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Measuring Systemic Risk in France

An application of CoVaR

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Abstract

Systemic risk measures have been proposed by several authors. Adrian and Brunnermeier (2011) have introduced a new methodology in measuring spillover effects and systemic risk contributions of institutions through the measure of Conditional Value at Risk. According to their work, the institution's contribution to systemic risk is defined by ΔCoVaR which represents the difference between CoVaR conditional on the institution being under distress and the CoVaR in the median state of the institution. Quantile regression was used in estimating VaR, CoVaR.

The purpose of this thesis is to apply Adrian and Brunnermeier (2011) methodology in order to quantify the contribution of firms listed in the CAC 40 Index, on the systemic risk in France. EuroStoxx 50 Index has been added to the analysis in order to quantify eventual interconnectedness between the French stock market and the European financial system.

Keywords: Systemic Risk, VaR, CoVaR, quantile regression

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Introduction

Nowadays, it is very hard to find a situation in which one exceptional event happens for some economic agents without having any impact on other economic agents, especially in the financial sector. The subprime crisis, the collapse of Lehman Brothers and discovering the high deficit of Greece are the most notable exemples of these events which happened in the financial world and have made disastrous repercussions on number of economies which find itself with a high level of unemployment and week or even negative growth rate.

Mondialisation has made the financial sector a very important place in the global economy. Thus, with the free exchange of assets and workers worldwide, states, companies and people from all over the world are living in total dependance with each others. And when a problem happens and affects an important economy, it is usually common to be extended to other economies, which reflect the importance of contagion between financials entities.

The most relevant exemple is the investment bank Lehman Brothers. Due to its high exposition to derivatives related to subprimes, it has led to its collapse in September 15^{th}, 2008. Many financial institutions have invested in assets linked to Lehman Brothers and thus have endorsed huge losses. This collapse has made as a consequence, a crisis of trust among banks which could not take the risk to lend money between each others. This situation has made investments and consumption decreasing. Therefore, problems related to Lehman Brothers have been spread to the real economy as a whole.

These facts have made crucial for regulators to take adequate measures in order to prevent the collapse of the financial system, which can be defined as the systemic risk. To do so, regulators need sustainable masures in order to quantify this risk and to identify the level of contagion among financial institutions. One of these measures, which has been used for a long time, is the Value at Risk (VaR). This measure has demonstrated its weakness as a measure of risk, especially during the last financial crisis. It has became obvious that risk analysts should not only rely on it given the fact that it takes into account only the risk of the firm or institution, independently from the financial system and without taking consideration about the contagion between financial institutions.

In this context, Adrian and Brunnermeier (2011) have developed a new measure of risk which can be applied to quantify systemic risk. It is the Conditional Value at Risk (CoVaR) which represents intuitively the Value at Risk of a financial system conditionally on the fact that a financial institution is being at its VaR level. They have also defined the ΔCoVaR as the difference between the VaR of the financial system, conditionally to the facts that a financial institution is being in distress and that this same institution is being on its normal financial situation. Thus, the ΔCoVaR enable to capture the marginal contribution of a particular institution on the systemic risk as a whole.

In this thesis, we will use Adrian and Brunnermeier (2011)'s CoVaR methodology in order to quantify the institutions' spillover effects and systemic risk contribution in one of the most important European stock market which is the French stock market.

Thus, the purpose of this thesis is to analyse the impact of each firm as listed in the CAC 40 Index on the French financial system, by identifying sectors and companies which contributes the most and the less on systemic risk.

We have also included the Eurostoxx50 Index in our research, which reflects the European financial market. By applying the same methodology, as if it was a single institution, and thus seeing any possible linkages with the French stock market and an eventual contribution on systemic risk in France.

In other words, using Adrian and Brunnermeier (2011)'s methodology we will try to answer the following question:

- Which are the companies (and sectors) who contribute the most (and the less) to the systemic risk in France?

- Does the European financial system contribute to the systemic risk in France?

This report is devided in two parts. The first one represents the theoretical framework in which we will make a revue of the literature on systemic risk by defining at a first time the systemic risk, then presenting the most notable measures of systemic risk found in the literature and last but not the least, introduce some researches and works in which the authors have used Adrian and Brunnermeier (2011)'s methodology as well as presenting the main results they have found.

In the second part, an empirical application will be made using Adrian and Brunnermeier (2011)'s methodology to identify spillover effects and systemic risk contribution in the

French stock market. This part is divided on three sections. In the first and second section, a data presentation and the principal descriptive characteristics will be emphasized. In the second one, we will present the estimations results of firms and sectors' contribution to the systemic risk in France.

Chapter 1

Theoretical Framework

1.1 Systemic Risk

After the recent financial crisis, the subject of prevention and management of systemic risk has became vital. The concept of systemic risk is not new, but the analysis of systemic risk related to the behavior of financial institutions was limited to academic studies so far, with no real measures taken in financial regulation. The magnitude of the consequences of the subprime crisis on the financial system and on the economy as a whole, has relocated systemic risk at the top of international works on financial regulation.

But what is systemic risk? A simple definition refers to the risk of an entire financial system to collapse. Although there is no completely unique definition of systemic risk.

Murphy (2012) refers systemic risk to *"the possibility that the financial system as a whole might become unstable, rather than the health of individual market participants"*.

Bandt and Hartmann (2000) define systemic risk as *"the consequence of a systemic crisis which affects negatively and significantly a considerable number of financial companies and financial markets, which results in the collapse of the whole of the financial system"*.

Kaufman and Scott (2003) have specified systemic risk as *"the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, and is evidenced by co-movements (correlation) among most or all the parts"*.

In the absence of a widely accepted academic definition, a common definition of systemic risk would be a disruption in the functioning of financial services which is caused by the deterioration of all or part of the financial system by giving a negative impact on the real economy.

Systemic risk can also be understood through the notion of negative externalities. We talk about negative externalities to describe a situation in which the activity of an economic agent has a negative impact on the situation of another agent, without bearing the caused damage sudden to him.

For the financial sector, systemic risk would therefore correspond to the cost actually generated by a systemic crisis on the financial sector and supported by the real economy. The concept has also a meaning within the financial sector itself since the bankruptcy of a financial institution, beyond the direct impact it has on shareholders and creditors, may weaken other financial institutions because of its interconnections. Thus, the entire financial system and the real economy are likely to be affected by the materialization of a risk taken by one institution. It is therefore appropriate to identify the part of financial systemic risks that threaten the whole community and generate costs that are not assumed by agents causing these risks.

