T.C
ISTANBUL COMMERCE UNIVERSITY
GRADUATE SCHOOL OF FINANCE
INTERNATIONAL FINANCE PROGRAM

Evaluation of Systemic Risk between American and European Financial Markets

MA Thesis

Safa MASTOURI
100044151

Istanbul, 2018

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T.C. İSTANBUL TİCARET ÜNİVERSİTESİ

T.C.

İSTANBUL TİCARET ÜNİVERSİTESİ

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ABSTRACT

This thesis focuses on the study of systemic risk in the American and European financial systems for the period from 20/08/2004 to 28/02/2014. This topic is arousing attention from financial actors, since the crisis of 2007. The need for a proper regulation has motivated the use of regulatory reform to ensure financial stability. To assess systemic risk, Adrian and Brunnermeier (2011) advocated the use of CoVaR integrating quantile regression, instead the Value at Risk, which is unable to detect systemic risk. Thus, we seek to calculate CoVaR for the United States and European markets. In the light of related findings, we conclude that the life insurance sector contributes most to systemic risk in the USA, while in the Euro zone it is the financial services sector. It appears also that large financial institutions are not necessarily the most responsible for triggering systemic risk.

Key words: Systemic Risk, Financial regulation, Value-at-Risk, CoVaR, Quantile regression.

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AIG	: American Insurance Group
ICVCs	: Open-ended Investment Company with variable capital
MBS	: Mortgage-Backed Security
CoVaR	: conditional, contagion or co-movement value at risk
VaR	: Value at Risk
ABS	: Asset Backed Securities
CMBS	: Commercial Mortgage Backed Security
SBS	: Shadow Banking System
SIVs	: Structured Investment Vehicles
CDS	: Credit Default Swaps
LTCM	: Long Term Capital Management
Fed	: Federal Reserve Bank
GDP	: Gross Domestic Product
FSB	: Financial Stability Board
IMF	: International Monetary Fund
ESRB	: European Systemic Risk Board
EBA	: European Banking Authority
EIOPA	: European Insurance and Occupational Pensions Authority
ESMA	: European Securities and Markets Authority
FSOC	: Financial Stability Oversight Council
FDIC	: Federal Deposit Insurance Corporation
FIO	: Federal Insurance Office
SFIS	: Systemically Important Financial Institutions
CAPM	: Capital Asset Pricing Model
APT	: Arbitrage Pricing Theory
SMB	: Small minus Big
HML	: High minus Low
HS	: Historical Simulation
ARCH model	: AutoRegressive Conditional Heteroskedasticity model
GARCH model	: Generalized AutoRegressive Conditional Heteroskedasticity model

POT	: Peaks-Over-Threshold approach
CAViaR	: Conditional Autoregressive Value at Risk model
MES	: Marginal Expected Shortfall
SRISK	: Systemic Risk
LRMES	: Long-Run Marginal Expected Shortfall
S&P 500_exFin	: S&P 500 Ex-Financial index
SE 600_exFin	: STOXX Europe 600 ex_Financials Index
V-Lab	: Volatility Laboratory (known as V-Lab)
CRM	: Center for Risk Management
DIP	: Distress Insurance Premium
OLS	: Ordinary Least Squares method
KS	: two-sample Kolmogorov-Smirnov test
Bk	: Banking Sector
li	: Life Insurance Institutions
nli	: Non-life Insurance Institutions
fs	: Financial Services Sector
MC	: Market Capitalization
OECD	: Organisation for Economic Co-operation and Development
EBA	: European Banking Authority
EIOPA	: European Insurance and Occupational Pensions Authority
TBTF	: Too Big to Fail

General Introduction

"If you cannot measure a thing, go ahead and measure it anyway",
Knight (1921).

Today, it is recognized that an unfavorable event affecting the financial sphere has negative repercussions on economic fundamentals at the national, regional and international levels.
Whether it was the bursting of the Internet bubble in 2000, the subprime crisis in 2007, the bankruptcy of the American bank "Lehman Brothers" in 2008, the increase in the budget deficit and the rise in the level of " Greece and other European countries, economies have found themselves in recession with rising unemployment rates, slowing economic growth, excessive debt ratios, rampant inflation, and so on. These are indicators revealing an unfavorable climate to trust, where uncertainty and risk prevail.
Since a long time, the financial system has played a major role in the proper functioning of modern economies. Nevertheless, the recent financial crisis of 2007 clearly shows that its failure can be harmful for the interconnected economies. This has prompted researchers and regulators to become aware of the insecurity of the financial system and the seriousness of so-called systemic risk.
The damage inherent in this risk is felt dramatically only after it has materialized. In this sense, vigilance must be exercised in the continuous supervision of the financial system and the timely analysis of the signals raised according to Schwaab et al. (2011).
That is why the UK financial authorities, for example, did not hesitate to assist "Northern Rock" in 2007, which was not a big bank at the time. With the flow of customers to withdraw their deposits, authorities considered that potentially a systemic risk could occur if the bank in question went bankrupt. A year later, American financial authorities did not think the same for the big bank "Lehman Brothers". Thus, they regret today not having acted in time to bail out.

In fact, we must not rely on forecasts based on trial and error or make random decisions not based on observation and analysis of the financial situation, according to Gauthier et al. (2012).
Given the vulnerability of the economic situation, because of internal or external financial fluctuations, it is more imperative than ever to pay particular attention to the optimization of

financial regulation and to raise awareness among decision-makers of the importance of developing rules for maintaining financial stability.

Stein (2010) states that "the primary objective of financial reform must not only strengthen a set of large institutions, but it must also reduce the fragility of the entire financial system ".

According to Moshirian (2012), risks to the financial system are not merely an aggregation of the risks associated with each institution, but also include a non-negligible component of endogenous risk that reflects the interrelationships between the various institutions.

In particular, banks have attracted interest from regulators, which have imposed minimum levels of capital on them, such as a cushion to avoid unforeseen losses (the Basel Accord). This means that so far the systemic importance of other financial sectors and institutions has been ignored.

On their side, Demirguc and Detragiache (2011) when analyzing a sample of 3,000 banks in 86 countries, rejected the assumption that consistent regulation and continuous supervision of the banking sector are sufficient to ensure the stability of the financial system.

In this respect, it seems interesting to study other financial sectors such as insurance companies and financial services companies since they can have a decisive impact on the real economy as illustrated by the failures or the near-bankruptcy of Long Term Capital Management (LTCM) in 1998 and American International Group (AIG) in 2008. The aim is thus to orient regulators towards the best procedure to adopt by providing them with necessary tools and elements needed to make timely decisions.

In order to meet this challenge, it is important not only to reform the regulatory framework for financial governance, but also to promote a more reliable methodological approach.

According to Moreno and Pena (2013), risk must not be considered in isolation from each financial institution. Hence the interest of designing more rigorous measures to take account of the interconnections within the financial system taken as a whole and towards the real economy.

Indeed, the most widely used measure of risk is that called Value-at-Risk (VaR), which calculates an institution's monetary loss for a given probability and period. The problem is that it does not consider the institution to be a component of a system that may be detrimental to financial stability and economic growth. This measure has limited scope and is incapable of detecting the systemic nature of the risk.

Recently, Adrian and Brunnermeier (2011) developed the systemic risk assessment approach, known as "CoVaR". The latter has the particularity of taking into account the effects of contagion and of identifying the sectors or financial institutions that contribute more to the systemic and individual risks corresponding to the other institutions.

In our study, the "CoVaR" is estimated for two different geographical areas and influences regionally and globally: the United States and the "Euro" zone.

To differentiate ourselves from previous work, the empirical strategy for our study is based on a double analysis: inter-sectoral and inter-company studies seeking to identify the sector and the most responsible institution for the triggering of systemic risk respectively. In addition, we intend to study the insurance sector in depth, splitting it into life and non-life insurance in order to be among the pioneers having addressed this aspect. Specific tests will be applied to verify the results obtained.

In concretizing the famous adage "**prevention is better than cure**", the problem that we will try to solve can be summarized by the following question:

How is it possible to protect the financial system against systemic risk and ensure its stability before it is too late?

This main question leads us, with reference to the study we are considering to undertake on the American and European markets, to investigate the following issues:

- Do banks contribute the most to systemic risk compared to other financial sectors?
- Are large financial institutions more responsible for the emergence of systemic risk? Is size a good indicator for assessing the systemic nature of financial institutions?

For all the considerations previously mentioned, our master study comprises four main chapters:

The first chapter is devoted to the explanation of the concept of systemic risk, which has given rise to a lot of ink since the cataclysm of 2007 and thus has been the focus of several researchers. The latter endeavored to give the systemic risk a clear definition and to detect its potential sources. They also addresses the regulatory reform component to minimize systemic risk.

Through the second chapter, we propose to discuss the evolution of the risks notions as well as the measures relating to each type of risk. However, we intend to focus on risk assessment methods, which have been designed since the 1950s, with a particular attractiveness to "VaR" which is the basis of our recommended reference measure namely "CoVaR" applied empirically in the chapters to come.

Concerning the third chapter, it is dedicated to the presentation of the data and the methodology considered. Similarly, we will reserve its beginning to the clarification of the motivation behind our study in relation to the previous empirical work, in addition to the identification of the research hypotheses adopted.

Finally, the last chapter preceding the general conclusion will be the presentation of the empirical work results, accompanied by the interpretations and preliminary conclusions arising from their respective analysis, taking into account the two regions selected in the present study.

Chapter 1

Systemic risk and financial regulation

Introduction

In 2007, the global financial system experienced an exceptional crisis, the first of its kind and almost unprecedented. It has successively affected different institutions and sectors in many countries before turning into a severe economic crisis, where the GDP of developed countries fell by 3.5%, according to the report of the International Monetary Fund (2009).

We conclude that the financial system, which played a central role in promoting economic growth, can systematically have devastating effects on the economy as a whole.

The financial system is described as fragile in the sense that a shock is transmitted from one institution to another otherwise the entire financial system and all of its components.

This interaction between the various institutions within the financial system on the one hand and between the financial and economic spheres on the other is due to the contagion phenomenon studied in finance since the 1990s but often under-estimated or even neglected by professionals and regulators when quantifying the risk.

This is why the notion of risk has also undergone a remarkable evolution. We are currently talking about the systemic risk that will ultimately destabilize the financial system as well as the healthy functioning of the rest of the economy through contagion.

The increased reflection on this risk has also put into question the effectiveness of the current so-called micro-prudential regulation to ensure the sustainability of various financial institutions and consequently the stability of the entire financial system. This led to the emergence of so-called macro-prudential regulation, where the entire financial system was under scrutiny, thus requiring stricter prudential rules than before.

In this chapter, we propose to clarify in the first place the concept of systemic risk. We will also focus on the study of the vast reform of financial regulation, which is essential for the stability of the financial system.

1. Systemic risk:

The concept of risk continues to evolve, due to the development of the financial system and its dependence on the real economy.

1.1. Impact of the financial system on the real economy:

According to the report of the Banque de France (2013), the financial system can be broken down into three inseparable elements, namely: financial markets, financial intermediaries (such as banks, insurance companies or institutional investors) and financial institutions that assure the transfer of payments, exchange, clearing and settlement of securities.

Its role is to mobilize resources between agents with a financing capacity and those experiencing a need for financing, directly through financial markets or indirectly via financial intermediaries. It thus makes it possible to finance the State, to ensure the production of the companies and to support the consumption of the households, essential engines of the economic growth.

According to some authors, like McKinnon (1973), King and Levine (1993), Levine (1997), Beck et al. (2000), Ang and Mckibbin (2007), the financial system and economic growth are two positively correlated variables.

Certainly, a seriously weakened financial system is detrimental to the economy.

This observation was verified mainly following the crisis of "supbrimes"[1] (2007). The latter has cast its shadow over several financial institutions, such as Bear Sterns / Fannie Mae Bank and Freddy Mac[2] / American Insurance Group (AIG) / Merrill Lynch Bank, all of which have been bailed out by the US Treasury and the Fed, exception of Lehman Brothers Bank.

As an indication, it is necessary to review the following rescue actions:

- March 14, 2008: the buyout of Bear Sterns by US bank JP Morgan, to whom the Fed has released an envelope of about $ 30 billion.
- September 7, 2008: the placing under government tutelage of Fannie Mae and Freddie Mac.
- September 14, 2008: The acquisition of Merrill Lynch by Bank of America, to which the Fed has provided $ 25 billion.

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[1] The development of the real estate market has prompted banks to provide mortgages to households that do not have the collateral necessary to access ordinary borrowing (hence the "Subprime" which is a credit score of a borrower).

[2] These are two private organizations created since 1970 and which have invested heavily in the purchase of mortgages to sell them when they are transformed into securities on the financial markets, to other investors.

- September 16, 2008: The Fed grants $ 85 billion to rescue AIG.

The bet made by the authorities that the financial system could absorb the shock of the collapse of Lehman Brothers has undoubtedly failed.

According to Dumontaux and Pop (2012): "Lehman was a big bank operating in certain countries such as London, Hong Kong, and Tokyo. The government mistakenly thought that after the crisis of the Bear Stearns Bank and its sell off in March 2008, the financial markets were preparing for future bankruptcies. "

The announcement of the bankruptcy of the 4th investment bank in the United States on Monday September 15th, 2008 triggered a wave of shock with multiple consequences, perceptible even in the real economy.

According to Chakrabarty and Zhang (2010), financial institutions in the United States (related or not to this failing bank) have all suffered at various levels. The banking market has become very risky. The suspicious banks of each other are reluctant to lend to each other. Therefore, they are forced to decide between two attitudes: do not easily grant credit to different economic agents which is called "credit crunch" according to Claessens and Kose (2013), or significantly increase the cost of credits.

The surge of information asymmetry, the rise of liquidity shortages, and the increase of investor anxiety about the current critical situation have created an ambiguous environment.

These problems can also be harmful to the various sectors of the real economy, such as industry, health, telecommunication, etc. They all suffered a slowdown in their activities.

On a global scale, such an event has affected several countries, mainly European ones. Indeed, "Although the crisis began in the United States, it becomes clear that European banks have been much more exposed to risk than it has been admitted," Honigman (2009).

On their part, Acharya et al. (2009) pointed out that Lehman's bankruptcy is a clear example of a systemic risk event that led to the near failure of the financial system.

Goodhart (2010) went even further considering the government's decision not to rescue Lehman Brothers as the most serious economic policy mistake. The crisis could have been avoided if the authorities bailed out the bank in question.

Thus, researchers and financial regulators have realized the danger of systemic risk, highlighting the negative impact of the financial system's insecurity on the real economy.

1.2. Definitions of systemic risk:

Systemic risk is often recognized as a "hard-to-define-but-you-know-it-when-you-see-it" concept. To understand properly this notion, we need to go through its literature reviews.

The systemic risk as defined by Bandt and Hartman (2002) has some basic perceptions that first must be clarified as follows:

- A systemic event reflects the revelation of bad news concerning either a financial institution or a narrowly defined market, or several markets and institutions in the broad sense. This type of event is likely to lead to a successive sequence of negative effects on one or more financial institutions or markets. .
- Following the above event, it should be emphasized that idiosyncratic shock (or disruption) initially affects an institution or a financial market before spreading to other institutions or markets. On the contrary, the systematic shock is directly harmful to all institutions or financial markets.
- Contagion is generally defined by Dirk (2010) as a phenomenon resulting in the occurrence of a shock shaking one or more markets, countries or institutions and spreading to other markets, countries or institutions.

At a more specific level, Bandt and Hartman (2002) identify chains of contagion between financial institutions.

The first is the chain of exposure (or actual chain), where the shock is transmitted from one institution to another having links with it. This channel joins, among others, the definition of the contagion which occurs between two relatively close economies thanks to the commercial or financial links according to Claessens and Forbes (2004). Empirically, Iyer and Peydro (2010) have shown that the more a bank lends money on the interbank market, the greater the likelihood of contagion from one failed bank to another bank.

The second is the chain of information, marked by the fact that the shock is rather transmitted between institutions, when the economic agents change their behavior according to the imperfect information circulating and decrypted differently by them. Such a channel reflects the definition of contagion in the strict sense, which occurs between two economies with different structures and no direct link, according to Forbes and Rigobon (2002).

From their side, Racickas and Vasiliauskaite (2011) explain the so-called "bank run"[3] phenomenon. Concretely, a client with the least concern about his bank at any time can withdraw all his funds to avoid any potential risk. Thus, the bank in question will be encountered with serious problems of liquidity and solvency[4].

- A systemic crisis, caused by a systemic event (broadly defined or strict), impedes the smooth functioning of the financial system which will have a negative impact on economic growth.

The following table, presented by Bandt and Hartman (2002) provides a clear view of systemic risk, focusing on financial institutions:

Table 1. Contagion between financial institutions

	A systemic event in the strict sense		**A systemic event in the broad sense**	
Probability of shock's occurrence	**Low**	**High**	**Low**	**High**
- Idiosyncratic Shock	✓	✓Contagion	✓	✓ Contagion leading to a systemic crisis.
- Systematic Shock			✓	✓ Contagion leading to a systemic crisis.

Source: ECB Working Paper, **"Systemic Risk: A Survey - European Central Bank"**, 2002, N°35.

[3] As an example, we cite the British bank "Northern Rock" (2007), the American bank "Wachovia" (2008), the Dutch bank "DSB Bank" (2009), the Swedish bank "Swedbank" (2010), etc.

[4] These two terms do not have the same meaning. A company said to be solvent, if all of its assets (consisting of fixed assets, inventories, or even cash) are greater than all its liabilities (bank debts, suppliers, etc.). Moreover, liquidity is in a sense, the short-term solvency, in other words, the ability of the company to meet its immediate deadlines.

Obviously, the appearance of shocks and their spread are uncertain. Systemic risk has two dimensions, which are the severity of systemic events and the probability of occurrence of shocks. Indeed, the strongest systemic events are in particular systemic crises with low probability of emergence, which could lead some to consider them less worrying. However, once the crisis appears, its effects could be very serious. Such a finding gives rise to another dimension of systemic risk, namely the impact of systemic events in the financial sector on other sectors of the economy.

On one hand, we can also distinguish an horizontal view of systemic risk where shocks shake the financial system and a vertical view where the real economy is affected.

On the other hand, it is clear that other more specific definitions for systemic risk are proposed in the literature.

Following the studies of the Financial Stability Board, International Monetary Fund and Bank for International Settlements for the G20, the systemic risk can be identified as *"a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy."*

The Bank for International Settlements[5] (2006) describes systemic risk as an event that causes significant economic loss or lack of confidence, raising concerns about the situation of a significant part of the system, sufficiently serious to have negative effects on the real economy.

Mishkin (2008) defines systemic risk as a sudden event that shakes financial markets and prevents them from efficiently channeling capital where investment opportunities are best.

The European Central Bank (2009) defines systemic risk, as a risk of financial instability, to the detriment of the financial system functioning, to such an extent that economic growth and well-being suffer significantly.

According to Lepetit (2010), financial instability resulting from total or partial deterioration of the financial system components can have a negative impact on the real

[5] "Bank for International Settlements" (BIS) is the oldest international financial organization created in 1930, which promotes international monetary and financial cooperation and serves as a bank for central banks.

economy. Thus, systemic risk is related to the cost generated by the financial sector and borne by the real economy.

As reported by Ron Rimkus, content director at CFA Institute (2016); *"Systemic risk is the risk of a large-scale failure of a financial system whereby a crisis occurs when providers of capital (depositors, investors, and capital markets) lose trust in either the users of capital (banks, borrowers, leveraged investors, etc.), or in a given medium of exchange (the US dollar, Japanese yen, pound sterling, gold, etc.)."*

In other words, the risk propagates from unhealthy institutions to alternatively healthy ones through a transmission mechanism. If this channel does not exist then the risk would not be systemic but rather fundamental in nature.

In the light of all the definitions previously mentioned, we can identify a key element of systemic risk, namely the fragility of the financial system.

In this respect, it is appropriate to study the causes of this precariousness responsible for systemic risk.

1.3. Sources of systemic risk:

The positive relationship between the development of the financial system and economic growth is no longer unanimous. Several researchers, such as Goodhart (2006), Hendricks et al. (2006), Chakrabarty and Zhang (2010), Arnold et al. (2012) show that developments in financial systems are promising at a certain level, but may also be sources of systemic risk.

In this connection, the main changes in the financial system should be reviewed.

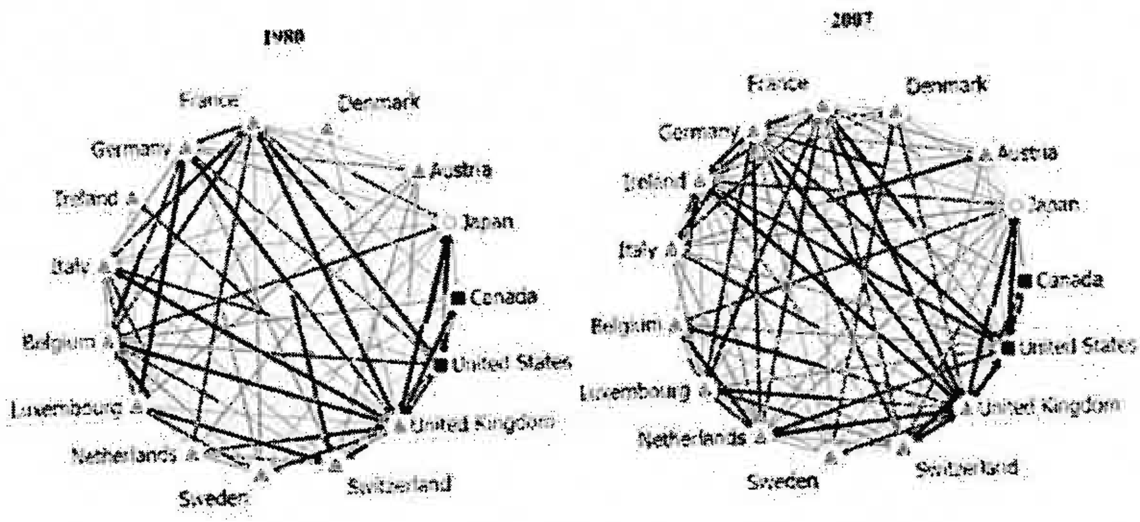
The first of the transformations is generated by financial globalization at the end of the 20th century, combined with the liberalization of trade and the opening up of economies.

According to Racickas and Vasiliauskaite (2011), financial institutions are becoming global and increasingly constrained to operate in a competitive international market. This implies the abolition of geographical borders, widening of investors' field of investigation, a better allocation of funds, a reduction in easily accessible credit costs, a range of good opportunities and especially the awareness of a higher risk.

Financial systems are related to each other. This growing interconnection and the growth in activities beyond borders, increase only the risks of contagion and the likelihood of systemic crisis.

Haldane et al. (2011) were inspired by ecology to show the danger of the complexity and massive connectivity of financial institutions globally. By analogy with tropical forests, the complexity of this environment was assimilated to a source of wealth, strength and resilience during the 1950s. Nevertheless, it was only in 1972 that an ecologist Robert May showed that ecosystems simpler, like savannah, are more robust and more resistant to natural disasters. This contradicts the widely accepted hypothesis of "diversity-stability". It shows that the interconnection networks between the various financial institutions constituted an appreciable asset at a certain level. Nevertheless, they accentuate the transmission of shocks and the emergence of systemic risk.

Figure 1. Illustration of the intensification of interconnection phenomena



Source: IMF Working Paper, **"A network analysis of global banking: 1978-2009"**, 2013, N°25.

Figure 1.1 presented by Minoiu and Reyes (2013) gives an insight into the density of interbank lending between countries represented by nodes. The thicker and darker lines indicate that cross-border flows are larger in 2007 than in 1980. The greater the interconnection and complexity, the greater the risk.

The second transformation is the acceleration of financial innovation, which has contributed to the diversification of the supply of financial products and services with the primary goal of mitigating risk, providing investment opportunities and hedging strategies more effective. Specifically, the following should be noted:

- Securitization is a major financial innovation. This technique by excluding risky assets from banks' balance sheets allows them to get rid of the credit risk.

The banking operators will not constitute own funds required according to the prudential rules put in place, in accordance with the actual volumes of the credits granted. Certainly, they will be encouraged to grant more credits that can be converted into securities and sold to make more profits.

Hull (2010) testified that when granting a new loan, the banker would no longer ask the question "Can I assume the risk associated with this loan?" but rather "Can I make money selling it on the market[6]?"

