“A European sectorial-based risk analysis: Assessment of the systemic risk using CoVaR”

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Abstract

CoVaR and ΔCoVaR are two risk measures that aim to asses respectively the financial spillover effect and systemic risk contribution of institutions. This method, first developed by Adrian and Brunnermeier (2011) showed to be a popular technique in the systemic risk research field. CoVaR is defined as the q%-th VaR of an institution conditioned by the q%-th VaR of another institution representing different financial states. In this paper, we use the CoVaR on the different European economic sectors in order to measure the spillover effect of each sector and their systemic risk contribution over the period from the second February 2001 up to the 1rst of April 2018. We apply the quantile regression on data which are taken from market available indexes returns. Our results tend to indicate that the sectors most at risk were Banks, Insurance and Basic resources. We also find that among the sectors with the highest spillovers when in distress are Banks and Real estate. Time dependent estimates show that the sectorial risks taken in isolation tend to evolve concomitantly and with similar amplitude across sectors, which does not seem to be the case for the spillover effect of these sectors. The systemic risk contribution also has a very different pattern across sectors through time. Following this observation, we conclude that there is no positive correlation between the fact that a sector might be risky by nature and the fact that it bears contagion risk or contributes more to the systemic risk. Therefore we can say that it is not because a sector is very risky (because it has a high VaR), that we could expect this sector to have high spillover effect (as measured by their CoVaR).

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1. Introduction

The financial crisis of 2008 triggered a signal to the public about the fragility of the financial system and the interconnectedness that has for long been ignored. Globalisation, financial innovation and deep integration pushed the financial sphere to be more complex, dangerous and hard to assess than ever. Interconnectedness among institutions became a new channel of shock propagation and negative externalities became the rules rather than the exception. Negative shocks suffered by a single individual easily propagate to one another and consequently, analyzing the phenomena behind systemic risk has been a common interest among risk management practitioners. In time of financial distress, those spillover effects proved to be a credible threat for the financial stability and showed their heavy impact on the real economy.

The most widely-used risk assessment tool, namely Value-at-Risk (VaR), also became the most widely criticized measure due to its incapability of capturing the systemic nature of entities. VaR has been used by regulators and financial entities to determine capital levels and riskiness of firms studied in isolation. Financial regulators implemented those measurement benchmarks into the micro-prudential regulation usually referred to as Basel I and Basel II. However, they took a more macro-oriented approach when passing to Basel III with a focus on counter-cyclical buffers as well as conservation capital buffers. Henceforth, systemic risk is gaining the attention it requires in the finance and risk management practices.

The study of systemic risk usually implies the study of banks and other highly leveraged financial actors. The literature on systemic risk also corroborates this broadly admitted consensus: financial institutions are the riskiest and contribute the most to the systemic crisis so far. Evidently, those institutions are already subject to a specific monitoring (SSM, central banks), regulation (Basel III, Solvency II,...) and evaluation (stress-tests). But a perspective that has rarely been taken into account in the systemic risk literature is the propagation of risk through credit dependency (financial liabilities) and through investment books (financial assets). As a result, this paper focuses on the economic sector that taken together would constitute a large part of the European financial markets. Their respective systemic risk contribution is estimated using the CoVaR developed by Adrian and Brunnermeir (2011).

Finding ways to identify sources of systemic risk propagation is not only key for the financial regulators, but also at a corporate level to minimize risk exposure toward other firms/sectors. Therefore, the aim of this paper is to analyse the systemic risk composition of the different economic sectors in the European economy as proxied by a composite financial index and estimated using a combination of quantile regression and CoVaR methodology as given by Adrian and Brunnemeir (2011). This essay is structured as follow: the following part gives a deeper description of the problem statement regarding this paper; In chapter 3, we summarise the relevant literature about systemic risk assessment; In chapter 4, we give an insight regarding the two most popular risk measures and their application in a systemic risk context; In the fifth chapter, we focus on the methodology of conditional and unconditional CoVaR as given by Adrian and Brunnermeir (2011); In chapter 6, data are presented and statistically analysed when chapter 7 presents the results regarding our empirical work. Chapter 8 eventually concludes.

2. Problem statement

This paper aims at studying the systemic risk contributions and exposures to systemic risk of different economical sectors in the European economy using the Adrian and Brunnemeir's CoVaR methodology. At the end of this paper we should be able to answer the question: *"To what extent, using a backward-looking time series analysis, can we assess the current situation (both in absolute and in relative term) of the systemic risk, using a CoVaR approach of the different sectors in the European economy?"*

Firstly, this paper focuses on questions like *"which sectors have the highest and lowest VaR/CoVaR?"*. These questions regarding VaR and CoVaR deal with the sectorial risk in isolation and then with the sectorial spillover effects on the financial system. That being, we will assess and analyse the 1%-VaR of the European financial system conditional on a specific sector being at its 1%-VaR as well.

Furthermore, we will focus on *"which sector contributes the most to the systemic risk in Europe"*. This question relates to the so called ΔCoVaR which is a technique that enables to assess each sector's marginal contribution to the overall European systemic risk by taking the 1%-CoVaR and subtracting the 50%-CoVaR (this median CoVaR is the 1%-VaR of the European system conditional on sectors being at their 50%-VaR). This ΔCoVaR should help us to analyse to what extent sectors are most at risk in time of distress and which sectors can be considered more systemic than others.

The CoVaR and ΔCoVaR serve as tools for risk management purposes and they should help us in an informative way toward the purpose of this paper. The normative implications of our results should lead us to define which sectors should require a specific risk management regulation or monitoring in order to ensure a better aggregate financial stability.

3. Literature review

There are many different measures of systemic risk proposed in the literature. Despite this fact, there is a consensus or at least a reputability standing for three of those measurements (Benoit, Colletaz and Hurlin, 2011). The first pool of measurement is based on the systemic expected shortfall (i.e. the expected loss conditional on the loss being greater than the VaR) of financial institutions suggested by Acharya et al. (2010). The expected shortfall is the average of daily returns when the portfolio's loss exceeds its VaR limit. They build a systemic risk measure (SES) which represents the expected undercapitalization of banks facing a potential systemic event (represented by an undercapitalization of the whole system). Following their previous paper, Acharya et al. (2016) use both the systemic expected shortfall and the marginal expected shortfall to develop a model in which the undercapitalisation of the financial sector harms the whole economy (thus expanding the burden of their analysis). Although their paper is quite new and disruptive in the way they measure systemic risk, they do not perform codependence analysis of financial institutions.

Another commonly used method has been developed and is called SRISK (Brownlees and Engle, 2016). This method computes the capital shortfall of individual firms depending on their size, leverage and risk. The capital shortfall estimation being itself developed by Acharya et Al.(2012). Most of these methods have in common the micro-evidence based approach which means that it starts from bank specific variables to quantify the contribution of each institution to systemic risk. All these previously cited methods can be seen as top-bottom measures, in the sense that they aim at determining the impact of distress occurring at the level of the financial system on individual institutions.

The third broadly admitted measurement is CoVaR. This method might be seen as a bottom-up measure of risk since it assesses the impact of a stress event at the level of a single institution and the transmission of the underlying risk to the whole system. This conditional-contagion-comovement value at risk measurement method, developed by Brunnermeier and Adrian (2011), is relevant when it comes to measure systemic risk depending on tail events. They define this CoVaR as the VaR of a system conditionally on the distress of an individual institution. Note that the value at risk represents the worst asset loss expected to be suffered by an institution i or a system j over a given period of time with a given probability. They assume that a distress situation for an institution represents a 1%-VaR level. Thus, the VaR (1%) is the loss an institution should expect to happen at least once, 1% of the time given a t period.

Apart from this CoVaR, Adrian and Brunnermeir (2011) offer an implicit measurement of institution's systemic risk. This measurement called delta CoVaR represents the marginal contribution of each institution to overall systemic risk. This is derived by subtracting the CoVaR conditional on the institution i being at its 50%-VaR level (median state) to the CoVaR conditional on i being at its 1%-VaR level (distress state). This so-called delta CoVaR is defined mathematically by:

$$\Delta CoVaR_{1\%}^{j|i} = CoVaR_{1\%}^{j|Xi=VaR_{1\%}^{i}} - CoVaR_{50\%}^{j|Xi=VaR_{median}^{i}}$$ [1]

They suggest calling $\Delta CoVaR_{q}^{j|i}$ the "exposure CoVaR" where i would be defined as the financial system.

The motive of their paper is based on the acknowledgment that traditional VaR measurements do not reflect systemic risk since on the one hand it does not take negative spillovers into account and on the other hand it builds up with bubbles and materializes only during crisis. The risk undertaken by a systemic institution may cause negative externalities not internalised in risk requirements. Henceforth, the objective of their paper is dual. First, they propose a new method for systemic risk estimations as aforementioned. Second, they offer a method to build countercyclical and forward-looking measurement for predicting systemic risk based on institutional characteristics.

Their estimation of CoVaR and ΔCoVaR is performed conditionally and unconditionally for 1226 financial institutions and intermediaries in the US over a period from 1986 to 2010. The unconditional estimation gives them a time-invariant CoVaR of the institutions while the conditional CoVaR offers a function of the risk

[1]It might seem unclear but a more theoretical insight will be given in the theoretical part

depending on macro variables supposed to capture the evolution of the tail risk over time. Those variables should give an insight about the volatility, the liquidity spread, the credit spread and the expectations of the financial tail risk. Therefore, they include the slope of the US yield curve, the aggregate credit spread, the VIX index and the weekly real estate sector return in excess of the market return. Apart from this CoVaR and ΔCoVaR, they built the forward ΔCoVaR which is a prospective measure of marginal systemic risk contribution of institutions. This is constructed with a regression of the ΔCoVaR on different firm's characteristics such as leverage, maturity mismatch, market-to-book value, size and equity return volatility. There is a strong positive correlation between the leverage, the maturity mismatch and the size of institutions to their systemic risk contribution (Brunnermeier and Adrian, 2011)

One of the main conclusions arising from this paper and giving a rationale for their new CoVaR measurement method is that there is a very weak link between an institution's VaR and its contribution to systemic risk (ΔCoVaR). The CoVaR has two advantages according to them. Traditional VaR leads to inappropriate regulation since between two identical firm (for their VaR) but having different CoVaR, it is rational for the least systemic risky to take riskier behaviour to catch up the other one. (Brunnermeier and Adrian, 2011) The other advantage is that there are no reasons for a reverse causality of CoVaR's between two institutions. Thus $\Delta \mathrm{CoVaR}_q^{j|i} \neq \Delta \mathrm{CoVaR}_q^{i|j}$ meaning that it might be that institution i's distress implies a large increase in risk for institution j when the opposite is not necessary true.2 Some papers in the literature tried to stick to this methodology and to apply it to several situations.

Arias et al. (2010) analyse the market risk codependence of the Colombian financial institutions with the objective to identify which institutions have the highest contribution to the systemic risk. They also provide a balance sheet analysis of those institutions toward their respective hold of Colombian Treasury Bonds (TES) with different maturity and duration. That, in order to give a more comprehensive approach of the risk differences across banks, pension funds and other institutional investors. To estimate their results, they use the combination of quantile regression as well as the CoVaR approach. To build the conditional CoVaR estimation and to incorporate the

[2]For more detailed explanations, see (Brunnermeier and Adrian, 2011)

idiosyncratic risk into the analysis3, they use state variables. These latters' are the followings: the inflation expectations, weekly stock market returns, weekly exchange rate returns, VIX, slope of the yield curves, weekly credit growth, EMBI+, five years CDS and the Colombian interbank rate. They first conclude, independently of the institution's nature, that risk codependence increases during distress periods. Following that conclusion, they agree that the most market-risk contributing agents should be carefully monitored and that regulators should intend to minimize the adverse consequences of herding behaviours when designing their risk requirements policies. Secondly, they provide evidence that financial corporations and financial cooperatives are, according to the ΔCoVaR estimations, the most market-risk contributors to the Colombian financial system. The explanation lies in the fact that having a dynamic portfolio composition and higher changes in portfolios' returns make them more systemic. Indeed, they are more sensitive to current changes in VaR estimations. Finally, they insist on the fact that the ΔCoVaR approach does not explain propagation channels of risk and that it still has to be strictly interpreted as a codependence measurement.

In a comparable way, Roengpitya and Rungcharoenkikul (2010) analyse the systemic risk contribution in the Thai banking system using quantile regression and the CoVaR methodology. The data set includes weekly equity prices for 6 major commercial banks in Thailand; over the period from May 1996 to March 2009 (this includes the Asian crisis).Apart from the standard codependence measure as in Arias et al. (2010), they also check whether differences in ΔCoVaR among financial institutions might find rationales in their balance sheets characteristics. They use panel data analysis to reach such results. The first result shows that individual returns of banks exhibit different structural volatilities. The second one is that VaR's are positively correlated which gives evidence of a common underlying trend. The third observation is that bank 3 seems to contribute most to systemic risk and is ranked 4rth for its VaR. On the other hand, bank 4 has the lowest VaR (most to lose) and the smallest CoVaR. Concluding from the CoVaR analysis, they state that statistically significant evidences of negative externalities exist and that regulators have to take this into

[3]This will be further explained in the methodology part of this paper

account when assessing capital requirements. They find a coefficient of 0.26 for the correlation between the size of the bank and their systemic importance. They reach other conclusions for the balance sheet analysis and their firm-to-firm CoVaR. The explanatory variables size and interbank deposits are significant when it comes to explain the degree of financial linkages and spillover effects between banking institutions.

Similarly to Roengpitya and Rungcharoenkikul (2010), Borri et al.(2012) analyse the systemic risk of the banking sector but this time on the European one on a period ranging from 1999 to 2010. They reach similar conclusions considering the importance of the size when assessing systemic risk. However, they also conclude that leverage as well as the location of the bank's headquarter in a very concentrated national banking industry are very good predictors of the systemic banking contribution. They also argue for a less micro-based approach of risk analysis since they consider that measures of risk based on higher frequency market prices are more likely to anticipate systemic risk than balance sheets.

Bernal et Al. (2014) focus their systemic risk analysis on the US and European financial sectors and provide innovative tests for assessing significance of results. They assessed the contribution of the different sectors of the financial system to systemic risk. They focus on three specific sectors, namely banks, insurance companies and other financial services companies. Using the ΔCoVaR and quantile regression for a period ranging from 2004 to 2012, they reveal that in the Euro-area, the banking and the other financial service sectors contribute more to the systemic risk in case of tail events than the insurance sector. To give an idea, for whole period, they find a ΔCoVaR for the financial services of -2.171. It appeared on the opposite that the US insurance industry is the systemically riskiest sector among the three. They developed a significance and a dominance test for the empirical results using the bootstrap Kolmogorov-Smirnov test. This indicates that their conclusions are statistically significant. A comparison with our results will be given in the empirics given the similarities in the time period, the sectors considered and the geographical area.

Aside from this literature sticking to the CoVaR methodology of Brunnermeier and Adrian (2011), a part of the literature slightly departed from it when some authors tried to extend its scope of action. Lopez-Espinosa et Al. (2012) use a specific asymmetric CoVaR such that they use both positive and negative shocks to the banking system. They investigate 54 international complex and systemic banks in order to evaluate their contribution to their respective financial markets. They find evidence that in defiance of previously cited papers, size and leverage are not key determinant of the systemic contribution within the class of large international banks. In contrast, short term wholesale funding is a key determinant when it comes to trigger systemic risk episodes.

Girardi and TolgaErgün(2013) modify the definition of financial distress in the framework of Brunnemeier and Adrian (2011). They define it as the return of the institution being at most at its VaR when the original definition (see above) indicated exactly at its VaR. They also define the ΔCoVaR as the change for an institution from its CoVaR at its benchmark state to its CoVaR under financial distress. The benchmark state is here a one-standard deviation event when in the original paper it was the median VaR. They analyse the risk contribution of four US financial groups, namely depositories, insurance companies, broker-dealers and other non-depository companies. Their results concede that depositories contribute the most to systemic risk.

Wong and Fong (2010), in analysing interconnectivity among economies, attempted to extend the ΔCoVaR methodology. They analyse the interconnectivity in terms of credit risk linkages using 11 Asian-Pacific economies' sovereign CDS spreads to proxy the VaR on a period from October 2004 to September 2009. Even if they use both the CoVaR methodology and the quantile regression to estimate the economies risk contribution, they are innovative in the way that they apply it on CDS and not on individual institutions as before. We could model their quantile regression as follow:

$$\Delta X_i = \beta_{0,q}^{i|j} + \beta_{1,q}^{i|j} X_j + \sum_{k=1}^{K} \gamma_{k,q}^{i|j} R_k + \varepsilon_q^{i|j}$$

i and j are standing for the two economies they investigate. ΔX_i is thus the CDS spread change of economy i and it is computed with a constant ($\beta_{0,q}^{i|j}$, namely idiosyncratic characteristics of economy i), the CDS spread of economy j ($\beta_{1,q}^{i|j} X_j$), and a vector of common state variables R_k. $\beta_{1,q}^{i|j}$ therefore represents the measure of risk dependency between economy i and economy j. The CoVaR represents the quantile regression estimation of this model. At the end, they argue that on average the VaR of an Asian-Pacific economy rises by 45% if another regional economy faces a stress event (1%-VaR level). China and Korea are found to make the largest impact for risk spillovers on other regional economies. Indonesia and Philippines are the most vulnerable in term of suffering the highest conditional risk. Their conclusion shows that, for most of their economies of interest, the conditional risk measure is significantly greater than the unconditional risk (standard VaR). This is an evidence of an unexplained transmission channel among those economies.

Adams, Füss and Gropp (2014) suggest a state dependent sensitivity VaR (SDSVaR) to quantify the contagion effects among systemic financial institutions. They estimate a system of quantile regression for 4 sets of financial institutions (commercial banks, investment banks, hedge funds, and insurance companies). The SDSVaR distinguishes itself from the CoVaR of Brunnermeir and Adrian (2011) in the way that they model the distribution of the value-at-risk. They first calculate the VaR for each set of institutions, and then they regress it over the whole range of quantiles of the others. They make those VaR's moving through time depending on the financial health of the institutions. Therefore risk spillovers are very limited in time of tranquil market periods. They conclude that hedge funds have a way more sensitive CoVaR to economic turmoil and that therefore they should be more tightly monitored. Commercial banks also play a significative role when it comes to financial transmission. Following their methodology, they build an impulse response function (IRF) and find that they reach their maximum in term of CoVaR after 10 to 15 days. The normative implication of their paper is that we should avoid reducing supervisory requirements of depositories in the future.