The identification of systemic risk requires a deep analysis on the activities of the entire financial sector. In the absence of a criterion that can distinguish between financial institutions with a high level of systemic risk contribution and financial institutions that are less risky. Systemic risk can not be identified only from a detailed analysis of business and financial strategies. We can not exclude any category of financial actors in the analysis of systemic risk, otherwise they will not be apprehended properly.

1.2 Literature on systemic risk measures

In the literature, various measures of systemic risk have been proposed and are based on information on financial markets. This part aims to list the most important works on measuring systemic risk with a brief explanation.

The first instrument of systemic risk measurement is based on the "Credit Default Swaps" (CDS). These are financial instruments that provide insurance against the risk of a counter-party default, which may be a company or a country. Usually, a principal component analysis on CDS spreads is performed and the first principal component is often considered as the source of systemic risk since it represents the common factor influencing CDS spreads.

Then, the LIBOR-OIS spreads rates (difference between interbank rate and the rate and the "Overnight Index Swap") reflect the liquidity risk and default risk in the next coming months.

The third group of systemic risk measures is based on the work of Lehar (2005). it suggest to take into account the probability of default of a certain percentage of banks since it is directly linked to the value of assets and bank debt. Other authors have used "collateralized debt obligations" (CDOs) to estimate systemic risk.

Other methods was found in the literature including the work of Lahmann and Kaserer (2011), who have proposed another systemic risk measure, the Systemic Expected Shortfall (SES) as the product of the probability of a systemic default event and the expected tail loss in case this systemic risks occurs. According to their work, they have found that SES indicator reacts to the financial crisis events with global importance and that the results for the regional sub-samples also capture appropriately the specific regional financial market events.

Achraya et al. (2010) have applied this methodology in measuring financial institutions' contribution to systemic risk. They have demonstrated empirically the ability of SES to predict emerging risks during the financial crisis of 2007-2009, particularly the outcome stress tests performed by regulators, the decline in equity valuations of large financial firms during the crisis and the widening of their credit default swap spreads. They have also proposed the marginal expected shortfall (MES) as a measure of banks contribution to systemic risk. Banks with higher MES are the ones that contribute the most to the market decline, hence they are more likely to be systemically risky.

Brownlees and Engle (2011) have investigated times series dynamics of MES by applying T-GARCH models. They conclude that institution higher volatility and less diversification to the market (given by a higher MES) contributes much more on systemic risk.

Billio et al. (2012), on their work on measuring connectedness and systemic risk, have used principal components analysis and Granger-causality networks. They justify the use of these econometric measures because of the broad view of connections among all groups of financial institution the PCA provides and the ability of the Granger-causality networks to capture the intricate web of pairwise statistical relations among individual firms in Finance and Insurances industry.

A a result of their work, they have shown that these indirect measures are capable of detecting periods of dislocation and distress and also have out of samples characteristics.

They have also emphasized the fact that ACP and Granger-causality networks have the ability to capture specific facets of financial and insurance sectors, which was demonstrated by empirical results who have suggested that the banking and insurance sectors may be an important source of connectedness.

They also underlined that the illiquidity of bank and insurance assets being coupled with the fact that banks and insurers are not designed to withstand rapid and large losses would make these sectors a natural repository for systemic risk.

Finally, Adrian and Brunnermeier (2011) have proposed a new method to measure systemic risk, the Conditional Value at Risk (CoVaR) which focuses on how an individual bank contributes to systemic risk.

The CoVaR (Conditional Value at risk) corresponds to the VaR (Value at Risk) of the market returns obtained given the effect of a specific event on the firm's returns. In this methodology, the contribution of the institution to systemic risk is defined by Δ CoVaR, as the difference between its CoVaR and the CoVaR calculated in the median state.

This new measure is the topic of an entire section in the next chapter, and will be the basis of the empirical study of this work.

1.3 Researches on systemic risk contribution using CoVaR methodology

Motivated by the growing importance of systemic risk in the global banking system, several researches have been made on systemic risk measures using Adrian and Brunnermeier (2011)'s methodology, and have demonstrated how it is an important and a helpful tool in examining risk spillover and systemic risk contributions of different entities.

Roengpitya and Rungchaoenkitkul (2010) used the concept of conditional Value at Risk to quantify risk and financial linkages among six major Thai commercial banks over the period of 1996Q2 - 2009Q1. They have found that larger banks contribute more to systemic risk in Asia. They have demonstrated that there was additional risk imposed onto the overall system by individuals banks, both during the Asian crisis time and in subsequent periods. They have also applied the concept to measure financial linkages over time as well as other bank characteristics that drive such inter-bank relationship. As a conclusion of their work, they emphasized the utility of this methodology for regulators.

Conversely, Lopez-Espinoza et al. (2012) in their work on identifying the main factors behind systemic risk in a set of international major banks using CoVaR approach, they have found no evidence that a larger size increases systemic risk within the class of large global banks. They have emphasized that short-term wholesale funding is a determinant key in triggering systemic risk episodes by emerging as the most relevant systemic factor. These results support the Basel Committee's proposal to introduce a net stable funding ratio, penalizing excessive exposure to liquidity risk.

Borri et al. (2012) studied the systemic risk contribution of 223 European listed banks during the period 1999-2010 using CoVaR methodology. As a result, they analyse the systemic risk spillovers from European banks to the rest of the world, and from the rest of the world to European banks, that are likely to be relevant. In their analysis, the systemic event of Lehman Brothers failure shows up only indirectly, through its negative effects on European banks. In the sample of European banks, they have found that Δ CoVaR may be a very useful policy tool, by helping on evaluating which are the bank characteristics more relevant in terms of contribution to systemic risk. First, they have found that Δ CoVaR is highly persistent: risky banks tend to stay risky. Second, they emphasized the fact that recent policy debate has focused on the danger posed by large banks and on the need to curb their size. Thus, the size is indeed a predictor of a bank contribution to systemic risk, but it is not the only one.

Another relevant conclusion of their work is that banks having their headquarters in countries with a more concentrated banking system, tend to contribute more to European wide systemic risk even after controlling for their size. Therefore, any financial regulation designed only to curb banks size would not completely eliminate systemic risk. According to them, on average, balance sheet variables are very weak predictor of banks' contribution to systemic risk, if compared to market based variables.