Indeed, the transferor (usually a bank) groups receivables (real estate loans, consumer loans, residential mortgages, etc.) into a portfolio to sell to the Special Purpose Vehicle -SPV. The latter will finance its acquisition by issuing securities representing these receivables subscribed by several investors (pension funds, open-ended investment company with variable capital- ICVCs, insurance companies, etc.). Securities acquired "backed" in the portfolio are generically referred to as "Mortgage-Backed Security-MBS" or "Asset Backed Securities- ABS" or "Commercial Mortgage Backed Security-" CMBS "(securitization of commercial real estate loans e.g. offices, shopping centers, etc.).

All these frequently used products offer a contrasted balance sheet. On the one hand, they are designed to increase the profitability of investor-owned portfolios and reduce risk. On the other hand, they favor the information asymmetry, the complexity, the lack of transparency for financial arrangements and complicate the risk assessment for individual and above all institutional investors.

German et al. (2013) rushed to put in place well-defined rules to reduce the risks inherent in securitized products.

- The emergence of a new financial sector called "Shadow Banking System" (SBS) which plays an approximate role to that of traditional banks, but with little regulation and supervision.

According to the Financial Stability Board (2012), SBS is "a credit intermediation system involving entities and activities outside the banking system". These entities use

6 Hull J. (2010), "Risk Management and Financial Institutions", page 349.

fundraising with deposit characteristics, maturity transformation, leverage, and so on. These activities include securitization, securities lending and repurchase transactions etc. Such a system includes investment banks[7], hedge funds[8], Structured Investment Vehicles[9] (SIVs), pension funds and mutual funds etc.

For Krugman (2008), "the banking system of the shadow is at the origin of the financial cataclysm occurred in 2007"

Currently, the attention of financiers and economists is converging on China where the SBS has deeply penetrated the financial systems. Zhang (2013) in his book "Inside China's Shadow Banking: The Next Subprime Crisis? "expresses his concern about the possibility of reliving a crisis similar to that of "subprime ", if the state does not take the necessary decisions and preventive measures.

- The changes that have occurred in the insurance industry in recent years have led to question about this sector position in the financial stability and its potential to trigger systemic risk.

According to Harrington (2009) and Billio et al. (2012), Credit Default Swaps[10] (CDS) have significantly changed the profile of insurers by transferring a significant portion of the credit risk previously carried by banks. This has activated the chains of transmission of negative shocks affecting the insurance industry and the real economy. For instance, the near bankruptcy of AIG, which invested heavily in CDS, was quickly saved by the state to avoid the catastrophe that could take place if the latter goes bankrupt.

Trainar (2010) focuses on reinsurance activities after which all or part of the risk taken out by the insurer is transferred to another insurance. The insurer is always liable to its client; however, the reinsurer bears the cost of risk if it takes place. This forms a "spiral of retrocessions" linking several actors and increasing the probability of shock transmission likely to affect all the financial system.

[7] It is a bank (or a banking division) that does not receive deposits. Its clients are mainly companies, investors to which it carries out activities of "Corporate Finance" or "Global Capital Markets" (financial markets).

[8] They are collective investment funds that benefit from a flexible legal framework, seeking high returns and using, massively, complex strategies based on derivatives, short selling and leverage (indebtedness).

[9] These funds borrow money by issuing short-term, low-interest securities for lending by buying long-term securities at higher interest rates.

[10] It is a kind of insurance contract established between two parties: the buyer of the protection pays a premium to the seller who undertakes to compensate him if the borrower fails to repay all or part of his debt.

- The emergence of financial composites where several financial activities (banking activities, insurance activities ...) are grouped together within the same group. As an example, there is the case of Allianz, an insurance company in Germany with banking subsidiaries and Crédit Agricole, a French bank with branches in the insurance sector.

At first glance, according to Freixas et al. (2009), these clusters appear to be beneficial to financial institutions allowing them to diversify the risk. Of course, the supervision and control, the implementation of the procedures of management and effective control are not simple tasks to carry out.

- The multitude of hedge fund activities and their undeniable growth on the financial markets (between 2000 and 2007, their number has more than doubled from 3335 to 7321 funds according to estimates by Hedge Fund Research (2013)), have created strong exposures for other institutions.

Mallaby (2010) explains the example of Long Term Capital Management (LTCM), created in 1994, so well-known that several financial institutions including domestic and international banks[11] have invested. After the Asian crisis in 1997[12], the near collapse of LTCM, which invested heavily in sovereign bonds, quickly bailed out with the help of the Fed and its creditors in September 1998, led to losses suffered by institutions such as Merrill Lynch Reports Estimated Loss of $ 800 Million, ING Barings Announces 1200 Layoffs...

Other bankruptcies like, Lipper (2001), Lancer (2003), Amaranth (2006), MotherRock (2006), have highlighted the fact that hedge funds could destabilize the financial system.

According to Boyson et al. (2010) and Dixon et al. (2012), hedge funds focusing on securitized products are suspected of contributing more to the 2007 crisis.

All these changes are accompanied by the increase in the opacity of the financial markets; the inefficient allocation of capital, the incentive for investors to incur excessive risks, the loss of information and also the development of increasingly complex strategies and instruments.

We conclude that the financial system is unstable.

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[11] For example: the Japanese bank "Sumitomo", the Bank of China, the German bank "Dresdner Bank", the French bank "BNP Paribas", etc.

[12] This monetary crisis is caused by the depreciation of the Thai baht, affecting several countries of Southeast Asia (Philippines, Malaysia, Indonesia, etc.), emerging countries (Russia, Brazil, Argentina, etc.) and the countries of North America and Europe.

2. Systemic approach to financial regulation:

One of the biggest challenges for regulators and public authorities today is restoring financial and economic stability. The fragility of the financial system and its role in triggering systemic crises has led them to question the effectiveness and relevance of the rules put in place.

Borio and Drehmann (2009) and Gauthier (2012) stressed the need for a radical change in the current regulation, called micro-prudential, by integrating the issues related to systemic risk. Since then, macro-prudential regulation has emerged.

2.1. Macro-prudential regulation:

To understand this new notion, we intend to compare the micro-prudential approach to the macro-prudential approach, which are differentiated on several levels.

First, the objective of the macro-prudential approach is to limit systemic risk, that is to reduce the risk of system-wide contagion episodes to control their cost at the macroeconomic level. On the other hand, the aim of micro-prudential regulation is to mitigate the risk of default at the level of different institutions in order to protect the investor.

Second, the financial system is the perimeter of macro-prudential regulation. Nevertheless, the micro-prudential regulation is concerned with the different financial institutions apprehended individually.

As an illustration, the financial system can be compared to a portfolio of securities, in which each security would represent a financial institution. The micro-prudential approach would be concerned about the losses incurred on each of the securities, while the macro-prudential approach would focus on the losses recorded on the entire portfolio, taking into account the correlation existing between these securities.

According to Lepetit (2010), micro-prudential regulation proceeds from a bottom-up logic, since it focuses on the individual risks of the entities falling within its scope. It defines the capital requirements for each to ensure, among other things, financial stability. Admittedly, its macro-prudential counterpart is based on a "top-down" logic, where it begins by assessing systemic risk and finally appreciates the contribution of each financial institution to the so-called risk.

Finally, the risk is considered "endogenous" according to the macro-prudential approach, it means that it depends on the collective behavior of the financial institutions likely to influence the prices of the financial assets, the quantities borrowed or lent and therefore on the financing of the real economy. On the other hand, the risk is considered "exogenous", if one refers to the macro-prudential approach, where economic growth is not hindered by the individual behavior of financial institutions.

The table below shows the comparison between macro-prudential and micro-prudential perspectives, as presented by Borio (2009):

Table 2. Comparison between macro-prudential and micro-prudential

	Regulation Macro-prudential	**Regulation Micro-prudential**
Immediate objective	Limiting the systemic financial crisis	Limiting the individual difficulties of the institutions
Final goal	Avoid costs in terms of GDP	Protect investor / depositor
Correlations between institutions	In terms of systemic risk: from top to bottom	Not applicable
Calibration of prudential controls	In terms of systemic risk: from top to bottom	In terms of risk specific to each institution: from bottom to top
Risk's characteristic	Considered to be dependent on collective behavior ("Endogenous")	Considered Independent of Individual Behavior ("Exogenous")

Source: Banque de France FS Review, **"Implementing the macro-prudential approach to financial regulation and supervision"**, 2009, N°32.

2.2. Actors of macro-prudential regulation:

At the international level, the Financial Stability Board (FSB), created in April 2009, deals with macro-prudential regulation. Actually, it is composed by the national financial authorities (central banks, ministries of finance, etc.), the international or regional financial authorities (IMF, World Bank, European Commission, etc.) and several international organizations and groups developing standards, in financial stability (Basel Committee, International Association of Insurance and Regulatory Supervisors, International Accounting Standards Committee, etc.). Its role now is to ensure international financial stability through the exchange of information and in-depth cooperation in the areas of supervision and control of the financial system.

In 2010, the International Organization of Securities Commissions (IOSCO) has settled a research department whose principle is to monitor, mitigate and manage systemic risk by analyzing the perimeter of regulation on a continuous basis. Similarly, the Basel Committee has required banks to hold a minimum amount of capital to avoid unforeseen losses and to hedge against any market risk. In response of the financial crisis, BIS has resolved the Systemic Risk issue in the context of Strengthening of the Global Capital within the Basel III Framework in 2010 (BCBS 2010). For instance, credit institutions hold less capital in reserve when dealing with low risk loans than when dealing with high-risk loans. However, currently the proposed Basel VI capital floor initiative will break up the rational link between risk and capital holdings. In fact, this regulatory reform has not yet found its way into the official language of banking supervisors since some authorities are considering it as finalization of the Basel III framework. The final output of present negotiations and discussions about Basel VI regulatory accord will be on January 2019.

In addition, Masera (2010) undertakes a comprehensive comparative study between the regulators of the European and American financial systems following the 2007 crisis.
At the level of the "Euro" zone, in the light of the De Larosière report[13] (2009), macro-prudential regulation is entrusted to the European Systemic Risk Board (ESRB), created on 1st January 2011. Its role is to detect the threats potential financial stability, based on the signals issued on the current situation and formulate the necessary macro-prudential recommendations.
On the other hand, three other supervisory committees have been created, at more specific levels, such as the European Banking Authority (EBA) whose mission is to ensure a relevant level of supervision and regulation for the benefit of the banking sector. European Insurance and Occupational Pensions Authority (EIOPA) responsible for ensuring the stability of insurance and the European Financial Market Authority (EFMA), whose mission is to ensure the transparency and proper functioning of the markets.

[13] The European Commission has entrusted the task of drafting a comprehensive report on the supervision of the European financial system by a group of 8 experts of very high level and chaired by Jacques de Larosière, former director of the IMF. This report was presented to the committee on February 25, 2009.

At the US level and under Dodd-Frank's law[14], the Financial Stability Oversight Council (FSOC) was created in July 2010, in order to identify the risks likely to cause the financial system to function properly in the United States and to implement market discipline and information disclosure, in order to cope with emerging systemic threats. Similarly, the power of the Fed has strengthened. It is responsible for the supervision and regulation of banks, savings banks and non-bank financial institutions with assets of more than $ 50 billion. The Federal Deposit Insurance Corporation (FDIC) is in charge of the supervising banks and national savings banks with a balance sheet of less than $ 50 billion. The Federal Insurance Office (FIO) is responsible for the insurance sector, with the exception of health insurance.

2.3. Tools of macro-prudential regulation:

After having exposed the actors of the macro-prudential regulation, it is legitimate to present the tools put in place, making it possible to protect the financial system against the systemic risk, by reinforcing its capacity to absorb the financial shocks, without inducing adverse impacts to the economy.

Systemic risk can be monitored and perceived from two distinct angles:

It is a question of focusing on the distribution of risk within the financial system as well as on the accumulation of risks at the level of different institutions at a given moment. It is thus an approach aimed at ensuring the stability of the sectional system at each period, when the shock is systematic or idiosyncratic (the transverse dimension) and its stability over time, that is to say the possible amplification of the initial shock (the temporal dimension).

According to Borio (2009), macro-prudential regulation "means taking a snapshot of the financial system and following its evolution as in a film".

In this sense, the main objective of macro-prudential regulation can be subdivided into two sub-objectives which are the increase of the resilience of the system (the transversal dimension) and the fight against procyclicality[15] (the temporal dimension).

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[14] This is a law proposed by Senators Chris Dodd and Barney Frank, passed by the US Congress on July 21, 2010.

[15] Procyclicality favors the occurrence of unsustainable expansion phases characterized by easing credit conditions, lowering the risk premium, increasing market liquidity, and so on. When this process suddenly reverses and the contraction phase occurs, it can intensify the disturbances and lead to a deep recession.

Regarding the first sub-objective, the prudential instruments are developed according to the contribution of different financial institutions to systemic risk. This gives rise to stricter rules for those who participate most (capital requirements, prohibition of certain activities, etc.).

To do this, the Financial Stability Board has established a list of 5 criteria, namely size, interdependence, cross-border activity, substitutability[16] and complexity[17], to identify systemically important financial institutions (SFIS) on a global scale. It is not enough to avoid the bankruptcy of any institution, but also one must be vigilant, trying to minimize the probability of bankruptcy of the most important institutions. Thus, we realize that it is not recommended to apply the same standards for institutions with varying levels of risk.

Concerning the second sub-objective, the regulators should rely on safety tools (called "buffers") in times of economic expansion and during periods of tension in order to absorb shocks that have occurred.

According to Borio (2009), these instruments act as "a sort of smooth anchor or speed limiter" to mitigate risk taking by institutions during periods of growth, thus avoiding a systemic crisis.

Regulators require, for example, the holding of a counter-cyclical capital buffer, with a view to increasing banks' capital, during times of euphoria by limiting the supply of credit and in the conglomerate event reducing the regulatory capital requirements by rising this supply.

Conclusion

The instability of the financial system is a key element of the occurrence of a systemic crisis. Indeed, the evolution of this system can generate disturbances likely to lead to its dysfunction and thus trigger massive damage to the real economy.

Losses suffered by a financial institution tend to spread to other institutions and within the financial and economic system as a whole. The 2007 financial crisis, among other things, has been distinguished by highlighting the greater interest in analyzing systemic

[16] The probability of disruption of world economic activity as a result of the difficulties or failures of an institution increases if it cannot easily be replaced.

[17] The more complex the operations of a financial institution, the more difficult it will be to ensure the orderly resolution of a default.

risk and the imperative need to reform current regulation to ensure financial stability, which is essential for the economic growth. In terms of macro-prudential regulation, it was adopted with the aim of improving and supplementing micro-prudential regulation. Hence, it is crucial to monitor and analyze on a continuous basis the economic and financial situation in addition to diagnose systemic risk and implement the measures pertaining to good financial governance. To this end, researchers have focused their efforts on the search for approaches to optimize the available risk measures in order to be able to quantify the systemic risk and identify the most threatening components of the financial system, which must be regulated with more rigor.

Chapter 2

Evolution of different risk measures

Introduction

Financial markets are characterized by risk and uncertainty. However, it is essential to distinguish between such notions that generally have a negative implication. Knight (1921) clarifies this distinction as follows: "With regard to risk, the distribution of results among a set of cases is known and estimable, whereas this is not true for the uncertainty where the situation to be treated presents a high degree of singularity".

In other words, a situation is risky when the prediction can be made from mathematical probabilities or frequencies. Consequently and following the search for gain, efficiency and speed in a less controlled environment, institutions are led whatever their field of activity to manage and control the risk.

Risk management has grown rapidly. Dowd (2005) lists the main factors explaining this development, among which are:

- Instability and increased volatility of the economic environment.
- The growth of "trading" activities since the 1960s.
- Advances in information and communication technology.

Nevertheless, according to Hansen (2013), it is essential to detect clearly the difference between systematic and systemic risk which are often confused.

The systematic risk, also known as market risk, is the variation in future profits as a result of unpredictable adverse events such as fluctuations in interest rates, exchange rates, commodity prices, or even wars and natural disasters. With systemic risk, it is the entire financial system or the real economy that is affected and not a company or an investor.

From an etymological point of view, the word system comes from the Greek verb "sunistanai", which means "To Stand Together / Being together". It goes beyond the individual systematic risk and takes into account the interactions between the different components of the system. In other words, any institution is a potential source of risk.

In this regard, we will review the main measures for each type of risk.

1. Measures of systematic risk:

At first glance, it seems appropriate to present the different methods of market risk assessment, before approaching the VaR as the reference risk measure, from which the main risk measure named CoVaR, which we propose to test empirically.

1.1. Traditional risk measures:

In 1952, the modern theory of portfolio was born with the publication of the founder Harry Markowitz. He was the pioneer who showed that portfolio diversification reduces the total risk for an expected rate of return. Therefore, if the expected return of a portfolio E (R_p) is equal to the weighted average of the securities that make it up, this is not true for the risk appreciated by the variance (σ_p^2) (or standard deviation $\sigma_p = \sqrt{\sigma_p^2}$) calculated as a function of the covariance of each pair of securities multiplied by their respective weights in the portfolio. We have, therefore, the following equations:

$$E(R_p) = \sum_{i=1}^{n} w_i E(R_i) \quad (2.1)$$

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i \ w_j \ \sigma_{ij} = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i \ w_j \ \sigma_i \sigma_j \ \rho_{ij} \quad (2.2)$$

σ_i , σ_j : variance of titles i and j

ρ_{ij} : Correlation between i and j

w_i , w_j : Respective weights of securities i and j in the portfolio of n securities.

Diversification mitigates the specific risk of each security (so-called diversifiable risk), by excluding the risk common to all securities (said to be non-diversifiable risk).

This is why in 1964 Sharpe, Lintner and Mossin proposed the Capital Asset Pricing Model (CAPM) which states that only non-diversifiable systematic risk is remunerated. The higher the risk, the more investors require high profitability to avoid it. This conclusion is translated by the equation below:

$$E(R_i) = R_f + \beta_i \ (E(R_m) - R_f) \quad (2.3)$$

$E(R_m) - R_f$: Market risk premium

$E(R_i)$: Expected profitability of the security i

R_f : Risk free rate

$E(R_m)$: Expected profitability of the market

β_i : Represents the systematic risk calculated by the ratio between the covariance of the security i with the market and the variance of the market portfolio

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)} = \frac{\sigma_{im}}{\sigma_m^2} \tag{2.4}$$

Racicot and Theoret (2006) classify CAPM as a mono-factorial model, where the expected rate of return is calculated solely based on the risk of the market security i.

A decade later, in 1976, Ross developed an alternative to the CAPM called "Arbitrage Pricing Theory" (APT), based on a multi-factorial model (multi-beta).

The profitability of the security i is influenced by several factors common to all the securities and a specific factor in title i, independent of the other factors considered in the model represented by the following equation:

$$R_i = \alpha_i + \sum_{k=1}^{m} \beta_i^k F_k + \varepsilon_i \qquad \text{With } i = 1 \ldots n \tag{2.5}$$

α_i : Constant

R_i : Rentability of security i

F_k : k risk factors common to all titles i

β_i^k : Sensitivity of the security i to the various factors F_k

ε_i : Risk factor specific to security i

Each beta is a systematic measure of risk (relative to each common factor) to which a risk premium is attached, as reflected in the following model:

$$E(R_i) = R_f + \sum_{k=1}^{m} \beta_{ki} \pi_{ki} \qquad \text{With } i = 1 \ldots n \tag{2.6}$$

π_{ki} : Represents the risk premiums associated with the n^{th} factor influencing the security i.

Racicot and Theoret (2006) criticize the fact that the APT remains silent on the definition of the common factors considered.

In 1992, Fama and French developed another multi-factorial model with the distinction of integrating a known and limited number of factors. It contains three factors and is written as follows:

$$E(R_i) = R_f + \beta_{im} (E(R_m) - R_f) + \beta_{is} E(SMB) + \beta_{ih} E(HML) \tag{2.7}$$

R_i : Performance of the security i

R_f : Risk free rate

R_m: Performance of the market portfolio

SMB: Difference between the returns of small-cap and large-cap stocks (SMB, Small minus Big).

HML: Difference between the highest and the lowest book-to-market (book value / market value) book yield (HML, High minus Low).

β_{im}, β_{is} and β_{ih} measure the sensitivity of the yield of security i to the various variables.

Previously explicit models are used to evaluate the systematic risk, but always in relation to the expected return. They can be considered as "risk-return" measures where these two notions are inseparable from each other.

According to Dowd (2005), these methods are not highly recommended for calculating market risk. The standard deviation and the betas do not allow considering the market risk satisfactorily.

Faced with this situation, the researchers felt the urgent need to design a new risk measure without necessarily passing through the calculation of the yield. Hence the publication of the Value-at-Risk (VaR) in the early 90s.

This figure provides a historical overview of different approaches to risk estimation.

Figure 2. Chronological evolution of systematic risk measures

1.2. Value-at-Risk:

The increased volatility of the financial market, the development of a multitude of complex derivatives and especially a series of financial accidents[18] have created the intense need for a global risk measure.

[18] For instance: the famous October 1987 stock market crash, called the Black Monday of Wall Street, the bankruptcy of Barings Bank in 1995 as well as Orange County in the United States in 1994, the near-bankruptcy of Long Term Capital Management in 1998

Researchers and professionals have focused their efforts on any quest likely to lead to the design of a simple and understandable effective risk management tool.

VaR first emerged in the insurance sector in the late 1980s. In July 1993, VaR was presented in an article published after the G30[19] meeting as a recommendation for market risk measurement.

In October 1994, VaR became popular following the publication by JP Morgan of its RiskMetrics™ system as well as data and documents needed for its application.

Since 1998, the Basel Committee[20] has required banks to hold a minimum amount of capital to hedge against any market risk using the VaR method, which has become a reference measure of risk on the financial markets.

1.2.1. Definition and estimation method:

According to Jorion (2007), VaR measures the maximum amount of losses in monetary units, which would not be exceeded over a given time horizon and at a given level of confidence, excluding adverse events "worst case scenario".

Hull (2010) states that VaR reflects the following statement: "We are certain to **1-q%** that we do not lose more **v** euros in the next **t** days"

1-q %: Level of confidence ; **t**: Time horizon.

q: Probability of adverse event where coverage rate, usually set at 1% or 5%

VaR (t, q) is defined as:

$$P(X^i \leq VaR^i(t,q)) = q \qquad (2.8)$$

Alternatively, in an equivalent manner:

$$P(X^i > VaR^i(t,q)) = 1-q \qquad (2.9)$$

X^i : Represents the loss, it is a positive or negative random variable.

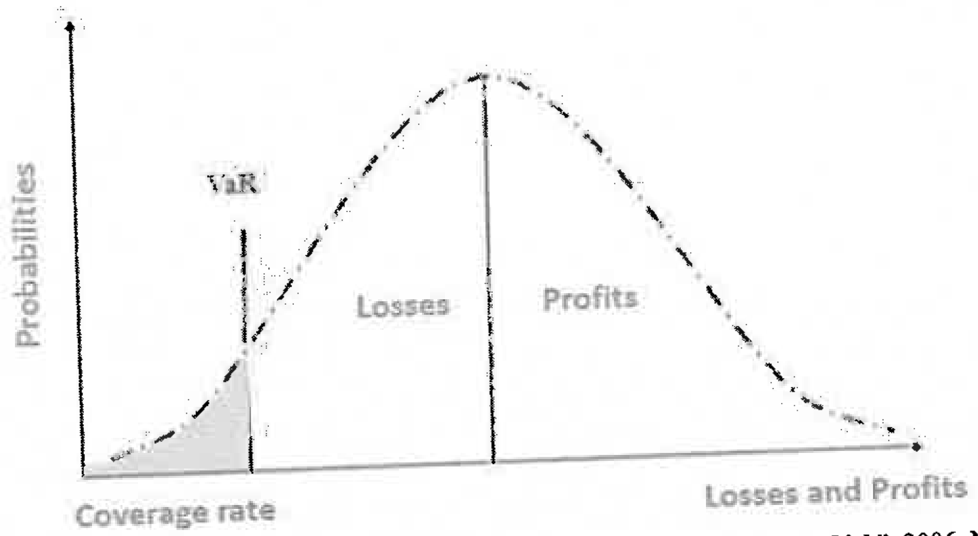
For example, if the hedge ratio q equals 1% and t equals 1 business day, there is a 99% chance that the portfolio will not experience a loss greater than the calculated VaR.

