other words, the "Too Big To Fail" (TBTF) argument is only a valid argument for those large banks that take on excessive risk and their risky undertakings necessitate bailout policies.

Introducing Expected Systemic Loss (ESL), Moore and Zhou (2014) show that TBTF was a key determinant for the US banks, in 2000-2010, having size under a specific threshold. In addition to TBTF, systemic importance is magnified with intensive participation in non-traditional banking activities. In other words, the systemic importance of banks can also be identified by the "Too Non-traditional To Fail" principle such as relying on money market funds and earning non-interest incomes.

Adrian and Brunnermeier (2016) used a fixed-effects panel regression, denoted as the forward-looking risk measure, on a total of 1,226 financial institutions in the US. The authors connected quarterly CoVaR estimations of the collected financial institutions to their individual characteristics. The authors provide evidence that financial institutions with higher leverage, more maturity mismatch, and larger size enforce larger systemic externalities one quarter, one year, and two years later, both at the 1% and the 5% levels of CoVaR.

Sharifova (2012) utilized the CoVaR approach to unveil the degree and also the sources of cross-border interconnectedness/linkage between the US and the European banks over 2000-2011. She argues that those systemically important banks are not essentially the riskiest ones in terms of their individual risk or *VaR*. Moreover, the solvency indicators, namely leverage and long-term debt-to-equity ratio, turn out to be statistically significant drivers of the US banks' exposure to the European banks. However, Sharifova's (2012) research cannot statistically justify analogous risk contributions of the US banks to the European peers.

Beltratti et al. (2012) studied the performance of stock returns of large worldwide banks with assets in excess of $10 billion across the crisis period of 2007/2008. The authors used this period's variations to grasp those factors that describe the poor performance of banks in the course of a credit crunch. The research's empirical evidence strongly supports those theories that relate the fragility of banks with factors such as short-term capital market funding, higher leverage, less traditional business engagements, and greater returns instantly before the crisis.

López-Espinosa et al. (2012) applied the CoVaR approach to distinguish the primary triggers of contagion risk in international banking. The authors conclude that short-term wholesale funding is a major source of systemic risk incidents in banking. The risky funds are mainly raised with financial instruments such as Certificates of Deposits (CDs), central bank funds, commercial papers, and repurchase agreements (or repos). Within the class of those international banks, they find no strongly convincing evidence that either size or leverage contribute to systemic risk. On the other hand, the article puts forward the view that risky funding triggers more interconnection, larger exposure to maturity mismatch, and more liquidity risk. Their results encourage the Basel proposal to implement "net stable funding ratios" and to penalize excessive exposures to liquidity risk.

On a sample of 20 European banks and 13 US banks, Rodríguez-Moreno and Peña (2013) studied the impact of banks' portfolio holdings of credit derivatives[1] on risk dispersion. The authors also incorporated other variables related to size, interconnectedness, substitutability, and balance sheet characteristics into their analysis. For the examined sample of banks, they conclude that holdings of foreign exchange and credit derivatives raise the banks' contributions to systemic risk while holdings of interest rate derivatives lessen that risk. More than derivatives holdings, the ratio of non-performing loans to total loan and leverage ratio influence systemic risk expansion.

Bostandzic and Weiß (2013) document that US banks not only experience higher global systemic risk but also significantly contribute more to the risk than the European banks. The authors show that the annual Marginal Expected Shortfall (MES)[2] and Systemic Risk Index (SRISK)[3] for the US banks are substantially higher than those for the European banks of analogous size and value. Furthermore, exceptional reliance on non-interest income, less traditional lending, and less qualified loan portfo-

[1] Credit Default Swap

[2] MES measures the negative mean net equity returns of a financial institution conditional on any bad outcomes or downward movements in the markets.

[3] SRISK measures the expected capital shortfall of a financial firm in the case of a systemic event or crisis.

lios lead to the systemic relevance of banks.

3 Data

Daily banking equity indices of 15 European countries and the equity index of the European banking system were obtained from Datastream. The banking equity indices[1] are gathered on a daily frequency spanning from the beginning of 1999 to the end of 2013. The daily observations are the MSCI of banking equity indices in those examined countries. The chosen countries are listed in Table 1 with the descriptive statistics on their logarithmic stock returns. We select those banking industries that dominate the cross-border banking and also hold a higher share of foreign assets/liabilities in the European continent[2]. Some other European countries such as Iceland, Luxembourg, and Cyprus might have significant systemic risk implications for the European system but due to data unavailability are excluded from the analysis.

There are two abnormal minimum daily returns in Table 1 concerning the Irish and Dutch banking indices. Irish banking experienced a daily decline of 75.2% (of log returns or 37.5% of ordinary returns) on 19 January 2009, whereas the downturn in Dutch banking occurred on 14 October 2008, 129.9% of log returns or 72% of ordinary returns. We also collect the variables of each country's banking-specific qualities. These controls are all designated from the literature, excluding the bilateral loan variable. This new explanatory variable is released by the BIS statistics[3]. The BIS consolidated banking statistics provide quarterly data on banks' foreign claims by country of residence of counterparty.

We cannot collect indices for the balance sheet and income state-

[1] The forward-looking nature of equity market returns offers a natural choice of a proper measure of systemic risk (see Zhou, 2010).

[2] For instance, a few European economies, i.e. France, Germany, the UK, Switzerland, the Netherlands, besides the US and Japan comprise half of the cross-border banking assets/liabilities (Allen, 2011).

[3] *"The data cover financial claims, risk transfers and certain liabilities reported by banks headquartered in the reporting country as well as selected affiliates of foreign banks"* (BIS International Banking Statistics).