Former literature reviews give confirmation that the CoVaR methodology introduced by Brunnermeir and Adrian (2011) was of prior importance for examining risk contagion and systemic risk contribution to complex systems. While completing the gap that the micro-based approach of VaR analysis on financial institutions, CoVaR became a popular and helpful tool for researchers to assess risk spillovers. It is powerful in the way that its scope can be easily extended since it is not tied to a specific asset class (contrarily to some measurement exclusively tied to CDS) (Benoit, Colletaz and Hurlin, 2011). Many authors empirically proved the existence of an idiosyncratic shock transmission among individual interconnected institutions by controlling through common macro-state variables (see above). According to Adams, Füss and Gropp (2014) and many others, this transmission is proved to have a counter-cyclicality component, it becomes stronger in time of distress and vice versa. There are many more studies on the systemic risk, contagion effects and individual-risk based assessments; an informed reader might find stimulation in reading Boyson et al (2010), Sogavio and Goodhart (2009), Moreno and Penà (2012) and Van oordt and Zhou (2010).

4. Theoretical review

Aside the literature review which gave us a general framework within which systemic risk measurement was used, we will now give a more theory oriented point of view of risk, systemic risk regarding their mathematical definition and measurement methods.

4.1 Systemic risk: a definition

Despite a multitude of conceptual and etymological debates on what systemic risk is, I would summarize it as the risk of a complete collapse of any (financial) system. Following a legal approach of the definition, we might find common factors in all definitions being the fact that it usually follows a trigger event (economic shock, institutional failure, etc.) causing a chain of economic and financial events leading to a de facto collapse of the market (Schwarcz, 2008). The concepts and definitions with reference to systemic risk are broad and extensive regarding the importance of its consequences on financial markets as well as on the real economy. There is no unanimously admitted definition of systemic risk, this is partly explained because authors usually put an emphasis on different aspects of the concept. These aspects might be its initial shock, contagion effect or its broad consequences.

A widely admitted definition for a systemic event is provided by the IMF, BIS and FSB (2009): *"the disruption to the flow of financial services that is (i) caused by an impairment of all or parts of the financial system; and (ii) has the potential to have serious negative consequences for the real economy."*

Following this definition they provide a definition regarding the systemic risk: *"Systemic Risk is the risk of an event – labelled a systemic event – occurring in a given system that leads, at least temporarily, to an altered and damaged transitional "system" whose proper functioning is impeded. In the extreme, the structure of the system itself is damaged and the system no longer functioning."*

Authors usually disagree regarding the endogeneity of systemic risk regarding the system itself. (Zigrand, 2014) agree that *"...systemic risk comprises the risk to the proper functioning of the system as well as the risk created by the system."*

When others (Kaufman, 1995) focus more on a micro-led approach proposing that systemic risk is the *"probability that cumulative losses will accrue from an event that sets in motion a series of successive losses along a chain of institutions or markets comprising a system. . . . That is, systemic risk is the risk of a chain reaction of falling interconnected dominos"*

According to the Bank of international settlement and Caruana (2010) the concept of systemic risk tends to be split in the literature in two parts. Firstly it can be referred as micro-level contagion of a shock turning into a spillover effect. This concept is built on the fact that financial systems are a network of interconnected balance sheets and that a shock hitting one institution tends to spread to the others and increase in size the more institutions are hit. The second concept of systemic risk refers to the incidence of macroeconomic shocks having a wide ramification and a concurrent effect on the entire system. To translate these concept practically, we could think of the subprime crisis as the first realization of the second concept (a systemic real estate nationwide downturn affecting all sectors) followed by a systemic micro-led crisis (shock on AIG and Lehman Brother). (Brunnermeier and Oehmke, 2012)

4.2 Measurements

4.2.1 Measurement of risk

Two methods for assessing the risk are broadly admitted both in the literature and in practice, namely the Value at Risk (VaR) and Expected shortfall (ES).

The Value at Risk is defined as the worst loss that might be expected over a given period of time given a specific level of probability (known as the confidence level). We can take this definition reversely and define the Value at Risk as the minimum loss L* such that the probabilities of a potential loss L with L>L*, is less or equal to 1-α (being the confidence interval), it gives:

$$VaR_{\alpha}(X)= \min\{L :Pr(L>L^{*})\leq \alpha\} \quad (a)$$

In the continuous case: $$Pr(L>VaR_{\alpha}(X)) =1-\alpha \quad (b)$$

To give an example: If a company has a VaR1% (€ 10 million) at 1 year, one should expect it to be quite exceptional to suffer losses exceeding € 10 million over a 1y period; such higher losses should only happen in 1% of the cases. Another example, if the 99% one-day VaR of a stock is 6.5%, it means that for tomorrow, there is 99% of chance that the stock will not lose more than 6.5% of its value. VaR was often criticized as a measurement method of risk in the way that it creates a false sense of security since it doesn't account for the potential huge loss that might occur within the 1% area (imagine a company goes bankrupt). We can compare two stocks with the same VaR's to show this drawback

Stock 1: gain of 5% with a probability of 99%, loss of -40% with a probability of 1%

Stock 2: gain of 5% with a probability of 99%, loss of -5% with a probability of 1%

Both have VaR1%=-0.05 however we can obviously imagine that those stocks bear different risk profiles.

To account for the magnitude of the losses exceeding the VaR, the expected shortfall (ES) represents the second most used risk assessment tool. The expected shortfall is defined as the loss that goes beyond VaR; it assesses the tail of large losses and calculates the average of the losses greater than the VaR. Therefore it is defined as:

$$E[X:|X|>VaR_q(X)] \tag{c}$$

$$ES_q(X)= \frac{1}{1-q}\int_q^1 VaR_x(X)dx \tag{d}$$

(Crouhy et al., 2006), (Ducuroir, 2018), (Roengpitya and Rungcharoenkitkul, 2011) (Adrian and Brunnermeir, 2011)

Although both methods have flaws, VaR and ES stay the most used methods for both managing and measuring risk within portfolios, companies, assets etc. It has become an essential element of the modern portfolio theory of Markowitz. Applications can be found both from the regulator's assessment on the Basel capital requirement framework as well as in investment banking when asset managers assess their portfolio risk composition.

Those two measures can be considered as isolated tail-driven risk measurements. Consequently, taken alone these methods are inadequate regarding the purpose of this essay. They do not allow assessment of contribution to overall risk. Hence, we introduce in the next section the CoVaR and CoES.

4.2.2 Measurement of the systemic risk

The collateral-conditional-comovement value at risk (CoVaR) first introduced by Adrian and Brunnermeir (2011), is a risk measure aiming to measure interconnection in term of risks between two entities. As its name might suggest, it uses the concept of VaR as follows: the CoVaR is the Value-at-risk of an entity (financial institutions, state, firm, portfolio, financial market, etc.) conditioned by another entity's financial distress.

As mentioned above, the VaR is a number such that the following equality is respected:

$$Pr(\mathrm{X}\leq \mathrm{VaR_q(L)})=\mathrm{q} \tag{e}$$

X represents here the variable of interest (e.g. credit default swap, daily return, stock price, treasury bonds, etc.); q represents the quantile of interest; and L is the loss given confidence level.

CoVaR therefore needs to be the number such that:

$$\Pr(X^j \leq \mathrm{CoVaR}_q^{j|C(X^i)} | C\ X^i\ )=\mathrm{q} \tag{f}$$

Thus $\mathrm{CoVaR}_q^{j|i}$ is defined as the q$^{\mathrm{th}}$quantile of the conditional probability distribution above (6), such a notation is possible regarding the assumption made on the conditional event in this paper. Indeed, the conditional event $C\ X^i$ is usually defined as $\{X^i = \mathrm{VaR}_q^i\}$, i.e. the event conditioning the probability of the VaR of entity j is the VaR of entity i given a specific level of probability q. Adrian and Brunnermeir (2011) usually suggest q=1% as the conditioning event of financial distress of the entity i. The CoVaR analysis can be entity-to-entity driven (in that case i and j are entities of the same nature, e.g. two banks, two sectors, ...) but it can also be entity-to-system driven (in that case i is an entity when j=system, i.e. a group of entities forming a financial system).

In term of losses (instead of probabilities), the CoVaR of entity j (facing loss Y) conditional on entity i (facing loss X) is defined as follow:

$$\Pr(L^Y > \mathrm{CoVaR}^{Y|X} | L^X = \mathrm{VaR}^X)=1-\alpha \tag{g}$$

The mathematical definition given in (g) means that the probability that entity Y face a loss greater than the CoVaR value conditioned by the loss of the entity X being its VaR, is 1- α. Using the entity-to-system analysis, one could analyse the risk contribution of the system to individual risk (i.e. market risk) or could analyse the risk contribution of an entity to the whole system (i.e. systemic risk contribution). Adrian and Brunnermeir (2011) define these two concepts into ΔCoVaR. The former would represent what they call the *exposure CoVaR,* namely the sensitivity of a single entity towards financial system-wide events (interesting for risk management stress testing purposes). The $\Delta\text{CoVaR}_q^{j|i}$ is calculated as the 1%-CoVaR (i.e the 1%-VaR of the system conditional on the i's entity being at its 1%-VaR) minus the 50%-CoVaR (i.e. the 1%-VaR of the system conditioned by entity i being at its median state).

$$\Delta\text{CoVaR}_{1\%}^{j|i} = \text{CoVaR}_{1\%}^{j|X^i=\text{VaR}^i_{1\%}} - \text{CoVaR}_{1\%}^{j|X^i=\text{VaR}^i_{Median}} \tag{h}$$

Similarly, Acharya, Pedersen, Phlippon and Richardson (2010)built the CoES on the same principle:

$$\text{CoES}^i_{\alpha,\beta}(\text{Y,X}) = \frac{1}{1-\beta}\int_\beta^1 \text{CoVaR}^{Y|X}\,dt \tag{i}$$

Y and X being respectively the losses of the financial system and of a specific entity while α and β are the significance level (1% and 5%). Taking the definition of ES, CoES is therefore the loss that we could expect with significance level α above the CoVaR loss level at 1%.

5. Methodology

This paper uses econometric techniques to reach estimations of the studied phenomena and draw conclusions. The quantile regression (QR) is the method chosen to apply the CoVaR model of Brunnermeier and Adrian (2011). Different econometrical methods stands for estimating the CoVaR like the multivariate GARCH model as suggested in Brunnermeier and Adrian (2011) as well.

5.1 The quantile regression

The quantile regression, suggested by (Koenker and Basset, 1978) is an adequate method to measure interdependency of risk between different agents. It can conveniently be applied to estimate the co-dependency between institutions under different risk scenarios. As a matter of fact, it provides a more extensive analysis than OLS (ordinary least square) in the sense that it reports an estimation of the relationship among random variables under different quantiles. When choosing a tail quantile and the median, we can derive conclusions about the systemic risk contribution. Furthermore, this represents a very convenient methodology since it can be estimated with a large number of independent variables. (Arias et al., 2010). Adrian and Brunnermeier (2011) also tested using a GARCH bivariate model for each institution. However, using this method, they found no results differing significantly. They also argue in favour of the QR in the way that GARCH models require strong distributional assumptions that can be ignored using a QR. In the context of a master thesis, we will then limit ourselves to the QR estimation method.

It consists in minimising the sum of the residuals, weighted asymmetrically by a function depending on the quantile τ and on the fact that the residuals are positive or negative. This is different from OLS since it models the difference between the independent variable and the conditional quantiles of the dependent variable. (Koenker and Basset, 1978). This method has two main advantages. First, contrarily to OLS, the assumption of normality of the errors is way less important. QR seems to be way more robust to non-normal errors and outliers (Koenker and Bassett, 1982). Since most of the analysis is made on tail distributions, QR is thus more appropriate when studying systemic risk. It allows us also to characterise the impact of a covariate on the entire distribution of the independent variable and not only on its mean. Second, QR is invariant to monotonic transformations such as logarithms. Quantiles of h(y) being a monotonic transformation are simply $\mathrm{h}(\mathrm{Q}_{\mathrm{q}}(\mathrm{y}))$, thus the inverse transformation can be used to interpret the results back to y. This is not possible for the OLS and the mean since $E(h(y)) \neq h(E(y))$ (Baum, 2013).

Let's consider a simple model with β_q being the vector of unknown parameters to estimate, associated with a particular quantile q; x_i being a vector of independent variables; y being a vector of dependent variables and u a vector of the residuals:

$$y_i = x_i^{'}\beta_q + u_i \quad (1.1)$$

Thus,
$$u_i = y_i - x_i^{'}\beta_q \quad (1.2)$$

Using OLS, we would have a minimisation problem of the sum of the squared residuals. Instead, the QR approach minimises the sum of the un-squared residuals. Therefore, we have a problem under the form:

$$min_{\beta} \sum_i^N \rho_q(u_i) \quad (1.3)$$

Replacing by (1.2)
$$min_{\beta} \sum_i^N \rho_q(y_i - x_i^{'}\beta_q) \quad (1.4)$$

Where $\rho_q(u_i)$ is a weighting function for a given quantile q. The weighting is done depending on the signs of the residuals. They give a penalty $1-q\ |u_i|$ for overprediction (thus negative residuals) and a penalty $q|u_i|$ for underpredictions. They suggest the following representation of equation (1.4):

$$\min{}_{\beta} Q(\beta_q) = [\sum_{i\in\{i:y_t \geq x_i^{'}\beta_q\}} q\ |y_i - x_i^{'}\beta_q| + \sum_{i\in\{i:y_i < x_i^{'}\beta_q\}} (1-q)\ |y_i - x_i^{'}\beta_q|] \quad (1.5)$$

Depending on the quantile q chosen, the solution for β to this problem will be different. Although its computation requires linear programming methods, the quantile regression estimator is asymptotically normally distributed and the not requires a basic assumption of normality of the errors.

The interpretation of the estimator β_{qn} is the change in a quantile q of the dependent variabley_n, implied by a one unit variation of the independent variable x_n.

5.2 Estimation methods of VaR, CoVaR and ΔCoVaR

CoVaR and ΔCoVaR can be estimated either conditionally or unconditionally. In the unconditional framework, we obtain measures of VaR, CoVaR and ΔCoVaR that are constant over time and that do not control for macro-variables shocks that have an impact on both the economy and the specific firm. The unconditional VaR_q^i of an institution i is therefore simply the qth- quantile of its historical asset returns. The unconditional 1%-CoVaR represents the variation of the unconditional 1%-VaR of an individual j conditional on the institution i being at its unconditional 1%-VaR. The unconditional ΔCoVaR represents the difference between the 50%-CoVaR and the 1%-CoVaR. These two last estimates thus provide a static snapshot of the systemic risk at a given point of time based on historical movements of stock returns.

The conditional approach estimates models of the time variation of the joint distribution of asset returns as a function of lagged systematic state variables. Therefore it gives additional information to the CoVaR by controlling for the economy-wide shocks to explain how extreme events happening to a firm i impact the firm j's asset return. The conditionality allows us to differentiate the systemic risk (the one comprised in macro-state variables) from the idiosyncratic risk (the one truly bore by the institution). These macro-state variables are supposed to model economy-wide endogenous shocks and are assumed to explain a significant part of asset returns movements. We can consider those macro-state variables as indicators of investor's confidence, real business cycles, return of global markets, etc.

Consequently, the conditional approach of CoVaR will be referred to as a dynamic estimation when the unconditional one will be considered a static approach.

5.2.1 Unconditional estimations

To obtain the desired unconditional estimations, we use statistical software (Stata) and apply the aforementioned quantile regression technique. If we come back to the VaR's definition, it is the maximum potential loss during a time period if we exclude the worse outcomes (happening with probability q). Therefore, VaR_q^i is the value delimiting the quantile q of the return distribution of the firm i's stock.To obtain $\mathrm{CoVaR}^{\mathrm{Ind}|i}$, we first have to estimate (with historical simulation) the quantiles VaR of stock i for the quantiles we are interested in (1% for the extreme events and 50% for the median state). To do so, we run a QR of institution i stock on a constant, with q=1% and q=50%:

$$\mathrm{R}_q^i = \alpha_q^i + \varepsilon_q^i \tag{2.1}$$

α represents here a constant when ε is the idiosyncratic error. R is the unconditional return.

Estimates will provide: $$\mathrm{VaR}_q^i = \alpha_q^i \tag{2.2}$$

Doing the same for the system (the index)

$$\mathrm{R}_q^{index} = \alpha_q^{index} + \varepsilon_q^{index} \tag{2.3}$$

$$\mathrm{VaR}_q^{index} = \alpha_q^{index} \tag{2.4}$$

If we want to obtain the current $\mathrm{CoVaR}_{1\%}^{index\ |i}$, which is defined as the 1%-VaR of the system conditional on the 1%-VaR state of an institution i, we run a quantile regression of the index's return on a constant and the returns of the institution i:

$$\mathrm{R}_q^{index} = \alpha_q^{index\ |i} + \boldsymbol{\beta}_q^{index\ |i} R_i + \varepsilon_q^{index\ |i} \tag{2.5}$$

β is the coefficient of correlation between the return of the system and the return of each sector.

As defined previously, the $\mathrm{CoVaR}^{\mathrm{Ind}\ |i} = \mathrm{CoVaR}_q^{index\ |X^i = \mathrm{VaR}\,_q^i} = \mathrm{VaR}_q^{index}\ \ |\mathrm{VaR}_q^i$

Thus, using the estimates of (2.2) and the coefficients $\alpha_q^{index\ |i}$ and $\boldsymbol{\beta}_q^{index\ |i}$ from (2.5), we can build:

$$\mathrm{CoVaR}_q^{index\ |X^i = \mathrm{VaR}\,_q^i} = \alpha_q^{index\ |i} + \boldsymbol{\beta}_q^{index\ |i}\ \mathrm{VaR}_q^i \tag{2.6}$$

We also stated that ΔCoVaR was the difference between the CoVaR of the index when an institution is at its distress quantile (1%) minus the CoVaR when the institution is at its normal market conditions (50% quantile).