19 International forum of bankers, supervisors and academicians.

20 These are banking regulatory agreements drawn up by a committee composed of representatives of central banks and prudential authorities. There is Basel I signed in 1998, Basel II implemented between 2004 and 2008 and Basel III put in place between 2012 and 2019.

The following graph presented by Hurlin (2006), allows to better visualize the concept of VaR:

Figure 3. General distribution of profit and loss



Source: Master of Econometrics and Applied Statistics - Orléans university, "**Value-at-Risk**", 2006, N°5.

According to Hurlin (2006), VaR corresponds to the opposite quantile[21] of the distribution of losses and profits, defined analytically as follows: $\mathrm{VaR}\,(t, q) = -F^{-1}(q)$ (2.10)

According to Ossé (2001), the calculation of the VaR is subordinated to the choices of the time horizon t and the level of confidence 1-q. For example, the Basel Committee recommends a 10-day horizon with a 99% confidence level. The RiskMetrics™ method is based on a one-day horizon and a 95% confidence level.

In addition to the choice of these criteria, Manganelli and Engel (2001) recommend another choice in relation to VaR estimation methods grouped into three models, namely: non-parametric model, parametric model, semi-parametric model.

1.2.1.1. Non-parametric model:

The calculation is not based on distributional assumptions of profit and loss. This is what sets it apart from other models. The most used method is that of "Historical Simulation" (HS). It is based on the empirical distribution of historical yield data that are calculated and ranked in ascending order in the selected set of observations. VaR is determined by the level of

[21] A quantile is defined as the inverse of the distribution function.

confidence. If we have 500 historical data and the confidence level is 95%, the VaR is the 25th value on the list[22].

There are other methods inspired by HS, such as the "Bootstrapped HS" which consists of reconstructing subsamples drawn at random, from the original sample. In this case, the VaR corresponds to the average VaR of the samples considered.

The "Weighted HS" consists of attributing to the returns of the weights taking into account their seniority, their volatility or any other factor. We quote, for example, the "Aged-weighted HS" method where the most recent yields will be more weighted than those present at the beginning of the selected sample.

Whereas the HS method is based on a single scenario based on the market's subsequent behavior, the Monte Carlo simulation method relies on a multitude of random scenarios defined from an econometric model. It aims to simulate, on a number of occasions, the future behaviors of risk factors according to a certain number of assumptions, and to deduce from them a distribution of the profits and losses from which we estimate the quantile corresponding to VaR.

1.2.1.2. Parametric model:

The calculation of VaR is based on the assumption of normal distribution of the portfolio returns. In addition, it states that the portfolio's exposure to risk factors is linear.

Known as the variance / covariance method, the VaR estimate is obtained by applying the following formula: $VaR(t,q) = -\widehat{m} + z_q \widehat{\sigma_t}$ (2.11)

m and σ_t : represent the average and standard deviation of returns calculated as follows:

$$\widehat{m} = \frac{1}{n} \sum_{t=1}^{n} r_t \quad (2.12)$$

$$\widehat{\sigma_t^2} = \frac{1}{n-1} \sum_{t=1}^{n} (r_t - m)^2 \quad (2.13)$$

z_q [23] is the quantile of the normal law relative to the confidence level 1-q.

- The conditional variance with the ARCH model: $\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$ (2.14)

- The conditional variance using the GARCH model (1,1):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (2.15)$$

[22] The rank that corresponds to the VaR is calculated by multiplying N (number of historical data) and q (the chosen coverage rate).

[23] We have : $z_{95\%} = 1.65$ et $z_{99\%} = 2.33$

- The conditional variance applying the RiskMetrics™ model:

$$\sigma_t^2 = \gamma\, \sigma_{t-1}^2 + (1-\gamma)\; r_{t-1}^2 \qquad (2.16)$$

σ_{t-1} and r_{t-1} are the previous values of volatility and yield respectively.

γ is a fixed constant equals to 0.94.

1.2.1.3. Semi-parametric model:

It is worth mentioning that this model is about methods under the theory of extreme values, which are exclusively focusing on the study of the tails distribution of profits and losses, we cite in particular the theory of extreme generalized values as well as the generalized Pareto law[24] (or the POT - Peaks-Over-Threshold approach).

A second major category of semi-parametric methods relates to the quantile regression approach[25]. The latter consists in modeling directly the evolution of the quantile over time (instead of modeling the distribution of the losses and profits) and deducing from it the arrived quantile (that is to say the VaR). In this respect, it seems appropriate to highlight Engle and Manganelli's (2004) CAViaR (Conditional Autoregressive Value at Risk) model, which studies the evolution of the quantile over time using an autoregressive process.

1.2.2. Benefits of VaR:

VaR is an important tool for the following reasons:

- According to Linsmeier and Pearson (1996), VaR summarizes the risks of losses in a single figure easy to understand whatever the method advocated.

- With traditional risk measures, the standard deviation determines the degree of deviation of the yield from the mean and the betas calculate the degree of sensitivity of the yield to market fluctuations. Market risk is poorly appreciated according to Dowd (2005). VaR quantifies not only market risk, but also credit risk[26], operational risk[27] and liquidity risk[28].

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[24] The POT approach studies the distribution of excessive losses, above a (high) threshold, while the generalized extreme values theory focuses on the maximum or the minimum of the retained sample.
[25] This approach will be studied in detail in Chapter 3.
[26] Credit risk states that a counterparty is not honoring its commitments.
[27] Operational risk refers to the case of a failure in the processing of an operation (human errors, fraud, computer problems, etc.)
[28] Liquidity risk concerns financial securities that are difficult to sell on the market.

- According to the report of the Banque de France (2005), the VaRs published by banks in particular give relevant information on the market risks incurred by these banks.

- VaR is conducive to the risk evaluation of different types of assets (equities, bonds, derivatives). This makes it possible to measure the interaction between these constituting a portfolio. Well-diversified portfolios generally have lower VaR compared to a non-diversified portfolio according to Hull (2010).

1.2.3. Limits of VaR:

Despite its advantages, VaR has several limitations. So:

- The results obtained thanks to the VaR are totally dependent and vary according to the model adopted. This finding is proven empirically by Beder's 1995 study of three hypothetical portfolios applying eight different models. Such diversity is an insurmountable obstacle for managers. Hoppe (1998) describes it by saying: "To believe in an exact and plausible estimate of the actual risk is worse than to admit the unreliability of this estimate. False certainty is more dangerous than recognized ignorance".

- VaR gives no information on the extent of the loss when we are dealing with an atypical extreme event according to Ossé (2001). If a bank has a 99% VaR, this means that in 1% of cases, the loss may exceed the predicted VaR the value of which is unknown. This results in a false sense of security.

- VaR relies on simulations, approximations or even invalid hypotheses especially in parametric models (hypothesis of normality). Nevertheless, it is accepted that the past can never predict the future.

- By reference to the Banque de France report (2005), VaR does not take into account the change in liquidity on the financial markets, especially the shortage of liquidity, which amplifies tensions between economic agents and considerably increases the risk of loss. If a bank is in need of liquidity and cannot borrow from other banks, it will sell its assets at low prices.

- In addition to the methodological limitations, the Banque de France report (2005) criticizes the fact that the publication of VaR by banks is not subject to any standard common presentation or frequency of publication (quarterly, half-yearly, annual).

- According to Adrian Brunnermeier (2011), VaR is assessed individually for each institution, regardless of the interactions between financial institutions. As a result, it is unable to measure adequately the systemic risk.

Since then, researchers' attention has concentrated on the design of risk measures to characterize more accurately the interferences between financial institutions due to the dependence of the stability of the financial and economic system.

2. Measures of systemic risk:

Research on systemic risk measures has exploded since 2007. National supervisory authorities, central banks, and universities have developed a large number of approaches to estimating this risk. In the same way, financial institutions can no longer assess their risks in isolation and independently of the rest of the system that they belong to it.

2.1. From VaR to CoVaR:

In 2011, Tobias Adrian, Senior Vice President and Head of Capital Markets at the Federal Reserve Bank of New York, and Markus K. Brunnermeier, Professor at Princeton University, propose a new systemic risk measure named CoVaR[29].

Compared to the standard measure of systematic risk since the 1990s, which is VaR, these two researchers have intuitively added the prefix Co that designates the contagion.

This approach is recommended to determine the risk impacts between individual institutions or a group of institutions and to identify those who contribute the most to systemic risk.

2.1.1. Definition:

Let us recall, first, the mathematical definition of the so-called unconditional VaR:

$$P\,(X^i \leq VaR_q^i\,) = q \qquad (2.17)$$

$CoVaR_q^{i|j}$ is defined as the VaR for an institution i (or loss) under the effect of an event $C(X^j)$ of an institution j. This event is linked to the fact that the institution j reaches its level of VaR such that: $X^j = VaR_q^j$

[29] CoVaR should not be confused with CVaR or conditional VaR (called Expected shortfall-ES). The CVaR is defined as the loss expected on t days when it exceeds the VaR.
$CVaR(t,q) = E(X^i / X^i < VaR(t,q))$.

Analytically, $CoVaR_q^{i|j}$ is written as follows:

$$P(\ X^i \le CoVaR_q^{i|j} \mid X^j = VaR_q^j) = q \tag{2.18}$$

We clearly see the addition of a conditional event to equation (2.17).

Moreover, Adrian and Brunnermeier (2011) propose to calculate $\Delta CoVaR_q^{i|j}$ to evaluate how much the institution j contributes to the VaR of institution i, defined as follows:

$$\Delta CoVaR_q^{i|j} = \begin{pmatrix} \text{Var of the institution i} \\ \text{conditional on the institution j} \\ \text{reaching its VaR level} \end{pmatrix} - \begin{pmatrix} \text{VaR of the institution i} \\ \text{conditional on the institution j} \\ \text{being in the median state} \end{pmatrix}$$

$$\Delta CoVaR_q^{i|j} = CoVaR_q^{i|X^j = VaR_q^j} - CoVaR_q^{i|X^j = VaR_{q=Median}^j} \tag{2.19}$$

On the other hand, it is useful to note that indices i and j linked to financial institutions can separately refer to the financial system.

$\Delta CoVaR_q^{system|j}$ is used to evaluate the contribution of institution j to systemic risk which is none other than the VaR of the system and $\Delta CoVaR_q^{i|system}$ measures the increase in VaR of the institution i during a financial crisis.

2.1.2. Benefits of CoVaR:

This new measure has several advantages, among which are the following:

- The CoVaR allows to synthesize the dependencies between all the institutions of the system (taken two by two) and thus to establish a network mapping of interdependencies. This echoes the opinion of Allen et al. (2010), which highlighted the importance of mapping the relationship between financial institutions as we study financial fragility and systemic risk.

- ΔCoVaR focuses on the contribution of each institution to systemic risk, as opposed to VaR, which only takes into account individual risk. For example, two institutions X and Y publish the same VaR. Nevertheless, the ΔCoVaR relating to the institution X is equal to 0, but the one belonging to the other institution is greater than 0 in absolute value. If we rely solely on VaR, X and Y present a similar risk, whereas according to ΔCoVaR, institution Y is systemically riskier than institution X.

- CoVaR is adequate to overcome the difficulty that empirical risk measurements suffer from the presence of a limited number of observations in the tails of distribution. Indeed, the risk seems to be mitigated following the announcement of good news. However, once a new observation is stepped in one of the distribution tails, the risk value tends to increase rapidly. This means that the regulatory requirements will be stricter in times of crisis than in times of growth. This is called procyclicality, at the end of which behaviors vary according to economic cycles. It shows that the risk values are lower in periods of low volatility and too high during crises.

- Adrian and Brunnermeier (2011) focused on the responsibility of a financial institution chosen according to specific criteria for systemic risk. However, it is possible to estimate the exposure of any firm to the fact that the entire system or financial institution is in distress. This testifies the great flexibility of the CoVaR making this measure very useful.

2.1.3. Empirical work of CoVaR:

The literature is rich in empirical studies applying CoVaR as a measure of systemic risk.
The first study is, without doubt, that of Adrian and Brunnermeier (2011), who advocate a new methodology to evaluate the impact of financial units in critical condition on the entire financial system. For the empirical application, they use quantile regressions on very specific[30] models relating to 1226 listed US financial institutions of four different types (i.e. commercial banks, investment banks, insurance companies and real estate corporations) for the period from 1986 to 2010.

They calculate the weekly fluctuation of the market value of the assets of the institutions $X_t^i = \frac{A_t^i - A_{t-1}^i}{A_{t-1}^i}$, where A_t^i is obtained by multiplying the market capitalization (the share price of the company multiplied by the number of shares outstanding) by the debt ratio (total debt / total assets). In order to estimate the change in the market value of the assets of the financial system, we need simply to sum $A_t^{sys}=\sum_{i=1}^{1226} A_t^i$ and calculate the variation X_t^{sys}.

Adrian and Brunnermeier (2011) first find that institutions contribute differently to systemic risk and that VaR yields incomplete information on risk.
Subsequently, they focused on the characteristics of financial institutions that predict systemic risk, such as the level of indebtedness, size (equals equity capital) and maturity mismatch

[30] The CoVaR estimate will be presented in the next chapter in more details.

((short-term debt - cash) / total liabilities). The results indicate that all these characteristics are important factors in favor of the emergence of this risk.

The first part of the literature strictly follows the CoVaR methodology as presented by Adrian and Brunnermeier (2011).

Roengpitya and Rungcharoenkitkul (2011) apply CoVaR to the six major Thai commercial banks to assess their contribution to systemic risk during the period 1996-2009. They adapted the same variables as Adrian and Brunnermeier (2011) to Thailand's financial institutions and systems.

The results show that the diverse banks impose an additional risk on the Thai financial system and that the big banks do not necessarily contribute the most to systemic risk.

Castro and Ferrari (2013) identify and classify the 26 European banks most responsible for systemic risk, applying very specific tests[31] for the period between 1986 and 2010. They exploit as data the daily returns of the selected institutions X_t^i and the return financial system $X_t^{sys} = \sum_{i=1}^{26} w_t^i X_t^i$ with w_t^i being the weight of the institution i appreciated by market capitalization. The results indicate that not all banks contribute significantly to the risk retained.

Bernal et al. (2013) study systemic risk analyzing how financial sectors in different regulatory systems lead to systemic risk. They examine the existence of relations between the financial system and the real economy adopting daily returns for banking, insurance and financial services in the United States and some European countries (France, Germany, Belgium, Greece, Austria, Belgium, Spain, Italy, and the Netherlands) for the period stretching from 2004 to 2012. They deduce that insurance contributes relatively more to systemic risk in the United States. Whereas, the banking sector contributes relatively more to systemic risk for the selected European countries.

More recently, and essentially inspired by the latest study by Bernal et al. (2013), Drakos and Kouretas (2014) focused on analyzing the contribution of three financial sectors; banks, insurance companies and financial services companies to systemic risk in certain emerging countries (Mexico, Czech Republic, Hungary, Poland, Turkey, Romania, Hong Kong, Philippines, Malaysia, South Korea, Thailand and Singapore).

[31] The significance test will be explained in the next chapter.

The CoVaR is estimated by a quantile regression performed on the weekly yields of the sectorial indices for the period between December 1995 and February 2013. It shows that the banking sector contributes mainly to systemic risk in Mexico, the Czech Republic, Hungary, Romania, Hong Kong, Indonesia, the Philippines, and Thailand. In Malaysia, the insurance sector contributes the most to systemic risk, while in Poland, Turkey, South Korea and Singapore; it is the financial services sector that dominates.

The second part of the literature reviews deviates slightly from the original CoVaR methodology. Empirical studies so far have essentially used data from the stock market or balance sheets of the financial institutions involved.

Chan-Lau (2009) adapted the CoVaR on CDS spreads to study contagion effects in a sample of 25 financial institutions in Europe, Japan and the United States from 1 July 2003 to 30 September 2008. Such a study made it possible to assess to what extent the risk of default of one specific institution affects the default risk of another. The results reveal that the risk of default increases during periods of crisis.

Wong and Fong (2010) discussed the interconnection of the economies of 11 Asia-Pacific countries (Australia, Japan, China, Malaysia, Hong Kong, Philippines, Thailand, Singapore, Indonesia, South Korea and New Zealand) to understand how the risk of default of one of them can be changed depending on the circumstances of the other. They apply the CoVaR to estimate the spreads of the sovereign CDS (5 years) covering the period from October 15, 2004 to September 25, 2009. The results related to the CoVaR provide relevant information on the default risk of an economy compared to others and by reference to those obtained by means of VaR.

Other empirical studies do not apply quantile regression. Girardi and Ergün (2013) consider that the financial distress condition required for calculating CoVaR is related to a situation where the loss of institution i is greater than VaR, rather than being equal to it:

$$P(\ X^{i} \leq \ CoVaR_{q}^{i|j}\ |\ X^{j} \leq \ VaR_{q}^{j}\ ) = q \tag{2.20}$$

They are interested in evaluating the contribution of four financial groups in the United States (depository institutions, insurance companies, brokerage firms and other non-depository institutions) to systemic risk during the period from June 2000 to February 2008. Based on univariate GARCH models for the daily returns of 74 institutions, they lead to results showing that depository institutions contribute the most to systemic risk, followed by brokerage firms, insurers and other non-depository institutions.

The table below highlights the summaries of the works cited above:

Table 3. Overview of the summaries of empirical work

Years	Countries	Authors	Results
2011	USA	Adrian and Brunnermeier	- CoVaR reports better results compared to VaR. - Financial institutions contribute differently to systemic risk depending on their size, level of indebtedness, etc.
Researchers strictly applying CoVaR			
2011	Thailand	Roengpitya and Rungcharoenkitkul	- Thai banks do not contribute to systemic risk based on their size.
2013	Europe	Castro and Ferrari	- Banks do not contribute significantly to systemic risk.
2013	USA and some European countries	Bernal, Gnabo and Guilmin	- Banks contribute the most to systemic risk in Europe, while in the United States it is the insurance sector.
2014	Some emerging countries	Drakos and Kouretas	- The banking sector contributes the most to systemic risk in Mexico, Czech Republic, Hungary, Romania, Hong Kong, Indonesia, the Philippines, and Thailand. -The insurance sector is more responsible for systemic risk in Malaysia. - The financial services sector is dominant in Poland, Turkey, South Korea and Singapore.
Researchers who modified the CoVaR			
2009	Europe, Japon and USA	Chan-Lau	- The risk of default of one institution amplifies the default risk of another during periods of crisis.
2010	Countries of pacific	Wong and Fong	- Compared with VaR, the results obtained through CoVaR are more indicative of the

	Asia		interconnection between the 11 economies.
2013	USA	Girardi and Ergün	- Depositary institutions contribute the most to systemic risk before brokerage firms, insurers and other non-depository institutions.

Source: Author's reviews analysis

2.2. Risk measures alternatives to CoVaR:

In this respect, it should be pointed out that the literature has recently been enriched by the appearance of other proposals for systemic risk measures, all of which are aimed at characterizing the conditional link between the various financial institutions in differentiated formulations.

Acharya et al. (2011) recommend the Marginal Expected Shortfall (MES) to measure the average loss of an institution i when the financial system is in distress.

Consider N firms with X_{it} the yield of each and $X_{mt} = \sum_{i=1}^{N} w_{it} X_{it}$ the market return, where w_{it} is relative to the weight of the institution i in the financial system valued by the market capitalization of this one in relation to the total capitalization.

The ES of the financial system associated with the coverage rate q % corresponds to the average of the large expected losses, when this is greater than the VaR of the system.

$$ES_{mt}(q) = E(X_{mt} \mid X_{mt} < VaR_{mt}(q)) = \sum_{i=1}^{N} w_{it} \, E(X_{it} \mid X_{mt} < VaR_{mt}(q)) \qquad (2.21)$$

The MES is obtained thanks to the following partial derivative:

$$MES_{it}(q) = \frac{\partial ES_{mt}(q)}{\partial w_{it}} = E(X_{it} \mid X_{mt} < VaR_{mt}(q)) \qquad (2.22)$$

The higher an institution's MES, the greater the individual's contribution to the risk of the financial system.

Acharya et al. (2012) as well as Brownlees and Engle (2012) suggest "SRISK" to assess the capital shortage (or capital deficit) so that the affected financial institution restores its balance after a financial crisis. This indicator is calculated according to the following formula:

$$SRISK_{it} = max[0 \; ; \gamma \, D_{it} - (1-\gamma) \, w_{it} \, (1 - LRMES_{it})] \qquad (2.23)$$

γ : Level of prudential capital held by each institution set at 8%.

D_{it} : Liabilities' accounting value.

$LRMES_{it}$: corresponds to the Long-Run Marginal Expected Shortfall which is the expected loss for an institution i when the market falls below 40% over a period of six months calculated as: $LRMES_{it}\ (q) = 1 - \ \exp -(18 * MES_{it}(q))$ (2.24)

The higher the SRISK, the more institutions are responsible for systemic risk.

In this research paper, we have decided to study CoVaR for a number of reasons, including the following:

- CoVaR has the advantage of being a simple extension of VaR which is today the reference risk measure most used by financial institutions.

- MES and SRISK are calculated daily by Volatility Laboratory (known as V-Lab), created at the New York University Stern School of Business in 2010, under the direction of Professor Robert Engle and who collaborates with "Center for Risk Management "(CRM) based at HEC Laussane. The goal of these internet-accessible labs[32] is to provide real-time market dynamics data for several countries, regions and institutions for the benefit of researchers, regulators and professionals.

- According to Bisias et al. (2012), like CoVaR, there are measures that use CDS exclusively to determine credit risk. Thus, the "Distress Insurance Premium" (DIP) method proposed by Huang et al (2009) is used to calculate the price of the insurance necessary to cope with the losses that have occurred in the banking sector. Analytically close to the MES, DIP is equal to the expected debt loss, exceeding a certain threshold L_{min} defined by the equation developed with the Monte Carlo simulation, namely:

$$DIP = E(L/\ L \geq L_{min}) \quad (2.25)$$

L_i is the debt loss of the bank i and $L = \sum_{i=1}^{N} L_i$ is the total debt loss.

Other measures are applied only to the banking sector, such as the Banking Stability Index (BSI) suggested by Segoviano and Goodhart (2009), which reflects the number of banks likely to reach a state of distress while at least one bank is bankrupt. They define the banking system as a portfolio of banks. They calculate the probability of conditional failure for each pair of banks and identify those with a common probability.

[32] http://vlab.stern.nyu.edu/
http://www.crml.ch/index.php?id=4

Conclusion

Financial markets are essentially characterized by risk. This has led researchers to focus their work on designing reliable and effective systemic risk measures to safeguard financial stability.

Over the years, several methods of assessing market risk have emerged. Nevertheless, it was only in the early 1990s that a risk measure was introduced to optimize traditional measures namely Value-at-Risk.

It also makes it possible to summarize easily interpretable single-digit losses. Certainly, its calculation requires assumptions, simplifications and choices. Moreover, it was frequently criticized on certain levels. In particular, it has emerged following the recent financial crisis that has raised a series of questions about the legitimacy of VaR as a relevant risk measure, in the presence of adverse events. Although used by most financial institutions individually, it was considered unable to identify the systemic nature of risk.

Hence, the emergence of other more sophisticated and successful systemic risk measures, such as the CoVaR advocated by Adrian and Brunnermeier (2011). The latter has the advantage of providing regulators with more consistent information on the interdependence between different financial institutions on the one hand and between the financial and economic systems on the other. The use of such a measure is therefore conducive to appropriate regulatory reform to ensure financial stability.

Chapter 3

Estimation of CoVaR on the American and European markets

Introduction

The fragility of the financial system is likely to have a negative impact not only on the functioning of the financial system but also on the economic growth.

We do not limit our study to banks, as is often the case in the literature, or to the study of contagion effects among the various financial institutions that make up the financial system. Rather, we propose to pay particular attention to assessing the impact of systemic risk on the real economy.

In accordance with the methodology of Adrian and Brunnermeier (2011), we will first estimate the VaR of the real economy contingent on the financial system being in distress. Subsequently, we identify the component of the system that contributes predominantly to this loss.

Among other things, we plan to map the links between the financial system and the real economy. This mapping is interesting because it provides the public authorities with the necessary elements to make powerful decisions on the financial regulation.

We define systemic risk as the loss of the rest of the economy when one or more financial institutions fail.