Country	Mean	Std Dev	Min	Max	Skewness	Kurtosis
Austria	0.02	2.02	-13.53	14.32	-0.15	6.70
Belgium	-0.04	2.49	-25.48	18.57	-0.36	10.31
Denmark	0.02	1.70	-14.66	15.31	0.05	7.89
Finland	0.03	2.03	-18.21	19.62	0.02	9.76
France	0.01	2.20	-13.45	18.32	0.26	7.27
Germany	-0.02	1.99	-16.49	15.8	-0.08	9.49
Greece	-0.09	2.85	-16.32	22.05	0.34	7.62
Ireland	-0.08	3.84	-75.21	29.76	-1.72	49.11
Italy	-0.03	1.93	-11.96	15.79	-0.09	5.58
Netherlands	-0.08	2.98	-129.91	15.12	-21.40	919.44
Portugal	-0.04	1.72	-11.73	12.79	0.06	8.01
Spain	-0.01	1.91	-14.28	19.06	0.40	8.60
Sweden	0.02	1.92	-10.79	14.65	0.38	6.28
Switzerland	-0.01	1.91	-10.83	17.77	0.26	7.44
UK	-0.01	1.95	-19.47	18.80	-0.09	11.55
Europe	0.00	1.77	-11.78	15.68	0.05	8.22

Table 1: **Descriptive statistics of banking indices.** The table lists 15 big European countries and the whole Europe banking index. It also reports the basic descriptive statistics of the indices daily log returns such as mean, standard deviation, minimum, maximum, all in percentage, skewness, and kurtosis in 1999-2013.

ment at country-level banking. Therefore, we construct a market-capitalization-weighted index of the constituent list of each country's banking industry. The yearly market capitalization of constituent lists was collected from Datastream. Table 2 exhibits the average and standard deviation statistics of the control variables in non-crisis, crisis, and total periods for all banking businesses over 1999-2013. The table shows that the averages for some of the control variables, i.e. leverage ratio, *IPI*, unemployment growth rate, VaR, and market returns, vary largely during the crisis period. However, for other explanatory variables, it does not alternate significantly. There are some other interesting observations in this table. The leverage ratio (asset-to-equity ratio: *AE*), market-to-book ratio (*MB*), *IPI*, and mean of stock market returns (*R*) decrease significantly in crisis time while unemployment growth rate (*U*) and *VaR*-1% increase substantially during the crisis period. Despite some increasing or decreasing variations in those explanatory variables, we do not observe any considerable changes in total asset (*A*, namely the size proxy), bilateral loan (*BL*), and *PPI*.

4 Methodology and Variables

We follow the systemic risk literature to rel/ate $\triangle CoVaR$ to financial fundamentals. There exists an autoregressive (AR) process in the $\triangle CoVaR$ over time, meaning that, if we estimate the parameters by ordinary fixed/random effects, the regression estimation leads to endogeneity issues. Therefore, a dynamic panel regression is preferred to other regression methods. The most commonly used estimators to overcome the described problem are the Arellano and Bond (1991) and Arellano and Bover (1995) estimators. Arellano and Bond (1991) use all of the past information of dependent variable as instruments. We use primarily the Arellano and Bond (1995) GMM estimator as an efficient estimation procedure. We conduct the analysis by employing a GMM dynamic panel regression. The final specification of the panel regression takes the form of the model in equation 1.

Variables and Indication for Systemic Risk		Non-crisis		Crisis		Total	
Variable	**Indication**	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
Total Asset (*A*)	Size	20.3	1.59	20.87	1.54	20.50	1.60
Bilateral Loan (*BL*)	Credit Risk	12.28	0.95	12.4	0.87	12.32	0.92
Market/Book (*MB*)	Growth Expectations	1.81	0.81	0.94	0.64	1.50	0.86
Asset/Equity	Leverage	24.49	8.28	23.03	10.06	23.97	8.96
IPI	Industry Growth	0.02	0.03	-0.02	0.07	0.01	0.05
PPI	Production Inflation	0.02	0.02	0.02	0.04	0.02	0.03
Unemployment (*U*)	GDP Growth	-0.01	0.11	0.09	0.17	0.02	0.14
Mean of Returns (*R*)	Economic Condition	0.03	0.22	-0.12	0.39	-0.02	0.30
VaR	Market Risk	3.68	1.47	7.81	4.02	5.06	3.25

Table 2: **Descriptive statistics of the explanatory variables.** This table lists the selected explanatory variables, their indication for systemic risk, and also their sample mean in non-crisis, crisis, and total period of 1999-2013. Mean of returns variable is in percentage. *IPI*, *PPI*, and unemployment rate (*U*) are in logarithmic change (or growth rate). Total asset (*A*) and bilateral loan (*BL*) are in logarithmic format. Finally, market-to-book (*MB*) and asset-to-equity (*AE*) ratios are in absolute level.

$$\begin{aligned} \triangle CoVaR^{eu|i}_{i,t} &= \alpha_i + \beta_0 \triangle CoVaR^{eu|i}_{i,t-1} + \beta_1 CD_{i,t} + \beta_2 A_{i,t} + \beta_3 BL_{i,t} + \\ &\quad \beta_4 MB_{i,t} + \beta_5 AE_{i,t} + \beta_6 R_{i,t} + \beta_7 VaR_{i,t} + \beta_8 IPI_{i,t} + \\ &\quad \beta_9 PPI_{i,t} + \beta_{10} U_{i,t} + \epsilon_{i,t} \end{aligned} \tag{1}$$

In this equation, yearly $\triangle CoVaR^{eu|i}_{i,t}$ is regressed on the one-year lag of $\triangle CoVaR$, $\triangle CoVaR^{eu|i}_{i,t-1}$, and the main potential factors of risk contagion. The supposed risk drivers/determinants are crisis dummy (*CD*), total asset (*A*), bilateral loan (BL), market-to-book ratio (*MB*), asset-to-equity ratio (*AE*), the mean of stock market returns (*R*), Value-at-Risk (*VaR*), industrial production index (*IPI*), production price index (*PPI*), and, finally, unemployment (*U*). Among the explanatory variables, $\triangle CoVaR^{eu|i}_{i,t-1}$ is the only one-year lagged variable, whereas other explanatories are in the current year.