Girardi and Ergün (2013) have modified Adrian and Brunnermeier (2011)'s methodology of CoVaR by changing the definition of financial distress from institution being exactly at its VaR to being at most at its VaR. this change allows them to consider more severe distress events, to backtest CoVaR and to improve its consistency (monotocity) with respect to the dependance parameter. They have estimated the systemic risk contributions of four financial industry groups consisting of a large number of institutions for a sample period between June 2000 to february 2008 and the 12 months prior the begging of the crisis.

Among the relevant results they have found is that calculations show depository institutions were the largest contributors to systemic risk, followed by broker-dealers, insurance companies, and non-depository institutions. The results concluded about the depository institutions were in line with Billio et al. (2012) who have found that banks may be more central to systemic risk than other financial industry groups.

Finally, into this same work and by using 12 months of data prior to the beginning of June 2007, they have also computed industry groups' pre-crisis Δ CoVaR. They have noticed that Systemic risk of all industry groups increased substantially prior to the crisis.

1.4 Methodology

1.4.1 Quantile regression

Let's consider a regular linear regression

$$y_i = x_i'\beta + \epsilon_i, \tag{1.1}$$

the unbiased estimation of β requires that $\mathrm{E}(\epsilon_i|x_i) = 0$, without any other specific hypothesis regarding the distribution of ϵ_i.

A quantile regression model is similar to the linear regression model. It has the specificity for adding the possibility for each predefined quantile τ of the endogenous variable to be estimated. Thus, for the τ^{th} quantile, we have now the following regression model:

$$y_i = x_i'\beta_\tau + \epsilon_i, \tag{1.2}$$

where parameters to be estimated are $\beta_\tau' = (\beta_{0_\tau}, \cdots, \beta_{k_\tau})$.

A more coherent definition of this regression requires $\mathrm{E}(\epsilon_i|x_i) = 0$, but the τ^{th} quantile of the ϵ distribution is equal to zero. If $f_\tau(.)$ is the density of ϵ, we have:

$$\int_{-\infty}^{0} f_\tau(\epsilon_i|x)d\epsilon_i = \tau. \tag{1.3}$$

The quantile estimation for β_τ, $\hat{\beta}_\tau$ proposed by Koenker and Bassett (1978) do not consider a specific distribution for ϵ. It is simply obtained as the solution of the following minimization problem:

$$\min_\beta \frac{1}{N}\sum_{i=1}^{n} \rho_\tau(y_i - x_i'\beta_\tau), \tag{1.4}$$

where $\rho_\tau(.)$ is the loss function defined by:

$$\rho_\tau(u) = u \times (\tau - \mathbb{1}(u < 0)), \tag{1.5}$$

Usual quantile regression represents some disadvantages in the calculation of standard errors and their interpretations. Firpo et al. (2009) have introduced non conditional quantile regression who correct this inconvenience. It's based on the influence function of Hampel (1974).

The influence function (IF) discribes the influence of an infinitesimal variation in the distribution of a sample on a real-valued statistic $\nu(F)$, where F is a cumulative distribution function. The influence function IF of the statistic ν is defined by:

$$IF(y, \nu, F) = \lim_{\varepsilon \to 0} \frac{\nu(F_{\varepsilon,\Delta_y}) - \nu(F)}{\varepsilon} = \frac{\partial \nu(F_{\varepsilon,\Delta_y})}{\partial \varepsilon}|_{\varepsilon=0} \tag{1.6}$$

where $F_{\varepsilon,\Delta_y} = (1-\varepsilon)F + \varepsilon\Delta_y$ is a mixture model with a perturbation equal to Δ_y that puts 1 on any point y.

Firpo et al. (2009) have used the influence function by considering the distributional statistics $\nu(.)$ as being the quantile function ($\nu(F) = q_\tau$) in order to find how a marginal quantile of y can be modified by a small change in the distribution of the covariables. For this reason, they consider the Recentered Influence Function (RIF), defined as the original statistic plus the IF so that the expectation of RIF is equal to the original statistic.

Let's consider τ^{th} quantile q_τ implicitly defined as $\tau = \int_{-\infty}^{q_\tau} dF(y)$, Firpo et al. (2009) have demonstrated that the IF for the quantile distribution of y is given by:

$$IF(y, q_\tau(y), F) = \frac{\tau - \mathbb{1}(y \leq q_\tau)}{f(q_\tau)},$$

where $f(q_\tau)$ s the density value of y evaluated to the point q_τ. The corresponding RIF is simply defined by:

$$RIF(y, q_\tau, F) = q_\tau + \frac{\tau - \mathbb{1}(y \leq q_\tau)}{f(q_\tau)}, \tag{1.7}$$

with the propriety that

$$\mathrm{E}\left(RIF(y, q_\tau, F)\right) = \int RIF(y, q_\tau, F) f(y) dy = q_\tau.$$

The original idea of Firpo et al. (2009) consists on regressing the RIF on covariates, so that a change in the marginal quantile q_τ will be explained by a change in the distribution of covariates using a simple linear regression:

$$\mathrm{E}[RIF(y, q_\tau, F|X)] = X\beta. \tag{1.8}$$

Thus, the estimator of $\hat{\beta}_\tau$ by a simple OLS regression is as follows:

$$\hat{\beta}_\tau = \left(X'X\right)^{-1} X'\widehat{RIF}(y; q_\tau, F). \tag{1.9}$$

The only practical problem to solve is that the RIF depends on the marginal density of y Firpo et al. (2009) have suggested to use a kernel estimator for density and the sample quantile for q_τ such that an estimator of the RIF for each observation is given by:

$$\widehat{RIF}(y_i; q_\tau, F) = \hat{q}_\tau + \frac{\tau - \mathbb{1}(y_i \leq \hat{q}_\tau)}{\hat{f}(\hat{q}_\tau)}.$$

The standard deviations are then simply the standard deviations given by the regression.