To do this, our empirical study will be divided into two main parts:

- The first is entitled "inter-sectoral study". We will assess the impact of negative shocks affecting one of the different sectors of the financial system (i.e. banking, life and non-life insurance, financial services) on the real economies of Europe (and in the United States.
- The second is entitled "inter-company study" and will be devoted to determining the impact of the bankruptcy of an institution belonging to each chosen financial sector, on the real savings of the above-mentioned regions.

1. Motivation and generation of research hypotheses:

1.1. Motivation:

Through the literature, we have been able to draw various remarks.

As a simplification, when the word system is mentioned, it refers to economic sectors[33] with the exception of the financial sectors (real economy).

[33] There is the primary sector (agricultural activities, fishing and mining activities), the secondary sector (industrial activities), the tertiary sector (financial and real estate activities, services, trade).

Some researchers, like Bernal (2013), Drakos and Kouretas (2014), consider the CoVaR system subordinate to a well-defined financial sector, such as the banking, insurance and financial services sectors.

Others like Adrian and Brunnermeier (2009), Roengpitha and Rungcharoenkitkul (2011), Castro and Ferrari (2013), rather determine the CoVaR of the system or a well-defined financial sector vis-à-vis financial institutions especially banks.

For our study, we opt for an approach combining studies already conducted on the financial sectors (cross-sectoral study) and financial institutions (inter-company study).

Several researchers like Harrington (2009), Billio et al. (2012), Weib and Muhlnickel (2013) state that the profile of insurance, registered for a long time, has changed.

Insurance is no longer considered less risky compared to banks.

To distinguish ourselves from previous empirical work, we thought that it will be wise to look deeply into the insurance sector, distinguishing between life and non-life insurance.

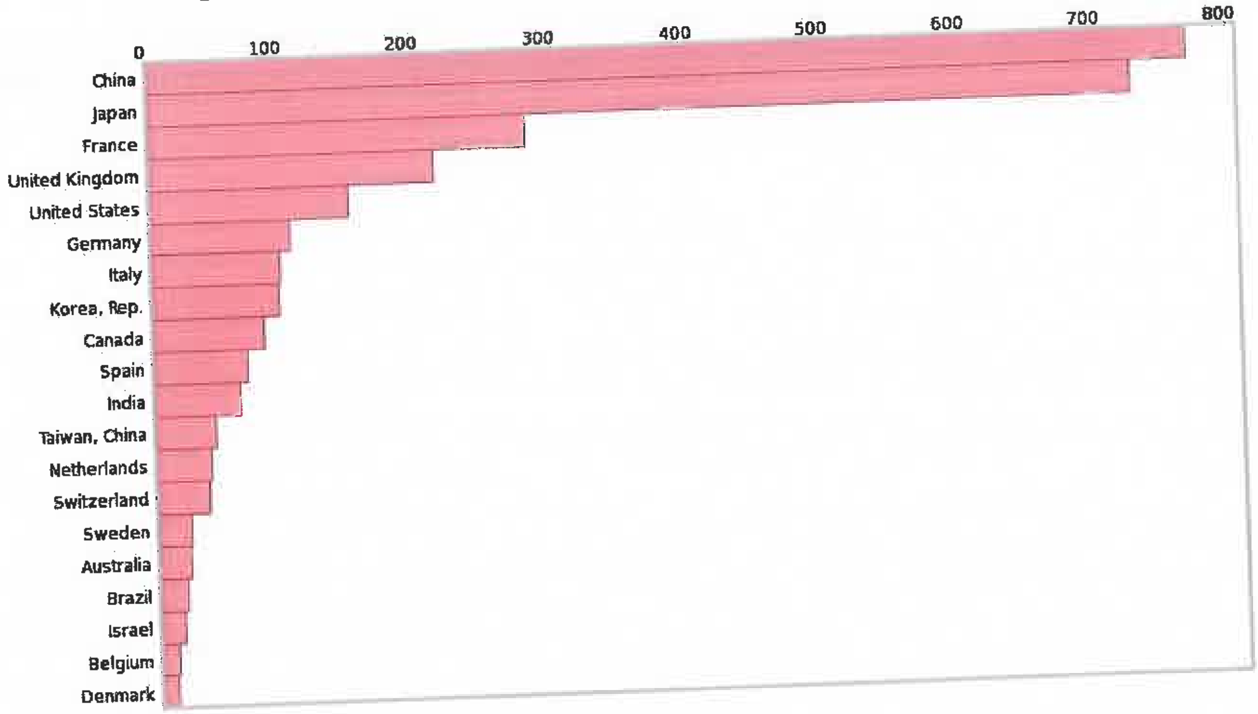
Subsequently, we plan to determine the CoVaR for two distinct regions: the United States and the "Euro" zone. Our goal is to guide the macro-prudential regulation actors mentioned in the first chapter, towards sectors and institutions, whose role is predominant in triggering systemic risk.

In these regions, systemic risk is widespread and the effect caused by the instability of their financial systems are more broad and complex at the national, regional and international levels.

Figure 4, developed by the V-Lab (Volatility Laboratory) on 31/12/2017, ranks country contributions[34] to systemic risk globally:

[34] This ranking is updated weekly.

Figure 4. Global systemic risk by country (SRISK in billions of $)



Source: V-Lab output (https://vlab.stern.nyu.edu), 2017

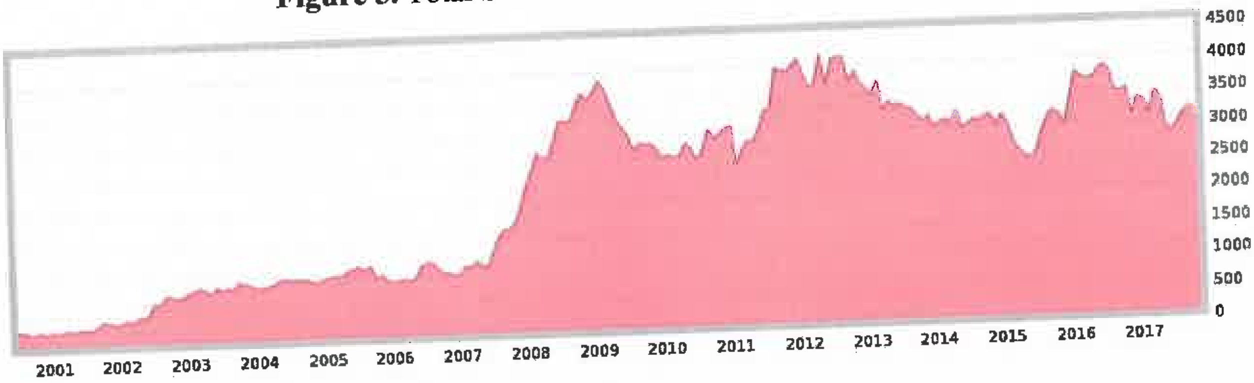
The United States ranks fifth after United Kingdom. As for the countries of the "Euro" zone, we can cite, in decreasing order of contribution, France, Germany, Italy, Spain, Netherlands and Belgium.

The SRISK is calculated for financial institutions belonging to the selected countries, according to three criteria namely:

- The size appreciated by the market capitalization.
- The financial leverage measured by the debt ratio of the financial institutions compared to their market capitalization.
- The Long Risk Marginal Expected Shortfall (LRMES), which calculates the expected losses for a financial institution in the event of a 40% fall in the market.

At the international level, the capital shortage caused by the financial system instability is appreciated by reference to the diagram below:

Figure 5. Total SRISK worldwide (in billions of $)



Source: V-Lab output (https://vlab.stern.nyu.edu), 2017

The amount of capital that needs to be injected, in order to recover the collapse of the global financial system, is rising sharply starting from the end of 2007. This amount reaches its maximum, approximately $ 4300 billion in 2009, and then begins to decline gradually, due to the government's response to rising systemic risk. For instance, we witnessed in 2009 the creation of the Financial Stability Board. As of 2011, the SRISK rises again until it peaks at around $ 4200 billion. Then, it begins to decline progressively until 2014, when it seems stable at around $ 3000 billion. But it started to increase again by 2016 to reach almost $ 4000 billion in 2017.

In addition, we suggest that the measure of CoVaR be supplemented through a test inspired by the study of Castro and Ferrari (2013). We have noticed, in the light of the available literature, that all those who calculated the CoVaR did not check the significance of their results.

1.2. Assumptions

In the cross-sectoral study, we seek to ascertain if the banking sector contributes the most to systemic risk compared to other financial sectors. Banks have been studied largely by researchers and are blamed for the financial system instability.

For example, we report the study by Chan-Lau (2009) on a sample of 25 banks in Europe, Japan and the United States, Roengpitha and Rungcharoenkitkul (2011) for 6 Thai banks and de Castro and Ferrari (2013) which covered 26 European banks.

With regard to the business-to-business study, we were guided by the desire to determine whether the major institutions, appreciated by market capitalization, contribute the most to systemic risk compared to other institutions. We assume that the financial system is more sensitive to large-cap financial institutions to which economic agents rush to invest. As soon as a problem is identified within one of these institutions, economic fundamentals are affected more negatively than in the case of weak capitalization institutions.

2. Presentation of the data

Data on the US and European markets at daily frequency, cover the period from 20/08/2004 to 28/02/2014, i.e. 2314 observations.

We will present the variables needed to estimate CoVaR, referring mainly to Adrain and Brunnermeier (2011) and Bernal et al. (2013).

2.1. The US market:

2.1.1. Sectoral indices:

The financial sectors studied are represented by specific indices, mentioned in the table below:

Table 4. Presentation of Sector Indices -USA-

Sectors	Notations	Data	Sources	Mesures
Banks	$DJUSBK_t$	Dow Jones U.S. Banks index	Thomson Reuters	$R_t^j =$ Performance of indices $\ln(P_t) - \ln(P_{t-1})$ P_t : asset price at date t
Life Insurance	$DJUSLI_t$	Dow Jones U.S. Life Insurance index		
Non-Life insurance	$DJUSNLI_t$	Dow Jones U.S. Non-Life insurance Index		
Financial Services	$DJUSFS_t$	Dow Jones U.S. Financial Services index		
System	$S\&P\ 500\_exFin_t$	S&P 500 Ex-Financial index	Bloomberg	

Source : Author's data presentation

The Dow Jones Indexes are calculated by classifying securities according to a four-tier system[35]. The financial industry contains the banking, insurance (life and non-life) and financial services sectors, which themselves are subdivided further into other subsectors.

For the system, the Dow Jones Index did not provide such an index. That is why to provide broad market exposure, we recommend using the S & P 500 Ex-Financial as the most significant index for the system which refers to the real economy.

This choice may also be justified by the fact that the S & P 500 Index is a more general index compared to the Dow Jones Index. Indeed, the first is calculated as a weighted average by the market capitalization of 500 shares of large companies. On the other hand, the second is estimated as a price-weighted average of the 30 largest companies, across a range of industries, except for transportation and utilities.

2.1.2. Financial Institutions

For each of the financial sectors studied, we will identify the financial institutions with the largest market capitalization on 28/02/2014, according to Thomson Reuters, presented in the table below:

Table 5. Presentation of Financial Institutions -USA-

Sectors	Notations	Institutions	Stock market capitalizations (Millions$)
Banks	WFG	Wells Fargo	257.651
	JPM	JPMorgan Chase	209.013
Life Insurance	MET	Metlife	57.689
	PR	Prudential Financial	39.353
Non-Life Insurance	AIG	Americain International Group	74.785
	BH	Berkshire Hathaway	310.653
Financial Services	GS	Goldman Sachs Group	71.124
	AE	Americain Express	92.218

Source: Author's data presentation

These institutions are used for the calculation of the sectorial indices mentioned above.

[35] Companies are included in these indexes once the main source of their income or if the majority of their income comes from the activities of the above sectors. Once selected, the titles are classified in 10 industries such as health, finance, technology, telecommunication, etc. which are divided into 41 sectors and 114 sub-sectors.

2.1.3. Control variables

Adrian and Brunnermeier (2011) define 7 control variables for estimating VaR and CoVaR in the US market, namely:

- VIX[36] is a volatility index listed in Chicago Board Options Exchange.
- Liquidity Spread short-term liquidity spread is calculated by subtracting the sovereign bond rate from the US repo rate[37]. It provides information on liquidity risk. A large gap means that economic agents cannot easily finance themselves and will face serious liquidity problems.
- The variation of the US sovereign bond rate of the same maturity provides an idea on the financing of the State by bond issue.
- The Yield Spread is calculated as the difference between the rates of two US sovereign bonds of different maturity. This gap between long and short rates is a good indicator of the future economy. The higher the maturity, the greater the risk and the higher the rates. Nevertheless, it may be negative (falling interest rate curve[38]), when investors have no confidence in the body underwriting bonds with a significant rate. This suggests a possible economic recession.
-The Credit Spread is measured by the difference between the bond rates issued by companies and those issued by the State having the same maturity. It provides information on credit risk. The smaller the gap, the better the economy is considered. In the growth phase, when the state or companies are doing best, investors do not demand high rates to finance them by buying their bonds. This is typically the opposite in recession, where investors are rather reluctant.
- The US equity market return is retained as an indicator of the current economy.
- The performance of the US real estate sector is integrated into the model as an indicator of the current economy. In the growth phase, economic agents will flow on the purchase of real estate compared with periods of economic turbulence.

The table below shows the daily data corresponding to our study period and necessary for the calculation of the control variables:

[36] It estimates the implied volatility of the stock market over the next 30 days, based on the average volatility, call and put options of the S & P 500.
[37] This is the rate that the central bank gives to refinance a bank in exchange for securities, in order to guard against the default risk (repayment).
[38] As an example of "Inverted Yield Curve" according to Anderson et al. (1996): France 1968-1971 / 1988-1993.

Table 6. Essential data for control variables -USA-

Data	Notations	Sources
American repo rate (3months)	$US\ RR_t$	Thomson Reuters
Rate of a US Treasury Bond (maturity)	$US\ T\_Bill_t$	Thomson Reuters
Credit Spread for the US Market (10years)	$USCDSP_t$	Bloomberg
VIX Share Price	P_t	Thomson Reuters
Dow Jones Real Estate Stock Price		Thomson Reuters
Stock Market Price S & P 500		Thomson Reuters

Source : Author's data presentation

The control variables are listed in Table (3.4) in order of appearance in this chapter:

Table 7. Overview of control variables -USA-

Notations	Variables	Mesures
VIX_t	VIX	$\ln(P_t) - \ln(P_{t-1})$
$USLQSP_t$	« Liquidity Spread »	$US\ RR_t$ (3months) - $US\ T\_Bill_t$ (3months)
$TBSP_t$	« Bond rate variation »	$US\ T\_Bill_t$(3months)- $US\ T\_Bill_{t-1}$(3months)
$USYDSP_t$	« Yield Spread »	$US\ T\_Bill_t$ (10 years) - $US\ T\_Bill_t$ (3months)
$USCDSP_t$	« Credit Spread[39] » (10years)	
$S\&P\ 500_t$	Performance of the S & P 500	$\ln(P_t) - \ln(P_{t-1})$
$DJUSRE_t$	Dow Jones Real Estate Return	$\ln(P_t) - \ln(P_{t-1})$

Source : Author's data presentation

2.2. The "Euro" zone:

2.2.1. Sectoral indices:

Like the US market, the sector indices of the selected European countries are mentioned in the table below:

[39] These indices are provided directly by Bloomberg based on the Business Rating and maturity of the bonds. For our study, bond issuers are rated (BBB).

Table 8. Presentation of sectoral indices – Eurozone

Sectors	**Notations**	**Data**	**Sources**	**Mesures**
Banks	$ESBK_t$	Euro Stoxx Banks Index	Thomson Reuters	R_t^j = Performance of indices $\ln(P_t) - \ln(P_{t-1})$
Life insurance	$ESLI_t$	Euro Stoxx Life insurance Index		
Non-Life insurance	$ESNLI_t$	Euro Stoxx Non-Life insurance Index		
Financial Services	$ESFS_t$	Euro Stoxx Financial Services Index		
System	$SE\ 600\_exFin_t$	STOXX Europe 600 ex_Financials Index	Bloomberg	

Source : Author's data presentation

These indices are calculated from a variety of banks (29), financial services institutions (17), life insurance (7) and non-life insurance (15).

In addition, it should be noted that these indices are exclusively related to the 18 countries[40] belonging to the European Union.

We can choose sector indices for countries across Europe, such as the STOXX Europe 600 Banks Index, but our goal is to raise the awareness of macro-prudential regulators (explained in the first chapter) of the most systemically risky sectors or institutions which are in their fields of application.

As a clue to the system, we choose to use the STOXX Europe 600 ex_ Financial Index instead of the Euro Stoxx ex_Financial Index. Such a choice is explained by the fact Euro Stoxx ex_Financial Index determines a Blue-chip representation of super sector leaders in the Eurozone. However, SE 600_exFin represents large, mid and small capitalization companies. It is evaluated from 462 companies belonging to 17 countries of the European region.

2.2.2. Financial Institutions:

We identified the financial institutions operating in the European countries with the largest market capitalization on 28/02/2014, according to Thomson Reuters, listed in the following table:

[40] These countries are: Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia and Spain.

Table 9. Presentation of financial institutions – Eurozone

Sectors	Notations	Institutions	Countries	Stock market capitalizations (Millions€)
Banks	BS	Banco Santander	Spain	75.910
	BP	Bnp Paribas	France	74.037
Life insurance	ING	ING Group	Netherlands	40.594
	AG	Aegon	Netherlands	23.916
Non-Life insurance	All	Allianz	Germany	59.208
	AXA	Axa	France	45.800
Financial Services	GBL	Bruxelles Lambert Group	Belgium	12.500
	DB	Deutsche Boerse	Germany	11.472

Source: Author's data presentation

These institutions are used for the calculation of the sectorial indices previously mentioned.

2.2.3. Control variables:

By analogy with the US market, we will identify control variables related to the European market. The following table summarizes the data needed for CoVaR estimation:

Table 10. Data presentation required for control variables - Euro zone

Data	Notations	Sources
Repo rate for the « Euro zone » (3months)	$EU\ RR_t$	Thomson Reuters
Rate of a German sovereign bond (maturity)	$Ger\ T\_Bill_t$	Thomson Reuters
« Credit Spread » for the « Euro zone » (10years)	$EUCDSP_t$	Bloomberg
VSTOXX[41] Share Price	P_t	Thomson Reuters
Euro Stoxx Real Estate Stock Market Prices		Thomson Reuters
Stock Exchange Course Euro Stoxx 50		Thomson Reuters

Source: Author's data presentation

[41] Bernal et al. (2013) use VDAX.

The control variables are shown in the below table:

Table 11. Overview of control variables - Euro zone

Notations	**Variables**	**Mesures**
$VSTOXX_t$	VSTOXX[42]	$\ln(P_t) - \ln(P_{t-1})$
$EULQSP_t$	« Liquidity Spread »	$EU\ RR_t$ (3months) -$Ger\ T\_Bill_t$ (3months)
$GBSP_t$	Bond rate variation	$Ger\ T\_Bill_t$(3months)-$Ger\ T\_Bill_{t-1}$ (3months)
$EUYDSP_t$	« Yield Spread »	$Ger\ T\_Bill_t$ (10years) - $Ger\ T\_Bill_t$ (3months)
$EUCDSP_t$	« Credit Spread » (10years)	
$ESTX\ 50_t$	Return of the Euro Stoxx 50	$\ln(P_t) - \ln(P_{t-1})$
$ESRE_t$	Return of Euro Stoxx Real Estate	$\ln(P_t) - \ln(P_{t-1})$

Source: Author's data presentation

3. Model and methodology:

In the previous chapter, we defined the $CoVaR_q^{i|j}$ as the VaR of the institution i conditional on the institution j reaching its VaR level.

In our study, the index i is relative to the system and the index j corresponds either to the financial sector (cross-sectoral study) or to the financial institution (inter-firm study).

Analytically, we have the following equations:

$$P(\ X^i \leq CoVaR_q^{sys|j} \mid X^j = VaR_q^j) = q \tag{3.1}$$

$$\Delta CoVaR_q^{sys|j} = CoVaR_q^{sys|X^j = VaR_q^j} - CoVaR_q^{sys|X^j = VaR_{q=Median}^j} \tag{3.2}$$

These equations are estimated using quantile regression following very specific steps. First, it is worth to give a clear insight into quantile regression.

3.1. Quantile regression:

Most of the empirical study investigates the average effect of the X exogenous variables on the endogenous variable Y using the Ordinary Least Squares (OLS) method. We can,

[42] It is the analogue of the VIX on the European market. It represents the implied volatility of the 50 largest stocks in the Dow Jones Euro Stoxx 50 Index.

moreover, compute a conditional mean function E (X/Y), where the impact of the independent variables is assumed to be constant throughout the distribution of the variable of interest. This constitutes a major limitation to the study of tails distribution according to Konenker and Hallock (2001).

In addition, if the assumptions on which OLS is based are not verified, such as the normal distribution of error terms, estimates may be unreliable.
To overcome these disadvantages, the quantile regression was introduced by Koenker Roger and Bassett Gilbert in 1987.

Several researchers, like Chen (2010), Hautfoeuille and Givord (2011), Eboulet and Matei (2013), claim that quantile regression is more robust than the OLS method. It is less sensitive to the presence of outliers or extremes and effective for a wide variety of error terms, regardless of their distribution.
Moreover, starting from the definition of the VaR, which is no other than, a quantile of distribution, the quantile regression proves to be more appropriate and deserves to be applied.
To understand this method well, some concepts need to be clarified.
Recall, first, the distribution function F_Y:

$$F_Y(y) = P(Y \leq y) \tag{3.3}$$

The quantile[43] of order q is nothing other than the inverse of the distribution function F_Y such that:

$$Q_Y = F_Y^{-1}(q) = inf\ \{y : F_Y(y) \geq q\} \qquad q \in\ ]0,1] \tag{3.4}$$

It should be pointed out that the first decile of any population, for example, does not mean the percentage of its poorest fringe, but rather the income threshold, below which are located 10% of the population.
According to Hautfoeuille and Givord (2011), quantile regression allows us to study the impact of exogenous variables on the different quantiles of the distribution of the endogenous variable, as stipulated in the following equation:

$$Q_Y(q|X_i) = X_i'\beta_i^{(q)} \qquad \text{With } i = 1 \ldots n \tag{3.5}$$

---

[43] The most commonly used quantiles are the median (q=0.5), the first and last deciles (q=0.1 and q=0.9), the first and last quantiles (q=0.25 and q=0.75).

For each quantile q corresponds to a vector of coefficients $\beta_i^{(q)} = (\beta_0^{(q)}, \beta_1^{(q)}, \dots, \beta_k^{(q)})'$ relative to k explanatory variables (including the constant) $X_i = (1, X_1, X_2, \dots, X_k)'$

The estimation of the unknown parameters of the model is defined as a solution to the problem of minimizing the following function:

$$\beta_i^{(q)} = argmin^{44}{}_{\beta \in R} \left[\Sigma_{i:\, Y \geq X_i' b_i^{(q)}} q \left| Y - X_i' b_i^{(q)} \right| + \Sigma_{i:\, Y \leq X_i' b_i^{(q)}} (1-q) \left| Y - X_i' b_i^{(q)} \right| \right] \quad (3.6)$$

Where: $0 < q < 1$

$\beta_i^{(q)}$ corresponds to the best estimate of the vector $b_i^{(q)} = \left(b_0^{(q)}, b_1^{(q)}, \dots, b_k^{(q)}\right)'$ which minimizes the sum of the positive and negative values of the differences between the observed value Y and the predicted value $X_i' b_i^{(q)}$ respectively weighted by q and (1-q).

To distinguish ourselves from previous work, we prefer to use quantile regression with resampling "Boostrap Quantile Regression" recommended by Machado and Silvas (2011). Indeed, the quantile regression is based on the minimization of a continuous function but not differentiable. This does not make it easy to calculate the variance of the estimators.

3.2. Steps of CoVaR estimation:

The CoVaR is appreciable following the steps explained below:

Step 1: Estimate the stock market returns of financial sector indices and financial institutions by the quantile regression (q is equal to 1% and 50%).

$$R_t^j(q) = \alpha^j + \delta_k^j M_t + \varepsilon_t^j \quad (3.7)$$

With k=1…7

R_t^j : Yield at time t of the financial sector (banking, life and non-life insurance, financial services) or financial institutions j.

α^j : Constant

M_t : denotes the vector of our 7 control variables

δ_k^j : represents the coefficient of each control variable k for the sector j

[44] Argmin (argument minimum) d'une fonction correspond à la valeur de la variable pour laquelle la valeur de la fonction étudiée atteint son minimum.