Therefore, using equation (2.6)

$$\Delta\mathrm{CoVaR}_{1\%}^{index\ |i} = \mathrm{CoVaR}_{1\%}^{index\ |X^i = \mathrm{VaR}\,_{1\%}^i} - \mathrm{CoVaR}_{1\%}^{index\ |X^i = \mathrm{VaR}\,_{50\,\%}^i} \tag{2.7}$$

Thus,

$$\Delta\mathrm{CoVaR}_{1\%}^{index\ |i} = \boldsymbol{\beta}_{1\%}^{index\ |i}\ (\mathrm{VaR}_{1\%}^i - \mathrm{VaR}_{50\%}^i) \tag{2.8}$$

These regressions enable the estimation and assessment of each sector's static (understand constant over time) systemic risk contribution to the European economy as proxied by the composite index MSCI.

5.2.2 Conditional estimations

The above estimations need to be refined and to become time specific. To do so, we will include in our estimation a set of macro-variables supposed to represent a number of information and events that have a transversal impact across all sectors and across the index. These variables can represent the business cycle, the investor's confidence, liquidity and credit spread or any other variables that could presumably be considered having an impact on the stock returns. These contemporary variables should be considered on conditioning controls that intend to make up for non-idiosyncratic market specific risk. These variables will be further explained in part 6.

The following quantile regression is run on a sector's daily return for the quantile q=1% and for the median (q=50%) for every sectors i of the list. This is performed to obtain a time varying 1%-VaR and 50%-VaR series controlled by macro-state variables included in the vector M. Note that in the empirics, M_1 will refer to the variable Volatility, M_2 to Eurostoxx50, M_3 to credit spread and M_4 to liquidity spread. Similarly, *γ1* will refer to the regression coefficient the variable Volatility and so on and so forth. The error term ε_t^i is assumed to be i.i.d with zero mean as well as independent of the vector M_t.

$$\mathrm{R}_t^i(q) = \alpha_q^i + \gamma_q^i M_t + \varepsilon_t^i \tag{2.9}$$

With the estimates of the parameters $\alpha$and β we can compute a conditional VaR time dependent series of the sector i.

$$\mathrm{VaR}_t^i(q) = \alpha_q^i + \boldsymbol{\gamma}_q^i \ M_t \tag{2.10}$$

Once again, the same logic can be applied to the system's return.

$$\mathrm{R}_t^{index}\ (q) = \alpha_q^{index} + \boldsymbol{\gamma}_q^{index}\ M_t + \varepsilon_t^i \tag{2.11}$$

qindex+γqindexMt (2.12)

Where the system is here proxied by the composite MSCI index.

In order to obtain CoVaR and ΔCoVaR estimations, we run quantile regressions for q=1% and q=50% such that:

$$\mathrm{R}_t^{index\ |i}(q) = \alpha_q^{index\ |i} + \boldsymbol{\beta}_q^{index\ |i} R_t^i + \boldsymbol{\gamma}_q^{index\ |i} M_t + \varepsilon_t^{index\ |i} \tag{2.13}$$

R represents the return of a sector i. That being estimated, we get:

$$\mathrm{CoVaR}_t^i(q) = \alpha_0^{index\ |i} + \beta_q^{index\ |i}\ \mathrm{VaR}_t^i(q) \qquad + \gamma_q^{index\ |i}\ M_t \tag{2.14}$$

Finally, we compute the individual sectorial systemic risk contribution (ΔCoVaR) to the European market by differencing the two CoVaR between the CoVaR in distress situation (q=1%) by the CoVaR at the median state (q=50%).

$$\Delta\widehat{\mathrm{CoVa}}\mathrm{R}_t^i(\mathrm{q{=}1\%}) = \widehat{\mathrm{CoVa}}\mathrm{R}_t^i(\mathrm{q{=}1\%}) - \widehat{\mathrm{CoVa}}\mathrm{R}_t^i(\mathrm{q{=}50\%}) \tag{2.15}$$

This way of approximating the CoVaR of an individual i to a system is called time varying conditional CoVaR by Adrian and Brunnermeir (2011). This estimation captures the time varying nature of risk and conditions the VaR on a number of available information available at each period t. This time varying nature is reflected by the t in the equations.

6. Data

The data used in this paper are constituted of macroeconomic and stock/indexes market data. All the data used here are publicly available on Bloomberg or on the Stoxx website.

6.1 The sectors

The sectorial indexes are the main substance of this essay. These data are collected using the daily recorded last-price of 18 different sectors all listed on different European stock exchanges (Eurozone exclusive) on a period from the second February 2001 up to the 1rst of April 2018. The indexes provided follow the procedure developed by STOXX. The composition and the choice of their index is explained extensively on their website (Stoxx.com, 2018). Index data is transformed according to:

$$R_t^i = \frac{P_{t+1}^i - P_t^i}{P_t^i}$$

R being the daily sectorial return. This percentage return is used because prices of index are not necessary representative of the level of capitalization. Indexes on sectorial stock portfolio have been chosen in this paper mainly because we can under some assumptions presume that the return of a stock reflects many different sorts of risks and that those risks in turn constitute the systemic risk. The firms composing these indexes can be found in appendix 1. They represent for more than 305 large companies of the Eurozone.

Table 1: Listed companies and sectors

Tickers	Sectors	Number of listedcompanies
SXAE	Automobiles & Parts	18
SX7E	Banks	27
SXPE	Basic Ressources	8
SX4E	Chemicals	17
SXOE	Construction & Materials	12

SXFE	Financial Services	10
SX3E	Food & Beverage	10
SXDE	Health Care	19
SXNE	Industrials	48
SXIE	Insurance	14
SXME	Media	12
SXEE	Oil&Gas	10
SXQE	Personal&HouseholdGoods	16
SX86E	Real Estate	13
SXRE	Retail	12
SX8E	Technology	19
SXKE	Telecommunications	12
SXTE	Travel&Leisure	7
SX6K	Utilities	21
Total		305

6.2 The system

The main goal of this paper being to assess the systemic risk of different sectors over the European economy (Eurozone) as a whole. We therefore decided not to base entirely the estimation on big capitalized firms (i.e. Eurostoxx 50). Even the Eurostoxx 600 seems inappropriate regarding the system we want to assess. The analysis is therefore built taking a set of different indexes. We therefore combine the MSCI large and medium cap with the MSCI small cap at the pro rata of their respective capitalization as provided by MSCI (MSCI.com, 2018). With respective capitalization of $9,328 and $1,453bn the two indexes are weighted by 86.52% and 13.47%. Once built up, this composite index represents the daily last price of more than 1440 European listed companies. Percentage daily returns are once more used for the simple fact that it becomes convenient to avoid currency problems when comparing the sectorial index (€) to the system index ($). We use the following transformation:

$$R_t^i = \frac{P_{t+1}^i - P_t^i}{P_t^i}$$

6.3 The macro-state variables

As already mentioned in the methodology part, several macro-state variables are being used to have controlled and precise conditional CoVaR. The choice toward those variables should be driven by the intuition and economic reasoning on what factors do influence the return of Eurozone companies in all different sectors of the economy. We should therefore choose carefully variables that have macroeconomic consequences on all companies independently on their reaction to it. According to Borri et al. (2012) and Bernal et al. (2014) these variables should first reflect the implied volatility in the stock markets (as represented by the VSTOXX). Moreover, the liquidity spread could also be a variable that affect all sectors' stock valuation, thus we include the difference between the 3month Euribor rate and the short-term German government bond yield (3 months). We also include the European equity return as represented by the Eurostoxx 50. We also include the credit spread change as represented by the difference between the 10-year macrobond BBB euro area corporate bond rate and the 10-year German bond rate. Those chosen variables should proxy the investor sentiment, trend and expectations about the business cycles. We could expect that the volatility would have a negative impact on the CoVaR (and ΔCoVaR) measurements. So should the liquidity spread regarding the financing stress and credit contagion implied by an increase of the former (Borio, 2000). On the other hand, a positive European market return should have a positive impact on the CoVaR (and ΔCoVaR) of a sector. Concerning the credit spread, it seems hard to assess ex ante its possible implication on the CoVaR measurement since it is likely that it is sector-specific. Given the high likelihood of trends and cycles within these macro-state variables, we decide to avoid non-stationary problems by first differencing these variables (see 6.4 statistical analysis). Thus:

$$V_t = D_t - D_{t-1}$$

Where V represents the first differenced macro-state variable (to keep the notation simple with the methodology part) and D represents the raw data of the macro-state variables.

6.4 Statistical analysis

As mentioned above, we used the closing prices of MSCI sectorial indexes for a period from the second of February 2002 up to the 1rst of April 2018. In this part, we will assess the summary statistics of our data, i.e. mean, volatility, normality and stationarity.

Table 2: Summary statistics

Sectors	mean	min	max	S.d	skewness	kurtosis
Automobiles & Parts	0,0005	-0,3004	0,2080	0,0223	5,3367	148,4819
Banks	0,0001	-0,1802	0,1944	0,0202	0,2741	10,8414
Basic Ressources	0,0003	-0,1297	0,1731	0,0203	0,1119	9,0857
Chemicals	0,0003	-0,0824	0,1338	0,0151	0,1920	9,0679
Construction &Materials	0,0003	-0,1015	0,1317	0,0160	0,1112	8,6534
Financial Services	0,0002	-0,0987	0,1303	0,0153	-0,0312	9,2273
Food &Beverage	0,0002	-0,0699	0,0682	0,0112	-0,2633	6,7780
Health Care	0,0001	-0,0835	0,1016	0,0135	-0,0119	6,8945
Industrials	0,0002	-0,0984	0,1227	0,0148	0,0083	9,3419
Insurance	0,0001	-0,1141	0,1455	0,0196	0,3349	9,8486
Media	-0,0001	-0,1050	0,1201	0,0145	-0,0163	9,0879
Oil&Gas	0,0002	-0,0963	0,1398	0,0160	0,1741	9,8117
Personal&HouseholdGoods	0,0002	-0,0900	0,0963	0,0147	0,0944	6,4421
Real Estate	0,0003	-0,0888	0,0918	0,0132	-0,0721	8,8477
Retail	0,0001	-0,1207	0,0798	0,0134	-0,1015	8,0901
Technology	0,0001	-0,1308	0,1102	0,0190	0,1131	7,0399
Telecommunications	-0,0001	-0,0949	0,1104	0,0146	0,2331	7,3127
Travel&Leisure	0,0002	-0,1192	0,0794	0,0148	-0,2234	7,0335
Utilities	0,0002	-0,1028	0,1766	0,0159	0,2549	13,0291
Index	0,0001	-0,0782	0,1024	0,0129	0,0359	8,8244

We can see from this table that the highest average daily return is found for the Automobile and parts sector (0.05%). On the other side, we find the lowest and even negative one for the Telecommunications and Media sector (both -0.01%). More interestingly, we find the highest standard deviations for Automobile and parts

(2,23%), Banks and Basic Resources (2,02% and 2.03%). The lowest volatile sector in term of daily returns is Food and Beverage (1,12%) and our index (1.29%). The sectors with the lowest daily drop recorded are Automobile and parts (-30,04%) and Banks (-18,02%). This drop for Automobile and parts was recorded during the peak of the financial crisi(October 2008) when it was recorded the day after the Brexit vote for the Banks (24/06/2016).

From the above summary statistics, we could already easily conclude that the distribution of the returns is far from normal (we should expect a Kurtosis of 3 and a skewness of 0). The high Kurtosis recorded already gives a basic hint about the "fat tail" events of this paper. The skewness/Kurtosis and Jarque-Bera test for normality are consistent with this first impression (see Table 3). The null hypothesis (normality of the distribution) is rejected for all the sectors. The Skewness/Kurtosis testing shows that some sectors (Financial services, Health care, Industrials, Media, Real estate and the Index) are unskewed relative to the normal distribution. However all sectors fail at the joint testing. The implication of this non-normality for our methodological approach is that bivariate techniques (e.g. GARCH estimation proposed by Adrian and Brunnermeir, 2011) would not give proper metrics. As suggested in the literature review, the extreme value theories seem to be more appropriate when attempting to capture tails events.

Table 3: Normality testing

Sectors	Tests		p-values
Automobile and parts	Skewness-Kurtosistesting	Skewness	0,000
		Kurtosis	0,000
	Jarque-Bera		0,000
Banks	Skewness-Kurtosistesting	Skewness	0,000
		Kurtosis	0,000
	Jarque-Bera		0,000
Basic Ressources	Skewness-Kurtosistesting	Skewness	0,005
		Kurtosis	0,000
	Jarque-Bera		0,000
Chemicals	Skewness-Kurtosistesting	Skewness	0,000
		Kurtosis	0,000
	Jarque-Bera		0,000
Construction &Materials	Skewness-Kurtosistesting	Skewness	0,005
		Kurtosis	0,000
	Jarque-Bera		0,000
Financial Services	Skewness-Kurtosistesting	Skewness	0,426
		Kurtosis	0,000

	Jarque-Bera		0,000
Food &Beverage	Skewness-Kurtosistesting	Skewness	0,000
		Kurtosis	0,000
	Jarque-Bera		0,000
Health Care	Skewness-Kurtosistesting	Skewness	0,761
		Kurtosis	0,000
	Jarque-Bera		0,000
Industrials	Skewness-Kurtosistesting	Skewness	0,832
		Kurtosis	0,000
	Jarque-Bera		0,000
Insurance	Skewness-Kurtosistesting	Skewness	0,000
		Kurtosis	0,000
	Jarque-Bera		0,000
Media	Skewness-Kurtosistesting	Skewness	0,678
		Kurtosis	0,000
	Jarque-Bera		0,000
Oil&Gas	Skewness-Kurtosistesting	Skewness	0,000
		Kurtosis	0,000
	Jarque-Bera		0,000
P&HGoods	Skewness-Kurtosistesting	Skewness	0,016
		Kurtosis	0,000
	Jarque-Bera		0,000
Real Estate	Skewness-Kurtosistesting	Skewness	0,066
		Kurtosis	0,000
	Jarque-Bera		0,000
Retail	Skewness-Kurtosistesting	Skewness	0,010
		Kurtosis	0,000
	Jarque-Bera		0,000
Technology	Skewness-Kurtosistesting	Skewness	0,004
		Kurtosis	0,000
	Jarque-Bera		0,000
Telecommunications	Skewness-Kurtosistesting	Skewness	0,000
		Kurtosis	0,000
	Jarque-Bera		0,000
Travel&Leisure	Skewness-Kurtosistesting	Skewness	0,000
		Kurtosis	0,000
	Jarque-Bera		0,000
Utilities	Skewness-Kurtosistesting	Skewness	0,000
		Kurtosis	0,000
	Jarque-Bera		0,000
Index	Skewness-Kurtosistesting	Skewness	0,361
		Kurtosis	0,000
	Jarque-Bera		0,000

Note: H_0=Significantly not different from a Gaussian distribution (i.e. Normality of the variable); the joint Skewness/Kurtosis test is not reported here but exhibits p-values of 0 for all variables

As mentioned in the macro-state variables part, we perform below an augmented dickey-fuller test for stationarity (see table 4). The null hypothesis is that the variable contains a unit root, and the alternative is that the variable was generated by a stationary process. As expected, all macro-state variables contain unit roots for at least one of the model tested (with constant and with trends, with just a constant and with none). When testing the differenced macro-state variables, we see that the null is rejected, solving for potential non-stationarity problems.

Table 4: Stationarity testing.

p-values	with constant and with trend	with constant	with none
Eurostoxx50	0,5969	0,2466	0,497
D.Eurostoxx50	0	0	0
VSTOXX	0,0279	0,0081	0,245
D.VSTOXX	0	0	0
Liquidityspread	0,034	0,018	0,124
D.Liquidityspread	0	0	0
Creditspread	0,7226	0,4435	0,237
D.Creditspread	0	0	0

Note: Augmented Dickey-fuller test for stationarity for macro-state variables. Tested for the models with trend and with constant, with just a constant and with none.Number of lags are not specified (automatic selection).

7. Empirics: systemic risk and conditional information

We will know assess empirically the systemic risk contribution of the sectors across the European economy. Results on the conditional estimates (VaR, CoVaR and ΔCoVaR) will be expressed in averages and quadrimestrial averages of the daily estimates both for convenience and to reduce the scope of the volatility of all the three estimates. Sectorial specific results can be found in appendix. The results will first be focused on the unconditional estimates as explained above. We will first focus on the analysis of the 1%-VaR and 1%-CoVaR, followed by a comparison between the individual spillover effect of each sector to the European economy (1%-CoVaR) and its individual contribution to the global European systemic risk (ΔCoVaR). In the second subdivision of this part, we will assess the conditional estimates of the sectorial systemic risk contribution. In this part we will assess the three different risk measures using several control macroeconomic variables to get a time dependent risk assessment. The analysis will follow the same structure as in the unconditional estimates part. Finally, we will conclude regarding the results of this essay.

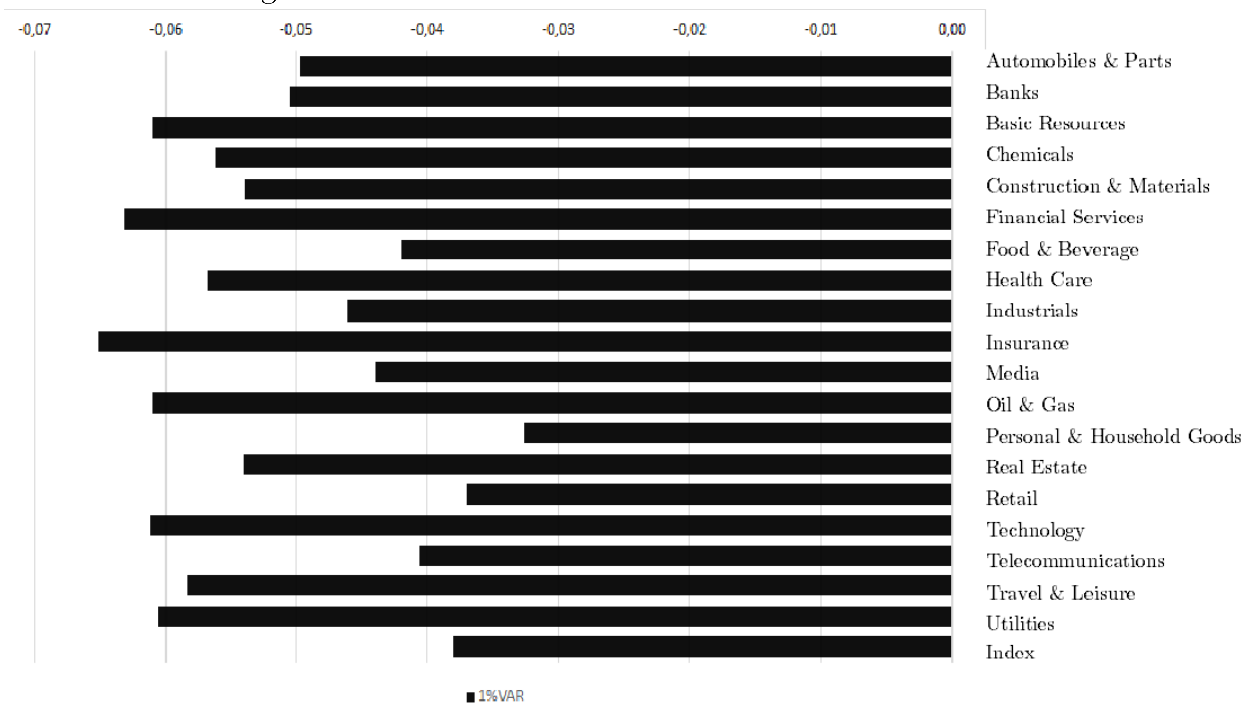
7.1 Unconditional estimates of sectorial risk contribution

The unconditional daily 1%-VaR estimate by sector and the one of the index will give us a first benchmark regarding which sector has the most to lose in case of distress. The interpretation of such estimate stays however very limited. Sectorial specific estimates of this subsection can all be found in the Appendix 1-2.