1.4.2 Value At Risk (VaR)

According to Jorion (2006) , VaR measures the worst expected loss over a given horizon under normal market conditions at a given level of confidence. For instance, a bank might say that the daily VaR of its trading portfolio is \$1 million at the 99 percent confidence level. In other words, under normal market conditions, only one percent of the time, the daily loss will exceed \$1 million. (Jorion (2006))

More formally, VaR describes the quantile of the projected distribution of gains and losses over the target horizon. Thus, the q% VaR is the "minimum large loss" that occurs only q% of the time, or the loss that is not exceeded (1-q)% of the time. Mathematically, the q-percent VaR can be defined as the number that satisfies:

$$Pr(X \leq VaR_q) = q \tag{1.10}$$

1.4.3 Conditional Value at Risk (CoVaR)

Tobias Adrian from the New York central bank and Markus Brunnermeir from Princeton University, have developed a new measure for determining both the systemic risk and the risk of the market. This measure is called the conditional value at risk, or CoVaR, and was introduced for the first time in 2009. This section will be based on the latest version of the paper developed by Adrian and Brunnermeier (2011) and will enable us to introduce the concept of CoVaR and define with more details the methodology and the model used for this measurement.

First of all, the CoVaR is part of a logic which affirms that it is increasingly important to take into account the contagion when we are dealing with measuring the market risk for a financial institution or a sector. Indeed, during stable periods, the comovements of financial institutions' assets and liabilities depend on their basics, whereas during most volatile period, these co-movements increase significantly between financial institutions. In this environment, the classical Value-at-Risk is not able to reflect systemic risk since it focuses only on the risk of a single institution (Kihoon 2010).

Then, Adrian and Brunnermeier (2011) defined the CoVaR of the "system" as the VaR of the entire financial sector conditionally to the fact that a single financial institution is in distress. The difference between the VaR conditionally that a single institution is in distress and the VaR conditionally the normal state of that institution is referred as ΔCoVaR. This measure captures the marginal contribution of a particular institution to the overall systemic risk. The two authors define systemic risk as a situation in which a financial institution is facing serious problems, which could result in the emergence of contagion to other financial institutions and a reduction in supply of credit and capital available to the rest of the economy.

There are several benefits from using ΔCoVaR measure. First, it focuses on the contribution of each institution to overall systemic risk while the current financial regulation only takes into account the risk faced by individual institutions, which can lead them to take excessive risks. To illustrate this point, imagine two institutions, A and B, which have the same VaR but the institution A publishes a ΔCoVaR equal to 0, whereas B publishes a ΔCoVaR greater than 0. If we rely only on the measure of VaR, we can conclude that both institutions have the same risk. But by taking into account the ΔCoVaR, the institution B is more risky since it contributes more to the systemic risk than A.

Second, ΔCoVaR allows to study "spillovers risk" among all the financial network. For example, $\Delta \text{CoVaR}^{j|i}$ captures the increased risk of an institution j when an institution i falls in distress. This increase, in addition of being causal, is also due to the effects of excessive risk that the institution i caused on the institution j.

A third advantage of the ΔCoVaR is the fact that it is easily extensible. It means that we can use a measure of Value-at-Risk (like CoVaR) but also other risk measures as the "expected shortfall" (ES), which captures the expected loss over the quantile α %. It is therefore possible to extend this approach to other risk measures, such as the "Co-Expected Shortfall" (Co-ES).

Finally, Adrian and Brunnermeier (2011) have only focused on the contribution that a financial institution adds to systemic risk. Whereas, it is entirely possible to measure the exposure of a company to the fact that the entire financial system (or another financial institution) is in distress. The purpose of this chapter is to present the methodology and the estimation of CoVaR, before making an empirical study which represents the second part of this thesis.

Methodology of estimating CoVaR and ΔCoVaR

Generally speaking, the CoVaR$_q^{j|i}$ is defined as the VaR of an institution j (or the financial system as a whole) conditionally to an event C(X^i) of an institution i. For the rest of this dissertation, conditional event takes into account the fact that X^i=VaR$_q^i$, which means that the CoVaR$_q^{j|i}$ is the VaR of an institution (or system) j conditional on an institution being in its VaR level. This allows to study the spillover effects on the entire financial system.

CoVaR is implicitly defined by the α-quantile of the conditional probability distribution:

$$Pr(X^j \leq CoVaR_q^{j|C(X^i)} \mid C(X^i)) = q \tag{1.11}$$

The contribution of the VaR of the institution i to the VaR of the institution (or system) j is defined as follows:

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=Var_q^i} - CoVaR_q^{j|X^i=Median^i} \tag{1.12}$$

Δ CoVaR$_q^{j|X^i}$ is defined as the difference between VaR of a j institution conditionally on a situation of panic in another institution i and the VaR of the same institution j related to the median state of the institution i. This measure, Δ CoVaR$_q^{j|i}$, therefore allows to quantify the effect of an institution i on institution j.

The j institution can also be the financial system as a whole. Adrian and Brunnermeier (2011) have defined it as a portfolio of 1,269 financial institutions. Consequently, they consider that the financial system is under disstress when all these financial institutions are at their VaR level.

From this definition, it is therefore possible to derive other measures such as the CoVaR$^{j \mid system}$. This measure is used to determine the VaR of an institution j when a financial crisis happens and therefore by comparing several financial institutions, to know the one which presents a greater risk in a crisis situation. Then Δ CoVaR$_q^{j|i}$ measures the increase in the VaR of an institution during a j financial crisis.

As explained by Adrian and Brunnermeier (2011), they estimate the CoVaR using quantile regression. According to them, this method is efficient to estimate CoVaR.

According to their work, the predicted value of a particular quantile (estimated using quantile regression) of the financial system, $\hat{X}_j^{system,i}$, conditional on an institution i can be defined as follows:

$$\widehat{X}_q^{system,i} = \hat{\alpha}_q^i + \hat{\beta}_q^i \ X^i \tag{1.13}$$

Considering the definition of Value at Risk, we can therefore deduce from the above equation as follows:

$$\widehat{VaR}_q^{system}|X^i = \hat{X}_j^{system,i} \tag{1.14}$$

This means that the predicted value of the quantile of the financial system distribution returns conditional on an institution i is equal to the VaR of the financial system conditional on X^i, since VaR_q with a given X^i is just the conditional quantile.