For the US market, equation (3.7) is rewritten as follows:

$$R_t^j(q) = \alpha^j + \delta_1^j VIX_t + \delta_2^j USLQSP_t + \delta_3^j TBSP_t + \delta_4^j USYDSP_t + \delta_5^j USCDSP_t + \delta_6^j S\&P\,500_t + \delta_7^j DJUSRE_t + \varepsilon_t^j \quad (3.8)$$

As regards the European market, the equation is as follows:

$$R_t^j(q) = \alpha^j + \delta_1^j VSTOXX_t + \delta_2^j EULQSP_t + \delta_3^j GBSP_t + \delta_4^j EUYDSP_t + \delta_5^j EUCDSP_t + \delta_6^j ESTX\,50_t + \delta_7^j ESRE_t + \varepsilon_t^j \quad (3.9)$$

Step 2: Estimate the performance of the system subordinate to the sector or institution j thanks to the quantile regression (q equal to 1% and 50%).

$$R_t^{sys|j}(q) = \alpha^{sys|j} + \beta^{sys|j} R_t^j + \delta_k^{sys|j} M_t + \varepsilon_t^{sys|j} \quad (3.10)$$

R_t^{sys} : System performance at time t

$\alpha^{sys|j}$: Constant

$\beta^{sys|j}$: measures the contribution of R_t^j to the system R_t^{system}

$\delta_k^{sys|j}$: represents the coefficient of each selected control variable

$\varepsilon_t^{sys|j}$: denotes the term error

Equation (3.10) contains the significant control variables considered in equation (3.7), with the exception of the S & P 500 index for the US market and the Euro Stoxx 50 index for the European market.

Step 3: Calculate VaR_t^j for each financial sector or institution using only the control variables with significant coefficients in Step 1.

$$VaR_t^j(q) = \hat{\alpha}^j + \hat{\delta}_k^j M_t \quad (3.11)$$

Coefficients $\hat{\alpha}^j and\ \hat{\delta}_k^j$ are extracted from equation (3.7).

Step 4: Calculate $CoVaR_t^{sys|j}$ with q equal to 1% and 50%, retaining the significant coefficients $\alpha^{sys|j}, \beta^{sys|j}, \delta_k^{sys|j}$ estimated in equation (3.10) and VaR_t^j determined by equation (3.11).

$$CoVaR_t^{sys|j}(q) = \hat{\alpha}^{sys|j} + \hat{\beta}^{sys|i} VaR_t^j + \hat{\delta}_k^{sys|j} M_t \quad (3.12)$$

Step 5: Calculate $\Delta CoVaR_t^{sys|j}$ by determining the difference between $CoVaR_t^{sys|j}$ with a quantile equal to 1% and the other with a quantile equal to 50%.

This measure assesses the contribution of various sectors or financial institutions to systemic risk.

$$\Delta CoVaR_t^{sys|j}(q) = CoVaR_t^{sys|j}(1\%) - CoVaR_t^{sys|j}(50\%) \quad (3.13)$$

$\Delta CoVaRs$ are negative because they are calculated from the low yields of the sectors or financial institutions.

As a result, the financial sector (or financial institution) with the largest value of $\Delta CoVaR$ (expressed in absolute value) is the one that contributes the most to systemic risk during periods of distress (crisis).

Step 6: Test the significance of the $\Delta CoVaRs$ obtained to verify further the ranking of the pre-selected sectors and financial institutions according to their contribution to systemic risk.

According to Castro and Ferrai (2013), the significance test aims to identify the sector or institution that is systemically and significantly risky. We examine whether $\Delta CoVaRs$ are statistically 0 (which means that the sector or institution is not systemically risky) or statistically different from 0 (which suggests that the sector or institution contributes significantly to risk systemic).

Given that the coefficients of each explanatory variable fluctuate according to the quantile chosen, we propose to verify whether the distribution functions of CoVaRs with different quantiles (1% and 50%) are identical or diverse.

The "two-sample Kolmogorov-Smirnov"[45] (KS) test makes it possible to compare two different distribution functions. From a statistical point of view, this test is defined as follows:

$$D_{mn} = \left(\frac{m\,n}{m+n}\right)^{\frac{1}{2}} sup_x \left[F_m(x) - G_n(x)\right] \quad (3.14)$$

$F_m(x)$ and $G_n(x)$ are the distribution functions of CoVaRs having respectively a quantile equal to 1% and 50% and a size m and n.

[45] This is a non-parametric test that does not require an assumption about the underlying data distribution, also called a "free distribution test".

The null hypothesis of the test states that the distribution functions of CoVaRs are equal to different quantiles and therefore the sector or financial institution does not contribute significantly to systemic risk.

$$H_0: \Delta CoVaR_t^{sys|j}(q) = CoVaR_t^{sys|j}(1\%) - CoVaR_t^{sys|j}(50\%) = 0 \quad (3.15)$$

$$H_0: CoVaR_t^{sys|j}(1\%) = CoVaR_t^{sys|j}(50\%) \quad (3.16)$$

Conclusion

This chapter has taken a critical step in estimating CoVaR for the US and European markets. The financial system is valued in relation to the sectors and financial institutions that make it up, represented by very specific indices. The real economic system is described by global indices representative of several sectors, like the industrial sector, technologies, telecommunication, transport, etc., except for the financial sector.

From a methodological point of view, we used a dual study (cross-sectorial study and inter-company study) to distinguish ourselves from previous work on systemic risk. The aim of this approach is to provide macro-prudential regulators with greater guidance to the financial sector and institution most responsible for the emergence of systemic risk. This encourages them to be very cautious and act immediately before it is too late, by developing preventive and mandatory regulations in order to ensure financial stability.

Similarly, through this chapter, we have shown the application of quantile regression, given its contribution to optimizing the systemic risk measurement approach using CoVaR. Finally, we gave an overview of the tasks allocated to the different steps to be followed in the next chapter.

Chapter 4

Contribution of the financial system to systemic risk

Introduction

Based on our empirical study, in this chapter we propose to concretize the tasks assigned to the different steps outlined above. This study concerns the estimation of the contribution of the financial system to systemic risk in both markets: the United States and the European countries during the period from 20/08/2004 until 28/02/2014.

The related methodology requires us to start with the calculation of VaR and CoVaR. The latter determines the amount of losses incurred by the system that refers to the real economy, in the case of dysfunction of a financial sector (inter-sectoral study) or a financial institution (inter-company study).

Once the above calculations are completed, we continue with the identification of the financial system component considered the most risky through the evaluation of the ΔCoVaR. Such a measure helps to orient the financial regulatory authorities in the United States and in the "Euro" zone towards the appropriate procedures to adopt in order to remedy the actual sources of financial instability.

In this respect, we used the STATA11.2 software to establish the regressions; to apply the "two-sample kolmogorov-smirnov test" noted KS, previously exposed in chapter 3 and the OxMetric 7.2 software in order to produce the graphical representations.

1. The US market:

1.1. Inter-sectoral study:

Before calculating VaR and CoVaR, we first estimate the performance of sector indices (including the system) through quantile regression (Steps 1 and 2), the results of which are presented in appendix A. (Tab A.1 / Tab A.2)

The researchers, having applied quantile regression like Castro and Ferrai (2013), Bernal et al. (2013), Drakos and Kourtas (2014), often interpret the sign and significance of the coefficients which change according to the fluctuation of the quantile of the endogenous variable distribution. This translates the purpose of the quantile regression stated in the previous chapter.

Similarly, we find that the sign and significance of selected control variables fluctuate from one index to another and from one quantile to another.

For example, for the DJUSBK (q = 1%), it should be noted that only USYDSP and USCDSP have a negative influence, while the S & P 500 and DJUSRE have a positive impact. By changing the quantile to 50%, the VIX becomes significant and positive. True, USYDSP is not always like that.

On the system yield corresponding to the quantile set at 1%, represented by S & P 500_exFin, VIX, USLQSP, USYDSP, USCDSP have a negative impact. On the other hand, DJUSBK, TBSP and DJUSRE have a positive impact. Once the quantile is set at 50%, USLQSP, USYDSP and USCDSP are no longer significant.

Likewise, with the other sectorial financial indices (DJUSLI, DJUSNLI and DJUSFS) and the representative system index (S & P 500_exFin), the number of significant control variables and their signs change.

Adrian and Brunnermeier (2011) show that the control variables integrated into their model have asymmetric effects on the quantile of the endogenous variable associated with it. The estimation of their coefficients is only an essential step in the measurement of systemic risk, which is most important to us. This is why we suggest discussing them superficially to the detriment of the interpretation and explanation of the risk measures that focus our interest.

In addition, we used the pseudo- R^2 of the quantile regression to evaluate the fit quality of the model by analogy to the R^2 of the OLS method. In this study, pseudo- R^2 reach a maximum of 76.95% and a minimum of 44.66% with an average of 60.75%, which implies a good specification of the model.

The results of steps 3, 4, 5 and 6 are given in Appendix A and the following table:

Table 12. Systemic Risk Assessment from Financial Sectors -USA-

Sectors	VaR^j	$CoVaR^{sys\|j}$	$\Delta CoVaR^{sys\|j}$	Test KS	(p-value)	Rating
Banks	-2.685557	-1.566132	-1.546435	0.6810*	(0.000)	4
Life insurance	-3.664091	-2.350383	-2.350999	0.8124*	(0.000)	1
Non-Life insurance	-1.896018	-2.158205	-2.238386	0.8102*	(0.000)	2
Financial Services	-1.663418	-1.774448	-1.77653	0.7277*	(0.000)	3

Source: STATA output
* ** *** significant coefficient respectively at the thresholds of 1%, 5% and 10%.

VaR^j, $CoVaR^{sys|j}$ and $\Delta CoVaR^{sys|j}$, calculated with a quantile equal to 1%, are negative and expressed as a percentage. They will be interpreted in terms of absolute value.

The VaR of the life insurance sector posted the highest loss amount, 3.664091% followed in descending order by the banking sector with 2.685557%, non-life insurance with 1.896018% and financial services with 1.663418%. As an example, we deduce that for a $ 1,000 million investment in the life insurance industry, there is a 99% chance of not losing more than $ 3,664,091 million.

Of course, we cannot conclude, a priori, that the life insurance sector is more risky compared to other sectors, by referring only to VaR.

According to the CoVaRs, the VaR of the system (S & P 500 ex_Fin) is equal to 2.350383%, if the life insurance sector reaches its VaR level equal to 3.664091%. In other words, the expected loss of the system is equal to $ 2350,383 million, in case the life insurance sector loses $ 3664,091 million.

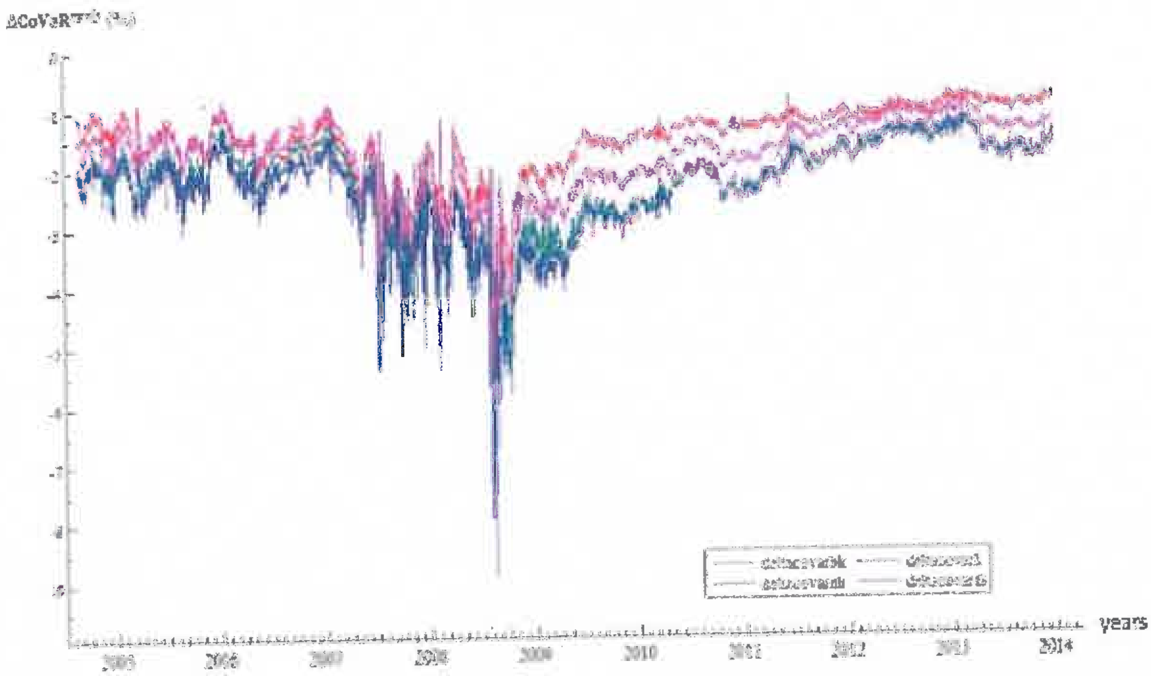
The VaR of the system conditional on the non-life insurance, financial services and banking sectors is equal to 2.158205%, 1.774448% and 1.566132% respectively. On the other hand, we realize that although the VaR of the banking sector is higher than that of the financial services sector, the failure of the latter leads to a greater loss of the system than that caused by the banking sector failure.

By reference, only to ΔCoVaRs, we find that the life insurance sector ranks first with a maximum equal to 2.350999%, continued in descending order by the non-life insurance sectors with 2.238386%, financial services with 1.77653% and banking with 1.546435%. As a result, life insurance contributes the most to the risk studied. If this sector reports an estimated loss of 1.896018%, the loss of the system increases by an average of 2.350999%.

Regarding the significance test applied to ΔCoVaRs by means of the KS test, the null hypothesis, claiming that the sector does not contribute significantly to systemic risk is rejected. With p-value less than 1%, the selected sectors all have a significant impact on the real economy during times of distress.

The graph below describes the evolution of $\Delta CoVaR^{sys|i}$ in the financial sectors: banking (bk), life insurance (li), non-life insurance (nli) and financial services (fs).

Figure 6. Evolution of the ΔCoVaRs of the financial sectors -USA-



Source: OxMetric 7.2 output

This chart shows, at first glance, that the life insurance sector still contributes the most to systemic risk. Between the end of 2004 and the beginning of 2007, ΔCoVaRs fluctuate in a relatively stable scope. Starting from 2007, it began to decline and become more negative, mentioning that the contribution of the financial sectors to the risk increases following the crisis of "subprime". The real economy is therefore going through a very critical period, where the failure of the financial system can lead to huge losses. We see a peak of about -9%, if the life insurance sector reaches its VaR level. After this fall, ΔCoVaRs show an upward trend from the beginning of the second half of 2008 until the end of our study period. This can be explained by the reaction of the financial regulatory authorities, who rushed to develop an urgent plan for macro-prudential regulation. The latter has succeeded as can be seen from the chart examined.

1.2. Inter-company study:

The results of the quantile regressions are given in Appendix A (Tab A.4 / Tab A.5) for the selected financial institutions and the system. The sign and significance of some control variables change with the fluctuation of the endogenous variable quantile.

The pseudo- R^2s oscillate between 31.75% and 71.42% with an average of 51.68% which implies a good specification of the model.

By examining the financial institutions with the highest market capitalization (MC), the results corresponding to steps 3,4, 5 and 6 are given in Appendix A and the below table:

Table 13. Systemic Risk Assessment from Financial Institutions -USA-

	VaR^j	**$CoVaR^{sys\|j}$**	**$\Delta CoVaR^{sys\|j}$**	**Test KS (p-value)**	**Rating**	**Rating/ MC**
JPM	-5.521724	-1.911472	-1.909168	0.4946 * (0.000)	2	2
WFG	-3.833567	-1.492767	-1.591403	0.4611* (0.000)	5	3
MET	-5.18497	-2.097967	-2.17895	0.5076* (0.000)	1	7
PR	-4.067688	-1.550506	-1.549309	0.4536* (0.000)	6	8
AIG	-10.05065	-1.832748	-1.817201	0.4898* (0.000)	3	5
BH	-1.032772	-1.272246	-1.264338	0.3397* (0.000)	8	1
GS	-3.719668	-1.310401	-1.308225	0.3972* (0.000)	7	6
AE	-2.770385	-1.656585	-1.655386	0.4704* (0.000)	4	4

Source: STATA output
* ** *** significant coefficient respectively at the thresholds of 1%, 5% and 10%.

Relative to the VaR, the insurance (non-life) AIG records the highest amount of loss 10.05065%. If it reaches this figure, the loss it causes for the system is equal to 1.832748%. Regarding our sample, it is ranked third because its contribution to systemic risk is on average equal to 1.817201%.

Taking into account the MC, the insurance (non-life) BH holds the largest capitalization. We notice that it marks the weakest loss amount 1.032772%. The VaR of the S & P 500 ex_Fin index is equal to 1.272246%, whether this institution is in a state of crisis. BH is ranked last, compared to other institutions where it negatively influences the VaR of the S & P 500 ex_Fin with an average of -1.264338%.

We note that the classification of financial institutions according to the MC does not coincide with that established according to the $\Delta CoVaR^{sys|j}$. Indeed, the VaR of the system increases by 2.17895% on average, once the loss of insurance (life) MET estimated 5.18497% is reached. It should be noted that it is ranked seventh with a low market capitalization compared to other institutions.

It is only for the second ranked JPM Bank and the establishment of the fourth ranked AE Financial Services that we find a similarity.

If JPM struggles and reaches its VaR level equal to 5.521724%, the S & P 500 ex_Fin index will have a VaR which rises by an average of 1.909168%. However, the VaR of the S & P 500 ex_Fin increases by 1.655386% if AE attains its VaR which is equal to 2.770385%.

Under the KS test, p-values below 1% indicate that all financial institutions selected contribute significantly to systemic risk.

In addition, it should be noted that compared with the ranking of the financial sectors established in the cross-sector study, we deduced that the life insurance sector contributes the most to systemic risk, pursued by the non-life insurance and financial services and banking sectors respectively.

Indeed, we did not achieve exactly the same classification at the level of the institutions belonging to the sector in question. Although the first place in the ranking is occupied by life insurance, it is not unimportant to complete the inter-sectoral study in order to have more information on the sectors contribution to the studied risk.

2. The European market:

2.1. Inter-sectoral study:

The results of the quantile regressions are presented in Appendix B (Tab B.1 / Tab B.2). Their sign and significance vary according to the quantile of the indices. It is the same for pseudo-R^2 which oscillates between 42.92% and 67.92% with an average of 56.12%.

The results of steps 3, 4, 5 and 6 are set out in Appendix B and in the following table:

Table 14. Systemic risk assessment from the financial sectors – Eurozone

Sectors	VaR^j	$CoVaR^{sys\|j}$	$\Delta CoVaR^{sys\|j}$	Test KS (p-value)	Rating
Banks	-1.373751	-1.786366	-1.782948	0.7256* (0.000)	2
Life insurance	-1.554512	-1.554512	-1.551701	0.7200* (0.000)	3
Non-Life insurance	-1.761402	-1.537627	-1.528183	0.6971* (0.000)	4
Financial Services	-2.387906	-1.946019	-1.942846	0.7718* (0.000)	1

Source: STATA output
* ** *** significant coefficient respectively at the thresholds of 1%, 5% and 10%.

The financial services sector is characterized by the highest VaR (2,387,906%) followed in descending order by the non-life (1,761,402%), life insurance (1.554512%) and banking sectors (1,373751%).

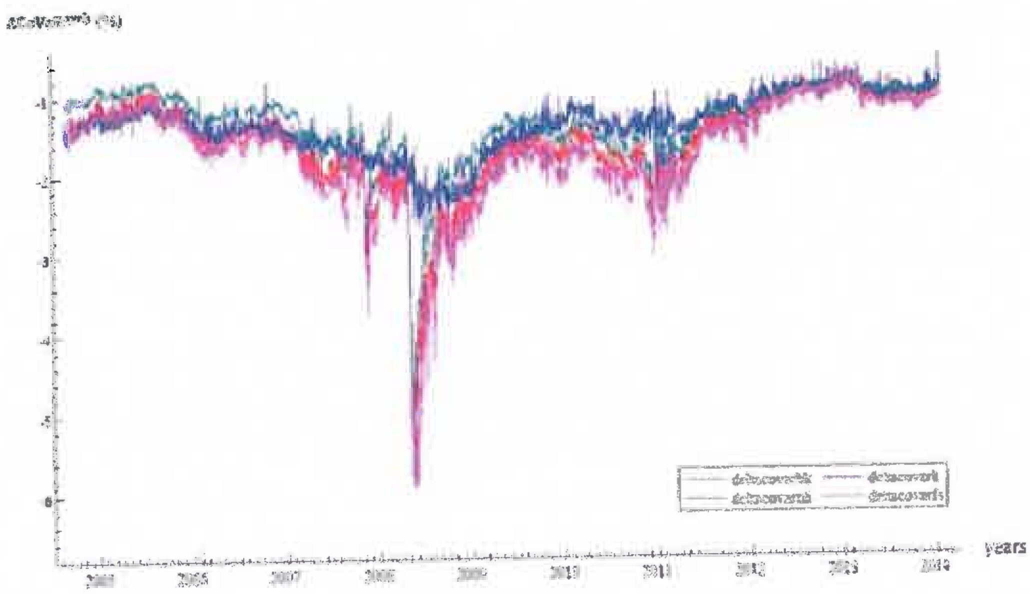
Once the VaR of the financial services sector is reached, the system (SE 600 ex_Fin) reports its expected loss of 1.946019%. Although the non-life insurance VaR (1.761402%) is higher than the life insurance VaR (1.554512%), the system VaR conditional on the non-life insurance sector is small (1.537627%) compared to that subordinated to life insurance industry (1.554512%). In this sense, we cannot say whether the financial services sector with the highest VaR necessarily contributes the most to systemic risk.

ΔCoVaRs reveal that the financial services sector negatively affects the VaR of the system in the event of default with an average of -1.942846%. In the second place, we are dealing with the banking sector having a negative impact causing to the European economy a loss of -1.782948%, followed in descending order by the life insurance sectors (-1.551701%) and non-life (-1.528183%).

The application of the KS test reveals that all financial sectors contribute significantly to the risk considered.

The figure below describes the evolution of $\Delta CoVaR^{sys|j}$ in the financial sectors: banking (bk), life insurance (li), non-life insurance (nli) and financial services (fs).

Figure 7. Evolution of the ΔCoVaRs of the financial sectors – Eurozone



Source: OxMetric 7.2 output

The analysis of this figure shows that until the end of 2005, the life insurance sector was the most exposed to systemic risk. Certainly, during the period from 2006 till the beginning of 2014, we observe that the financial services sector took over, evolving at a pace marked by sharp peaks. This is the most risky sector from a systemic point of view.

Between the end of 2006 and the end of the first half of 2008, ΔCoVaRs decline gradually and become more negative. This means a gradual growth in the systemic risk. The peak in the financial services sector indicates that the real economy tends to lose about -6.25% of the expected loss when this sector reaches its VaR level. After this decline, ΔCoVaRs move gradually upward until 2010, indicating that the contribution of these sectors tends to decrease due to the implementation of macro-prudential regulation. Then, they begin to drop again following the sovereign debt crisis of the "Euro" zone appeared in 2010. We were able to discover a new peak corresponding to the financial services sector estimated about -3.5% in the beginning of the second quarter of 2011. The upward phase is immediately resumed and the contribution of the financial sectors to systemic risk begins to fall until the end of our study period.

2.2. Inter-company study:

The results of the quantile regressions are presented in Appendix B (Tab B.4 / Tab B.5). Pseudo- R^2s vary between 41.54% and 63.44% with an average of 50.33%. It is the same for the sign of the control variables and their significance, which fluctuate according to the endogenous variable quantile.