4.1 $\triangle CoVaR$ Method

Based on the well-known concepts of *VaR* and covariation, the $CoVaR$ approach evaluates the tail-risk spillovers from individual banking industries to the entire banking system. Adrian and Brunnermeier (2016) estimate the marginal contribution of each single institution to the overall systemic risk, denoted by $\triangle CoVaR$. $\triangle CoVaR$ is the difference between $CoVaR - 1\%$ and the unconditional whole system's $CoVaR$, or $CoVaR - 50\%$. For this particular research, $\triangle CoVaR$ reflects the systemic risk of each individual county's banking index on the European banking equity index. In other words, it evaluates the covarying changes between the tails of various banking indices and the European banking equity index. Among several methods used to evaluate $\triangle CoVaR$, the existing study applies the Unconditional Correlation method, or simply $UC - \triangle CoVaR$.

Applying the $UC - \triangle CoVaR$ method in this paper is motivated by its two virtues. First, we intend to estimate the $\triangle CoVaR$ model on a yearly basis implying that the estimation lacks adequate observations, i.e. nearly 260 daily observations, at most. Second, the $UC - \triangle CoVaR$ offers reasonable and realistic results for tranquil periods and narrow timespans despite its intrinsic characteristic of constant correlation and standard deviation[1]. In other words, the estimation of correlation and standard deviation on a yearly basis makes this specification simple enough and fairly concurrent.

$$\triangle CoVaR^{eu|i}(q) = \Phi^{-1}(q)\rho_{(i,eu)}\sigma^{eu} \quad (2)$$

$\triangle CoVaR^{eu|i}(q)$ can be explained as the *VaR* of the European system given that country i's banking is at its q percent *VaR* level. Following Adrian and Brunnermeier's (2016) approach for constructing a MGARCH-$\triangle CoVaR$ method, we assume a country's banking index and the European index follow a bivariate normal distribution. Making very minor manipulations to their equation[2], the $UC - \triangle CoVaR$ is assessed by plugging in two estimates of correlation and standard deviation in equation 2. In this method, the correlation of each country's banking equity and the European banking system index, $\rho_{(i,eu)}$, and also the standard deviation of the European banking index, σ^{eu}, are unconditional.

4.2 Variables

Several idiosyncratic and macroeconomic factors have been designated in the literature to find out the liable contributors of financial instabilities. Total asset, bilateral loan, market-to-book ratio, leverage ratio, Industrial Production Index (*IPI*), Production Price Index (*PPI*), unemployment rate, stock market returns, *VaR*, and crisis dummy are the core explanatory variables that are more frequently mentioned as the potential suppliers of systemic risk.

Size of banking indices is the logarithm of total asset and is expected to have a differential influence on systemic risk depending on empiri-

[1] We are quite aware that the assumption of invariant correlation and standard deviation seems rather unrealistic during crisis times or in longer timespans.

[2] The authors evaluate the time-varying estimation, i.e. multivariate GARCH, of correlation and standard deviation. For more details, readers may refer to Adrian and Brunnermeier's (2016) paper.

cally dissimilar studies. Mainelli and Giffords (2010) state that, *"if no bank is allowed to become too large, then no single bank can threaten the stability of the financial system"*. Large banks tend to take part in more banking activities in order to diversify and manage their individual-risk in micro-level aspects. A well-diversified banking industry bears less individual risks, while, at the same time, exerts a higher level of systemic importance. Due to large common exposure and proper diversification strategies, a well-diversified banking system is more systemically connected to the rest of the systems (Zhou, 2010; Moore and Zhou, 2014). On the other hand, the increased organizational complexity of large banks may increase their default and systemic risk. However, discussion on the contrasting effects of banking size on systemic risk is not confined merely to the diversification consequences. Large and possibly monopolistic banks can increase their profitability and decrease their systemic risk externalities. For example, more profitable banks are less vulnerable to macroeconomic or liquidity shocks on account of higher capital buffers (Weiß et al., 2014). Taking everything into account, the degree of importance or the sign of size has to be determined empirically for the case of European banking.

The bilateral loan variable reflects the total credits borrowed by the banks of a country from their peers in the remaining 14 countries of the sample. As an example, let's say the bilateral loan for Greek banks is 57 billion dollars in 2013. This means that the total credit, which is borrowed from the listed banks in Greece from their counterparts in all other 14 European countries, amounts to 57 billion dollars in that year. This is a new control variable, which obviously has not been engaged in the early research on systemic risk determinants due to its unavailability at the individual banking level. We expect a positive relation between the total banking loans borrowed by a country from other sampled European countries and their dispersed systemic risk on the European banking system.

Market-to-book ratio, defined as the market value divided by the book value of common equity, shows expectations of the banking system and proxies for growth opportunities. A higher *MB* ratio implies that investors expect the management to create more value from a given set of assets. In the systemic risk context, it is supposed that glamour banking systems, i.e. those with a high *MB* ratio, potentially contribute to systemic risk and destabilize the financial system to a greater extent (Liu, 2015). The second balance sheet ratio, i.e. leverage ratio or the ratio of total asset to common equity, reveals the solvency of each banking index; the higher a banking system's leverage, the lower its solvency and the lower its capacity to withstand shocks. Less solvent banking industries enforce higher contagion risk on other countries' banking systems. Thus, we anticipate a positive relation of leverage ratio with the systemic risk gauge (López-Espinosa, Moreno, Rubia, and Valderrama, 2012; Adrian and Brunnermeier, 2016).

Risk managers and investors employ the *IPI* of different industries or the whole economy to study the growth in that industry or economy. Industrial production is one of those variables, which is closely related to business cycles and aggregate economic conditions. In the systemic risk literature, it is argued that there must be negative relation between the growth rate of *IPI* and systemic risk.

PPI measures the price level of producers' basket of goods and services. It represents the average wholesale prices received by domestic producers of goods and services. In a developed and healthy economy, the PPI figures have important implications for corporate clients of banking businesses and also policy-makers. A negative or very low inflation rate might be seen as an indication for insufficient economic growth. In contrast, when the producer-basket cost moderately increases it conveys optimistic implications for the GDP growth. Therefore, we expect a negative relation between variation in PPI and the systemic risk measure.

A lower rate of unemployment, as an additional macro indicator, means a higher rate of GDP growth and thereby less economic distress. That is to say, in an economic respect, a positive relationship between unemployment rate and contagion risk in the banking system is expected. However in their paper, Kim et al. (2013) show that, in the 1980s and the 1990s, unemployment rate is negatively related to systemic risk, contrasting the 2000s in which the relation is positive.