After that, a predicted value of a given quantile as X_i equals to the VaR^i. This means that the institution i will be on its VaR level. More formally, the CoVaR measurement can be deduced and is given by:

$$\widehat{CoVaR}_q^{system|X^i=Var_q^i} = \widehat{VaR}_q^{system}|VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i\ VaR_q^i \tag{1.15}$$

When CoVaR is calculated at the level of 1%, the VaR corresponding to the median level (50%) needs to be done in order to quantify the impact of an institution i (or sector index) on the financial system. Therefore, the $\Delta CoVaR_q^i$ being estimated can be deduced quite easily:

$$\Delta\widehat{CoVaR}_q^{system|i} = \hat{\beta}_i^i(VaR_q^i - VaR_{50\%}^i) \tag{1.16}$$

Chapter 2

Empirical application

In the second part of this thesis, Adrian and Brunnermeier (2011)'s methodology will by applied on the companies which are listed on the CAC 40 Index. The purpose is to quantify spillover effects and systemic risk contribution of these institutions on the systemic risk in France.

In the first and second section, the data as well as its corresponding descriptive characteristics will be presented. The estimation results of systemic risk contributions, given by the measures of VaR, CoVaR and ΔCoVaR, will be presented and discussed in the third section.

2.1 Data

In this empirical estimation, stock market data were used. They corresponds on daily closing prices of 39 firms's stocks as listed in the CAC 40 Index. Also, values of the index itself as well as those of the EuroStoxx 50 Index were collected from Bloomberg, for the period from December 1st 2005 to May 5th 2015. The stock corresponding to the company "Unibail-Rodamco SE" was not taken into account, due to missing values during the corresponding time of the study.

Firm and index data has been transformed to percentage returns.

In order to have wide and consistent analyses on the firms' contribution to systemic risk in the French market, the estimations and analysis are made in the basis of sectors. Each sector is constructed as a portfolio of n assets where n represents the number of firms which belong to each specific sector.

The classification of the French firms listed in CAC 40 by sectors was made according to the ICB (Industrial Classification Benchmark) which is an industry classification taxonomy launched by Dow Jones and FTSE in 2005. It is commonly used to segregate markets by a number of 10 sectors and therefore partitioned into many subsectors.

The following table indicates the number of companies classified on each sector.

The firms listed on the CAC 40 Index can be found in appendix 1.

TABLE 2.1: Classification of companies listed in CAC 40 by sector

	Sector	**Number of companies**
1	Consumer Goods	8
2	Consumer Services	4
3	Industrials	10
4	Utilities	3
5	Financials	4
6	Technology	1
7	Oil and Gaz	2
8	Health Care	2
9	Basic Materials	2
10	Telecommunications	2

2.2 Summary statistics

As explained in the previous section, daily closing stock prices of 39 stocks listed in the CAC 40 index are used in this empirical application during the period from December 2005 to May 2015.

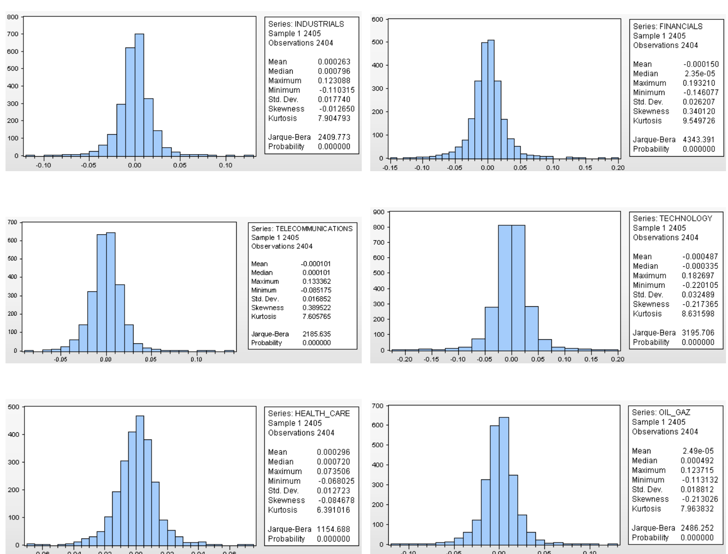
A summary statistics summarizing descriptive data characteristics of each sector are presented in the following table.

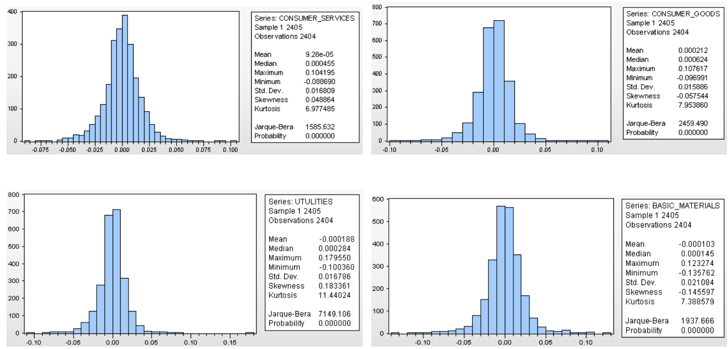
TABLE 2.2: Summary statistics of sector returns

Sector	Mean	St. Dev	Max	Min	Kurtosis	Skewness
Consumer Goods	0.00022	0.01588	0.10762	-0.09699	-0.05755	7.95387
Consumer Services	0.00009	0.01680	0.10419	-0.08868	0.04887	6.97748
Industrials	0.00027	0.01774	0.12307	-0.11031	-0.01264	7.90479
Utilities	-0.00019	0.01679	0.17956	-0.10042	0.18337	11.44025
Financials	-0.00015	0.02621	0.19322	-0.14608	0.34013	9.54973
Technology	-0.00049	0.03249	0.18269	-0.22011	-0.21737	8.63159
Oil and Gaz	0.00003	0.01882	0.12372	-0.11314	-0.21303	7.96384
Health Care	0.00029	0.01273	0.07351	-0.06803	-0.08468	6.39102
Basic Materials	-0.00011	0.02109	0.12328	-0.13577	-0.14559	7.38858
Telecommunications	-0.00011	0.01686	0.13337	-0.08518	0.38953	7.60577

According to the summary statistics of each sector, we can notice that Health care sector presents the largest return with 0.029%, followed by Industrial sector with 0.027%. The smallest return is observed for the Technology sector with -0.049%. We can also have a first indication from the above results of risk's degree of each sector given by the standard deviation which represents a measure of financial risk on itself. Therefore, we can notice that the Technology and Financial sectors present highest volatility with 3,249% and 2,621 % respectively.

Finally, according to the values given by the kurtosis and skewness, we can assume that sector returns are not normally distributed given that these two measures are different from 3 and 0 respectively. Jarque-Bera tests confirms the non normality of the sectors' Data with a $p - value < 5\%$, as presented in the following figures:





2.3 Estimation results

In this section, we are going to present the estimation results of VaR, CoVaR and ΔCoVaR corresponding to each sector as well as the CAC 40 Index and the EuroStoxx 50 Index.