As explained in the methodology, the VaR was build with the estimation of the coefficient from the quantile regression (see equation 2.2). See Appendix 3 for the individual sectorial results from this regression. Only the 1%-VaR is presented in figure 1. Indeed, the median-VaR estimation were all extremely close from 0 even though not necessary insignificantly different from it. No sectors had a 50%-VaR higher than 0.0007 with statistical significance. We therefore choose to omit the analysis of the unconditional 50%-VaR on purpose.

7.1.1 Unconditional VaR's

Figure 1: Unconditional sectorial 1%-VaR



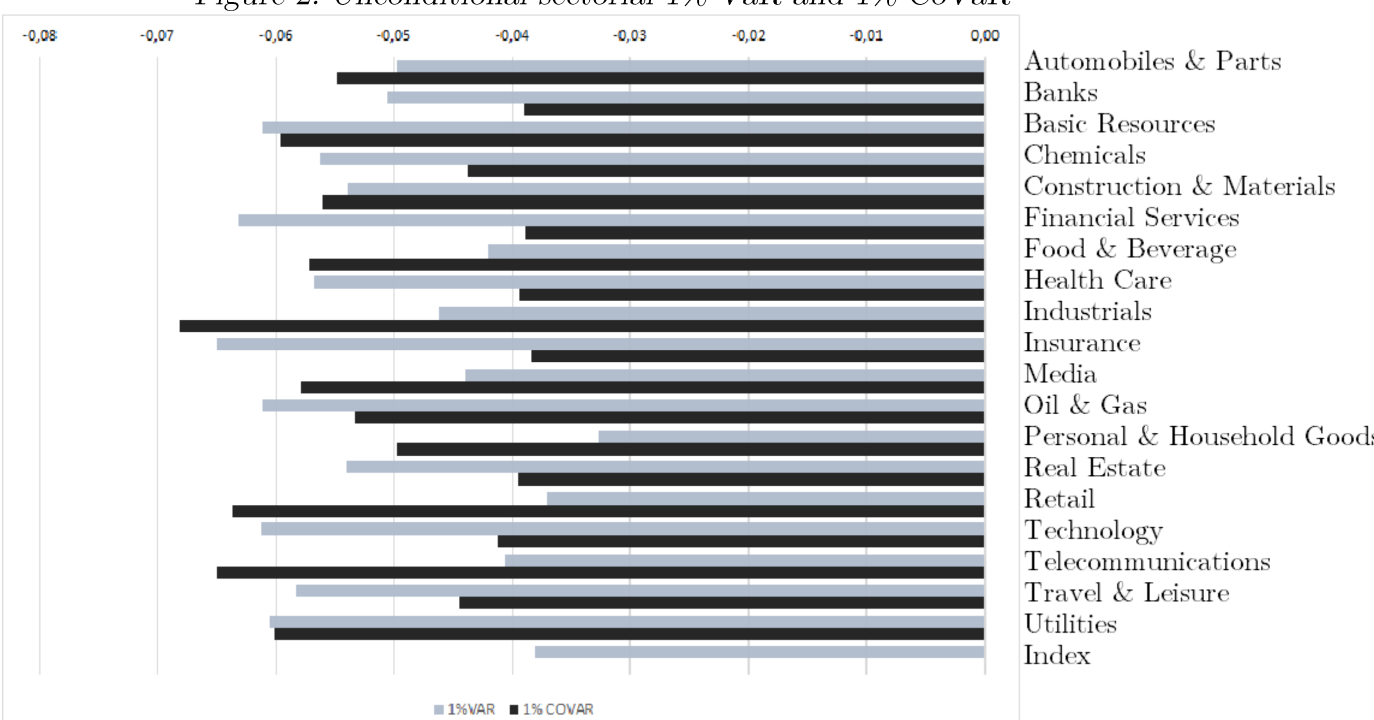
Technology sectors seems to have the highest daily 1%-VaR in absolute value since VaR's are negatives. Taking the definition of the Value at risk from the investor's side, it would mean that for investors holding a portfolio composed of securities perfectly matching the Insurance industry (given the MSCI definition) and given the estimated 1%-VaR of -0.065013 of this sector, this investor should not expect a daily loss of more than 6.5% in 99% of the case (inference says with a 99% confidence level). On the contrary, we can observe that the Food and Beverage, personal and household goods as well as the retail sector seem to have significantly lower 1%-VaR.

Such analysis should be conducted carefully given the flaws of the VaR measurements. However based on this, regulator should bear in mind that for risk management purposes, a particular attention should be given to the aforementioned sectors with the highest 1%-VaR. Regarding our results, it is not surprising to see that the insurance sector as well as the financial services sectors is part of this category. Indeed, these sectors already are subject to specific risk management regulation (Solvency II, AIFMD, etc.). What might strike us nonetheless in our result is both the absence of the banking sector and the presence of the Technology sector in this category. The banking sector plays an important role regarding the contribution to systemic risk and is subject to heavy regulation from the application of the Basel III agreements (as consequence of their role in the 2008 financial crisis). It is thus surprising to see that the Tech sector have a higher 1%-VaR than the banking sector. What is quite interesting to observe is also the relatively low 1%-VaR of our index. This might find explanation in the high degree of diversification that such an index represents, both in term of capitalization (since small cap are also included) and in term of activities (all sectors are included).

7.1.2 Unconditional CoVaR's

We will now analyse the results of both the 1%-VaR and 1%-CoVaR of each sector as represented by figure 2.We can observe that the sectors with the highest 1%-CoVaR are the Industrials, Telecommunications and Retail sector. On the other hand, the lowest unconditional 1%-CoVaR are recorded for the banking sector, the insurance sector, financial services and Health care sector.

Figure 2: Unconditional sectorial 1%-VaR and 1%-CoVaR



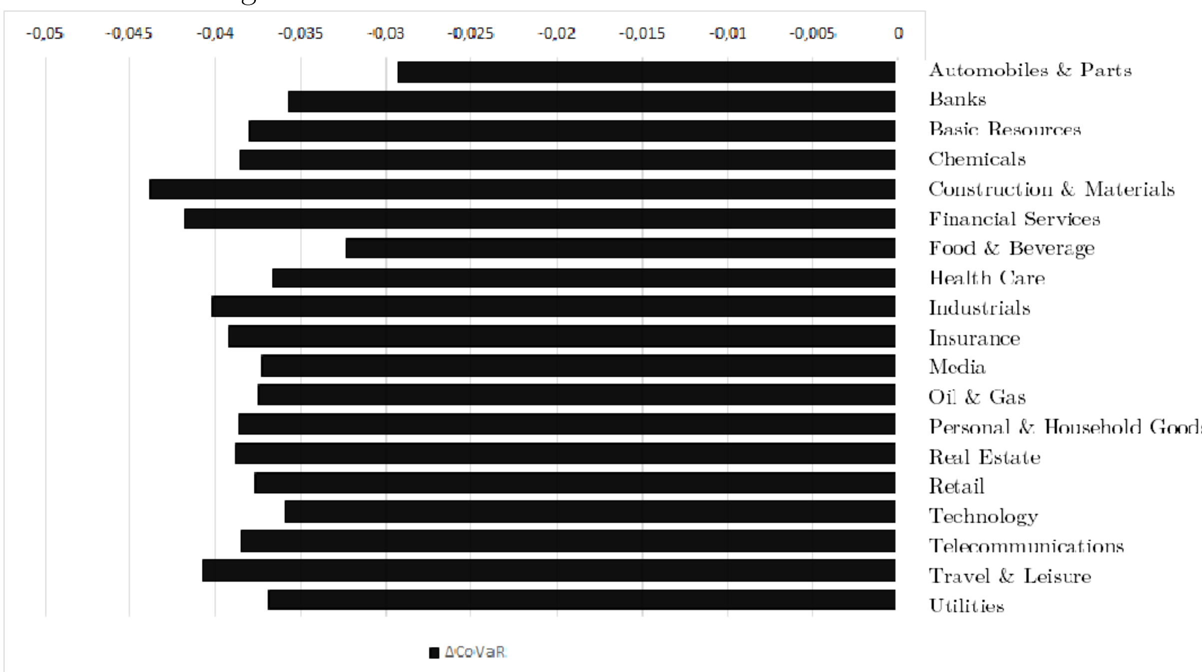
As developed in the methodology, the unconditional CoVaR is obtained by running a quantile regression of the sectors on the index (equation 2.6). Therefore, the index represents here the dependent variable (equation 2.5) regressed on an estimated constant, the betas and the returns of the different sectors (being independent variables here). The 1%-CoVaR of the European economy (as proxied by our index) conditional on a sector being in distress (thus facing a 1%-VaR situation) is equal to the obtained 1%-VaR of the index regarding this stress event. Therefore, when the industrials sector is on its exact 1%-VaR (thus facing a loss of 4.616% in asset value), the 1%-VaR of the European economy is at -0.681. All the estimates are available in appendix 4.

The 1%-CoVaR is a way to identify the negative spillover-effects of a sector on the European economy. Taken alone, such a measure might seem irrelevant regarding the thesis of this paper. We want to assess the systemic risk contribution, not spillovers. However, it is interesting to note that for a number of sectors, the spillover effect they have on the European economy (i.e 1%-CoVaR) is larger than their individual risk measure (i.e 1%-VaR). This is the case for the Automobiles and parts, Construction and materials, Food and Beverages, Industrials, Medias, Personal and household's goods, Retail and communication sectors. Another interesting feature is that some sectors with the highest 1%-VaR (e.g. Insurance and Financial services) tend to have among the lowest 1%-CoVaR. As we can see in the appendix 2, there seem to have a negative correlation between the 1%-VaR and the 1%-CoVaR. This figure does not aim to explain anything from that correlation in our specific case. The correlation has indeed a negative sign when using a statistical software (-0.5097). To summarize we observe that for 8 sectors out of 18, their 1%-CoVaR is much greater than their 1%-VaR meaning that their interconnectedness seems to play a role in the European economy while for 8 other sectors out of 18 the relatively high individual risk is offset by the fact that these sectors do not seem to spill over negatively.

7.1.3 Unconditional ΔCoVaR's

We will assess here each sectorial marginal risk contribution to the system's overall risk. The results considering this former are plotted on figure 3. The marginal systemic risk contribution as measured by the ΔCoVaR is the difference between the 1%-CoVaR (1%-VaR of the index when a sector is at its 1%-VaR) and the 50%-CoVaR (1%-VaR of the index when a sector is at its 50%-VaR).

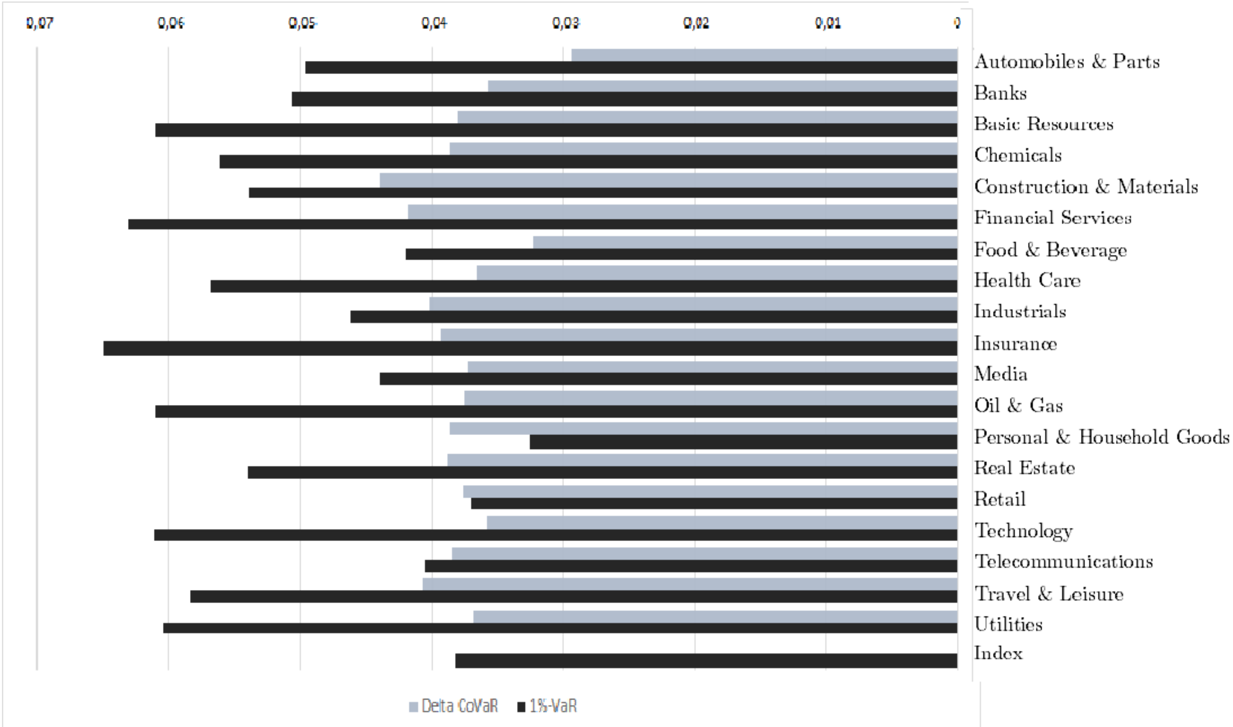
Figure 3: unconditional sectorial ΔCoVaR



We can conclude from figure 3 that the difference between different sectors regarding their individual systemic risk contribution to the European index is not so wide. Some sectors seem nonetheless to contribute more than others. The financial services as well as the construction and materials are the one contributing the most. The Food and beverage sector and the Technology sector are the least "systemic risk-contributors". Taking the financial services sector as an example, its ΔCoVaR of -0.04178 means that when the financial services sector faces a downturn such that it passes from a median state risk profile (at 50%-VaR) to a financial distress (at 1%-VaR), they negatively contribute by 4.178 % to the European overall systemic risk (thus adding 4.178% of additional risk).

7.1.4 Comparison: 1%-VaR and ΔCoVaR

Figure 4 :Unconditional sectorial 1% -VaR and ΔCoVaR



On figure 4, we can observe the difference between the individual unconditional riskiness of a sector (1%-VaR) as compared with its individual unconditional systemic risk contribution to the European economy (ΔCoVaR). We can observe that for all sectors except Personal and household goods and Retail sector, the ΔCoVaR is each time smaller than the 1%-VaR. We can't find a clear pattern however concerning the relationship between the unconditional 1%-VaR and the ΔCoVaR. A relatively more risky sector does not induce it to relatively contribute more to the systemic riskiness of the European economy.

Following what was said in most of the literature relative to systemic risk (Adrian and Brunnermeir, 2011) (Acharya et Al., 2012) etc. We can also conclude from our results on the unconditional VaR, CoVaR and ΔCoVaR that the micro-based and individual approach of risk is irrelevant or at least not sufficient when it comes to manage spillover risks. This confirmation is highlighted by the fact that for half of our considered sector, the spillover risks (i.e. 1%-CoVaR) is higher than the individual risk (i.e. 1%-VaR). Another outcome supporting this broadly admitted conclusion on the limitation of VaR is that for two sectors, the ΔCoVaR was estimated greater than the 1%-VaR. It means that for those two sectors, the isolated sectorial risk is smaller than the sectorial contribution to the European systemic risk. This is also a rationale of why Adrian and Brunnermeir, 2011 developed a method accounting for interconnectedness and cross-sectional macro-shocks, namely the following conditional systemic risk estimates. This supports also the rising literature on dynamic stochastic models and vectoral analysis on the channels of propagation.

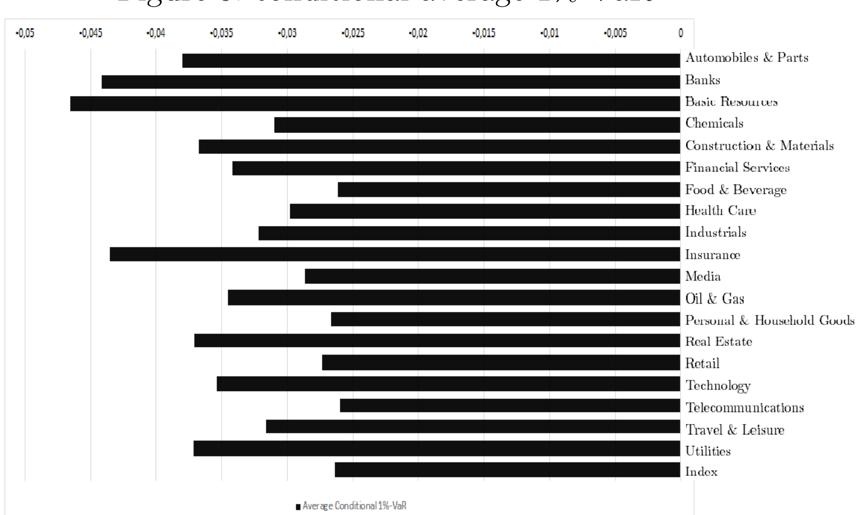
7.2 Conditional estimates of sectorial risk contribution

As previously mentioned in the methodology part, the conditional estimation method allows us to examine the way our risk measures move across time. We include additional variables (based on previous literature and economic reasoning) that are assumed to explain the behaviour of sectorial equity prices moves and that are supposed to capture the time varying nature of risk. These macro-state variables allow us also to control the idiosyncratic moves of risk included in the unconditional estimates method.