Economists presume that, when a country's stock market is performing well, the systemic risk embedded in the banking system will be less to some degree. Due to the close connection of banking and financial market contagions, there must be negative relation between the growth of stock market and the systemic risk measure (see Engle et al., 2015). Greenwood et al. (2015) record a significant relation between the vulnerability estimations of European banks and equity downturns that occurred in 2010-2011.

As the most prevalent method to measure portfolio risk, *VaR* concentrates on the risk of an individual institution in isolation. The simple historical simulation *VaR* of a banking equity index is simply the 1% or 5% quantile of the banking equity returns. In the right-hand side of equation 2, there is a nested *VaR*-term ($\Phi^{-1}(q)\sigma^{eu}$), which evidently indicates the risk of the European banking system itself, in contrast to the countries' individual risk[1].

The crisis dummy is a dummy representing the global and the European debt crises. Therefore, it is one in 2008-2012 and zero in other years of the examination. It is frequently cited in the literature that, during the recent financial crisis, systemic risk is more distinguished owning to elevation in the risk factors. This means that there is a one-to-one relationship between this dummy variable and the risk measure.

5 Estimation Results

This section analyzes the main determinants of systemic contagion from an individual country's banking to the European banking system. Acknowledging the role of different attributes in the risk expansion, we engage key country-level and macroeconomic characteristics in a regression model. In the first step, we compute the time invariant version of the $\triangle CoVaR$ measure, $UC - \triangle CoVaR$. In the second step, we investigate how distinct individual characteristics of banking industries and also economic conditions contribute to the systemic risk measure.

[1] The *VaR* variable, as an explanatory in the panel regression analysis, is the stand-alone risk of each country's banking index and not that of the European banking system.

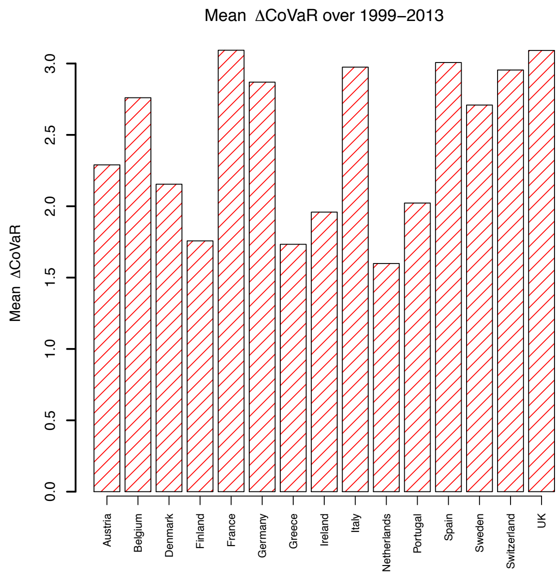

Figure 1: $\triangle CoVaR - 1\%$ **of all countries.** This figure shows the entire sample mean, in percentage, of $\triangle CoVaR - 1\%$ for the 15 banking indices over 1999-2013.

5.1 Estimation of $UC - \triangle CoVaR$

As an alternative method to quantile regression, which requires more observations, we estimate the $\triangle CoVaR$ measure by Unconditional Correlation (see equation 2). In order to make the interpretations more straightforward, we multiply the estimated values by minus one. Figure 1 shows the risk spillover of each European country on the banking system in Europe, namely the absolute value of $\triangle CoVaR$. The y-axis is the mean of different countries' $\triangle CoVaR$ over 15 years, 1999-2013. As is evident from this figure, the Dutch and British banking industries have the lowest and the highest mean of $\Delta CoVaR$, respectively, during the studied period.

Dutch financial safety has improved in recent years compared to the global crisis period. In the aftermath of the financial crisis, the large banks have preserved adequate capital buffers. In addition, the industry has become much more domestically oriented and smaller than before.

At the end of 2011, foreign lending by Dutch banks declined dramatically to such a degree that the industry's foreign activity made up just 15% of total sector assets. In contrast, the major British banks are heavily exposed to the US financial sector and also the banking systems of vulnerable Euro-area countries (Schildbach, 2011).

5.2 Correlation, *VaR* and $\triangle CoVaR$

One of the main channels of systemic risk progression is contagion or the micro channel. An initial shock causes a banking industry to fail, which subsequently leads to the failure of other banking sectors because of interconnection. Correlation is used as an indication for the interdependencies and "contagion" among banking businesses. In some studies, contagion is also related to "excess correlation"[1]. Correlation typically arises from exposure to common shocks. As a result, losses tend to spread across financial institutions during stress times, which, in turn, amplifies the threat of systemic contagion[2]. These stylized facts motivate the presence of the correlation in equation 2.

Figure 2 displays the correlation of each country's banking index with the European equity index over 1999-2013. Except for the Dutch banking, this figure shows that, for most indices, the correlations fairly increase over the time of investigation. Among some other causes of this observation, the implementation of the second banking directive and the advent of the euro are discussed more among economists. Along with ongoing integration and interconnection in the banking systems, the European countries' economic factors such as interest rates converge together, (see Schröder and Schüler, 2003, and Kaufman and Scott, 2003)[3].

Figure 3 compares the means of correlation, VaR, and $\triangle CoVaR$ for different countries in the crisis, 2008-2012, and non-crisis periods. The

[1] "Correlation over and above what is explained by fundamental factors" (De Bruyckere, Gerhardt, Schepens, and Vander Vennet, 2013).

[2] For more details, see Karimalis and Nomikos (2014).

[3] This is a well-documented fact that financial markets move more closely together during times of crisis. In other words, the conditional correlations between asset returns are much stronger in periods of financial distress (see López-Espinosa et al., 2012).