The following figure represents the Values at Risk. As explained in the methodology part, the 5%VaR was estimated using a quantile regression. We can conclude given the results that the Technology and the Financials sectors are the two sectors that have the highest 5% VaR whereas Health care present the lowest Value at Risk being -0.02. Which means that this sector or a portfolio constructed from firms from this sector can loose at the most 2 with a 95% confidence level.

Another interesting result from estimating VaR for the two Indexes is that their corresponding VaR is almost the same. That could be explained by the strong interconnectedness between these two indexes, especially given that 17 from the largest and most liquid institutions which are listed in the CAC 40 are present among those listed in the Eurstoxx 50.

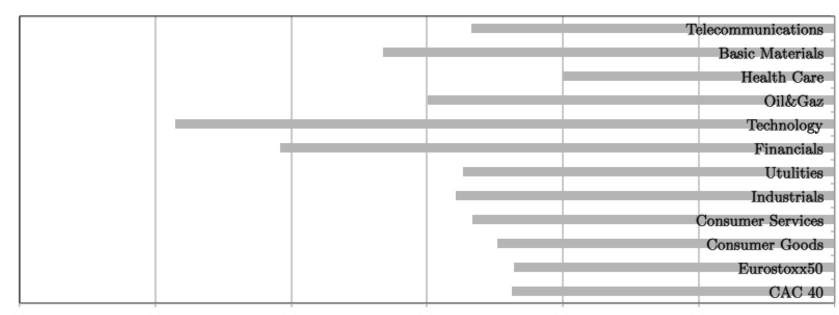


Figure 2.1: 5% VaR by sector (2005.12-2015.05)

In the next figure, a presentation of both 5% VaR and 5% CoVaR are presented for each sector and index. As explained before, the CoVaR was estimated also using a quantile regression with a dependent variable which is the CAC 40 Index returns with a constant and the sector returns. Consequently, the CoVaR quantifies the maximum loss incurred by the French market when a sector (or an index) is being on its 5% VaR. Therefore, high values of CoVaR in this graph would reflect spillover effects on the French stock market. So by observing only 5% CoVaR in isolation, we can identify what sectors have the highest spillover effects on the French stock market.

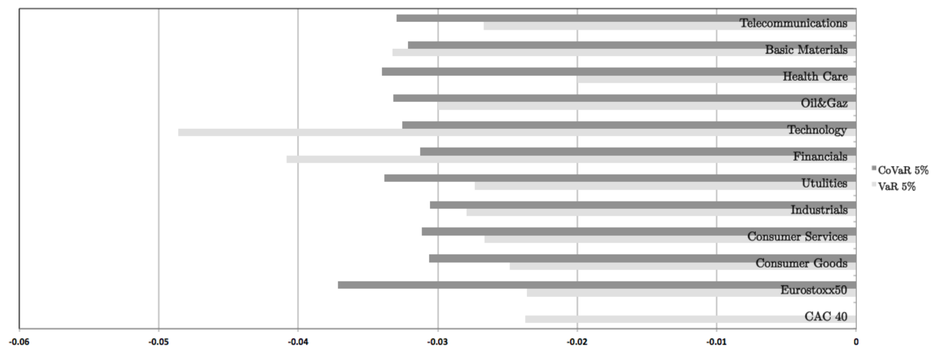


FIGURE 2.2: 5% VaR and 5% CoVaR by sector (2005.12-2015.05)

However, as demonstrated by the figure 2.2 we can notice that there are no 5% CoVaR spikes in isolation. As a conclusion, we can say that the spillover effects to the French stock market seems to be balanced between all sectors, and so we can conclude that there is no particular sector which represent by itself a major risk to the French market.

What we can also notice from figure 2.2 is that those sectors having lowest individual VaRs are not those who, at the same time, are characterized by lowest CoVaRs. So, even though a sector experiences a large VaR (in absolute value), which is a bad thing, this risk does not seem to spill over to the same extent, which is the case for Financials and Technology.

The opposite is also true, by taking the example of the health care sector which represent the larger 5% VaR value and one the lowest 5% CoVaR value. It means that even if the health care sector seems to be the most non risky sector on the French Market, its contribution to the systemic risk in this market seems to be relevant.

To summarize, as opposed to a sector's risk in isolation and as measured by 5% VaR, the 5% CoVaR risk measure is larger than 5% VaR in 7 out of 10 sectors. This indicates that interconnectedness and linkages do have a role.

Another proof of the high interconnection in the financial system, in a global dimension, is the high level of CoVaR corresponding to the returns of companies from the European Index which can be noticed from the same figure. It appears that the returns of the 50 most liquid and largest firms in Europe has the most important spillover effect on the French market. A fact which is understandable given the weight of the the French companies which are listed in the same index.

Figure 2.3 below illustrates each sector's marginal risk contribution to overall systemic risk of the French stock market. As before, the names on the right-hand side indicate the independent variable of a quantile regression where French system returns is the dependent variable. To recapitulate, marginal systemic risk contribution, as measured by ΔCoVaR, was calculated as the difference between 1%-CoVaR and 50%-CoVaR.

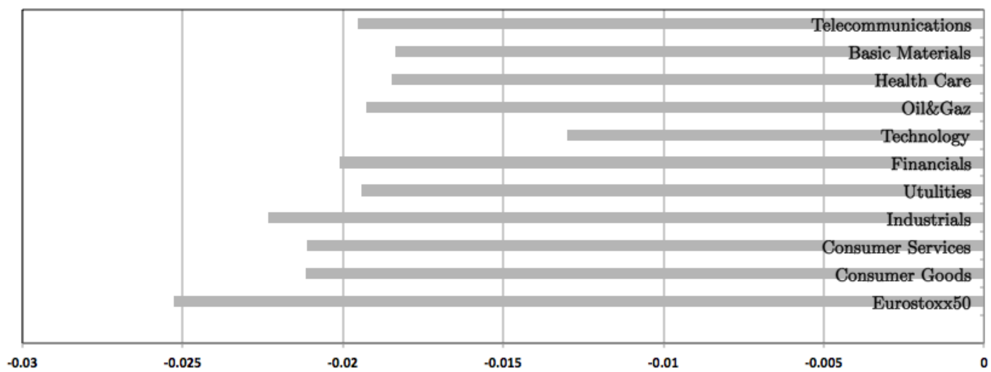


FIGURE 2.3: 5% ΔCoVaR by sector (2005.12-2015.05)

ΔCoVaR appears to be the largest for the EuroStoxx 50 variable. In practice, this means, not unexpectedly, that the European Companies which are listed in the EuroStoxx 50 contributes the most to over all systemic risk on the French stock market.