7.2.1 Conditional VaR's

First, we analyse the conditional average 1%-VaR for all sectorial indexes as represented by Figure 5.

Figure 5: conditional average 1%-VaR

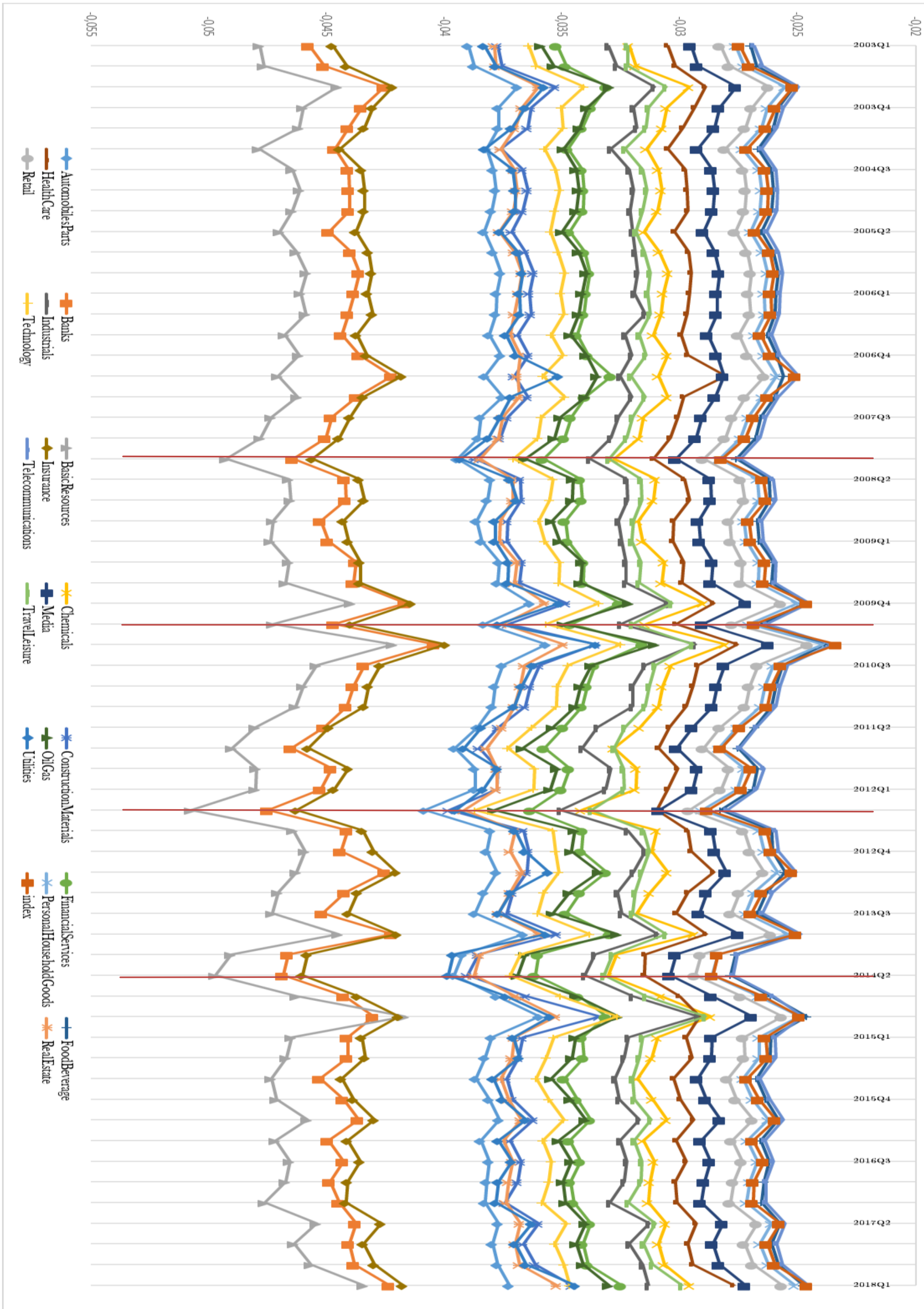


In comparison to unconditional measurements of VaR, results are not the same relatively between sectors regarding their VaR's. The highest individual sectorial risk measures are now recorded for the Basic resources, Banks and Insurance sector. Moreover, even if the conditional VaR is lower for all sectors as compared to the unconditional VaR, the conditional VaR has dropped more relatively for the Chemicals, oil and gas and Personal and household goods.

The most interesting feature regarding this conditional VaR is probably the behaviour of the Financial sectors. Indeed, refining the VaR's of these sectors with macro-variables showed to significantly affect it. The Banks sector now appears as one of the most individually risky sectors when the Financial services sector is now amongst the lowest risky sector. It demonstrates to a certain extent the importance of liquidity and credit spread when it comes to their specific core business.

We plot now the conditional 1%-VaR to see whether it evolves all at once across sectors and whether it reacts to economy-wide shocks (e.g. mortgage securities crisis, inter-banking liquidity crisis, sovereign-debt crisis...). The 1%-VaR's are plotted in Figure 6 for the period from 2003 to 2018 due to unbalanced data problems. These Var's are averaged quarterly (4 averages per year) in order to analyse trends and simultaneous moves visually (which seems impossible daily regarding the high frequency noise).

Figure 6: Quarterly averaged conditional sector 1%-VaR (2003Q1-2018Q1)



In accordance to what we could have expected, we can observe that globally risk measurements across different sectors follow the same pattern through time. Consistent with economical reasoning, we observe increase (in absolute value) in VaR's measurement for each European-wide financial and market shocks (as represented by the red lines on the graphs). These shocks represent in order; 2008Q1: the financial global collapse following the mortgage subprime crisis. 2010Q1: overall European deterioration of public finances (bond yield rate hike for several countries) and preparation of the first Greek bailout deal. 2012Q2: Recession in Europe and sovereign debt crisis following the second Greek bailout plan. The increase observed for the first and second quarter of 2014 is more difficult to explain regarding economic history and unfolding of the Sovereign debt crisis.

We observe that the index (supposed to be a proxy of the European-wide economy) has among the lowest VaR. On the other side, Insurance, Banks and the Basic resources sectors have among the highest VaR. These sectors might form a distinct subgroup regarding this risk measure. They are different by almost 100 basic points from the average of the other sectors.

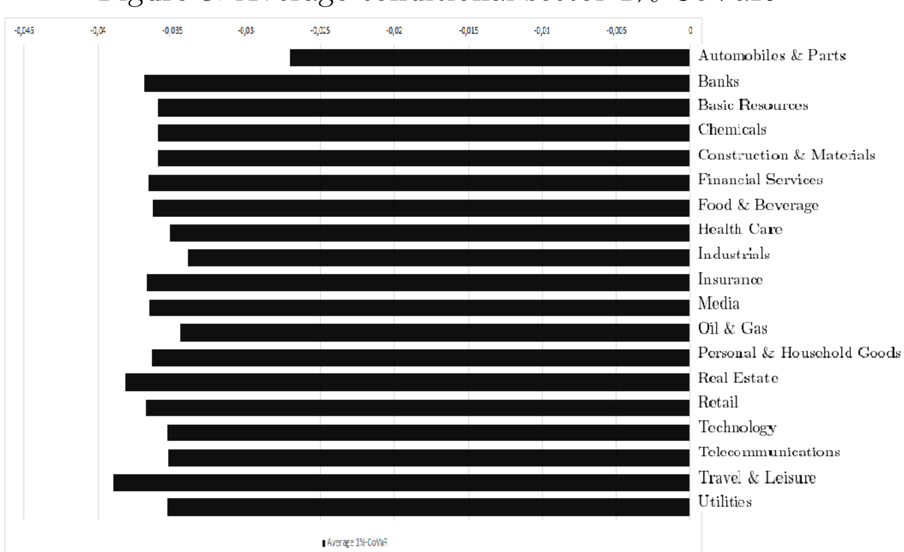
7.2.2 Conditional CoVaR's

The further plots and graphs will present the conditional CoVaR estimations. Figures 7 and 8 display respectively the averaged 1% and median CoVaR over the whole considered period to get a snapshot of the respective risk relation between the system and each sector. Figures 9 and 10 respectively plot the quarterly averaged CoVaR estimates (at 1% and 50%). All these estimates represent the evolution of the European economy VaR (as proxied by our index) conditioned by each sector being at its 1% and 50%-VaR level.

Figure 7:Average conditional sector 50%-CoVaR

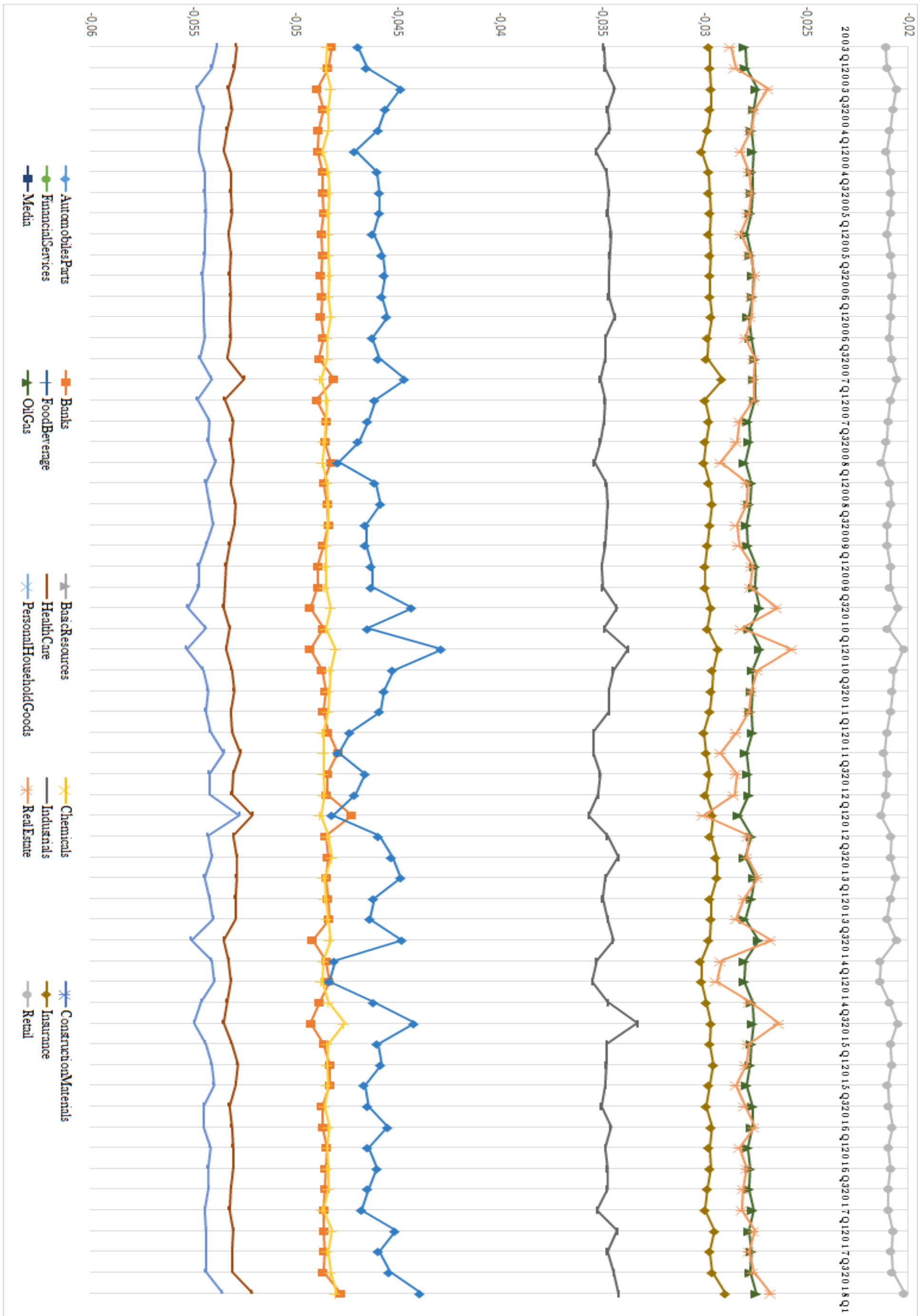
The two sectors impacting the most the 1%-VaR of the system when they are at their median state are Financial services and the Insurance sector. To give an intuition, the CoVaR of 50% of the Financial services sector at -0.00075 means that when this sector is in a median financial stress situation, it affects the European economy's VaR by -0.0075%. Quite surprisingly is also the relatively high 50%-CoVaR of the Healthcare sector.It is interesting to see that Retail, Media and Travel & Leisure sector seem to impact the least the VaR of the European economy. This might find an explanation in their consumer-oriented core business.

Figure 8: Average conditional sector 1%-CoVaR



The pattern across sectors changes significantly for the 1%-CoVaR. There seem to be way less variation across their 1% CoVaR. Except for the Automobile and parts which seems to act as an outlier, all sectors have a 1%-CoVaR comprised between -0.033 and -0.039. The differences between sectors is therefore way less pronounced than for the 1%-VaR's.

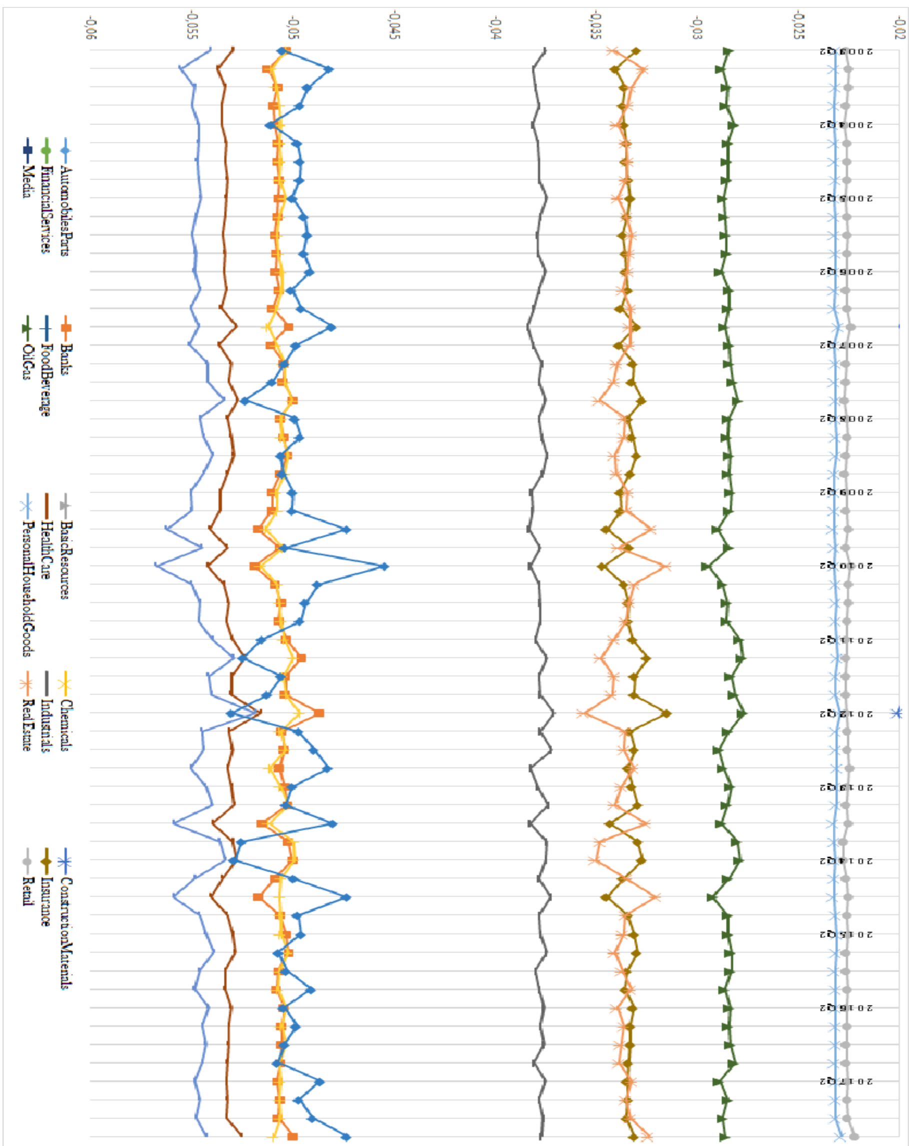
Figure 9: Quarterly averaged 1%-CoVaR (2003Q1-2018Q1)



The drops observed for the 1%-VaR are not as pronounced for the 1%-CoVaR of the sectors. It shows us that the risk linkages of each sector to the European economy tend to have a constancy across time. We can neither conclude that different sectors affect the system the same way when facing similar historic events. Indeed, the pattern is way less clear and some curves cross each other. From this illustration we can also observe the difference in volatility of the 1%-CoVaR. When some sectors such as Oil & Gas and Insurance tend to have a very stable risk linkage to the system's VaR, some other have a very volatile one (e.g. Real Estate, Automobile and parts, ...).

7.2.3 Conditional ΔCoVaR's

Figure 10: Quarterly averaged ΔCoVaR (2003Q1-2018Q1)



In figure 10 (presented above), we plot the conditional ΔCoVaR being quarterly averaged for the period 2013-2018. The ΔCoVaR is a proxy for Adrian and Brunnermeir (2011) of the systemic risk contribution of an individual institution (here sectors). As for the 1%-CoVaR, the ΔCoVaR does not show a clear pattern regarding economic shocks or common pattern of evolution between sectors. However, this plot allows us to distinguish a group of sectors that tend to have a higher systemic risk contribution. These are Basic resources, Healthcare, Banks, Chemicals and Automobiles and parts. The drop in term of systemic risk contribution in 2008Q1, 2010Q1 and 2012Q2 seems to be more pronounced for the Automobile sector, Real estate sector and Insurance sector. Nevertheless, our analysis does not allow us to show evidence regarding the Banking or Financial service sector. Which we might have expected regarding the aim of systemic risk literature. The Financial sector should induce a higher systemic risk contribution on the whole European economy compared to the other sectors.