Completion of steps 3, 4, 5 and 6 gives us the results shown in Appendix B and in the table below:

Table 15. Systemic risk assessment from financial institutions – Eurozone

	VaR^j	$CoVaR^{sys\|j}$	$\Delta CoVaR^{sys\|j}$	Test KS		Rating	Rating/ MC
BS	-1.0083034	-1.623259	-1.620416	0.5230*	(0.000)	5	1
BP	-7.037037	-1.65478	-1.652536	0.5294*	(0.000)	4	2
ING	-9.816358	-1.549419	-1.547159	0.5156*	(0.000)	6	5
AG	-6.978632	-1.67468	-1.672469	0.5498*	(0.000)	3	6
All	-2.886813	-1.441703	-1.442009	0.4706*	(0.000)	7	3
AXA	-4.311713	-1.302144	-1.298332	0.4223*	(0.000)	8	4
GBL	-1.648633	-1.72579	-1.726374	0.5580*	(0.000)	2	7
DB	-1.0079174	-1.766914	-1.766302	0.5597*	(0.000)	1	8

Source: STATA output
* ** *** significant coefficient respectively at the thresholds of 1%, 5% and 10%.

Thus, we note that ING life insurance records the largest amount of loss (9.816358%). However if its VaR is reached, the VaR of the SE600 ex_Fin index representative of the rest of the European economy is equal to 1.549419%. $\Delta CoVaR^{sys|ING}$ shows that the VaR of the system increases on average by 1.547159%. By limiting ourselves to VaR, ING is ranked first, compared to other financial institutions. Of course, it becomes sixth according to $\Delta CoVaR^{sys|ING}$.

BS Bank is distinguished by the highest market capitalization. However, it does not systematically contribute the most to the system loss if it is in a state of distress. The VaR of the system increases by an average of 1.620416%, when the VaR of BS equals 1.0083034%.

We observe, also, that the classification of financial institutions according to their MC does not coincide with that established in consideration of $\Delta CoVaR^{sys|j}$.

DB, which is a financial services company with the smallest market capitalization, is considered the most responsible for triggering systemic risk in the event that its estimated loss of 1.0079174% is reached.

Regarding the use of the KS test, it is important to emphasize that all institutions contribute significantly to systemic risk.

Nevertheless, we note that the ranking established during the inter-sectoral study revealed the great contribution of the financial services sector to the risk, followed by the banking, life and non-life insurance sectors respectively. This statement is verified with certain reservations at the level of financial institutions.

3. Robustness Test:

To further verify the reliability of our results, it seems appropriate to recalculate ΔCoVaRs of the financial sectors for the period between 20/08/2004 and 28/02/2014, always keeping the same coverage rate q = 1%, but choosing quantiles different from the median, as recommended by Adrian and Brunnermeier (2011).

From an analytical point of view, the recalculation in question is formulated by the following equation:

$$\Delta CoVaR^{sys|j} = CoVaR^{sys|j}_{q=1\%} - CoVaR^{sys|j}_{q=30\%,40\%,60\%,70\%} \quad (4.1)$$

The results are illustrated in Appendices A and B (Tab A.7 / Tab B.7) and in the below tables:

Table 16. ΔCoVaRs of financial sectors with various quantiles -USA-

	30%	40%	60%	70%	Rating
$\Delta CoVaR^{sys\|BK}$	-1.33021	-1.488213	-1.564442	-1.632782	4
$\Delta CoVaR^{sys\|LI}$	-2.20022	-2.316374	-2.374618	-2.462384	1
$\Delta CoVaR^{sys\|NLI}$	-1.719835	-2.100806	-2.179941	-2.249253	2
$\Delta CoVaR^{sys\|FS}$	-1.35152	-1.758847	-1.772485	-1.82782	3

Source: STATA output

Table 17. ΔCoVaRs of the financial sectors with various quantiles – Eurozone

	30%	40%	60%	70%	Rating
$\Delta CoVaR^{sys\|BK}$	-1.535677	-1.780514	-1.780354	-1.829317	2
$\Delta CoVaR^{sys\|LI}$	-1.342494	-1.552453	-1.567225	-1.726277	3
$\Delta CoVaR^{sys\|NLI}$	-1.311215	-1.539836	-1.539798	-1.674536	4
$\Delta CoVaR^{sys\|FS}$	-1.765006	-1.948371	-1.948584	-2.104104	1

Source: STATA output

Consequently, the ranking of financial sectors already established is maintained for both the US market and the Euro zone.

4. Discussion of the results:

4.1. Inter-sectoral study:

Our hypothesis, which assumed that the banking sector contributes the most to systemic risk, is rejected for the two regions selected in our study. In this sense, explanations deserve to be advanced.

In addition, we suggest comparing the US and the Euro markets in the various sectors.

4.1.1. Banking sector:

For the "Euro" zone, the banking sector is more influential on the real economy, if it is in critical condition compared to the insurance sector (life and non-life).

According to Pasiouras and Gaganis (2013), insurance is financed in the long term by subscribers' insurance policies largely on the one hand and by shareholders and lower-level debts on the other. While banks fund themselves mainly in the short term from deposits, interbank market, repo transactions, etc. Hence, the risk of liquidity deficiency for this sector is greater.

Banks are more interconnected than insurance companies through interbank lending. This amplifies the effects of contagion and increases the complexity of the banking sector according to Minoiu et al. (2013). Similarly, it should be noted that the appearance of single currency has further encouraged European banks to promote their cross-border activities.

The large size of the European banking sector relative to that of the insurance sector explains, among other things, the banks' responsibility for the emergence of systemic risk. The review of the statistics of the European Central Bank (2013) demonstrates that the total value of bank assets was estimated at 31.142 billion dollars in 2013, while that of insurance reached 7.844 billion dollars, or 25% below all the banks' assets.

The banking sector is ranked second in the "Euro" zone and fourth in the United States. This implies that banks negatively influence the European economy more than the US. Several figures can be mentioned to amply explain this deduction.

According to Allen et al. (2005), the financial system differs from region to region. To finance themselves, economic agents resort either to the financial markets or to financial intermediaries. In the US, markets have a bigger role in financing the economy compared to the "Euro" zone. This means that the European economy is financed mainly by bank loans rather than by issuing financial securities. In 2007, bank loans accounted for 146% of GDP in the European countries. In contrast, bank loans in the US are below 100% of GDP, or 64% as shown by the report of the Central Bank. European (2009).

Lima (2008) states that European banks perform more cross-border transactions compared to US banks. This indicates that the degree of internationalization of European banks is higher. According to Goldstein et al. (2011), more than half of European banking activities are conducted outside home countries in 2010. However, only one-quarter of banking operations are executed across US borders.
Of the 35 major banks ranked globally on September 30th , 2013 by relbanks[46], there are 12% of US banks and 43% of banks in the "Euro" zone which hold the largest assets.

[46] http://www.relbanks.com/

We have been able to notice that financial regulation is granted at the federal level in the United States, while in Europe, it is torn between "Euro" zone governments on the one hand and the European Central Bank on the other hand. In other words, there is a kind of divergence of their points of view, thus complicating the development of rigorous regulation.

4.1.2. Insurance sector (life and non-life):

Whether it is the US or European market, our empirical study reveal that life insurance is considered more responsible for the birth of systemic risk compared to non-life insurance.
Such a finding can be explained by the fact that non-life insurance offers a wide range of services, thus diversifying their risks. In the light of the report of the International Association of Insurance Supervisors (2004), non-life insurance refers to all property insurance (movable or immovable), civil liability (obligation to repair personal injury or property damage caused to others), except for life and health insurance.
In the US, insurance in general contributes the most to systemic risk compared to banks and financial services institutions.

Kwan and Laderman (1999) argue that US insurance is riskier than banking. They elucidate their results relying on the regulatory argument that we cite, for instance, the enactment in 1933 of the "Glass Steagall Act" for the purpose of separating banks from deposits of commercial banks, the announcement in 1994 of " Riegle-Neal Interstate Banking and Branching Efficiency Act "to limit the acquisition of foreign banks by US banks.

According to Laurent (2009), banks received more than $ 2 billion from the US government, a much higher amount than that granted to insurance. The US government has a closer relationship with the banking sector especially after the 2007 crisis.

Our study found that the US insurance sector (ranked first) negatively affects the rest of the economy in case of default, by reference to the one in the "Euro" zone (ranked last).

Lima (2008) states that the social security systems between the United States and European countries are different. The US government invests much more in insurance programs and pension funds than those in the selected European countries.

According to statistics from the Organization for Economic Co-operation and Development, OECD[47], it turns out that the US insurance market alone accounts for nearly half (48.8%) of the entire European market insurance coverage ratio (29.8%) in 2012. The US insurance penetration[48] ratio is equal to 11.6% of GDP, while that of the "Euro" zone countries reached 8.7% of GDP in 2012. For the life insurance, this ratio is equal to 5.9% of US GDP and 5.1% of European GDP. Of course, with respect to non-life insurance, this ratio is equal to 6.1% of GDP in the US and almost half to 3.1% of the GDP in the "Euro" zone countries.

The larger the size of the insurance sectors in relation to the economy as a whole, the greater its impact on the economy.

Similarly, the report published by the OECD (2011) certifies that US insurance losses a total of $ 189 billion, a much higher amount than losses generated by European insurance estimated at $ 69 billion between 2008 and 2010, which is less than half of the US loss bunch.

4.1.3. Financial services sector:

In the "Euro" zone, the financial services sector contributes the most to systemic risk, compared to the US, where this sector is more risky than banks. Such a deduction deserves to be argued by in-depth explanations, especially since the literature available and dealing with this sector is not dense enough. However, that did not prevent us from clarifying our results by putting forward two possible explanations.

The first has a regulatory aspect. Institutions in the financial services sector, such as brokerage, credit card, asset management, investment funds, etc. are subject to less rigid regulation compared to other financial institutions. Hence, the excess within these less regulated companies expose the economy to a more serious systemic risk. In view of the intense regulation of banks and insurance, investors mistakenly believe that the risk generated by them is greater.

In addition, we have recognized that the recent regulatory reform that took place especially following the crisis of "subprime" according to Masera (2010), did not affect precisely the sector concerned. As an indication, we mention the European Banking Authority (EBA) and the European Insurance and Occupational Pensions Authority (EIOPA) which focused on the regulation governing the banking and insurance sectors.

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[47] http://www.oecd.org/fr/statistiques/

[48] This ratio indicates the level of development of the insurance sector in a country. It is measured as the ratio of the premium subscribed for a given year to the GDP.

The second explanation relates to qualified institutions "TBTF: Too Big to Fail". According to Kaufman (2011), governments develop and implement bailouts for large institutions, whose likely bankruptcy could jeopardize the smooth functioning of the financial and economic system. Since the financial services sector is composed of small institutions compared to the banking and insurance sectors. In the light of the US business-to-business study, we noticed that Goldman Sachs and Americain Express are considered small compared to the JPMorgan and Wells Fargo banks. Similarly, in the "Euro" zone, Deutsche Boerse and Groupe Bruxelles Lambert are also minor compared to other financial institutions.

The bankruptcy of such a sector will have more negative effects on the real economy because it is less sheltered from the regulatory authorities. This implies that it is not automatically rescued in the execution of rescue plans by the State.
According to our results, the European financial services sector (ranked first) is much more risky than the US (ranked third).

The comparison of the level of risk severity between these two regions is not obvious. For this reason, we consider it interesting to refine the explanation of the causes of the difference between the two regions of study, for which we have found no figures or studies that could help us in argument.

4.2. Inter-company study:

The assumption that large institutions necessarily contribute the most to systemic risk is abandoned with some reservations. This finding is validated, among other things, by the study by Roengpitya and Rungcharoenkitkul (2011) showing that the major Thai banks are not necessarily the most responsible for the occurrence of the systemic risk.
On the one hand, a large size of financial institutions is conducive to the diversification of their activities and therefore to hedging against risk. For instance, it has been shown that the US Berkshire Hathaway (non-life) insurance with the largest market capitalization contributes the least to systemic risk. Intuitively, the Deutsche Boerse financial services institution with the smallest capitalization in the Euro zone contributes the most to systemic risk.
On the other hand, large institutions may contribute more to this risk, as is the case the US bank Wells Fargo ranked second, distinguished by a large market capitalization and considered the most important responsible for triggering it.

In this regard, Rose and Wieladek (2012) criticize the concept of TBTF. They also mention the interest of taking into consideration the problem of moral hazard. In fact, governments willing to bail out large institutions with detrimental difficulties to financial stability, offer, among other things, an implicit guarantee. Therefore, they encourage them to incur more risk and provide less effort in risk management.

In conclusion, we can say that the size criterion does not provide us with relevant information about the systemic nature of financial institutions. For this reason, the Financial Stability Board decided to supplement it with other indicators such as interdependence, cross-border activity, substitutability, complexity and designed systemic scale of financial institutions.

In the same vein, it is worth noting that several researchers, like Tabak et al. (2013) and Molyneux et al. (2013), advocate the substitution of the term TBTF by "Too Systemically Important To Fail".

Conclusion

In this chapter, we have tried to identify the sector and institution that contributes the most to systemic risk. The advantage of such an attempt lies in the fact that it allows the regulatory authorities to take the necessary curative measures to safeguard the stability of the financial system.

Comparing CoVaR to VaR, we found first that the sector or financial institution with the highest amount of loss does not necessarily contribute the most to the risk studied. This is a confirmation of the finding already mentioned by Adrian and Brunnermeier (2011), highlighting the consistency of the measure advocated.

Our empirical study suggests that in the United States the life insurance sector contributes the most to systemic risk, pursued by non-life insurance, financial services and banks respectively. Of course, within the "Euro" zone, we conceive that it is rather the financial services sector, which is most responsible for triggering such a risk, successively pursued by the banking, life and non-life insurance sectors. We have also attempted to explain these deductions by comparing the results for the two regions selected. Nevertheless, our mission was not easy for the financial services sector due to lack of a sufficient literature reviews dealing with it.

Finally, it should be noted that we have completed the cross-sectorial study by the part devoted to the calculation of CoVaR, at the level of financial institutions. The results show that the big financial institutions do not automatically contribute the most to the systemic risk. Assessing the systemic nature of financial institutions by size alone may mislead regulatory authorities by neglecting the actual sources of the systemic risk.

General Conclusion

Systemic risk is a topic that has been receiving a lot of attention since the recent financial crisis of 2007. This is an event created by the destabilization of the financial system. The precariousness of the latter is due to certain factors, including financial globalization, which intensifies the links within the financial system of a country and vis-à-vis the financial systems of other countries as well as the financial innovation to accentuate the complexity of financial practices and the asymmetry of information. The result is increased risk-taking and a pressing need to protect the financial system against shocks that could hinder its operation and thereby undermine economic growth.

This is why regulators and researchers have set themselves the goal of optimizing financial regulation and measures of effective risk.

The risk should no longer be assessed individually against each financial institution and the same rules should no longer be applied for all institutions regardless of their imperfectly determined risk. This was what practically involved micro-prudential regulation. Despite its existence, financial institutions like Bear Sterns, Fannie Mae, Freddy Mac, etc. have not been sheltered from the 2007 crisis. They had been forced to face severe problems, in particular the bank Lehman Brothers, whose bankruptcy affected the entire financial and economic system.

Not only banks were affected, but also other financial institutions, such as American Insurance Group insurance quickly rescued on September 16, 2008 by the competent US authorities. This observation reflects, among other things, the importance of the role of other financial institutions in the destabilization of the financial system.

We must not focus on systematic risk, at the expense of the systemic risk that macro-prudential regulation aims to mitigate as much as possible, which in other words means ensuring the stability of the entire financial system.

We found, on the one hand, that the measures taken up to the year 1994 were not designed exclusively for risk assessment according to Dowd (2005) and that VaR is a reform at that time. However, despite the use of this tool in accordance with the recommendation of the

Basel committee to control the risk and safeguard the longevity of financial institutions, the latter including banks suffered unexpected colossal losses, following the cataclysm of 2007. This phenomenon can be explained by the inability of VaR to identify the systemic nature of risk and to take into account the interactions existing within the financial system and with the real economy. Hence, the imperative need to ensure not only the sustainability of financial institutions, but also that of the entire financial system integrating all its components.

In this regard, several systemic risk measures have been proposed, such as MES, SRISK, DIP, etc. Among them, we opted for the CoVaR advocated by Adrian and Brunnermeier (2011) to assess systemic risk in two different regions namely: the United States and the European countries. To do this, we split our empirical study into two parts: cross-sectorial and inter-companies study on the one hand, and focused on the analysis of the insurance sector subdividing it into life and non-life insurance on the other hand. The selected study period is between 20/08/2004 and 28/03/2014. With reference to the study by Castro and Ferrari (2013), we verified the results obtained applying the Kolmogorov-Smirnov test.

The results acquired revealed the specific character of each region selected and allowed the establishment of sector and institution rankings in consideration of their level of contribution to the systemic risk.

Commonly, it appears that the sector or institution with the highest VaR does not necessarily contribute the most to systemic risk. This finding is consistent with the results of Adrian and Brunnermeier (2011), Wong and Fong (2011). This argues, among other things, for the contribution of this measure and clarifies its purpose. However, is this measure adequate for estimating systemic risk? Indeed, such a question is not required in this study, whose main purpose was to identify the most systemically risky component of the financial system. This troubling issue deserves future research focusing on the application of several systemic risk measures, in order to select the most reliable one. Hansen (2013) attests that the risk measure is not a simple task to perform with certainty, stating that: "even if the risk is quantifiable, its knowledge remains incomplete and unsatisfactory".

On the cross-sectorial study, the results show that the life insurance sector contributes the most to systemic risk in the US market, while in the countries belonging to the "Euro" zone, the real economy is clearly more influential in case a problem arises in the financial services sector.

Similarly, we conclude that the insurance sector (life and non-life combined) is more risky in the US than in the "Euro" zone. On the other hand, the banking and financial services sectors play a much more prominent role in the birth of the systemic risk in the "Euro" zone, compared to the USA.

Regarding the inter-companies study, our results reveal that, at the level of the two selected regions, the major financial institutions do not automatically contribute the most to systemic risk, as has been proven by the study by Roengpitya and Rungcharoenkitkul (2011).
The size criterion can be an effective source of error for financial regulators. Indeed, it has been shown that smaller institutions are likely to have impacts that are more negative on the real economy than those classified as large. It is therefore important to explore the most risky institutions systematically in consideration of other criteria, such as substitutability, complexity, interdependence, cross-border activity, etc.

As for the interpretation of the results, it was a challenge when we analyzed the financial sectors considered particularly the financial services sector. This can be explained by the fact that the literature dealing with the latter is insufficient to comprehensively understand its responsibility for triggering systemic risk. This limit does not facilitate the explanation of our results.
In addition, it should be noted that the distribution of selected financial institutions can be criticized, although their choice is based on global sector indices. Indeed, we have noticed that major financial institutions, including banks offer insurance or financial services, like the American bank Wells Fargo.

In addition, CoVaR calculates, according to Adrain and Brunnermeier (2011), the VaR of the rest of the economy subject to a financial institution reaching its VaR level. Such a calculation does not take into consideration the case where this loss exceeds the expected VaR.

In spite of the limitations mentioned above, and with regard to the verification of the robustness of the results, we have been able to admit that in order to mitigate systemic risk, it is necessary to continuously supervise and strictly regulate the functioning of the financial system. Thus, the intervention of the regulatory authorities must be reduced to save the institutions in difficulty, by establishing an honest competition between them and limiting the problem of moral hazard highlighted by Rose and Wieladek (2012). According to Klomp and

Haan (2012), if the banking sector were properly regulated, the repercussions it generates on the real economy would have a small impact on the latter during the 2007 crisis.

However, being aware of the imperatives of good financial governance, the competent authorities are called to focus more on the regulation of the financial services sector especially within the "Euro" zone.

Of course, it is not enough to regulate in order to maintain financial stability, but we must above all ensure compliance with the rules in force. Financial actors need to be optimistic, motivated and attentive to tough decisions that may jeopardize their individual interests, but that are beneficial to the well-being and stability of the entire financial system. As an example, we are referring to the Volcker Law proposed by the former Fed Chairman since July 2010 at the US Congress. It aims to limit the speculative activities of banks and, among other things, end the shadow banking system by requiring hedge funds and private equity to register with the Securities and Exchange Commission (SEC). This reduces the opacity in the operation of such organizations and evaluate the systemic risk that arises from their activities. Due to pressure and opposition from financial lobbyists, this law was not coming into effect, as it was planned on July 20th, 2012 postponed to July 2015.

As a research perspective to recommend, it would be desirable, as we have already expressed, to focus future studies on the comparison between several systemic risk measures in order to deduce the most reliable. Concerning European countries, it would be interesting to direct further work towards assessing the impact of problems affecting weak economies such as those of Greece, Ireland and Portugal, etc. on powerful economies like Germany, France, etc.

Finally, given the actual currency fluctuations and recent financial events happening after 2007 crisis, it is desirable to carry out further studies dealing with the effects of systemic risk on the financial system and more generally on the real economy.

APPENDICES

Appendix A.: « United States »

Table A.1: Quantile Regression of Sector Indices - Step 1 -

These tables present the results of the quantile regressions using the "bsqreg" command of the STATA 11.2 software with a number of replications equal to 100. The selected quantiles are set at 1% and 50%. The coefficients correspond respectively to the constant and to the different control variables (VIX_t, $USLQSP_t$, $TBSP_t$, $USYDSP_t$, $USCDSP_t$, $DJUSRE_t$, $S\&P\ 500_t$). The pseudo-R^2 provides information on the fit quality of the model for each quantile.

* ** *** These stars imply that the coefficient is significant at the 1%, 5% and 10% thresholds, respectively.

1%	α (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	δ_7 (p-value)	Pseudo – R^2
$DJUSBK_t$	2.955587* (0.001)	-.0328965 (0.292)	-2.965056 (0.203)	4.01997 (0.540)	-.5515814* (0.000)	-.8331915* (0.000)	.3351597** (0.026)	1.093401* (0.000)	0.6342
$DJUSLI_t$	5.034081* (0.000)	.0276011 (0.352)	-1.3061 (0.517)	-7.430825 (0.220)	-.670284** (0.019)	-1.343989* (0.000)	.081822 (0.642)	1.705278* (0.000)	0.6326
$DJUSNLI_t$	1.657555* (0.000)	.0051942 (0.770)	-2.165072** (0.040)	1.009205 (0.624)	-.318335* (0.000)	-.4547808* (0.000)	.0648316 (0.424)	1.000724* (0.000)	0.6508
$DJUSFS_t$	1.847527* (0.000)	.0173313 (0.257)	-.8381003 (0.173)	.5420186 (0.701)	-.308822* (0.000)	-.5312759* (0.000)	.26268* (0.000)	1.183385* (0.000)	0.7695

50%	α (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	δ_7 (p-value)	Pseudo – R^2
$DJUSBK_t$	.1690642 (0.108)	.0251733* (0.000)	-.0543585 (0.683)	.4486326 (0.540)	-.0185028 (0.166)	-.0357625** (0.041)	.3071278* (0.000)	1.146109* (0.000)	0.4466
$DJUSLI_t$	-.1263707 (0.266)	.0240959* (0.000)	-.0144693 (0.907)	-.4954074 (0.273)	-.0085262 (0.512)	.0233537 (0.226)	.1935845* (0.000)	1.396473* (0.000)	0.4674
$DJUSNLI_t$	.0221666 (0.648)	.0046067 (0.235)	.1010198 (0.282)	1.666401* (0.002)	.0083533 (0.226)	-.0137002 (0.155)	.1116575* (0.000)	.8986438* (0.000)	0.5221
$DJUSFS_t$	-.0063499 (0.911)	.0044463 (0.152)	-.0372464 (0.722)	.8537937* (0.010)	.0004323 (0.947)	.0007552 (0.942)	.3051143* (0.000)	1.007507* (0.000)	0.6227

Table A.2: Quantile Regression of System Performance - Step 2 –

By using the "bsqreg" command of STATA 11.2 with a number of replications equal to 100, these tables report the results of the quantile regressions of the system's performance S & P 500 ex-Fin. The selected quantiles are set at 1% and 50%. α is the constant and β is the coefficient of return for the financial sector ($DJUSBK_t$, $DJUSLI_t, DJUSNLI_t\ et DJUSFS_t$). The coefficients $\delta_1, \delta_2, \delta_3, \delta_4, \delta_5$ and δ_6 correspond respectively to the control variables retained (VIX_t, $USLQSP_t$,$TBSP_t$,$USYDSP_t$,$USCDSP_t$ et $DJUSRE_t$). The pseudo-R^2 provides information on the fit quality of the model for each quantile.

* ** *** These stars imply that the coefficient is significant at the thresholds of 1%, 5% and 10% respectively.