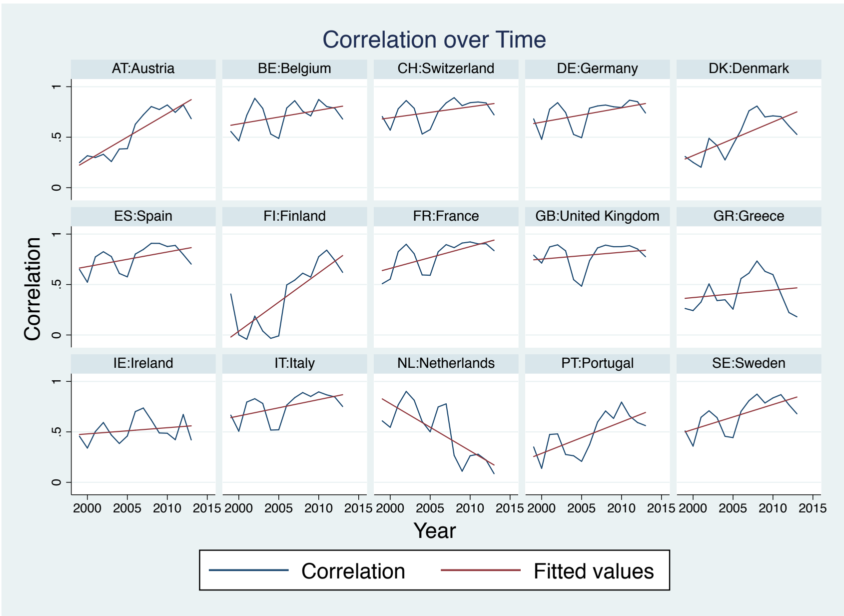

Figure 2: **Correlation over 1999-2013.** The plot exhibits the development in correlations of the European countries' indices with the European banking index in 1999-2013. The red lines in each subplot are the linear fitted lines.

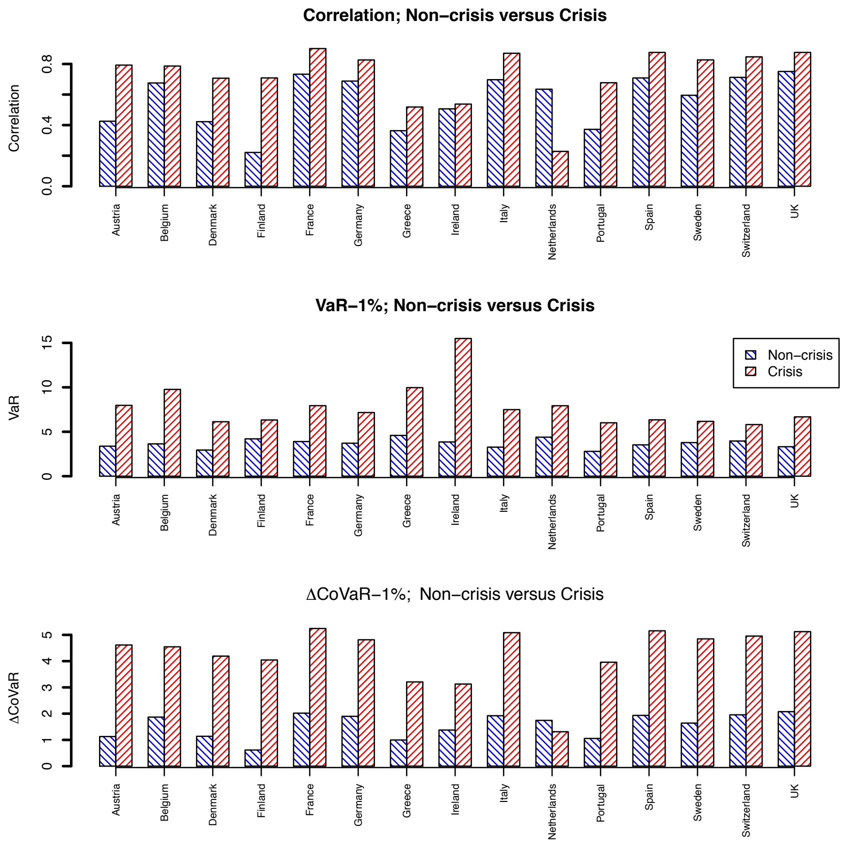

Figure 3: **Correlation, VaR, and $\triangle CoVaR$ in the non-crisis and crisis periods.** The mean of correlation (between the individual banking indices and the European index), $VaR - 1\%$ (of each country's banking equity index), and $\triangle CoVaR - 1\%$ in the crisis and non-crisis periods are plotted in this bar plot. The first shaded bar of each country belongs to the non-crisis period, while the second bar represents the crisis period, 2008-2012.

first subplot of this figure shows the variations in the mean of correlation between the individual banking indices and the European index. Excluding the Dutch banking sector, for all other indices there is a larger correlation in the last crises. The second subplot presents the change in the mean of one-day $VaR-1\%$ of different banking indices in non-crisis and crisis times over the course of the study period, 1999-2013. For all of the countries, there is a higher level of $VaR-1\%$ during the crisis period. The third subplot demonstrates that the mean of $\triangle CoVaR-1\%$ increases during distressed periods compared to non-crisis periods.

Figure 4 shows the variation in $\triangle CoVaR-1\%$, correlation, and $VaR-1\%$ for the British and Dutch banking sectors. These banking industries have the highest and the lowest systemic risk contribution to the European system. As mentioned earlier, correlation between banking stock indices has been used as a measure for the interdependencies and systemic risk potential among banks[1]. A consequent rise in the correlation of asset/liability of banking industries, due to more interconnection or integration, increases the probability of a systemic crisis in banking. As the first plot shows, the $\triangle CoVaR$ for the Dutch banking industry substantially declines after the financial crisis at the of 2007, whereas the measure for the British banking industry widens after the crisis. Similar to the variations in the $\triangle CoVaR$, the correlation of the Dutch and British banking industries significantly decreases and increases, respectively, after 2007. Contrasting the first and the second plots reveals the close association between theses measures, i.e. $\triangle CoVaR$ and correlation.