Taking a closer look at which particular sectors in the French stock market that contribute most to French systemic risk, we find Industrials, Customer services and Customer goods. The sectors contributing the least are Technology, Basic materials and Health care.

ΔCoVaR measures how much an institution's transition, from being at median state (at 50% VaR) and then going into financial distress (5%VaR), contributes to the VaR of the French stock market.

Figure 2.4 below illustrates 5% VaR and ΔCoVaR, i.e. we can observe the riskiness of a firm in isolation versus its marginal contribution to overall systemic risk.

Given these results, it appears that VaR is probably not sufficient when it comes to measuring and managing risk. Infact, we can notice that in all the cases spillover effects as measured by CoVaR, are lower than risk as measured by VaR with a significant difference in some of the cases (Basic materials, Oil & Gaz and especially for Financials and Technology). Nevertheless, the good thing according to these results is that when a firm is in a situation of risk in isolation, that could have a smaller contribution to overall systemic risk, at least for the case of the French market.

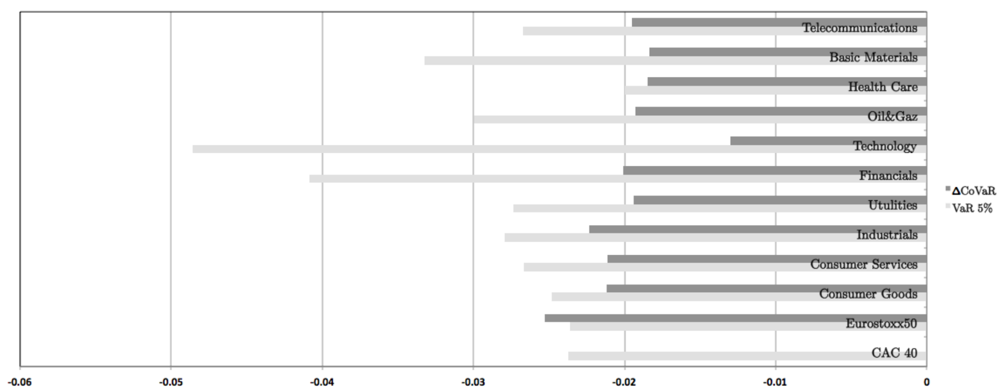


Figure 2.4: 5% VaR and 5% ΔCoVaR by sector (2005.12-2015.05)

Conclusion

In this thesis, we have used a measure of systemic risk which are CoVaR in order to evaluate the impact of different sectors (and individual institutions) on systemic risk in France. Therefore, we wanted to determine the marginal contribution of a particular sector (or institution) on systemic risk.

The demonstrated results we have found for the period between 2005 and 2015, have shown that the European financial sector was the one who is contributing the most to systemic risk in France. This result was expected given the strong interconnection between these two entities and especially by knowing that French companies which are listed in the EuroStoxx 50 Index represents a weight of almost 35%. An interesting way to expend this work would be to use the same methodology in order to mesure the contribution of the firms which are listed in the EuroStoxx50 on the systemic risk in Europe. A significant contribution of the French companies would be very expected given the interconnectedness which has been demonstrated in this work.

Conversely to similar researches which has concluded that the financial sector is the one which present the most significant contribution in systemic risk, we have found that Industrials, Customer goods and Customer services sectors are those which contribute the most in the systemic risk in France.

Another way to expend this work would be by adding additional macro variables to the stock returns for estimating CoVar. This methodology was also presented by Adrian and Brunnermeier (2011) as a second way in order to estimate systemic risk contribution by taking into account variables which are presumed to explain stock returns as business cycle or investor sentiment..

Appendices

Appendix 1

List of firms listed in the CAC 40.

Unibail-Rodamco SE is not included due to missing Data.

	Firm	Sector
1	L'Oreal SA	Consumer Goods
2	Vinci SA	Industrials
3	Alcatel-Lucent	Technology
4	TOTAL SA	Oil and Gaz
5	Air Liquide SA	Industrials
6	AXA SA	Financials
7	BNP Paribas SA	Financials
8	Danone SA	Consumer Goods
9	Cap Gemini SA	Industrials
10	Carrefour SA	Consumer services
11	Accor SA	Consumer services
12	Cie de Saint-Gobain	Industrials
13	Vivendi SA	Consumer services
14	Essilor International SA	Health care
15	LVMH SE	Consumer Goods
16	Michelin	Consumer Goods
17	Kering	Consumer Goods
18	Lafarge SA	Industrials
19	Peugeot SA	Consumer Goods
20	Publicis Groupe SA	Consumer services
21	Renault SA	Consumer Goods
22	Safran SA	Industrials
23	Valeo SA	Industrials
24	Solvay SA	Basic Materials
25	Technip SA	Oil and Gaz

	Firm	Sector
26	GDF Suez	Utulities
27	Electricite de France SA	Utulities
28	Orange SA	Telecommunications
30	ArcelorMittal	Basic Materials
31	Bouygues SA	Telecommunications
32	Alstom SA	Industrials
33	Veolia Environnement SA	Utulities
34	Sanofi	Health care
35	Societe Generale SA	Financials
36	Schneider Electric SE	Industrials
37	Airbus Group NV	Industrials
38	Credit Agricole SA	Financials
39	Pernod Ricard SA	Consumer Goods
30	ArcelorMittal	Basic Materials
31	Bouygues SA	Telecommunications
32	Alstom SA	Industrials
33	Veolia Environnement SA	Utulities
34	Sanofi	Health care
35	Societe Generale SA	Financials
36	Schneider Electric SE	Industrials
37	Airbus Group NV	Industrials
38	Credit Agricole SA	Financials
39	Pernod Ricard SA	Consumer Goods

Appendix 2

VaR 5% and VaR 50% estimations of firms listed in the CAC 40.