1%	α (p-value)	β (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	Pseudo – R^2
$R_t^{sys\|BK}$	-.082833* (0.000)	-2.554743* (0.001)	3.435069*** (0.066)	-.1051007*** (0.096)	-.1547365* (0.001)	.1778936* (0.000)	.0637424** (0.016)	.2865435 (0.252)	0.6974
$R_t^{sys\|LI}$	-.0729745* (0.000)	-2.268999* (0.001)	3.528066** (0.044)	-.1195148** (0.017)	-.2009806* (0.000)	.1378588* (0.000)	.1461735* (0.000)	.5438909*** (0.077)	0.7190
$R_t^{sys\|NLI}$	-.0627747* (0.000)	-1.762753* (0.000)	1.593778 (0.276)	-.1886475* (0.000)	-.1571182* (0.000)	.1023885* (0.000)	.2994854* (0.000)	.4217593*** (0.074)	0.7289
$R_t^{sys\|FS}$	-.0599349* (0.000)	-2.205476* (0.000)	.8142115 (0.395)	-.1460926* (0.004)	-.1058492* (0.004)	.0599936** (0.025)	.2744135* (0.000)	.17278 (0.444)	0.7387

50%	α (p-value)	β (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	Pseudo – R^2
$R_t^{sys\|BK}$	.0868159 (0.131)	.0879455* (0.000)	-.0758271* (0.000)	-.0307995 (0.572)	.6859554** (0.030)	.0007595 (0.918)	-.0104954 (0.296)	.1639056* (0.000)	0.4927
$R_t^{sys\|LI}$	.0513122 (0.304)	.1646184* (0.000)	-.0653742* (0.000)	-.0122267 (0.858)	.5164045 (0.125)	.001683 (0.802)	-.0066539 (0.435)	.1266591* (0.000)	0.5266
$R_t^{sys\|NLI}$	.0791473*** (0.062)	.2964785* (0.000)	-.0585085* (0.000)	-.0391545 (0.514)	.2276048 (0.492)	-.0044174 (0.526)	-.0073302 (0.319)	.1255455* (0.000)	0.5314
$R_t^{sys\|FS}$	.0516449* (0.000)	.3133166* (0.000)	-.0538115* (0.000)	-.0153513 (0.837)	-.2843127 (0.446)	.0014002 (0.790)	-.0048658 (0.506)	.0516449* (0.000)	0.5403

Table A.3 : Calculation of VaR, CoVaR and ΔCoVaR sector indices
- Steps 3,4 and 5 -

This is a table provided by STATA 11.2 and which provides an overview of the means, standard deviations, minimum and maximum VaRs, CoVaRs and ΔCoVaRs for US sector indices for the period between 20/08 / 2004 and 28/02/2014.

Variable	Obs	Mean	Std. Dev.	Min	Max
varbk	2314	-2.685557	2.409908	-22.67381	7.609976
covarbk	2314	-1.566132	1.175995	-11.11344	3.725791
varbk50	2314	-.1805652	1.953399	-17.05712	12.83762
covarbk50	2314	-.0196969	.9425145	-6.647206	4.751858
deltacovarbk	2314	-1.546435	.6172015	-5.822803	-.7188487
varli	2314	-3.664091	2.865642	-24.10061	10.64812
covarli	2314	-2.350383	1.366223	-15.26734	3.169342
varli50	2314	.02205	2.035818	-16.69774	15.45769
covarli50	2314	.0005163	.9506781	-6.868478	4.888692
deltacovarli	2314	-2.350999	.858362	-9.941071	-.5087987
varnli	2314	-1.896018	1.582041	-15.94002	5.68702
covarnli	2314	-2.158205	1.216721	-12.64874	2.691924
varnli50	2314	.0124799	1.383933	-10.8108	10.27118
covarnli50	2314	.0801811	.9843405	-7.07454	5.16546
deltacov~nli	2314	-2.238386	.7433254	-7.010827	-.5009066
varfs	2314	-1.663418	2.168068	-19.97726	10.48562
covarfs	2314	-1.774448	1.22072	-12.17955	3.313473
varfs50	2314	.014987	1.90383	-15.97408	12.19962
covarfs50	2314	.0020818	.9914311	-7.26742	5.313579
deltacovarfs	2314	-1.77653	.6506469	-6.199326	-.3774221

Output of the application of the "Two-samples KS test" on the ΔCoVaRs sectoral indices - Step 6 –

```
. ksmirnov delta_covarnli, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group           D       P-value  Corrected
 ----------------------------------------------
 1:                  0.8102       0.000
 2:                  0.0000       1.000
 Combined K-S:       0.8102       0.000      0.000

Note: ties exist in combined dataset;
      there are 4555 unique values out of 4628 observations.

. ksmirnov delta_covarfs, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group           D       P-value  Corrected
 ----------------------------------------------
 1:                  0.7277       0.000
 2:                  0.0000       1.000
 Combined K-S:       0.7277       0.000      0.000

Note: ties exist in combined dataset;
      there are 4556 unique values out of 4628 observations.

. ksmirnov delta_covarbk, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group           D       P-value  Corrected
 ----------------------------------------------
 1:                  0.6810       0.000
 2:                  0.0000       1.000
 Combined K-S:       0.6810       0.000      0.000

Note: ties exist in combined dataset;
      there are 4625 unique values out of 4628 observations.

. ksmirnov delta_covarli, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group           D       P-value  Corrected
 ----------------------------------------------
 1:                  0.8124       0.000
 2:                  0.0000       1.000
 Combined K-S:       0.8124       0.000      0.000

Note: ties exist in combined dataset;
      there are 4547 unique values out of 4628 observations.
```

Table A.4: Quantile Regression of Institutional Indices - Step 1 –

These tables provide the results of the quantile regressions (1% and 50%) for the institutions in question. The coefficients correspond to the constant and the different control variables (VIX_t, $USLQSP_t$, $TBSP_t$, $USYDSP_t$, $USCDSP_t$, $DJUSRE_t$, $S\&P\ 500_t$).

* ** *** These stars imply that the coefficient is significant at the thresholds of 1%, 5% and 10% respectively.

1%	α (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	δ_7 (p-value)	Pseudo – R^2
WFG	4.953239* (0.000)	.0052704 (0.903)	-4.302742 (0.149)	2.666821 (0.624)	-.7975782** (0.017)	-1.317282* (0.000)	.1843596 (0.442)	1.472411* (0.000)	0.5413
JPM	1.665802 (0.191)	.0025994 (0.957)	-6.754767** (0.032)	-8.005018 (0.290)	-.6312468* (0.001)	-.5340455** (0.033)	.5007659 (0.025)	.8470875** (0.022)	0.5253
MET	4.120125* (0.000)	.08019*** (0.084)	-8.506539* (0.009)	.8429965 (0.877)	-.9822766* (0.001)	-1.215307* (0.000)	-.0718012 (0.804)	2.41659* (0.000)	0.5215
PR	7.41919* (0.000)	.0405933 (0.422)	-9.793739*** (0.059)	-7.136 (0.588)	-1.050596* (0.005)	-1.719937* (0.000)	-.0966086 (0.720)	2.111894* (0.000)	0.5388
AIG	12.7861* (0.001)	.0169777 (0.854)	-5.42177* (0.004)	2.75654 (0.149)	-1.75214* (0.008)	-2.575572* (0.000)	.5770413 (0.268)	1.283924 (0.169)	0.4812
BH	2.239915* (0.000)	-.026528 (0.194)	-2.707386** (0.027)	-.1970139 (0.916)	-.3564664* (0.000)	-.6144643* (0.000)	-.0190701 (0.877)	.6022398* (0.007)	0.4608
GS	2.26535*** (0.091)	-.029301 (0.566)	-2.436766 (0.115)	5.780018* (0.005)	-1.064365* (0.000)	-.7259044* (0.006)	-.0070511 (0.961)	1.443208* (0.001)	0.5028
AE	2.22586** (0.040)	.0715346 (0.119)	-3.792321 (0.229)	-6.500234 (0.372)	-.5855171* (0.000)	-.7070606* (0.000)	.19102 (0.338)	1.450341* (0.000)	0.5671

50%	α (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	δ_7 (p-value)	Pseudo – R^2
WFG	.0249985 (0.811)	.0272708* (0.001)	.3002383 (0.173)	.574046 (0.567)	.0142766 (0.447)	-.0258654 (0.213)	.3433646* (0.000)	1.070627* (0.000)	0.3265
JPM	-.0085402 (0.949)	.024467* (0.001)	.1339756 (0.427)	-.6862211 (0.472)	-.008689 (0.626)	-.0111417 (0.635)	.2821873* (0.000)	1.223914* (0.000)	0.3748

MET	-.1937941 (0.184)	.02653* (0.005)	-.0620372 (0.741)	-.0627072 (0.932)	.0036999 (0.794)	.0348188 (0.165)	.136144* (0.002)	1.557303* (0.000)	0.3499
PR	-.0878864 (0.557)	.0468845* (0.000)	-.0076028 (0.964)	-.5736036 (0.544)	-.0028496 (0.858)	.0157475 (0.545)	.2758638* (0.000)	1.600771* (0.000)	0.3627
AIG	.3800072** (0.072)	.0290445* (0.002)	.1748799 (0.427)	1.788656** (0.049)	-.052274** (0.050)	-.0811072** (0.025)	.1222099* (0.002)	1.463103* (0.000)	0.3175
BH	.0890679 (0.260)	.0013355 (0.839)	.0698645 (0.612)	-1.684355** (0.032)	-.02624** (0.024)	-.0165009 (0.229)	.0038359 (0.868)	.6139849* (0.000)	0.3759
GS	-.0213059 (0.846)	-.004070 (0.622)	.001019 (0.995)	1.834214** (0.026)	-.0034772 (0.801)	.0035687 (0.858)	.1657245* (0.000)	1.120048* (0.000)	0.3244
AE	.0457001 (0.683)	.0234925* (0.001)	-.2220027 (0.189)	1.66716* (0.000)	.0173142 (0.203)	-.0093731 (0.642)	.2947552* (0.000)	1.111789* (0.000)	0.3931

Table A.5 : Quantile Regression of System Performance - Step 2 -

These tables present the results of the quantile regressions (1% and 50%) of the system yield, S & P 500 ex_Fin, subordinated to the selected financial institutions. α is the constant and β is the coefficient of performance of the institution. The coefficients $\delta_1, \delta_2, \delta_3, \delta_4, \delta_5$ *and* δ_6 refer to the same control variables (Table 3), except for S & P 500. * ** *** These stars indicate that the coefficient is significant at the 1%, 5% and 10% thresholds, respectively.

1%	α (p-value)	β (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	**Pseudo – R^2**
$R_t^{sys\|WFC}$	3305309 (0.286)	0244445 (0.251)	-.0819868* (0.000)	-2.605843* (0.000)	2.620002 (0.145)	-.1267623 (0.183)	-.153606* (0.004)	.2268038* (0.000)	0.6898
$R_t^{sys\|JPM}$	2222153 (0.401)	0719308* (0.000)	-.0841798* (0.000)	-2.85622* (0.000)	3.475253** (0.040)	-.1092563** (0.046)	-.1285544* (0.004)	.1674879* (0.000)	0.6969
$R_t^{sys\|MET}$	3723397 (0.218)	083695* (0.000)	-.0739136* (0.000)	-2.683791* (0.000)	3.534127** (0.024)	-.1080719** (0.019)	-.1623153* (0.005)	.1974198* (0.000)	0.7015
$R_t^{sys\|PR}$	.0586168 (0.814)	.0954292* (0.000)	-.0889212* (0.000)	-2.392516* (0.000)	.860952 (0.567)	-.095233*** (0.062)	-.1189494** (0.016)	.1386866* (0.000)	0.7142
$R_t^{sys\|AIG}$	.239474 (0.377)	.0320964 (0.209)	-.0814054* (0.000)	-2.734587* (0.000)	2.686633*** (0.072)	-.1213319** (0.041)	-.1287172* (0.007)	.218507* (0.000)	0.6891

$R_t^{sys\|BH}$	.0504687 (0.832)	.1347063* (0.001)	-.0694262* (0.000)	-2.345361* (0.000)	3.390685* (0.002)	-.1478435* (0.002)	-.1164904* (0.007)	.2108634* (0.000)	0.7051
$R_t^{sys\|GS}$	.4732044** (0.046)	.0961384* (0.000)	-.0719884* (0.000)	-1.98518* (0.000)	1.611891 (0.217)	-.1749091* (0.005)	-.188304* (0.000)	.2231976* (0.000)	0.7139
$R_t^{sys\|AE}$	.4196098 (0.162)	.0662658*** (0.095)	-.0826452* (0.000)	-2.232225* (0.000)	1.861602 (0.149)	-.1447295*** (0.070)	-.1807304* (0.001)	.1963246* (0.000)	0.6940

50%	α	β	δ_1	δ_2	δ_3	δ_4	δ_5	δ_6	**Pseudo – R^2**
	(p-value)	(p-value)	(p-value)	(p-value)	(p-value)	(p-value)	(p-value)	(p-value)	
$R_t^{sys\|WFC}$	.101404** (0.038)	.0431045* (0.000)	-.0788499* (0.000)	-.0424299 (0.519)	.6848951** (0.027)	-.0009768 (0.864)	-.0125415 (0.139)	.1912708* (0.000)	0.4854
$R_t^{sys\|JPM}$	.0772909 (0.105)	.0716431* (0.000)	-.0746252* (0.000)	-.0746252 (0.668)	.7247358** (0.024)	.0027293 (0.654)	-.0094432 (0.266)	.1858437* (0.000)	0.4904
$R_t^{sys\|MET}$	082015** (0.050)	.0881238* (0.000)	-.0710366* (0.000)	-.0274062 (0.711)	.5446587 (0.133)	.0025018 (0.666)	-.0104222 (0.147)	.1749136* (0.000)	0.5047
$R_t^{sys\|PR}$	.0847299*** (0.062)	.0944708* (0.000)	-.0713096* (0.000)	-.0221036 (0.725)	.8797644** (0.010)	.0020075 (0.756)	-.0115535 (0.126)	.1638215* (0.000)	0.5079
$R_t^{sys\|AIG}$	.0825948 (0.147)	.0225617* (0.001)	-.0760808* (0.000)	-.0384236 (0.611)	.692019** (0.021)	.0000719 (0.991)	-.0091988 (0.374)	.2247368* (0.000)	0.4864
$R_t^{sys\|BH}$	.0750333 (0.114)	.109698* (0.000)	-.0746347* (0.000)	-.0568826 (0.396)	.8047493* (0.004)	-.0009503 (0.864)	-.0074762 (0.381)	.2133796* (0.000)	0.4972
$R_t^{sys\|GS}$	.1027867*** (0.077)	.07836* (0.000)	-.0696922* (0.000)	-.0004551 (0.995)	.6899237* (0.009)	.0010015 (0.862)	-.0160012 (0.140)	.2018551* (0.000)	0.4953
$R_t^{sys\|AE}$	.0609446 (0.233)	.1089493* (0.000)	-.0691338* (0.006)	-.0218188 (0.682)	.55297*** (0.078)	.0020512 (0.768)	-.0075692 (0.341)	.1766459* (0.000)	0.5047

Table A.6 : Calculation of VaR, CoVaR and ΔCoVaR of institutional indices - Steps 3,4 and 5 -

This is a table provided by STATA 11.2 which provides an overview of the means, standard deviations, minimums and maximums of VaR, CoVaR and ΔCoVaR for US financial institutions during the period from 20/08/2004 to 28/02/2014.

Variable	Obs	Mean	Std. Dev.	Min	Max
varjpm	2314	-5.521724	2.829693	-31.00914	6.07589
covarjpm	2314	-1.911472	1.327769	-15.39128	3.485173
varjpm50	2314	.0197813	1.999695	-16.97636	13.8949
covarjpm50	2314	-.0023035	.9534433	-6.808392	4.949748
deltacovar~m	2314	-1.909168	.8036131	-10.10459	-.0395131
varwfc	2314	-3.833567	2.676474	-22.24007	7.761363
covarwfc	2314	-1.492767	1.180424	-10.97927	3.848152
varwfc50	2314	.0178478	1.926321	-16.79474	12.38286
covarwfc50	2314	.0986361	.9250619	-6.417397	4.846633
deltacovar~c	2314	-1.591403	.6216495	-6.545423	-.7946832
varmet	2314	-5.18497	4.257926	-45.20717	9.846795
covarmet	2314	-2.097967	1.46063	-16.84301	3.706692
varmet50	2314	.02437	2.112809	-16.91769	16.94296
covarmet50	2314	.0809825	.9396953	-6.685176	4.96382
deltacovar~t	2314	-2.17895	.9305777	-11.98592	-.0201583
varpru	2314	-4.067688	3.673508	-29.91416	13.12736
covarpru	2314	-1.550506	1.26374	-11.88814	4.055501
varpru50	2314	.0263952	2.355315	-19.8847	17.46072
covarpru50	2314	-.0011962	.9627303	-6.92806	4.999664
deltacovar~u	2314	-1.549309	.6810578	-6.226982	-.2994081
varaig	2315	-10.05065	6.888783	-59.79979	3.20e-07
covaraig	2314	-1.832748	1.257783	-12.80177	3.316616
varaig50	2314	-.5260194	1.985745	-16.49007	14.96526
covaraig50	2314	-.0155469	.9483012	-6.82954	4.986174
deltacovar~g	2314	-1.817201	.8109742	-7.732172	-.655475
varbh	2314	1.032772	1.029773	-9.721273	4.965476
covarbh	2314	-1.272246	1.204437	-13.42402	3.667314
varbh50	2314	-.0384202	.7655103	-5.876144	6.631619
covarbh50	2314	-.0079086	.9534341	-6.820165	4.95939
deltacovarbh	2314	-1.264338	.6700063	-8.271963	.4378923
varae	2314	-2.770385	2.171496	-19.20451	10.38955
covarae	2314	-1.656585	1.174008	-10.89632	3.720224
varae50	2314	.0172449	1.913822	-16.22809	12.73757
covarae50	2314	-.0011998	.9543729	-7.040711	5.132863
deltacovarae	2314	-1.655386	.5896671	-5.848271	-.7151554
vargs	2314	-3.719668	2.509374	-23.77357	8.451307
covargs	2314	-1.310401	1.183544	-10.82871	4.047444
vargs50	2314	.015751	1.773626	-14.04255	12.90273
covargs50	2314	-.0021757	.9540563	-6.929936	5.064735
deltacovargs	2314	-1.308225	.5442452	-5.238027	-.2577695

Output of the application of the "Two-samples KS test" on the ΔCoVaRs of institutions - Step 6 -

. ksmirnov delta_covarjpm, by(gr)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

Smaller group	D	P-value	Corrected
1:	0.4946	0.000	
2:	-0.0047	0.971	
Combined K-S:	0.4946	0.000	0.000

Note: ties exist in combined dataset;
there are 4547 unique values out of 4628 observations.

. ksmirnov delta_covarwfc, by(gr)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

Smaller group	D	P-value	Corrected
1:	0.4611	0.000	
2:	-0.0026	0.991	
Combined K-S:	0.4611	0.000	0.000

Note: ties exist in combined dataset;
there are 4554 unique values out of 4628 observations.

. ksmirnov delta_covarmet, by(gr)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

Smaller group	D	P-value	Corrected
1:	0.5076	0.000	
2:	-0.0064	0.948	
Combined K-S:	0.5076	0.000	0.000

Note: ties exist in combined dataset;
there are 4552 unique values out of 4628 observations.

. ksmirnov delta_covarpr, by(gr)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

Smaller group	D	P-value	Corrected
1:	0.4536	0.000	
2:	-0.0055	0.961	
Combined K-S:	0.4536	0.000	0.000

. ksmirnov delta_covaraig, by(gr)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

Smaller group	D	P-value	Corrected
1:	0.4898	0.000	
2:	-0.0032	0.987	
Combined K-S:	0.4898	0.000	0.000

Note: ties exist in combined dataset;
there are 4544 unique values out of 4628 observations.

. ksmirnov delta_covarbh, by(gr)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

Smaller group	D	P-value	Corrected
1:	0.3397	0.000	
2:	-0.0032	0.987	
Combined K-S:	0.3397	0.000	0.000

Note: ties exist in combined dataset;
there are 4627 unique values out of 4628 observations.

. ksmirnov delta_covargs, by(gr)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

Smaller group	D	P-value	Corrected
1:	0.3972	0.000	
2:	-0.0150	0.742	
Combined K-S:	0.3972	0.000	0.000

Note: ties exist in combined dataset;
there are 4555 unique values out of 4628 observations.

. ksmirnov delta_covarae, by(gr)

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

Smaller group	D	P-value	Corrected
1:	0.4704	0.000	
2:	-0.0076	0.927	
Combined K-S:	0.4704	0.000	0.000

Note: ties exist in combined dataset;
there are 4556 unique values out of 4628 observations.

Table A.7 : Robustness test

These tables provided by STATA 11.2 present the means, standard deviations, minimums and maximums of ΔCoVaR relating respectively to the American sector indices during the period between 20/08/2004 and 28/02/2014. ΔCoVaRs are calculated by subtracting CoVaRs (q = 1%) from those estimated for different quantiles, equal to 30%, 40%, 60% and 70% respectively.

Variable	Obs	Mean	Std. Dev.	Min	Max
deltacov~k30	2314	-1.33021	.5232037	-5.188867	-.5907483
deltac~rli30	2314	-2.20022	.7974603	-9.577359	-.3989257
deltac~nli30	2314	-1.719835	.6383356	-5.926258	-.2009408
deltacov~s30	2314	-1.35152	.5334684	-5.044469	-.2438625
deltacoba~40	2314	-1.488213	.6060171	-6.062088	-.6715529
deltac~rli40	2314	-2.316374	.8187833	-9.408381	-.6499947
deltac~nli40	2314	-2.100806	.7332324	-6.756501	-.3589067
deltacov~s40	2314	-1.758847	.6466272	-6.156218	-.4259853
deltacov~k60	2314	-1.564442	.621647	-5.891985	-.6787864
deltac~rli60	2314	-2.374618	.8540018	-9.471877	-.7294596
deltac~nli60	2314	-2.179941	.7591554	-7.137585	-.4457362
deltacov~s60	2314	-1.772485	.7529578	-8.636148	-.0250163
deltacov~k70	2314	-1.632782	.6407167	-6.433203	-.7378051
deltac~rli70	2314	-2.462384	.8944561	-10.0842	-.5592259
deltac~nli70	2314	-2.249253	.7815282	-7.360847	-.2902297
deltacov~s70	2314	-1.82782	.8154807	-9.259923	.1709874

Appendix B.: « Euro Zone »

Table B.1: Quantile regressions of system sector indices - Step 1 -

These tables show the results of the quantile regressions of sector index returns (banks, life and non-life insurance, financial services). The selected quantiles are set at 1% and 50%. The coefficients correspond respectively to the constant and to the different control variables ($VSTOXX_t$, $EULQSP_t$, $GBSP_t$, $EUYDSP_t$, $EUCDSP_t$, $ESRE_t$, $ESTX50_t$). The pseudo-R^2 provides information on the fit quality of the model for each quantile.

* ** *** These stars show that the coefficient is significant at the thresholds of 1%, 5% and 10% respectively.