7.2.4 The case of banking: role of the conditional variables

It could be interesting to check for the European banking sector what our estimates seem to reveal when compared to other papers which already assessed that sector (Bernal et al. 2014). Following the equations giving the steps in the methodology, here are what we have compared to what they have (note that the equation number are the same as the one used in the Methodology part):

(2.9) $$\mathrm{R}_t^{Banks}\ (q)=\alpha_q^{Banks} + \gamma 1_q^{Banks}\ M1_t + \gamma 2_q^{Banks}\ M2_t + \gamma 3_q^{Banks}\ M3_t + \gamma 4_q^{Banks}\ M4_t + \varepsilon_t^{Banks}$$

- estimated in our case (significance levels ***=0.01 **=0.05 *=0.1) :

$$\mathrm{R}_t^{Banks}\ (q)=-0.0251^{***} - 0.00041^{**} M1_t + 1.2554^{**} M2_t + -0.0072 M3_t + -0.0041^{**} M4_t + \varepsilon_t^{Banks}$$

- In their case (note that they don't show the alpha and they have more macro-state variable than us, this is represented by the Mn_t) :

$$\mathrm{R}_t^{Banks}\ (q)= \gamma 1_q^{Banks}\ M1_t + \gamma 2_q^{Banks}\ M2_t + \gamma 3_q^{Banks}\ M3_t + \gamma 4_q^{Banks}\ M4_t + \gamma \mathrm{n}_q^{Banks}\ Mn_t + \varepsilon_t^{Banks}$$

$$\mathrm{R}_t^{Banks}\ (q)= -0.0716^{***}\ \mathrm{M1_t} + 0.9870^{***}\ M2_t - 0.059^{**}\mathrm{M3_t} - 0.0379^{***}\mathrm{M4_t} + \varepsilon_t^{Banks}$$ [4]

4. Data taken from table 9 of Bernal et al. (2014)

$$(2.14) \qquad CoVaR_t^i(q) = \alpha_0^{index\ |Banks} + \beta_q^{index\ |Banks}\ VaR_t^{Banks}\ (q) + \gamma 1_q^{index\ |Banks}\ M1_t + \widehat{\gamma 2}_q^{index\ |Banks}\ M2_t + \widehat{\gamma 3}_q^{index\ |Banks}\ M_{3t} + \widehat{\gamma 4}_q^{index\ |Banks}\ M4_t$$

- estimated in our case (significance levels ***=0.01 **=0.05 *=0.1) :

$$CoVaR_t^i\ q\ = -0.113^{**} - 0.1204^{***}\ VaR_t^{Banks}\ (q) - 0.00031^{***} M1_t + 0.9380^{***} M2_t + 0.00319 M_{3t} - 0.0120 M4_t$$

- In their case (note that *M2* disappears for them because they consider their system equal to the Eurostoxx50 variation when we build a more extensive system than the Eurstoxx50, this is explained in the Data part):

$$CoVaR_t^i(q) = \beta_q^{index\ |Banks}\ VaR_t^{Banks}\ (q) + \gamma 1_q^{index\ |Banks}\ M1_t + \widehat{\gamma 3}_q^{index\ |Banks}\ M_{3t} + \widehat{\gamma 4}_q^{index\ |Banks}\ M4_t + \widehat{\gamma n}_q^{index\ |Banks}\ Mn_t$$

$$CoVaR_t^i\ q\ = 0.1937^{***} VaR_t^{Banks}\ (q) - 0.03252\ M1_t + 0.0105\ M_{3t} - 0.0061 M4_t + \widehat{\gamma n}_q^{index\ |Banks}\ Mn_t$$

The differences regarding these estimations might come from the fact that as previously mentioned, they use a bench of macro-state variables way more extensive than our (7 for them when we use only 4). The insignificance of many of these variables might add some noise to the model which might change the estimates. On the other hand, these variables when significance will reduce the bias of omitted variables. Another explanation could come from the fact that the time period is a bit different (from 2004 to 2012) when we use a time period from 2001 to 2018. Moreover, they use a definition of the "*financial system*" different from our since we decided to use a more extended definition than just the Eurostoxx50. Finally, the differences could come from the fact that their banking sector includes only Eurozone banks when our includes also non-Eurozone banks.

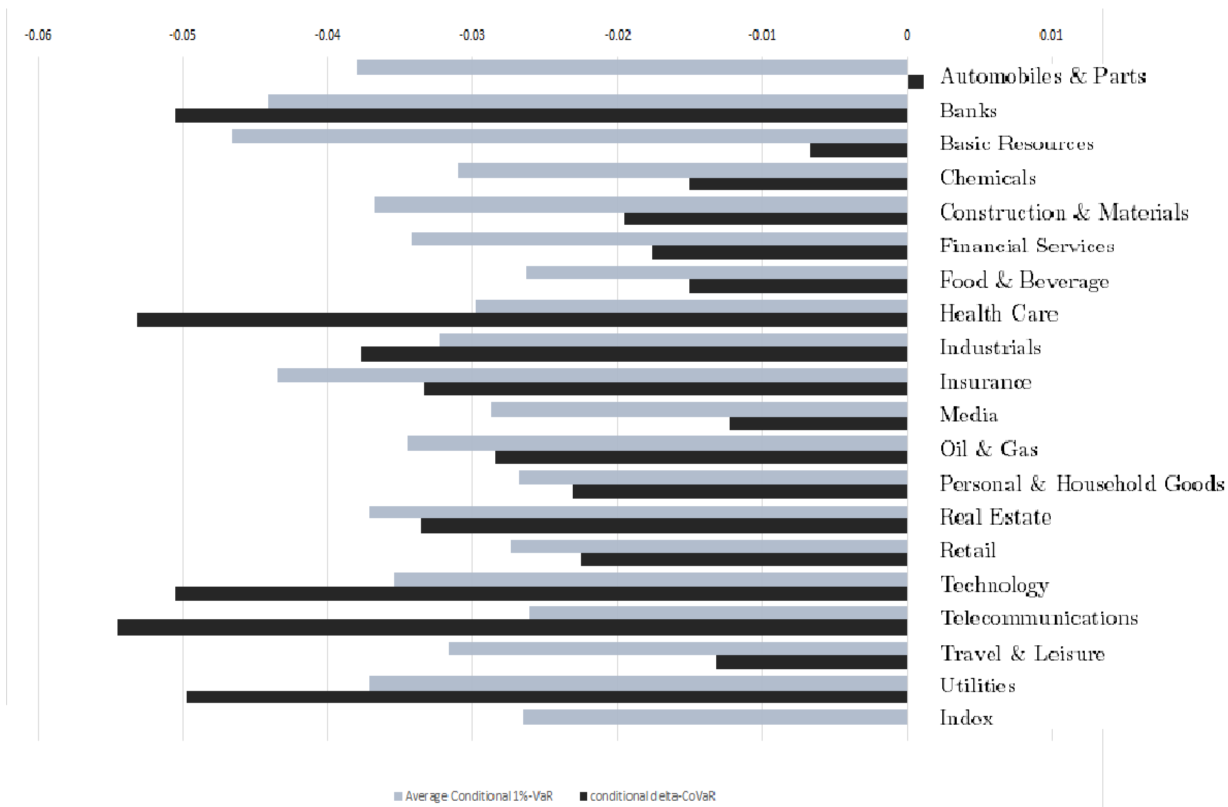
Their total ΔCoVaR (at median state) is -0.0136 but they recognize that it is not a significant result. Our ΔCoVaR is -0.0506 and is way more in line with what we initially found in the literature (e.g. Borri et al (2012) which accounted a systemic risk bank's ΔCoVaR of -0.054[5] or Krygier (2014) who had a ΔCoVaR of -0.0398[6] for the Nordic banks)

5. See table 5 of Borri et al (2012): Systemic Risk in the European Banking Sector

7.2.3 Comparison: VaR's, CoVaR's and ΔCoVaR

Conditional CoVaR and ΔCoVaR differ from the VaR analysis in the way that it measures the entity's risk conditional on the financial distress of another entity (i.e. sectors). Henceforth, it is interesting to compare the 1%-VaR estimates with ΔCoVaR estimates to examine whether we can find a relation between the sectorial risk in isolation and the sector's connection to the system's risk. Therefore, we observe in figure 11 the averages of sectorial 1%-VaR and ΔCoVaR.

Figure 11: Averaged 1%-VaR and ΔCoVaR(2003Q1-2018Q1)



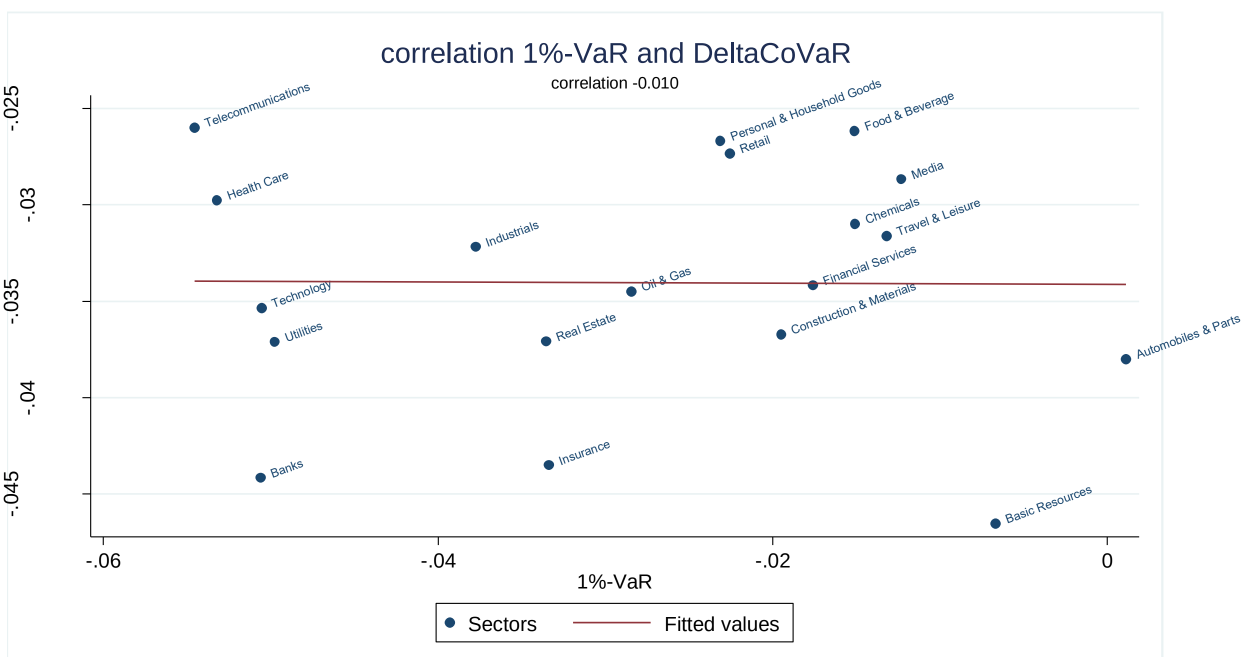
We see that for 13 sectors, the average 1%-VaR is higher than their ΔCoVaR, i.e. the isolated sectorial risk is larger than the risk contribution this sector has on the European stock market. However, some sectors such as Banks, Health care, Technology

6. See figure 13 of Krygier (2014): Measuring systemic risk in the Nordic countries: An application of CoVaR

or Telecommunication seem to have a higher systemic risk contribution than their isolated risk. From a risk management perspective, this could be seen as an indicator for a specific focus on those sectors. For intuition, the banking sector has a 1%-VaR of -0,0441 and a ΔCoVaR of -0,0506. This means that on average, the banking sector should expect to lose 4,41% of its aggregated stock value at least 1% of the time over a period of 15 years. On the other hand, the 1%-VaR of the European economy is affected by 5,06 points of percentage when the value-at-risk of the banking sector moves from being at its median-VaR level (i.e. the expected loss) into financial distress as represented by its 1%-VaR level.

In comparison with the unconditional estimates, it is interesting to note that the sectorial 1%-VaR is not necessarily always greater than the ΔCoVaR. The only methodological change between the unconditional and conditional estimates is the inclusion of macro-state variables which makes the conditional estimates time-dependent. Therefore we can easily conclude that the difference is due to the inclusion of these variables. The estimates of the VaR and CoVaR are *in fine* controlled for these additional explanatory variables. It should therefore produce more accurate estimates of the sectorial risks.

Figure 12: On the correlation of 1%-VaR and ΔCoVaR between sectors



As figure 12 seems to show, there is no apparent link between the risk in isolation and the contribution to the systemic risk. This very loose relationship and the absence of positive correlation seems to back what the literature previously stated. (Wong and Fong, 2010; Adrian and Brunnermeir, 2011). Henceforth a low sectorial averaged 1%-VaR does not translate into a necessarily low ΔCoVaR.

However what is interesting in our results is the existence of strongly significant correlations between time dependent 1%-VaR and ΔCoVaR. But contrarily to the literature (Fullenkamp, 2013; Brunnermeir et Adrian, 2011), these correlation are not all positive, i.e. some are significant and negative. The only sector for which the 1%-VaR and the ΔCoVaR are not correlated is the Travel&Leisure. These results seem to show that the link between idiosyncratic risk and systemic risk contribution is more complex than it might seem and that this relationship is highly sector-dependant. (see table below)

Sectors	Correlation between time dependent 1%-VaR and Delta-CoVaR
Automobiles & Parts	-0.9584*
Banks	-0.8858*
Basic Resources	0.9918*
Chemicals	0.8577*
Construction & Materials	0.9348*
Financial Services	0.9725*
Food & Beverage	0.9982*
Health Care	-0.7144*
Industrials	-0.4259*
Insurance	-0.8649*
Media	-0.9476*
Oil & Gas	-0.8791*
Personal & Household Goods	-0.3323*
Real Estate	0.9945*
Retail	0.8692*
Technology	-0.9016*
Telecommunications	-0.9456*
Travel & Leisure	-0.0340
Utilities	0.9945*

*significant at a 0.01 confidence level

As we have seen in this part, the inclusion of additional explanatory variables (liquidity spread, volatility, Eurostoxx50, credit spread), induced our estimates to adopt complete different patterns across sectors. We have observed that the highest isolated sectorial risk was recorded in the Banks, Insurance and Basic resources sectors. We have also seen that concerning the 1%-CoVaR, the automobile sector seemed to be an outlier with the lowest estimate. Besides, we have observed that all the estimates were highly dependent on global economic stress events (bank's bankruptcy, bailouts, sovereign crisis, etc.)

7.2.6 A critical point of view on the empirics

These results regarding the conditional estimates show us how difficult it is to assess risk and systemic risk contribution vis-à-vis economic sectors that seem to react very differently to similar economic shocks. The difficulty of assessment of such results might also be due to errors in the choice of macro variables, sectors under considerations or initial assumptions.

Regarding the choice of macro-state variables, our results seem to confirm the fact that credit spread and liquidity spread, as defined initially (the credit spread is the difference between the 10-year macrobond BBB euro area corporate bond rate and the 10 year German bond rate; the liquidity spread is the difference between the 3 months Euribor rate and the short term government bond yield (3 months), are very bad predictor for the behaviour of most of sectorial VaR's and CoVaR's (see appendixes 5 to 8). This might partly explain the differences between unconditional and conditional estimates. However, since they are statistically insignificant, their value is very close to zero which means that their impact is very limited to the rest of the estimations (see equation (2.14) to understand the impact).

Another criticism we might have regarding this essay could be the sectors under consideration. Nonetheless, the aim of this paper being to use systemic risk assessment method to apply it to all economical sectors, this standard classification which is broadly used in the literature and in the media seemed appropriate. The criticism could however find rationales toward the initial objective and the loose link between financial risk contagion and credit risk/market risk. As a matter of fact, we made the assumption that a propagation channel between credit and financing sources existed between sectors. This choice of assumption was based on previous literature (Chang, Lin and Zhu, 2008); (Hull, 2008) but some might question this fact.

The last criticism that might pop up regarding our results could be regarding the risk management method itself and its assumptions. Actually, the underlying assumption toward the use of daily returns when assessing the VaR, CoVaR and ΔCoVaR is that market information is complete and perfect. Stock valuation is therefore supposed to take into account all possible risks, all interpretations of the future financial risks. Despite the fact that it might be the case for traditional studied sectors of risk management (Banks, Insurance, Financial intermediaries, etc.), it could be questionable for non-financial sectors usually focused on their core business rather than on their financial health.

7. Conclusion

The aim of this paper was to measure the systemic risk contribution of each sector in the European economy and to see which sector contribute the most to systemic risk in Europe. Measuring contagion risks and systemic risk contribution, respectively measured by CoVaR and ΔCoVaR, is important for assessing the risk of sectors in isolation, but also for the economy as a whole, since financial markets and financial funding become more and more integrated and interconnected.

Adrian and Brunnermeir (2011) suggest a new way to assess systemic risk. This implies the estimation of a "comovement-conditional-contagion" VaR. It means the 1%-VaR of a financial system when an institution i is facing a financial distress. Intuitively, it estimates the impact of an institution being in distress on the VaR of a financial system in which the institution is included. The estimation of how much an institution contributes to the systemic risk in the financial system requires to calculate the 1%-CoVaR and 50%-CoVaR. The 50%-CoVaR (i.e. median state CoVaR) represents how much the 1%-VaR of the system is affected by the institution i being at its median-state risk level as represented by its 50%-VaR. The systemic risk contribution, called ΔCoVaR, is the difference between the 50%-CoVaR and the 1%-CoVaR. There are many estimation methods but we use the quantile regression and historic simulation to obtain empirical results.