Firm	**VaR 5%**	**VaR 50%**
Pernod Ricard SA	-0.024035***	0.00024
L'Oreal SA	-0.023628**	0.000386
Danone SA	-0.022647***	0
LVMH SE	-0.029305***	0.000363
Michelin	-0.037784***	0.000638
Kering	-0.040174***	0
Renault SA	-0.041993***	0.000422
Peugeot SA	-0.045577**	0
Carrefour SA	-0.02962***	-0.000139
Accor SA	-0.033668***	0
Vivendi SA	-0.026079**	0.000339
Publicis Groupe SA	-0.026907***	0.000644
Safran SA	-0.033344***	0.000543
Valeo SA	-0.038588***	0.000293
Vinci SA	-0.031718***	0.000292
Schneider Electric SE	-0.04622***	0.000564
Airbus Group NV	-0.037785***	0.000779
Cap Gemini SA	-0.034599***	0.000482
Cie de Saint-Gobain	-0.037413***	-0.000295
Air Liquide SA	-0.022843***	0.000335
Lafarge SA	-0.037621***	0.000263
Alstom SA	-0.040099***	-0.00018
GDF Suez	-0.028659***	0
Electricite de France SA	-0.030259***	0.0003
Veolia Environnement SA	-0.035254***	0.00049
AXA SA	-0.03967**	0.000379
BNP Paribas SA	-0.040174***	0
Societe Generale SA	-0.04622***	0
Credit Agricole SA	-0.046697***	-0.000429
Alcatel-Lucent	-0.048575***	-0.000334
TOTAL SA	-0.02538***	0.00051
Technip SA	-0.039459***	0.000239
Essilor International SA	-0.020712**	0.000614
Sanofi	-0.025385**	0.000527
Solvay SA	-0.029942***	0
ArcelorMittal	-0.043594***	0.000207
Orange SA	-0.025864***	0
Bouygues SA	-0.034113***	-0.000253
Eurostoxx50	-0.023624***	0.000146

Appendix 3

CoVaR 5% and ΔCoVaR 50% estimations of firms listed in the CAC 40.

Firm	α	β	**CoVaR**	**ΔCoVaR**
Pernod Ricard SA	-0.014836***	0.391908***	-0.024255509	-0.009513567
L'Oreal SA	-0.016***	0.727***	-0.033177556	-0.017458178
Danone SA	-0.018591***	0.679422***	-0.03397787	-0.01538687
LVMH SE	0.014098***	0.665084***	-0.005392287	-0.019731712
Michelin	-0.015838***	0.476377***	-0.033837429	-0.018303357
Kering	-0.023697***	0.531562***	-0.037866972	-0.021354972
Renault SA	-0.015895***	0.40431***	-0.03287319	-0.017148809
Peugeot SA	-0.01777***	0.330873***	-0.032850199	-0.015080199
Carrefour SA	-0.017235***	0.568706***	-0.034080072	-0.016766022
Accor SA	-0.01628***	0.509829***	-0.033444923	-0.017164923
Vivendi SA	-0.016293***	0.663882***	-0.033606379	-0.017538435
Publicis Groupe SA	-0.018952***	0.624256***	-0.035748856	-0.017198877
Safran SA	-0.019***	0.377443***	-0.031585459	-0.012790411
Valeo SA	-0.017205***	0.398394***	-0.032578228	-0.015489957
Vinci SA	-0.01268***	0.572117***	-0.030826407	-0.018313465
Schneider Electric SE	-0.013024***	0.561132***	-0.038959521	-0.026251999
Airbus Group NV	-0.019045***	0.381916***	-0.033475696	-0.014728209
Cap Gemini SA	-0.017382***	0.45042***	-0.032966082	-0.015801184
Cie de Saint-Gobain	-0.012876***	0.514937***	-0.032141338	-0.019113432
Air Liquide SA	-0.013773***	0.829281***	-0.032716266	-0.019221075
Lafarge SA	-0.014593***	0.491694***	-0.03309102	-0.018627335
Alstom SA	-0.016938***	0.438575***	-0.034524419	-0.017507475
GDF Suez	0.016171***	0.563347***	2.60383E-05	-0.016144962
Electricite de France SA	-0.018937***	0.492796***	-0.033848514	-0.015059353
Veolia Environnement SA	-0.0174***	0.478662***	-0.03427475	-0.017109295
AXA SA	-0.012913***	0.466683***	-0.031426315	-0.018690187
BNP Paribas SA	-0.013063***	0.440164***	-0.030746149	-0.017683149
Societe Generale SA	-0.014535***	0.37104***	-0.031684469	-0.017149469
Credit Agricole SA	-0.014836***	0.391908***	-0.033136928	-0.018132799
Alcatel-Lucent	-0.019458***	0.269586***	-0.03255314	-0.013005098
TOTAL SA	-0.013233***	0.747524***	-0.032205159	-0.019353396
Technip SA	-0.018235***	0.400467***	-0.034037027	-0.015897739
Essilor International SA	-0.019397***	0.617866***	-0.032194241	-0.01317661
Sanofi	-0.017001***	0.66559***	-0.033897002	-0.017246768
Solvay SA	-0.018073***	0.482683***	-0.032525494	-0.014452494
ArcelorMittal	-0.015403***	0.391683***	-0.032478029	-0.017156107
Orange SA	-0.017588***	0.561125***	-0.032100937	-0.014512937
Bouygues SA	-0.015642***	0.459858***	-0.031329136	-0.015570792
Eurostoxx50	-0.024293***	0.145864***	-0.03716018	-0.02526035

Appendix 4

VaR 5%, CoVaR 5% and ΔCoVaR 5% estimations of sectors.

Sector	VaR	VaR	**CoVaR**	**ΔCoVaR**
Consumer Goods	-0.033142	0.00025612	-0.029278876	-0.016747208
Consumer Services	-0.029068	0.000211	-0.034220057	-0.017167064
Utulities	-0.031390667	0.000263	-0.022699075	-0.016104536
Industrials	-0.036023	0.000307	-0.033286444	-0.017784454
Financials	-0.04319025	-0.0000125	-0.031748465	-0.017913901
Technology	-0.048575	-0.000334	-0.03255314	-0.013005098
Oil & Gaz	-0.0324195	0.000374	-0.033121093	-0.017625568
Health Care	-0.0230485	0.000571	-0.033045621	-0.015211689
Basic materials	-0.036768	0.0001035	-0.032501762	-0.015804301
Telecommunications	-0.029988	-0.0001265	-0.031715036	-0.015041864

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