In contrast to the close relation of correlation and $\triangle CoVaR$, a banking business might have a low VaR but a high $\triangle CoVaR$ or vice versa. Comparing the first and the third plots in Figure 4 indicates that even though the $\triangle CoVaR$ for the Dutch banking industry largely drops after 2007 but its VaR ascends in 2008. The VaR of a banking equity index only represents the stand-alone risk measure of that banking industry regardless of any adverse movement for other banking indices. This means that relying merely on VaR might over- or under-estimate the externali-

[1] It is the so-called correlation channel for systemic risk (see De Nicolo and Kwast, 2002).

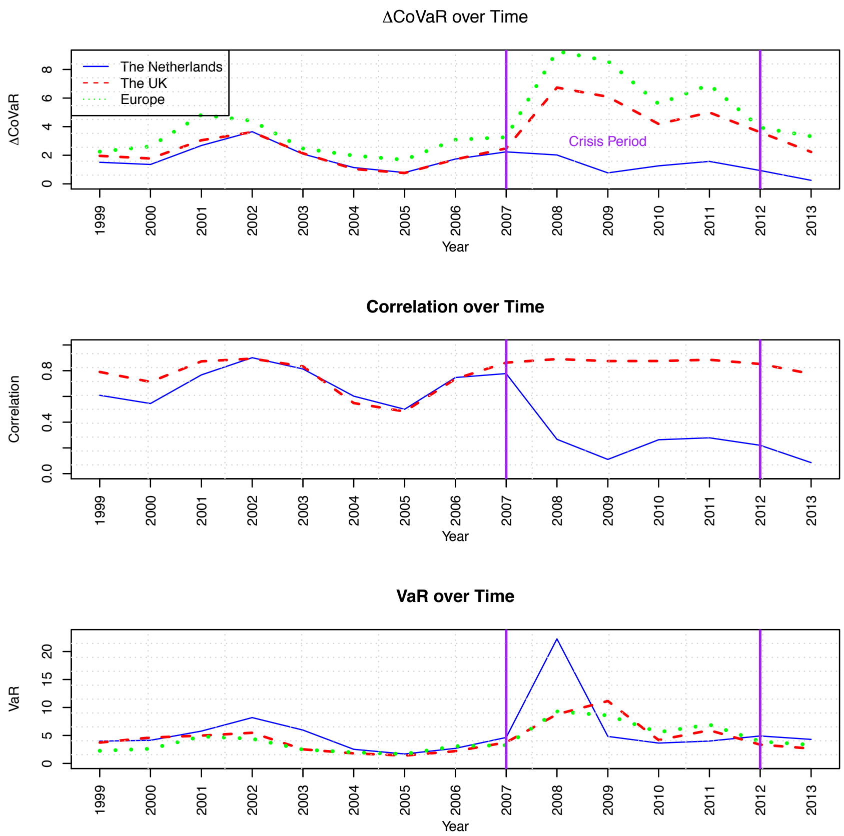

Figure 4: $\triangle CoVaR - 1\%$**, correlation, and** $VaR - 1\%$ **for the Dutch and British banking systems.** This figure shows the yearly $\triangle CoVaR$, correlation, and VaR for the British and Dutch banking indices from 1999 to 2013. These two banking systems have the highest and the lowest average $\triangle CoVaR$, respectively, over this period. The vertical purple lines show the beginning and the end years of the financial crisis in Europe, namely the end of 2007 and the end of 2012, respectively.

Country	$UC-1\%$	$QR-1\%$	$QR-99\%$
Austria	-2.29	-4.46	3.92
Belgium	-2.76	-6.13	5.32
Denmark	-2.15	-3.46	2.82
Finland	-1.76	-3.40	2.84
France	-3.09	-5.47	5.34
Germany	-2.87	-4.75	4.70
Greece	-1.73	-3.36	3.69
Ireland	-1.96	-9.12	5.57
Italy	-2.97	-5.21	4.44
Netherlands	-1.60	-3.80	2.91
Portugal	-2.02	-3.56	3.37
Spain	-3.01	-5.15	4.16
Sweden	-2.71	-4.60	4.67
Switzerland	-2.95	-5.16	4.47
UK	-3.09	-5.31	4.53

Table 3: $\Delta CoVaR-1\%$ **and -99%.** This table reports the quantile regression estimations of 1% and 99% of $\Delta CoVaR$ also the mean of $UC-\Delta CoVaR-1\%$ over 1999-2013 for all the examined banking indices.

ties of each country's banking to the European system. Consequently, the market disciplines targeting safety and soundness of the market might be misleading if they are founded upon such a naïve measure, VaR.

5.3 Asymmetry in $\triangle CoVaR$

The rapid integration and interconnection of banking sectors, over the past two decades, has exposed the sectors to greater externalities and overseas vulnerabilities. A number of empirical studies have recently devoted their focus to the strong interdependence and correlation in extreme markets conditions. In an empirical study, López-Espinosa et al. (2012) show that tail returns asymmetries play an essential function in measuring and capturing the sensitivity of systemic risk. Therefore, in the following, we check whether the $\triangle CoVaR-1\%$ is symmetric or asymmetric in extreme scenarios.

The quantile regression estimation of the measure for country i's banking index is performed by the following equation,

$$\hat{X}^{eu,i}_{t,q} = \hat{\alpha_q}^{eu,i} + \hat{\beta}^{eu,i}_q X^i_t. \tag{3}$$

where $\hat{X}^{eu,i}_{t,q}$ denotes the predicted value of eu's return conditional on the banking i's return. The quantile regression coefficient, $\hat{\beta}^{eu,i}_q$, estimates the change in a specified q-th quantile of $CoVaR^{eu|X^i_t}$ produced by a one-unit change in VaR^i_q. If we use VaR^i_q as a predictor, it gives the $CoVaR^{eu,i}_q$ measure for the conditioning event $C(X^i)$ in which $X^i_t = VaR^i_q$. Having said that, $\Delta CoVaR^{eu|i}_q$ is presented by the following relations:

$$CoVaR_q^{eu|X^i_t=VaR^i_q} = \hat{\alpha_q}^{eu,i} + \hat{\beta}^{eu,i}_q VaR^i_q \tag{4}$$

$$CoVaR_q^{eu|X^i_t=VaR^i_{50\%}} = \hat{\alpha_q}^{eu,i} + \hat{\beta}^{eu,i}_q VaR^i_{50\%} \tag{5}$$

therefore, $\Delta CoVaR^{eu|i}_q$ is given by:

$$\Delta CoVaR^{eu|i}_q = \hat{\beta}^{eu,i}_q (VaR^i_q - VaR^i_{50\%}) \tag{6}$$

Note that the unconditional VaR^i_q and $VaR^i_{50\%}$ are estimated by simple historical simulation and $\beta^{eu,i}_q$ is estimated by the q-th quantile of quantile regression.