The estimation of this CoVaR can be done in a conditional and an unconditional way. The unconditional estimation is based on historical simulation and yields a time-independent measure of CoVaR and ΔCoVaR based on the distribution of daily returns of sectorial indices. On the other hand, the conditional estimates imply to condition the VaR of the sectors as well as the CoVaR on some macro-state variables (supposed to represent economy-wide shocks). Thanks to those macro-state variables (e.g. Eurostoxx50, VSTOXX, credit spread and liquidity spread), we obtain time-varying estimates. Our analysis is performed on 18 sectors (taken from the MSCI classification) when the European financial system is built as an index of more than 1440 European companies. The period considered is from the second February 2001 up to the 1rst of April 2018. The 18 considered sectors are the following: *Automobiles & Parts, Banks, Basic resources, Chemicals, Construction and Materials, Financial*

Services, Food and Beverages, Healthcare, Industrials, Insurance, Media, Oil & Gas, Personal and Household goods, Real Estate, Retail, Technology, Telecommunications, Travel & Leisure, Utilities.

Concerning the unconditional estimates, our results indicate that the riskiest sectors taken in isolation (1%-VaR) were the *Insurance, Financial services and Technology sector.* We were quite surprised not to see the Banking sector included in this category. Similarly, the sectorial contagion risk as measured by the 1%-CoVaR was not the highest for the Banking, Financial services nor the Insurance sector. Confirming the randomness of the relationship that exists between VaR and CoVaR. We found out that the most systemic risk contributing sector was *Financial Services* as well as the *Construction & Materials* (those two have the highest unconditional ΔCoVaR). The unconditional estimates exhibited that for all sectors, the unconditional ΔCoVaR was always smaller than the 1%-VaR. This would mean that whatever the sector, the sectorial financial risk taken in isolation is always greater than the sectorial systemic risk contribution.

Turning to the conditional estimations, we found average estimates for VaR, CoVaR and ΔCoVaR that were quite different from the prior analysis done in the unconditional case. As a reminder, these estimations are conditioned by macro-state variables supposed to represent the business cycle, the investor's confidence, trends and other concepts supposed to have an impact on all sectors simultaneously. By doing so, we create time-dependent estimates that are controlled for the market specific risks that affect all sectors altogether. We observe that the riskiest sectors turn to be *Banks* and *Insurance* as well as *Basic resources* when the *Financial Services* sector seems to be the least risky sector taken in isolation. Through time we find similar reaction to significant financial distress events (sovereign crises, banking crisis, etc.) for the VaR's of different sectors. We do not find the same pattern regarding the CoVaR's. Indeed, the different sectors have very different CoVaR both in term of level but also in term of volatility. Some sectors such as *Automobiles & Parts*, *Basic resources* and *Real Estate* seem to have very volatile CoVaR compared to the others. Regarding the ΔCoVaR, roughly the same results appear compared to the ones we had with the CoVaR. However it is interesting to see that for the conditional estimates, the average systemic risk contribution of *Banks*, *Telecommunications* and *Technology* are higher than their average individual risk (VaR) which was not the case when we estimated it unconditionally.

Globally, our results tend to show us that there is a very loose link between sector's VaR's and sector's ΔCoVaR, i.e. a sector's risk taken in isolation (VaR) does not imply that this same sector contributes more to the systemic risk of the whole financial system. These results were found both conditionally and unconditionally. This conclusion backs what the previous literature (Adrian and Brunnermeir, 2011; Acharya et al, 2012) said on the fact that there is no positive relationship between an institution VaR and ΔCoVaR.

In the last part of this paper, we took a critical point of view toward the significance and relevance of our results. Undeniably, the difficulty of interpretation regarding our estimates could partly be the consequences of the choices and assumptions made at the very beginning of our models. We first think that the choice of the macro-variables can have a significant impact on the relative difference between VaR's, CoVaR's and ΔCoVaR of all sectors. Some might also criticize the classification of sectors and the usefulness of this sectorial based analysis. Finally, we agree also on the fact that systemic risk measurements are based on very strong assumptions regarding market risks and on the behaviour of market traded securities.

The empirical findings of this paper support their own way the growing field in contagion risk management research that focuses on systemic risk and on measurement methods such as CoVaR. Moreover we tried to give a new insight to the systemic risk literature by taking the non-financial sectors into account. By doing so we created a bridge between the credit channel contagion and the financial risk management field. The further literature should deepen this link to understand better the transmission of economy-wide shocks to the so-called *real-economy.*

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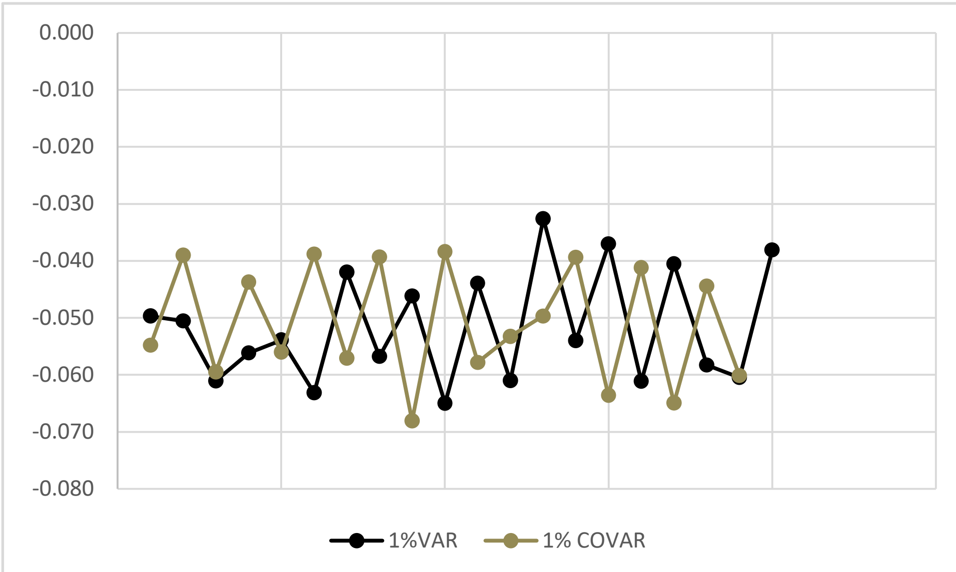
Appendices

Appendix 1 List of companies in each sectors (indexes) and their geographical distribution

DAIMLER	Automobiles & Parts	DE	BCO SANTANDER	Banks	ES	ARCELORMITTAL	Basic Resources	LU
VOLKSWAGEN PREF	Automobiles & Parts	DE	BNP PARIBAS	Banks	FR	UPM KYMMENE	Basic Resources	FI
BMW	Automobiles & Parts	DE	ING GRP	Banks	NL	STORA ENSO R	Basic Resources	FI
CONTINENTAL	Automobiles & Parts	DE	INTESA SANPAOLO	Banks	IT	TENARIS	Basic Resources	IT
MICHELIN	Automobiles & Parts	FR	BCO BILBAO VIZCAYA ARGENTA	Banks	ES	VOESTALPINE	Basic Resources	AT
FIAT CHRYSLER AUTOMOBILES	Automobiles & Parts	IT	UNICREDIT	Banks	IT	AURUBIS	Basic Resources	DE
RENAULT	Automobiles & Parts	FR	GRP SOCIETE GENERALE	Banks	FR	IMERYS	Basic Resources	FR
FERRARI	Automobiles & Parts	IT	DEUTSCHE BANK	Banks	DE	OUTOKUMPU	Basic Resources	FI
VALEO	Automobiles & Parts	FR	KBC GRP	Banks	BE	ANHEUSER-BUSCH INBEV	Food & Beverage	BE
PEUGEOT	Automobiles & Parts	FR	CREDIT AGRICOLE	Banks	FR	DANONE	Food & Beverage	FR
PORSCHE PREF	Automobiles & Parts	DE	CAIXABANK	Banks	ES	PERNOD RICARD	Food & Beverage	FR
FAURECIA	Automobiles & Parts	FR	ABN AMRO GROUP	Banks	NL	HEINEKEN	Food & Beverage	NL
RHEINMETALL	Automobiles & Parts	DE	ERSTE GROUP BANK	Banks	AT	KERRY GRP	Food & Beverage	IE
NOKIAN RENKAAT	Automobiles & Parts	FI	COMMERZBANK	Banks	DE	HEINEKEN HLDG	Food & Beverage	NL
PIRELLI & C. S.P.A.	Automobiles & Parts	IT	BCO SABADELL	Banks	ES	DAVIDE CAMPARI	Food & Beverage	IT
PLASTIC OMNIUM	Automobiles & Parts	FR	BANK OF IRELAND GROUP	Banks	IE	GLANBIA	Food & Beverage	IE
HELLA	Automobiles & Parts	DE	MEDIOBANCA	Banks	IT	REMY COINTREAU	Food & Beverage	FR
SCHAEFFLER AG	Automobiles & Parts	DE	NATIXIS	Banks	FR	VISCOFAN	Food & Beverage	ES
BASF	Chemicals	DE	BANKINTER	Banks	ES	BAYER	Health Care	DE
AIR LIQUIDE	Chemicals	FR	BANCO BPM	Banks	IT	SANOFI	Health Care	FR
LINDE TENDERED	Chemicals	DE	BANKIA	Banks	ES	PHILIPS	Health Care	NL
AKZO NOBEL	Chemicals	NL	FINECOBANK	Banks	IT	FRESENIUS	Health Care	DE
KONINKLIJKE DSM	Chemicals	NL	UBI BCA	Banks	IT	ESSILOR INTERNATIONAL	Health Care	FR
COVESTRO	Chemicals	DE	AIB GROUP	Banks	IE	FRESENIUS MEDICAL CARE	Health Care	DE
UMICORE	Chemicals	BE	RAIFFEISEN BANK	Banks	AT	MERCK	Health Care	DE
SOLVAY	Chemicals	BE	BCO COMERCIAL PORTUGUES	Banks	PT	UCB	Health Care	BE
SYMRISE	Chemicals	DE	BPER Banca	Banks	IT	GRIFOLS	Health Care	ES
ARKEMA	Chemicals	FR	VINCI	Construction & Mater	FR	QIAGEN	Health Care	DE
BRENNTAG	Chemicals	DE	CRH	Construction & Mater	IE	ORPEA	Health Care	FR
LANXESS	Chemicals	DE	SAINT GOBAIN	Construction & Mater	FR	EUROFINS SCIENTIFIC	Health Care	FR
K + S	Chemicals	DE	HEIDELBERGCEMENT	Construction & Mater	DE	IPSEN	Health Care	FR
EVONIK INDUSTRIES	Chemicals	DE	BOUYGUES	Construction & Mater	FR	GALAPAGOS	Health Care	BE
FUCHS PETROLUB PREF	Chemicals	DE	ACS	Construction & Mater	ES	ABLYNX	Health Care	BE
IMCD	Chemicals	NL	EIFFAGE	Construction & Mater	FR	RECORDATI	Health Care	IT
WACKER CHEMIE	Chemicals	DE	FERROVIAL	Construction & Mater	ES	BIOMERIEUX	Health Care	FR
TOTAL	Oil & Gas	FR	KINGSPAN GRP	Construction & Mater	IE	ORION B	Health Care	FI
ENI	Oil & Gas	IT	HOCHTIEF	Construction & Mater	DE	GERRESHEIMER	Health Care	DE
REPSOL	Oil & Gas	ES	WIENERBERGER	Construction & Mater	AT	VIVENDI	Media	FR
TECHNIPFMC	Oil & Gas	FR	BOSKALIS WESTMINSTER	Construction & Mater	NL	RELX NV	Media	NL
NESTE	Oil & Gas	FI	EURONEXT	Financial Services	FR	PUBLICIS GRP	Media	FR
GALP ENERGIA	Oil & Gas	PT	AAREAL BANK	Financial Services	DE	WOLTERS KLUWER	Media	NL
OMV	Oil & Gas	AT	BOLSAS Y MERCADOS	Financial Services	ES	PROSIEBENSAT.1 MEDIA	Media	DE
SIEMENS GAMESA	Oil & Gas	ES	AZIMUT HLDG	Financial Services	IT	SES	Media	LU
SBM OFFSHORE	Oil & Gas	NL	DEUTSCHE BOERSE	Financial Services	DE	SPRINGER (AXEL)	Media	DE
SAIPEM	Oil & Gas	IT	GRP BRUXELLES LAMBERT	Financial Services	BE	RTL GRP	Media	LU
MONCLER	P&H Goods	IT	EXOR NV	Financial Services	IT	TELENET GRP HLDG	Media	BE
UBISOFT ENTERTAINMENT	P&H Goods	FR	AMUNDI	Financial Services	FR	EUTELSAT COMMUNICATION	Media	FR
OSRAM LICHT	P&H Goods	DE	WENDEL	Financial Services	FR	LAGARDERE	Media	FR
HUGO BOSS	P&H Goods	DE	ACKERMANS & VAN HAAREN	Financial Services	BE	JCDECAUX	Media	FR

SEB	P&H Goods	FR	SIEMENS	Industrials	DE	INMOBILIARIA COLONIAL	Real Estate	ES
CHRISTIAN DIOR	P&H Goods	FR	EDENRED	Industrials	FR	ICADE	Real Estate	FR
AMER SPORTS	P&H Goods	FI	RANDSTAD	Industrials	NL	COFINIMMO	Real Estate	BE
BIC	P&H Goods	FR	ALSTOM	Industrials	FR	Kering	Retail	FR
LVMH MOET HENNESSY	P&H Goods	FR	BUREAU VERITAS	Industrials	FR	Industria de Diseno Textil SA	Retail	ES
UNILEVER NV	P&H Goods	NL	GEA GRP	Industrials	DE	AHOLD DELHAIZE	Retail	NL
L'OREAL	P&H Goods	FR	Getlink	Industrials	FR	CARREFOUR	Retail	FR
ADIDAS	P&H Goods	DE	PRYSMIAN	Industrials	IT	ZALANDO	Retail	DE
HENKEL PREF	P&H Goods	DE	ADP	Industrials	FR	DELIVERY HERO AG	Retail	DE
HERMES INTERNATIONAL	P&H Goods	FR	KION GROUP	Industrials	DE	JERONIMO MARTINS	Retail	PT
LUXOTTICA	P&H Goods	IT	SARTORIUS PREF.	Industrials	DE	KESKO	Retail	FI
BEIERSDORF	P&H Goods	DE	ELIS	Industrials	FR	ETS COLRUYT	Retail	BE
SAP	Technology	DE	AALBERTS INDUSTRIES	Industrials	NL	CASINO GUICHARD	Retail	FR
ASML HLDG	Technology	NL	LEONARDO	Industrials	IT	METRO AG	Retail	DE
NOKIA	Technology	FI	REXEL	Industrials	FR	DISTRIBUIDORALIMENTACION	Retail	ES
INFINEON TECHNOLOGIES	Technology	DE	DASSAULT AVIATION	Industrials	FR	IBERDROLA	Utilities	ES
CAP GEMINI	Technology	FR	BOLLORE	Industrials	FR	ENGIE	Utilities	FR
DASSAULT SYSTEMS	Technology	FR	MAN	Industrials	DE	E.ON	Utilities	DE
STMICROELECTRONICS	Technology	IT	HUHTAMAKI	Industrials	FI	VEOLIA ENVIRONNEMENT	Utilities	FR
ATOS	Technology	FR	ANDRITZ	Industrials	AT	RWE	Utilities	DE
UNITED INTERNET	Technology	DE	SCHNEIDER ELECTRIC	Industrials	FR	SNAM RETE GAS	Utilities	IT
ILIAD	Technology	FR	DEUTSCHE POST	Industrials	DE	FORTUM	Utilities	FI
INGENICO	Technology	FR	SAFRAN	Industrials	FR	EDP ENERGIAS DE PORTUGAL	Utilities	PT
SCOUT24	Technology	DE	AMADEUS IT GROUP	Industrials	ES	RED ELECTRICA	Utilities	ES
GEMALTO	Technology	NL	LEGRAND	Industrials	FR	GAS NATURAL SDG	Utilities	ES
ALTRAN TECHNOLOGIES	Technology	FR	KONE B	Industrials	FI	TERNA	Utilities	IT
SILTRONIC	Technology	DE	WIRECARD	Industrials	DE	ENDESA	Utilities	ES
SOPRA STERIA GROUP	Technology	FR	ATLANTIA	Industrials	IT	EDF	Utilities	FR
ASM INTERNATIONAL	Technology	NL	ABERTIS INFRAESTRUCTURAS	Industrials	ES	ENAGAS	Utilities	ES
BE SEMICONDUCTOR	Technology	NL	THALES	Industrials	FR	UNIPER	Utilities	DE
SOFTWARE	Technology	DE	AENA SME	Industrials	ES	ENEL	Utilities	IT
DEUTSCHE TELEKOM	Telecommunications	DE	THYSSENKRUPP	Industrials	DE	ENEL	Utilities	IT
TELEFONICA	Telecommunications	ES	CNH Industrial NV	Industrials	IT	ITALGAS	Utilities	IT
ORANGE	Telecommunications	FR	WARTSILA	Industrials	FI	RUBIS	Utilities	FR
TELECOM ITALIA	Telecommunications	IT	MTU AERO ENGINES	Industrials	DE	INNOGY	Utilities	DE
KPN	Telecommunications	NL	SMURFIT KAPPA GRP	Industrials	IE	SUEZ ENVIRONNEMENT	Utilities	FR
ELISA CORPORATION	Telecommunications	FI	TELEPERFORMANCE	Industrials	FR	A2A	Utilities	IT
ALTICE NV A	Telecommunications	NL	AIRBUS	Industrials	FR	ACCOR	Travel & Leisure	FR
PROXIMUS	Telecommunications	BE	EURAZEO	Industrials	FR	RYANAIR	Travel & Leisure	IE
CELLNEX TELECOM	Telecommunications	ES	METSO	Industrials	FI	SODEXO	Travel & Leisure	FR
FREENET	Telecommunications	DE	FRAPORT	Industrials	DE	PADDY POWER BETFAIR	Travel & Leisure	IE
1&1 Drillisch	Telecommunications	DE	VOPAK	Industrials	NL	LUFTHANSA	Travel & Leisure	DE
TELEFONICA DEUTSCHLAND	Telecommunications	DE	PHILIPS LIGHTING NV	Industrials	NL	AIR FRANCE-KLM	Travel & Leisure	FR
ORANGE	Telecommunications	FR	GRENKE N	Industrials	DE	ELIOR GROUP	Travel & Leisure	FR
TELECOM ITALIA	Telecommunications	IT	KONECRANES	Industrials	FI			
KPN	Telecommunications	NL	SPIE	Industrials	FR			
ELISA CORPORATION	Telecommunications	FI	DUERR	Industrials	DE			
ALTICE NV A	Telecommunications	NL	BPOST SA	Industrials	BE			
PROXIMUS	Telecommunications	BE	ALLIANZ	Insurance	DE			
CELLNEX TELECOM	Telecommunications	ES	AXA	Insurance	FR			
FREENET	Telecommunications	DE	MUENCHENER RUECK	Insurance	DE			
1&1 Drillisch	Telecommunications	DE	ASSICURAZIONI GENERALI	Insurance	IT			
TELEFONICA DEUTSCHLAND	Telecommunications	DE	SAMPO	Insurance	FI			
UNIBAIL-RODAMCO	Real Estate	FR	NN GROUP	Insurance	NL			
Vonovia SE	Real Estate	DE	AEGON	Insurance	NL			
DEUTSCHE WOHNEN	Real Estate	DE	AGEAS	Insurance	BE			
GECINA	Real Estate	FR	SCOR	Insurance	FR			
KLEPIERRE	Real Estate	FR	ASR NEDERLAND NV	Insurance	NL			
LEG IMMOBILIEN	Real Estate	DE	POSTE ITALIANE	Insurance	IT			
MERLIN PROPERTIES SOCIMI	Real Estate	ES	CNP ASSURANCES	Insurance	FR			
AROUNDTOWN (FRA)	Real Estate	DE	MAPFRE	Insurance	ES			
BUWOG	Real Estate	AT	HANNOVER RUECK	Insurance	DE			
FONCIERE DES REGIONS	Real Estate	FR						

Appendix 2: on the relation between unconditional 1%-VaR and 1%-CoVaR.