1%	α (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	δ_7 (p-value)	Pseudo – R^2
$ESBK_t$	-1.382003* (0.001)	-.0085957 (0.715)	-2.83862* (0.000)	1.20085 (0.445)	.0904248 (0.527)	-.1068543* (0.001)	.2495992* (0.003)	1.159118* (0.000)	0.6712
$ESLI_t$	1.461619** (0.018)	.0235668 (0.389)	-4.51816** (0.020)	-2.059422 (0.571)	-.3191856 (0.211)	-.6674025* (0.000)	.1786772 (0.264)	1.17954* (0.000)	0.6091
$ESNLI_t$	.758206** (0.049)	.0245126 (0.122)	-.623294 (0.444)	-2.096629 (0.478)	-.1269369 (0.474)	-.4366813* (0.000)	.2220061** (0.013)	.9482787* (0.000)	0.6599
$ESFS_t$	-.0615858 (0.808)	-.0079202 (0.706)	-2.45612* (0.000)	-2.329248 (0.196)	-.0843866 (0.608)	-.2580057* (0.000)	.3444901* (0.000)	.5839007* (0.000)	0.6081

50%	α (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	δ_7 (p-value)	Pseudo – R^2
$ESBK_t$	-.1232345 (0.161)	.0131027* (0.003)	-.333482** (0.049)	-.3184401 (0.487)	-.0011425 (0.934)	.0239738 (0.201)	.1077075* (0.000)	1.218982* (0.000)	0.5641
$ESLI_t$	.0203885 (0.845)	.0063924 (0.284)	.29654*** (0.086)	.0079266 (0.990)	.0184417 (0.366)	-.0181851 (0.378)	.1734202* (0.000)	1.11671* (0.000)	0.5000
$ESNLI_t$	.0338086 (0.541)	.0045131 (0.289)	.0445566 (0.680)	.0071339 (0.982)	.0019538 (0.879)	-.0071929 (0.532)	.0908996* (0.000)	.8899998* (0.000)	0.5849
$ESFS_t$	.0304824 (0.684)	-.0005232 (0.899)	.0254645 (0.810)	.2441726 (0.534)	.0038591 (0.805)	-.0045476 (0.771)	.4022357* (0.000)	.5637113* (0.000)	0.5067

Table B.2: Quantile Regression of System Performance - Step 2 -

These tables present the results of the quantile regressions of the system performance evaluated by SE 600 ex_Fin. The selected quantiles are set at 1% and 50%. α is the constant and β is the coefficient of return for the financial sector ($ESBK_t$, $ESLI_t$, $ESNLI_t$ *and* $ESFS_t$). The coefficients $\delta_1, \delta_2, \delta_3, \delta_4, \delta_5$ *and* δ_6 correspond respectively to the control variables selected ($VSTOXX_t$, $EULQSP_t$, $GBSP_t$, $EUYDSP_t$, $EUCDSP_t$, $ESRE_t$). The pseudo-R^2 provides information on the fit quality of the model for each quantile. * ** *** These stars imply that the coefficient is significant at the thresholds of 1%, 5% and 10% respectively.

1%	α (p-value)	β (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	Pseudo – R^2
$R_t^{sys\|BK}$	-.3578698 (0.229)	.1329287* (0.000)	-.058163* (0.000)	-1.50132* (0.002)	-.3310251 (0.795)	.1145476 (0.287)	-.2269783* (0.002)	.2458247* (0.000)	0.5476
$R_t^{sys\|LI}$	.758206** (0.049)	.9482787* (0.000)	.0245126 (0.122)	-.6232941 (0.444)	-2.096629 (0.478)	-.1269369 (0.474)	-.4366813* (0.000)	.2220061** (0.013)	0.6599
$R_t^{sys\|NLI}$	.0078767 (0.979)	.1446383* (0.006)	-.0644507* (0.000)	-1.462099* (0.018)	1.258794 (0.456)	.1137735 (0.387)	-.2890189* (0.001)	.2100362* (0.007)	0.5566
$R_t^{sys\|FS}$	-.2483651 (0.480)	.2521662* (0.000)	-.0487748* (0.006)	-1.507105* (0.013)	.6522572 (0.631)	.2179101 (0.101)	-.2537889* (0.006)	.2115417** (0.039)	0.5482

50%	α (p-value)	β (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	Pseudo – R^2
$R_t^{sys\|BK}$	-.0182187 (0.786)	.1523* (0.000)	-.0633322 (0.000)	-.017695 (0.850)	.0566784 (0.845)	.0211705 (0.175)	.0039894 (0.776)	.2162233* (0.000)	0.4292
$R_t^{sys\|LI}$	-.0311345 (0.497)	.2414472* (0.000)	-.0548108 (0.000)	-.0937589 (0.227)	-.2038198 (0.476)	.0067604 (0.468)	.0095066 (0.343)	.1455567* (0.000)	0.4837
$R_t^{sys\|NLI}$	.0338086 (0.541)	.8899998* (0.000)	.0045131 (0.289)	.0445566 (0.680)	.0071339 (0.982)	.0019538 (0.879)	-.0071929 (0.532)	.0908996* (0.000)	0.5849
$R_t^{sys\|FS}$	.0002121 (0.997)	.3474029* (0.000)	-.0607206 (0.000)	-.0167686 (0.879)	-.0765894 (0.817)	.0231939*** (0.074)	-.0022572 (0.831)	.1098002* (0.000)	0.4661

Table B.3 : Calculation of VaR, CoVaR and ΔCoVaR of sectoral indices of the system - Steps 3,4 and 5 -

This table prepared by STATA 11.2 gives an overview of the means, standard deviations, minimums and maximums of the VaR, CoVaR and ΔCoVaR relating to the European sector indices during the period from 20/08/2004 until 28/02/2014.

Variable	Obs	Mean	Std. Dev.	Min	Max
varbk	2314	-1.373751	1.70579	-11.84308	9.499278
covarbk	2314	-1.786366	1.157371	-10.56871	3.655043
varbk50	2314	-.0055962	1.375135	-7.977837	9.91503
covarbk50	2314	-.0034174	.905304	-5.533628	5.604838
deltacovarbk	2314	-1.782948	.667496	-5.738822	-.6384228
varli	2314	-1.25955	1.301478	-9.218155	6.884486
covarli	2314	-1.554512	.9187829	-7.333581	3.180252
varli50	2314	-.0031709	1.305558	-7.604167	8.651802
covarli50	2314	-.0028116	.8915374	-5.444096	5.181216
deltacovarli	2314	-1.551701	.3867643	-2.926739	-.5595369
varnli	2314	-1.761402	2.06953	-17.01837	11.24646
covarnli	2314	-1.537627	1.050825	-9.898765	3.266061
varnli50	2314	-.0510206	1.811716	-10.87537	12.7218
covarnli50	2314	-.0094438	.8602249	-5.332011	4.968987
deltacov~nli	2314	-1.528183	.5557803	-5.362237	-.5022658
varfs	2314	-2.387906	2.283958	-19.87627	8.963235
covarfs	2314	-1.946019	1.140903	-10.8445	2.6773
varfs50	2314	-.0069574	1.794425	-10.44945	12.84922
covarfs50	2314	-.0031731	.8811461	-5.396393	5.327502
deltacovarfs	2314	-1.942846	.7546726	-6.792899	-.7248792

Output of the application of the "Two-samples KS test" on the ΔCoVaRs sectoral indices of the system - Step 6 –

```
. ksmirnov delta_covarbk, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D          P-value  Corrected
 ----------------------------------------------
 1:                  0.7256      0.000
 2:                  0.0000      1.000
 Combined K-S:       0.7256      0.000      0.000

Note: ties exist in combined dataset;
      there are 4601 unique values out of 4628 observations.

. ksmirnov delta_covarli, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D          P-value  Corrected
 ----------------------------------------------
 1:                  0.7200      0.000
 2:                  0.0000      1.000
 Combined K-S:       0.7200      0.000      0.000

Note: ties exist in combined dataset;
      there are 4600 unique values out of 4628 observations.

. ksmirnov delta_covarnli, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D          P-value  Corrected
 ----------------------------------------------
 1:                  0.6971      0.000
 2:                  0.0000      1.000
 Combined K-S:       0.6971      0.000      0.000

. ksmirnov delta_covarfs, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D          P-value  Corrected
 ----------------------------------------------
 1:                  0.7718      0.000
 2:                  0.0000      1.000
 Combined K-S:       0.7718      0.000      0.000

Note: ties exist in combined dataset;
      there are 4602 unique values out of 4628 observations.
```

Table B.4: Quantile regressions of the specific institutional indices of the "Euro" zone - Step 1 -

These tables show the results of the quantile regressions (1% and 50%) for the selected financial institutions. The coefficients correspond to the constant and the different control variables ($VSTOXX_t$, $EULQSP_t$,$GBSP_t$, $EUYDSP_t$,$EUCDSP_t$,$ESRE_t$, $ESTX50_t$). * ** *** These stars indicate that the coefficient is significant at the thresholds of 1%, 5% and 10% respectively.

1%	α (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	δ_7 (p-value)	Pseudo – R^2
BS	-1.160514 (0.132)	.0266917** (0.032)	-1.573968 (0.110)	4.305168* (0.003)	-.3106129** (0.018)	-.2036593** (0.058)	.2282182** (0.047)	1.297678* (0.000)	0.6344
BP	.5143945 (0.545)	-.0563873** (0.032)	-9.702014* (0.009)	-6.076466 (0.437)	1.170091*** (0.076)	-1.182498* (0.000)	-.0414672 (0.899)	1.147468* (0.002)	0.5241
ING	2.524455** (0.033)	-.0841763 (0.439)	-8.960301* (0.001)	-2.833762 (0.386)	-1.305846** (0.018)	-1.370663* (0.000)	-.648793*** (0.084)	.4931706 (0.444)	0.5521
AG	2.953237** (0.036)	-.0381205 (0.698)	-9.957663* (0.000)	-2.676061 (0.626)	-1.135814* (0.010)	-1.420184* (0.000)	.0579062 (0.863)	-.180456** (0.049)	0.5392
All	-.095997 (0.895)	.0356751** (0.022)	-5.182132** (0.024)	-1.064173 (0.811)	.0526841 (0.722)	-.4521348* (0.001)	.3438736** (0.018)	.975221* (0.000)	0.6126
AXA	1.097697 (0.176)	.0720971** (0.030)	-3.116953** (0.018)	-.2201222 (0.955)	-.6707748* (0.004)	-.5921386* (0.001)	.128434*** (0.061)	1.731432* (0.000)	0.6248
GBL	-.1490384 (0.716)	-.033047 (0.141)	-1.227731** (0.044)	1.776886 (0.282)	-.1270785** (0.046)	-.3048526* (0.001)	.1308792*** (0.076)	.5240646* (0.001)	0.5330
DB	-2.435224*** (0.097)	-.0722351 (0.204)	-3.781403** (0.016)	2.92441 (0.619)	.492411 (0.232)	-.4481889** (0.035)	-.473997** (0.037)	1.237361* (0.000)	0.5460

50%	α (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	δ_7 (p-value)	Pseudo – R^2
BS	-.0768695 (0.442)	.0095206** (0.020)	-.0940078 (0.541)	-.4009011 (0.438)	-.0006423 (0.971)	.0171184 (0.415)	.0380153* (0.003)	1.235151* (0.000)	0.4664
BP	.0493776 (0.574)	.0129721 (0.110)	.0527979 (0.822)	-1.231133** (0.047)	.011191 (0.562)	-.0223911 (0.247)	.0074696** (0.080)	1.457528* (0.000)	0.4457

ING	.0902626 (0.710)	-.003348** (0.026)	-.5084294 (0.354)	-1.288335 (0.485)	.0706347 (0.201)	-.020656 (0.680)	-.1255534** (0.043)	.1242275** (0.033)	0.4327
AG	.3537979*** (0.089)	.0115943 (0.311)	-.2246487 (0.618)	-.133952 (0.926)	.0177461 (0.679)	-.0749706*** (0.084)	-.061449* (0.016)	.1950761* (0.002)	0.4738
All	.0261299 (0.740)	.0154177** (0.014)	-.002928 (0.985)	-.1676216 (0.773)	.0070685 (0.674)	-.0056019 (0.718)	.0620107** (0.038)	1.182555* (0.000)	0.4618
AXA	-.1149813 (0.417)	.0262101* (0.001)	.071266 (0.759)	.110056 (0.867)	.0481143 (0.125)	-.0015001 (0.958)	.062814*** (0.083)	1.510635* (0.000)	0.4938
GBL	.0182112 (0.840)	-.002964 (0.598)	-.1396722 (0.317)	-.1480849 (0.710)	.0074645 (0.674)	-.0033002*** (0.058)	.1889903* (0.000)	.5749689* (0.000)	0.4276
DB	.014393** (0.021)	.0017638 (0.883)	.0072376 (0.981)	.0092473 (0.993)	-.0136305 (0.597)	-.0022927 (0.941)	.1204463** (0.020)	.8319872* (0.000)	0.4414

Table B.5: Quantile Regression of System Performance - Step 2 -

These tables report the results of the quantile regressions (1% and 50%) of the Europe 600 yield ex-Fin conditional on selected financial institutions. α is the constant and β represents the coefficient of return of the institution. The coefficients $\delta_1, \delta_2, \delta_3, \delta_4, \delta_5$ *and* δ_6 denote the same control variables, except for Euro Stoxx 50. * ** *** These stars imply that the coefficient is significant at the 1%, 5% and 10% thresholds, respectively.

1%	α	β	δ_1	δ_2	δ_3	δ_4	δ_5	δ_6	**Pseudo – R^2**
	(p-value)	(p-value)	(p-value)	(p-value)	(p-value)	(p-value)	(p-value)	(p-value)	
$R_t^{sys\|BS}$	-.0664251 (0.818)	.0897567* (0.004)	-.0574094* (0.001)	-1.750282* (0.010)	1.402056 (0.347)	.0788205 (0.521)	-.285803* (0.002)	.3163491* (0.000)	0.5390
$R_t^{sys\|BP}$	-.1444234 (0.631)	.0476652 (0.154)	-.0776551* (0.000)	-1.078739** (0.019)	1.234243 (0.408)	.1612959 (0.231)	-.3103628* (0.000)	.2971012* (0.000)	0.5323
$R_t^{sys\|ING}$	.0150057 (0.959)	-.0175738 (0.437)	-.0733278* (0.000)	-1.156291** (0.039)	.908689 (0.596)	.0703909 (0.628)	-.3179141* (0.000)	.3337026* (0.000)	0.5251
$R_t^{sys\|AG}$	.0647368 (0.851)	-.0213001 (0.355)	-.0703463* (0.000)	-.9356515* (0.007)	.5621712 (0.730)	.0977882 (0.515)	-.343621* (0.000)	.3431457* (0.000)	0.5268
$R_t^{sys\|ALL}$	.0057039 (0.982)	.1454502* (0.000)	-.0467464* (0.003)	-1.774563* (0.004)	.1173449 (0.933)	.0192603 (0.888)	-.248388* (0.002)	.272726* (0.000)	0.5467

$R_t^{sys\|AXA}$	-.2215082 (0.454)	.0946484* (0.004)	-.0619471* (0.000)	-1.555076* (0.009)	.5979381 (0.686)	.0581195 (0.625)	-.2249536* (0.002)	.2503904* (0.000)	0.5468
$R_t^{sys\|GBL}$	.0094774 (0.971)	.0200403 (0.880)	-.074191* (0.000)	-1.540627* (0.003)	.4124452 (0.806)	.0961839 (0.469)	-.3126289* (0.000)	.321028* (0.001)	0.5271
$R_t^{sys\|DB}$	.0760877 (0.810)	.0114457 (0.713)	-.0722284* (0.000)	-1.595336* (0.019)	.2880561 (0.880)	.0643588 (0.638)	-.3196419* (0.000)	.3351198* (0.000)	0.5349

50%	α (p-value)	β (p-value)	δ_1 (p-value)	δ_2 (p-value)	δ_3 (p-value)	δ_4 (p-value)	δ_5 (p-value)	δ_6 (p-value)	**Pseudo – R^2**
$R_t^{sys\|BS}$	.0438693 (0.467)	.1158131* (0.000)	-.0681011* (0.000)	-.0386483 (0.683)	.2143617 (0.512)	.0262506 (0.124)	-.0115979 (0.391)	.2403987* (0.000)	0.4356
$R_t^{sys\|BP}$	.0138145 (0.828)	.092887* (0.000)	-.0710264* (0.000)	.0008754 (0.993)	-.0375347 (0.910)	.0054964 (0.714)	-.0004503 (0.972)	.2508992* (0.000)	0.4227
$R_t^{sys\|ING}$	.0249302 (0.720)	.0041369*** (0.081)	-.083777* (0.000)	-.0120536 (0.932)	.3467889 (0.401)	.019305 (0.323)	-.0069551 (0.593)	.3084467* (0.000)	0.4982
$R_t^{sys\|AG}$	.0236596 (0.729)	.0035542** (0.044)	-.0839136* (0.000)	-.0087704 (0.954)	.3497517 (0.371)	.0193835 (0.245)	-.0065415 (0.657)	.3074596* (0.000)	0.4990
$R_t^{sys\|ALL}$	.025874 (0.665)	.1925701* (0.000)	-.0621118* (0.000)	.00568 (0.960)	-.0530058 (0.874)	.0154538 (0.240)	-.0061785 (0.611)	.1967825* (0.000)	0.4593
$R_t^{sys\|AXA}$	-.0009151 (0.986)	.1451481* (0.000)	-.0644163* (0.000)	-.0933578 (0.369)	-.017416 (0.959)	.0168275 (0.147)	.0022992 (0.836)	.1940048* (0.000)	0.4556
$R_t^{sys\|GBL}$	-.000851 (0.988)	.183782** (0.011)	-.0714514* (0.000)	-.0597553 (0.557)	.0450828 (0.896)	.0167594 (0.272)	.0005052 (0.964)	.2316976* (0.000)	0.4325
$R_t^{sys\|DB}$	.0023064 (0.974)	.0456412 (0.128)	-.0822352* (0.000)	-.0050298 (0.970)	.232486 (0.478)	.0253428 (0.157)	-.0038899 (0.780)	.2786299* (0.000)	0.4154

Table B.6 : Calculation of VaR, CoVaR and ΔCoVaR of Financial Institutions - Steps 3,4 and 5 –

This table presented by STATA 11.2 provides an overview of the means, standard deviations, minimum and maximum VaRs, CoVaRs and ΔCoVaRs for European financial institutions during the period from 20/08/2004 to 28/02/2014.

Variable	Obs	Mean	Std. Dev.	Min	Max
varbp	2314	-7.037037	3.466154	-32.96442	3.697686
covarbp	2314	-1.65478	1.024854	-9.153462	3.187603
varbp50	2314	-.0091262	2.085526	-11.96321	15.21317
covarbp50	2314	-.002244	.8724701	-5.215127	5.231905
deltacovarbp	2314	-1.652536	.510507	-4.508303	-.7478104
varbs	2314	-1.0083034	1.856802	-10.65118	13.54471
covarbs	2314	-1.623259	1.068316	-10.0779	3.783015
varbs50	2314	-.0079033	1.767334	-10.13797	12.89207
covarbs50	2314	-.002843	.8664806	-5.483713	5.790975
deltacovarbs	2314	-1.620416	.6043907	-5.524157	-.6289638
varing	2315	-9.816358	3.298417	-29.23636	-2.50655
covaring	2314	-1.549419	.9036792	-7.606932	2.625451
varing50	2314	-.0001361	.1844426	-1.102407	.9293286
covaring50	2314	-.0022598	.8396681	-4.928697	4.230515
deltacova~ng	2314	-1.547159	.3821928	-3.109707	-.7478249
varag	2315	-6.978632	3.454872	-28.25687	.6595509
covarag	2314	-1.67468	.9164104	-7.564507	2.487529
varag50	2314	-.0012482	.2791276	-1.601161	2.036136
covarag50	2314	-.0022113	.8388196	-4.988467	4.229807
deltacovarag	2314	-1.672469	.4157202	-3.552978	-.7878195
varall	2314	-2.886813	2.345516	-21.64111	8.821482
covarall	2314	-1.441703	1.043274	-9.434558	2.677604
varall50	2314	-.0070351	1.692546	-9.660064	12.47784
covarall50	2314	.000306	.9207195	-5.353083	5.433429
deltacova~ll	2314	-1.442009	.5779415	-5.335036	-.4156218
varaxa	2314	-4.311713	2.593332	-22.15459	9.905333
covaraxa	2314	-1.302144	1.003673	-8.93576	3.769186
varaxa50	2314	-.0088765	2.046777	-11.54027	15.27111
covaraxa50	2314	-.0038117	.91078	-5.195626	5.828586
deltacovar~a	2314	-1.298332	.5110591	-4.732622	-.4543446
vargbl	2314	-1.648633	.931026	-8.3667	3.436282
covargbl	2314	-1.72579	1.030031	-9.470688	2.403391
vargbl50	2314	-.0034741	1.04482	-6.118155	7.301858
covargbl50	2314	.0005842	1.139358	-25.11381	24.72915
deltacova~bl	2314	-1.726374	.8973196	-24.7996	20.23446
vardb	2314	-1.0079174	1.770497	-10.15611	12.91514
covardb	2314	-1.766914	1.042959	-9.627818	2.347363
vardb50	2314	-.005193	1.326634	-7.720377	9.51284
covardb50	2314	-.000612	.907908	-10.76958	10.42502
deltacovardb	2314	-1.766302	.6551779	-10.54192	5.853369

Output of the "Two-samples KS test" application on the ΔCoVaRs of financial

```
. ksmirnov delta_covarbs, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D       P-value  Corrected
 ----------------------------------------------
 1:                  0.5230    0.000
 2:                  0.0000    1.000
 Combined K-S:       0.5230    0.000      0.000

Note: ties exist in combined dataset;
      there are 4598 unique values out of 4628 observations.

. ksmirnov delta_covarbp, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D       P-value  Corrected
 ----------------------------------------------
 1:                  0.5294    0.000
 2:                  0.0000    1.000
 Combined K-S:       0.5294    0.000      0.000

. ksmirnov delta_covaring, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D       P-value  Corrected
 ----------------------------------------------
 1:                  0.5156    0.000
 2:                  0.0000    1.000
 Combined K-S:       0.5156    0.000      0.000

Note: ties exist in combined dataset;
      there are 4599 unique values out of 4628 observations.

. ksmirnov delta_covarag, by( gr )

Two-sample Kolmogorov-Smirnov test for equality of distribution functions

 Smaller group       D       P-value  Corrected
 ----------------------------------------------
 1:                  0.5498    0.000
 2:                 -0.0001    1.000
 Combined K-S:       0.5498    0.000      0.000

Note: ties exist in combined dataset;
      there are 4601 unique values out of 4628 observations.
```

```
. ksmirnov delta_covarall, by(

Two-sample Kolmogorov-Smirnov

 Smaller group       D       P
 ------------------------------
 1:                  0.4706
 2:                  0.0000
 Combined K-S:       0.4706

Note: ties exist in combined d
      there are 4598 unique va

. ksmirnov delta_covarau, by(

Two-sample Kolmogorov-Smirnov

 Smaller group       D       P
 ------------------------------
 1:                  0.4223
 2:                  0.0000
 Combined K-S:       0.4223

Note: ties exist in combined d
      there are 4596 unique va

. ksmirnov delta_covardb, by(

Two-sample Kolmogorov-Smirnov

 Smaller group       D       P
 ------------------------------
 1:                  0.5597
 2:                 -0.0004
 Combined K-S:       0.5597

Note: ties exist in combined d
      there are 4599 unique va

. ksmirnov delta_covargbl, by(

Two-sample Kolmogorov-Smirnov

 Smaller group       D       P
 ------------------------------
 1:                  0.5580
 2:                  0.0000
 Combined K-S:       0.5580

Note: ties exist in combined d
      there are 4627 unique va
```

Table B.7 : Robustness test

These tables provided by STATA 11.2 summarize the means, standard deviations, minimums and maximums of ΔCoVaRs relative to the specific sector indices of the "Euro" zone during the period between 20/08/2004 and 28/02/2014. ΔCoVaRs are calculated by deducting CoVaRs (q = 1%) those evaluated for different quantiles, equal to 30%, 40%, 60% and 70% respectively.

Variable	Obs	Mean	Std. Dev.	Min	Max
deltcovar~30	2314	-1.535677	.5811483	-5.158556	-.2222896
deltac~rli30	2314	-1.342494	.5532365	-6.553548	.4293511
deltac~nli30	2314	-1.311215	.4327739	-4.259676	1.419883
deltacov~s30	2314	-1.765006	.7548332	-7.062284	.0402129
deltacov~k40	2314	-1.780514	.6838145	-6.066592	-.3927422
deltac~rli40	2314	-1.552453	.4894605	-4.725506	1.231325
deltac~nli40	2314	-1.539836	.6355918	-7.301749	.2791986
deltacov~s40	2314	-1.948371	.7932205	-7.490882	-.0218642
deltacov~k60	2314	-1.780354	.6801422	-5.961825	-.4278802
deltac~rli60	2314	-1.567225	.4109048	-3.355925	-.5497792
deltac~nli60	2314	-1.539798	.6315468	-7.180261	.2223933
deltacov~s60	2314	-1.948584	.7958367	-7.632277	.0246794
deltacov~k70	2314	-1.829317	.6857578	-6.048928	-.483978
deltac~rli70	2314	-1.726277	.5173936	-4.975791	.9567842
deltac~nli70	2314	-1.674536	.6525042	-7.208614	-.0155814
deltacov~s70	2314	-2.104104	.8230601	-7.798252	-.1034221

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