To examine this asymmetry, we run quantile regressions on the entire sample, 1999-2013, for all banking indices. Table 3 demonstrates the $\Delta CoVaR$ estimates at the 1% and 99% quantiles, which are evaluated by equation 6. The absolute value of those estimates are also plotted against each other in Figure 5. In this scatter plot, points sitting on the 45-degree line suggest equal $\triangle CoVaR$s during those times in which markets are growing, 99% quantile, or as markets are declining, 1% quantile. As 12 of 15 points are positioned below the 45-degree line, the plot declares comovement dissimilarities in two sides of the spectrum. That is, the externalities tend to be stronger in declining times, i.e. 1% quantile, than

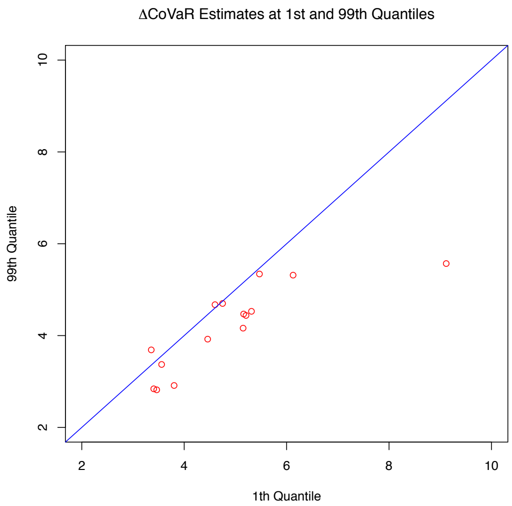

Figure 5: $\triangle CoVaR$ **in the upper and lower tails.** This plot depicts the spillover effects of the banking industries on European banking during times in which markets are distressed (quantile of 1%) or markets are developing (quantile of 99%). The estimates of $\triangle CoVaR$ are depicted in absolute value.

in growing times, i.e. 99% quantile. This finding is consistent with other studies that point to the risk broadening in bad scenarios of market returns[1].

5.4 Univariate Regression Estimation

We run dynamic panel regression of $\triangle CoVaR$ values on a set of a fundamental country's independent macroeconomic and banking industry-specific variables. Those variables include *VaR*, total asset, bilateral loan, market-to-book ratio, stock market returns, leverage ratio *IPI*, *PPI*, and unemployment rate. Table 4 reports the univariate regressions of the dependent variable, $\triangle CoVaR - 1\%$, on the potential explanatory variables. The signs of most variables are the same as the hypothetical sign in the

[1] For instance, Wong and Fong, 2011.

Variable	$\Delta CoVaR_t - 1\%$									
$\Delta CoVaR_{t-1}$	0.35***	0.01	0.44***	0.59***	0.80***	0.68***	0.51***	0.70***	0.69***	0.67***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)	(0.03)	(0.06)	(0.05)	(0.05)	(0.06)
VaR-1%	0.29***									
	(0.02)									
CD		2.62***								
		(0.17)								
A			1.26***							
			(0.21)							
BL				0.44*						
				(0.24)						
MB					0.61***					
					(0.15)					
R						-3.07***				
						(0.18)				
IPI							-5.96***			
							(1.87)			
PPI								12.59***		
								(2.67)		
AE									0.08***	
									(0.02)	
U										-1.37*
										(0.79)

Table 4: **Univariate regressions.** This table exhibits the univariate Arellano & Bond (AB)-panel regressions of the $UC - \Delta CoVaR - 1\%$ on each explanatory variable. All of the univariate regression coefficients are significant. ***, **, and * denote the significance levels at 1%, 5%, and 10%, respectively.

literature. However, the sign of *PPI* is the opposite of our expectation.

5.5 Multivariate Regression Model

The dynamic panel regression model of equation 1 relates $\triangle CoVaR_{i,t}^{eu|i} - 1\%$ to market financials, namely mean of stock market returns and *VaR* of banking equity returns, also corresponding individual bank qualities, total asset, bilateral loan, market-to-book ratio, and asset-to-equity ratio), and macro factors, namely industrial production index, production price index, unemployment, and crisis dummy. Table 5 presents the results of the panel regression of $\triangle CoVaR$ on the 15 banking businesses and European banking with respect to some financial and non-financial drivers.

Across all alternative model specifications, we consider Model 2 in Table 5 as the baseline regression model. The table demonstrates that banking-specific fundamentals do predict the systemic risk contribution of different banking industries, in an economically meaningful way. In contrast to the role played by *VaR*, crisis dummy *(CD)*, total asset/size (*A*), bilateral loan (*BL*), stock market returns (*R*), market-to-book ratio (*MB*), and *IPI*, we find no evidence that *PPI*, unemployment rate (*U*), and the banking leverage ratio (asset-to-equity: *AE*) determine the risk contagion in the European banking system.

Banking size is cited as an important determinant of a bank's contribution to systemic risk in other studies. The positive and statistically significant coefficient of total asset (*A*) suggests that bigger banking systems impose more of a systemic risk. At the onset of a crisis, bailout agreements are conducted to rescue large banking businesses. This implicit guarantee boosts the risk appetite of those banks since supposedly protected banks have less incentives to apply market disciplines[1]. This outcome supports the claim that large and interconnected European banks should be subject to greater regulatory standards by European macroprudential regulation schemes.

The results also highlight the relevance of crisis episodes *(CD)* in mea-

[1] See Moore and Zhou (2014) and López-Espinosa et al. (2012) for more details.