Appendix 3 Unconditional Greeks estimates

Sectors	α_i 1%-VaR	β_i 1%-VaR	α_i 50%-VaR	β_i 50%-VaR
Automobiles & Parts	-0.0244***	0.332*	-0.000193	0.518***
Banks	-0.0203***	0.532***	0.000191	0.551***
Basic Resources	-0.0222***	0.547***	-0.0000583	0.466***
Chemicals	-0.0183***	0.744***	-0.000174*	0.711***
Construction & Materials	-0.0199***	0.759***	-0.0000125	0.653***
Financial Services	-0.0175***	0.752***	-0.0000651	0.716***
Food & Beverage	-0.0227***	0.917***	-0.000143	0.844***
Health Care	-0.0235***	0.784***	-0.0000292	0.698***
Industrials	-0.0163***	0.811***	-0.000215*	0.748***
Insurance	-0.0156***	0.584***	-0.0000261	0.588***
Media	-0.0211***	0.731***	0.000141	0.731***
Oil & Gas	-0.0182***	0.675***	-0.0000605	0.681***
P&H Goods	-0.0177***	0.859***	-0.0000786	0.736***
Real Estate	-0.0287***	0.750***	-0.0000524	0.609***
Retail	-0.0204***	0.849***	0.0000258	0.785***
Technology	-0.0216***	0.560***	0.0000431	0.536***
Telecommunications	-0.0233***	0.743***	0.000446***	0.688***
Travel & Leisure	-0.0210***	0.766***	-0.000106	0.634***
Utilities	-0.0227***	0.646***	0.0000897	0.540***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. These estimates correspond to the obtained estimates of equation (5) in the methodology part.

Appendix 4 Unconditional VaR, CoVaR and ΔCoVaR estimates

Sectors	50%-VaR	1%-VaR	1%-CoVaR	50%-CoVaR	ΔCoVaR
Automobiles & Parts	0.000324	-0.0497***	-.04087972	-.00002572	-.01660458
Banks	0.000277	-0.0610***	-.05274275	.00034394	-.03261042
Basic Resources	0.000487	-0.0573***	-.05349472	.00016851	-.03160585
Chemicals	0.000715***	-0.0423***	-.04984986	.00033389	-.03204323
Construction & Materials	0.000523**	-0.0462***	-.05489049	.00032894	-.03542171
Financial Services	0.000626**	-0.0439***	-.05050628	.00038298	-.03350909
Food & Beverage	0.000442**	-0.0328***	-.05279016	.00023079	-.03050569
Health Care	0.000458*	-0.0371***	-.05261022	.00029051	-.02945899
Industrials	0.000456	-0.0418***	-.0502116	.00012522	-.03424809
Insurance	0.000389	-0.0608***	-.05117721	.00020282	-.03575836
Media	0.000136	-0.0396***	-.05007141	.00024016	-.0290404
Oil & Gas	0.000597*	-0.0460***	-.04921435	.00034643	-.03144112
P&H Goods	0.000561**	-0.0390***	-.05120613	.00033414	-.03401303
Real Estate	0.000692***	-0.0393***	-.05819117	.00036892	-.02999244
Retail	0.000000	-0.0394***	-.05386677	.00002583	-.03345677
Technology	0.000516*	-0.0539***	-.05174717	.00032011	-.03044259
Telecommunications	0.000000	-0.0385***	-.05189982	.00044572	-.02862233
Travel & Leisure	0.000569**	-0.0412***	-.05252146	.00025468	-.03198339
Utilities	0.000685***	-0.0438***	-.05098058	.00045995	-.02873388
Index	.0004447**	-0,0384***			

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. These estimates correspond to the obtained estimates of the left hand part of the equations in the equations (2), (6) and (7) of the methodology part.

Appendix 5 Conditional 50%-VaR estimated coefficients

Sectors	$\widehat{\gamma 1}_{50\%}^{index\ \vert i}$	$\widehat{\gamma 2}_{50\%}^{index\ \vert i}$	$\widehat{\gamma 3}_{50\%}^{index\ \vert i}$	$\widehat{\gamma 4}_{1\%}^{index\ \vert i}$	$\alpha_0^{index\ \vert i}$
Automobiles & Parts	-0.000126	1.023***	-0.00556	-0.00663	0.000246
Banks	-0.000169	1.125***	-0.00388	0.00363	-0.000424***
Basic Resources	-0.000749***	1.079***	0.00520	-0.00750	0.000421
Chemicals	-0.000143	0.895***	0.00502	-0.00126	0.000355*
Construction & Materials	-0.000430**	0.956***	0.00373	-0.00172	0.000280*
Financial Services	-0.000674***	0.816***	0.00594	-0.00724	0.000290
Food & Beverage	-0.000395**	0.569***	0.00178	-0.00236	0.000485***
Health Care	-0.0000982	0.675***	0.00438	-0.0147*	0.000216
Industrials	-0.000597***	0.897***	-0.000882	-0.00625	0.000349*
Insurance	-0.0000745	1.148***	0.000297	0.000477	0.0000467
Media	-0.000437***	0.717***	0.00289	-0.00297	-0.0000329
Oil & Gas	-0.000448**	0.886***	-0.00642	-0.00307	0.000113
P&H Goods	-0.000183	0.840***	0.00175	-0.00421	0.000216
Real Estate	-0.000733**	0.578***	0.00307	-0.0184*	0.000113
Retail	-0.000382***	0.716***	0.00594	-0.00330	-0.000201
Technology	-0.000602***	0.877***	0.00747*	-0.00985	0.000256
Telecommunications	0.000121	0.774***	0.000482	0.00233	-0.000334*
Travel & Leisure	-0.000560***	0.710***	0.00810	-0.00432	0.000058
Utilities	0.0000508	0.821***	0.00100	0.00532	0.000169
Index	-0.000267***	0.814***	0.00253	-.0039799	0.000615

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. These estimates correspond to the obtained estimates of equation (12) in the methodology part. As explain in point 5.2.2 of the Methodology, $\widehat{\gamma 1}$ is the estimated coefficient for the variable Volatility, $\widehat{\gamma 2}$ is the estimated coefficient for the variable Eurostoxx50, $\widehat{\gamma 3}$ to credit spread and $\widehat{\gamma 4}$ to liquidity spread.

Appendix 6 Conditional 1%-VaR estimated coefficients

Sectors	$\widehat{\gamma 1}_{1\%}^{index\ \mid i}$	$\widehat{\gamma 2}_{1\%}^{index\ \mid i}$	$\widehat{\gamma 3}_{1\%}^{index\ \mid i}$	$\widehat{\gamma 4}_{1\%}^{index\ \mid i}$	$\alpha_0^{index\ \mid i}$
Automobiles & Parts	0.000535	0.721***	-0.000830	-0.0518	-0.0327***
Banks	-0.000504	1.143***	-0.0235	-0.00302	-0.0252***
Basic Resources	-0.000674	1.262***	0.0450	-0.0703**	-0.0336***
Chemicals	-0.00102	0.828***	-0.00261	-0.00835	-0.0188***
Construction & Materials	-0.000833*	1.043***	0.0267***	-0.0333**	-0.0193***
Financial Services	-0.000467	0.940***	0.0168	-0.00137	-0.0204***
Food & Beverage	0.000236	0.618***	-0.0150	-0.0244	-0.0215***
Health Care	-0.000228	0.503***	0.000709	-0.0237	-0.0279***
Industrials	-0.00101	0.914***	0.0213*	-0.0355***	-0.0186***
Insurance	0.0000314	1.380***	0.0234	0.0104	-0.0219***
Media	-0.000165	0.766***	0.00639	0.0102	-0.0186***
Oil & Gas	-0.000696	0.884***	-0.0160	-0.00985	-0.0223***
P&H Goods	-0.000347	0.807***	0.0226*	-0.00569	-0.0167***
Real Estate	-0.000658	0.669***	0.0246	-0.0192	-0.0297***
Retail	0.00000409	0.626***	-0.00955	-0.0463	-0.0203***
Technology	0.000329	0.835***	0.0176	-0.0696***	-0.0267***
Telecommunications	0.000301	0.681***	0.00633	-0.0122	-0.0199***
Travel & Leisure	-0.00138*	0.780***	0.0244	-0.0124	-0.0246***
Utilities	-0.000318	0.896***	-0.0297	-0.0160*	-0.0261***
Index	-0 .000367***	0.779***	0.00752	-0.01402	-0.0003

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. These estimates correspond to the obtained estimates of equation (12) in the methodology part. As explain in point 5.2.2 of the Methodology, $\widehat{\gamma 1}$ is the estimated coefficient for the variable Volatility, $\widehat{\gamma 2}$ is the estimated coefficient for the variable Eurostoxx50, $\widehat{\gamma 3}$ to credit spread and $\widehat{\gamma 4}$ to liquidity spread.

Appendix 7 50%-CoVaR estimated coefficients

Sectors	$\widehat{\gamma 1}_{50\%}^{index\ \|i}$	$\widehat{\gamma 2}_{50\%}^{index\ \|i}$	$\widehat{\gamma 3}_{50\%}^{index\ \|i}$	$\widehat{\gamma 4}_{50\%}^{index\ \|i}$	$\boldsymbol{\beta}_{50\%}^{index\ \|i}$	$\alpha_0^{index\ \|i}$
Automobiles & Parts	-0.00030***	0.801***	0.00245	-0.00319	0.000136**	0.0124
Banks	-0.00032***	0.883***	0.00120	-0.00302	0.000125*	-0.0558***
Basic Resources	-0.00022***	0.756***	0.00219	-0.00257	0.000107*	0.0586***
Chemicals	-0.00027***	0.762***	0.00183	-0.00183	0.000103	0.0567***
Construction & Materials	-0.00021**	0.738***	0.00337	-0.00238	0.000119	0.0813***
Financial Services	-0.00022**	0.748***	0.00227	-0.00311	0.000118	0.0830***
Food & Beverage	-0.00024***	0.765***	0.00255	-0.00433	0.000123*	0.0815***
Health Care	-0.00024***	0.784***	0.00148	-0.00228	0.000152*	0.0420***
Industrials	-0.00018*	0.687***	0.00217	-0.00118	0.000133*	0.143***
Insurance	-0.00028***	0.840***	0.00298	-0.00392	0.000138**	-0.0212*
Media	-0.00024***	0.776***	0.00304	-0.00393	0.000120*	0.0484***
Oil & Gas	-0.00024***	0.750***	0.00243	-0.00355	0.0000976	0.0774***
P&H Goods	-0.00025***	0.742***	0.00301	-0.00245	0.000139*	0.0866***
Real Estate	-0.00023***	0.786***	0.00236	-0.00242	0.000104	0.0561***
Retail	-0.00025***	0.782***	0.00344	-0.00378	0.000145**	0.0486***
Technology	-0.00025***	0.798***	0.00215	-0.00313	0.000104	0.0184*
Telecommunications	-0.00028***	0.829***	0.00223	-0.00374	0.000136*	-0.0179
Travel & Leisure	-0.00027***	0.774***	0.00292	-0.00221	0.000123	0.0611***
Utilities	-0.00029***	0.844***	0.00265	-0.00300	0.000161**	-0.0400***
Index	-0.00030***	0.801***	0.00245	-0.00319	0.000136**	0.0124

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. These estimates correspond to the obtained estimates of equation (14) in the methodology part. As explain in point 5.2.2 of the Methodology, $\widehat{\gamma 1}$ is the estimated coefficient for the variable Volatility, $\widehat{\gamma 2}$ is the estimated coefficient for the variable Eurostoxx50, $\widehat{\gamma 3}$ to credit spread and $\widehat{\gamma 4}$ to liquidity spread.

Appendix 8 1%-CoVaR estimated coefficients

Sectors	$\widehat{\gamma 1}_{1\%}^{index\ \mid i}$	$\widehat{\gamma 2}_{1\%}^{index\ \mid i}$	$\widehat{\gamma 3}_{1\%}^{index\ \mid i}$	$\widehat{\gamma 4}_{1\%}^{index\ \mid i}$	$\boldsymbol{\beta}_{1\%}^{index\ \mid i}$	$\alpha_0^{index\ \mid i}$
Automobiles & Parts	-0.00038***	0.818***	0.00847	-0.0129	-0.0087***	0.0511*
Banks	-0.00031***	0.938***	0.00319	-0.0120	-0.0088***	-0.113**
Basic Resources	-0.00028***	0.713***	0.000885	-0.0107	-0.0083***	0.0802***
Chemicals	-0.00035***	0.774***	0.00886	-0.0163	-0.0088***	0.119
Construction & Materials	-0.00033***	0.771***	0.00414	-0.0149	-0.0091***	0.108**
Financial Services	-0.00027***	0.724***	0.00363	-0.00960	-0.0081***	0.0924**
Food & Beverage	-0.00024***	0.715***	0.00195	-0.0116	-0.0080***	0.143***
Health Care	-0.00032***	0.787***	0.00941	-0.0141	-0.0087***	0.0584
Industrials	-0.00029***	0.682***	0.000884	-0.00586	-0.0082***	0.233***
Insurance	-0.00033***	0.816***	0.00841	-0.0131	-0.0087***	0.0108
Media	-0.00034***	0.768***	0.00878*	-0.0121	-0.0088***	0.144***
Oil & Gas	-0.00027***	0.656***	0.0107**	-0.0146	-0.0080***	0.109**
P&H Goods	-0.00028***	0.662***	0.00453	-0.0108	-0.0088***	0.155**
Real Estate	-0.00031***	0.739***	0.00608	-0.0120	-0.0081***	0.116***
Retail	-0.00032***	0.763***	0.00875*	-0.0155	-0.0086***	0.133**
Technology	-0.00031***	0.769***	0.00784	-0.0150	-0.0088***	0.0671**
Telecommunications	-0.00028***	0.887***	0.0105	-0.0183	-0.0087***	-0.0575
Travel & Leisure	-0.00032***	0.728***	0.000896	-0.0163*	-0.0083***	0.152***
Utilities	-0.00032***	0.935***	0.00306	-0.0203*	-0.0086***	-0.124***
Index	-0.00038***	0.818***	0.00847	-0.0129	-0.0087***	0.0511*

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. These estimates correspond to the obtained estimates of equation (14) in the methodology part. As explain in point 5.2.2 of the Methodology, $\widehat{\gamma 1}$ is the estimated coefficient for the variable Volatility, $\widehat{\gamma 2}$ is the estimated coefficient for the variable Eurostoxx50, $\widehat{\gamma 3}$ to credit spread and $\widehat{\gamma 4}$ to liquidity spread.

Appendix 9 Conditional average VaR, CoVaR and ΔCoVaR

Sectors	50% VaR	1% VaR	50% CoVAR	1% CoVaR	ΔCoVaR
Automobiles & Parts	-0.00083863	-0.03801116	-0.02707289	-0.0005544	0.00113008
Banks	-0.00031384	-0.04416814	-0.03688228	-0.00055786	-0.05060609
Basic Resources	-0.00075784	-0.04653682	-0.03599777	-0.00033162	-0.00668104
Chemicals	-0.00077159	-0.03100276	-0.03602926	-0.00038747	-0.0150637
Construction & Materials	-0.00074611	-0.03672789	-0.03596141	-0.00054404	-0.01947955
Financial Services	-0.00103284	-0.03419558	-0.03656131	-0.00074927	-0.01757939
Food & Beverage	-0.00074206	-0.02616842	-0.03632883	-0.00057254	-0.01508201
Health Care	-0.00061022	-0.02977235	-0.03512781	-0.00064989	-0.05320088
Industrials	-0.00103324	-0.03219073	-0.0339301	-0.00053108	-0.03775322
Insurance	-0.00076117	-0.04352396	-0.0366978	-0.00069126	-0.03336433
Media	-0.00001106	-0.02867013	-0.03653766	-0.00032611	-0.01230322
Oil & Gas	-0.00054566	-0.03449403	-0.03448944	-0.00056948	-0.02843226
P&H Goods	-0.00068748	-0.02668229	-0.0363774	-0.00044801	-0.02312491
Real Estate	-0.00088669	-0.03708651	-0.03814521	-0.00063526	-0.03354219
Retail	-0.00013294	-0.02733098	-0.0367605	-0.00035923	-0.02255601
Technology	-0.00093103	-0.03536517	-0.0353162	-0.00052467	-0.05055068
Telecommunications	-0.00001724	-0.02598728	-0.03526985	-0.00053505	-0.05454803
Travel & Leisure	-0.00034333	-0.03161349	-0.03893548	-0.00038778	-0.01316978
Utilities	-0.00064776	-0.03713067	-0.03530767	-0.00050174	-0.04975777
Index	-0.00083863	-0.03801116	-0.02707289	-0.0005544	0.00113008

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. These estimates correspond to the obtained estimates of the left hand part of the equations in the equations (12), (14) and (15) of the methodology part.

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