Model	AB (1)	AB(2)	AB (3)	AB (4)	FE (5)
Variable	$\Delta CoVaR$-**1%**	$\Delta CoVaR$-**1%**	$\Delta CoVaR$-**5%**	$\Delta CoVaR$-**Tail-1%**	$\Delta CoVaR$-**Tail-1%**
$\Delta CoVaR_{t-1}-1\%$	0.24***	0.23***			
	(0.06)	(0.05)			
VaR -1%	0.06***	0.05**		0.11***	0.08***
	(0.02)	(0.02)		(0.03)	(0.03)
CD	1.63***	1.63***	1.08***	1.94***	1.92***
	(0.22)	(0.19)	(0.13)	(0.25)	(0.18)
A	0.40*	0.42**	0.26*	-0.06	0.23***
	(0.21)	(0.20)	(0.14)	(0.29)	(0.07)
BL	0.44**	0.43**	0.36***	0.60**	0.27**
	(0.19)	(0.18)	(0.12)	(0.25)	(0.11)
MB	0.56***	0.59***	0.44***	0.62***	0.60***
	(0.10)	(0.09)	(0.06)	(0.12)	(0.10)
R	-1.44***	-1.51***	-0.92***	-0.39	-0.53*
	(0.24)	(0.21)	(0.15)	(0.28)	(0.28)
IPI	-5.94***	-5.69***	-3.61***	-3.11**	-3.68***
	(1.27)	(0.98)	(0.68)	1.36	(1.29)
PPI	-0.99				
	(2.27)				
AE	0				
	(0.01)				
U	-0.59				
	(0.48)				
$\Delta CoVaR_{t-1}-5\%$			0.23***		
			(0.05)		
VaR -5%			0.13***		
			(0.03)		
$Tail-\Delta CoVaR_{t-1}-1\%$				0	
				(0.06)	
Cons.	-13.40***	-13.77***	-9.79***	-6.43	-8.17***
	(3.07)	(3.01)	(2.07)	(4.45)	(1.47)

Table 5: **Multivariate regressions.** This table reports the Arellano & Bond (AB) estimation results with different choices of independent and dependent variable, i.e. $\Delta CoVaR-1\%$, $\Delta CoVaR-5\%$ and $Tail-\Delta CoVaR-1\%$. Model 3, with $\Delta CoVaR-5\%$, examines the robustness of the results in the Model 2 specification. The second robustness check of $Tail-\Delta CoVaR-1\%$ is reported in Model 4. Model 5 demonstrates the fixed-effects (FE) panel regression of $Tail-\Delta CoVaR-1\%$, on the explanatory variables. ***, **, and * denote the significance levels at 1%, 5%, and 10%, respectively.

suring systemic risk contributions and the poor performance of banks. The recent crises provide sound evidence of the overall increase in systemic risk. The positive and statistically meaningful coefficient of *CD* indicates that systemic risk spread is driven by the global solvency problems and the sovereign debt crisis in a number of Eurozone member countries. Other causes of the risk in European banking are the *VaR* of each single banking system, the performance of every country's stock market (*R*), the market-to-book ratio (*MB*), the industry growth (*IPI*), and also the new introduced variable denoted as bilateral loan (*BL*).

We also check the robustness of the regression results (of Model 2) by estimating a similar panel regression but with $\triangle CoVaR - 5\%$ as the dependent covariate, instead of $\triangle CoVaR - 1\%$. The robustness check confirms the model specification concerning the significance and also the sign of the risk determinants. However, the magnitude of the risk drivers varies rather largely but to a different extent for those risk contributors. In other words, the absolute values of all coefficients are less in Model 3 compared to Model 2, though the reduction is more considerable for systemic risk causes such as size, bilateral loan, and crisis dummy.

Another robustness check, presented in Model 4, concerns the way that we estimate the correlation element in equation 2. As mentioned in 5.3, the disproportionate estimates of systemic risk in the lower and upper tails empirically suggest the importance of correlation factor for the extreme events. To take account for this asymmetry, in a new way of computing the $\triangle CoVaR$ measure, correlation is evaluated from those observations that are in the 25% quantile simultaneously, instead of the entire sample correlation. To this end, we match those observations that are on quartile or 25% quantile on the same date. Then, in equation 2, we insert this new estimate of correlation to better explain the covariation in the tail observations. These estimates of $\triangle CoVaR$ allow an assessment of systemic risk contribution for different degrees of tails. The estimated values of the new $\triangle CoVaR$s, denoted by $Tail - \triangle CoVaR - 1\%$, are very close to the ordinary computation method of the entire sample correlation.

As Table 5 presents, Model 4 with the new estimates returns interesting results. The significance of controls in Model 4 is quite different compared to the principal Model 2, although the signs are the same. Interestingly, the size of banking (*A*) and $\triangle CoVaR_{t-1}$ are not anymore statistically significant. Unlike these two variables, the magnitude of other variables such as bilateral loan (*BL*), *VaR* − 1%, and crisis dummy *(CD)* is larger. Since $\triangle CoVaR_{t-1}-1\%$ in Model 4 is not significant, a fixed-effects (FE) regression of $Tail - \Delta CoVaR - 1\%$ on the explanatory variables is estimated in Model 5. As an extra convincing robustness test, Model 5 supports our results in the principal Model 2.

6 Conclusion

In this paper, the risk spillover from a sample of countries to the European banking system is examined by applying the well-known $\triangle CoVaR$ measure. The percentage of foreign assets to total assets is high for the banking systems of the studied European countries. By running the Arellano and Bond GMM estimator, we find a few interesting results on empirical conductors of tail-risk interdependence. The empirical evidence supports that banking size (or total asset) is a persistent determinant of systemic risk across Europe. Most prominently, larger banking industries are more interconnected, complex, and susceptible to take on excessive risk. The systemic risk indicator is elevated in the global subprime and European sovereign debt crisis due to higher correlation and volatility. Other drivers are categorized as *VaR*, market-to-book ratio, market returns, *IPI*, and bilateral loan. Finally, the empirical analysis shows that there is a strong degree of asymmetric response to the risk dispersion during development and recession periods.

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