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Systemic Risk in Different Sectors of the European Economy: A CoVaR Approach

Abstract

This thesis investigates the presence of systemic risk in eight different sectors of the European economy. By using the Conditional Value at Risk (*CoVaR*) approach to measure systemic risk, it is shown that systemic risk is present in the sectors. Systemic risk has increased for six out of the eight sectors examined in the most recent financial crisis, excluding the technology and telecom sector. These sectors however, show systemic risk after the internet bubble burst. The analysis shows that systemic risk in real sectors of the economy does not have the same size and build-up as the financial sector. Only the utilities sector shows the same systemic risk movement as the financial sector, although in higher magnitude. Furthermore, the results show that there is co-movement between systemic risk in six of the eight sectors examined and systemic risk in the financial sector, excluding the technology and telecom sectors.

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1. Introduction

The global economy has become more and more interconnected and interdependent the last decades. The high interdependency of the financial markets became very clear during the recent international financial crisis. This crisis has shown that the supervision at that point was not accurate enough to prevent the failure of the financial system, resulting in a crisis in the global economy. This risk of failure of many financial institutions as a reaction on the failure of one single financial institution through the interconnectedness of this sector is referred to as systemic risk (Martínez-Jaramillo et al., 2010). To prevent harm to the real economy the need for a good measure of systemic risk is not only of academic importance, but also could help regulators consider how to reduce the risk and costs of a systemic crisis (Acharya, 2016). Acharya (2016) also argues that the existing financial regulation does not consider systemic risk sufficiently to prevent harm to the real economy from happening.

Most studies in this research area are done on the presence of systemic risk in the financial sector. This thesis adds to the existing literature an investigation on the presence and development of systemic risk in other sectors next to the financial sector in the years before and after the most recent periods of economic downturns. This is related to the work of Muns and Bijlsma (2011), however in this thesis more sectors are investigated. Additionally, as Muns and Bijlsma (2011) focus on the US market, in this thesis I look at the European economy.

Adrian and Brunnermeier (2011) mention the build-up of systemic risk in the background in periods of economic expansion and low risk, pointing at the increase in interconnection of the companies. Secondly, they state that systemic risk is realized in times of economic recessions, indicating that the increased dependence among companies leads to spillovers of losses in recessionary periods. They refer to this build-up in booming times and realization in periods of worsened economic circumstances as the "volatility paradox" (Adrian & Brunnermeier, 2011). If a negative economic shock occurs, the damage of spill-overs of other sectors has most likely less direct impact on the real economy than the financial industry (Muns & Bijlsma, 2011). Therefore, this research investigates whether systemic risk is not only strongly existent within the financial sector, but also in other large sectors of the European economy. Following on this, my research question is;

Does systemic risk in the real sectors of the European economy show the same size and build-up as the financial sector and is there a spill-over of real sector systemic risk to systemic risk in the financial sector in the period of 1 January 1998 till 31 December 2016?

Questions that will help getting an insight in the development of systemic risk and answering my research question are:

- *What is the amount of systemic risk in the real sectors of the European economy?*
  Answering this question will help to investigate whether systemic risk in other sectors of the European economy exists and to what extend it is expected to influence the real European economy.
- *Does systemic risk in real sectors show the same build-up as the systemic risk in the financial sector?*
  When elaborating the other sectors, this study will investigate whether the systemic risk build-up follows the same path as the systemic risk build-up of the financial sector.
- *Is there a spill-over of systemic risk in the real sectors to systemic risk in the financial sector?*
  In addition to measure the importance of systemic risk in other sectors, it is studied whether real sectors influence systemic risk in the financial sector.

In this thesis, the daily rate of return of the market value of the total assets of the individual companies for the period 1998-2016 is used to measure their risk. Following the study of Adrian and Brunnermeier (2016), the Value at Risk (VaR) measure is used as the indicator for risk of the individual companies. The Conditional Value at Risk ($CoVaR$), developed by Adrian and Brunnermeier (2016), is used to measure the systemic risk. This method analyzes the returns of the sector at the VaR level, conditional on whether the companies in the sector are at their VaR level. With this measure, the contribution of one company to the systemic risk in the sector can be determined (Adrian and Brunnermeier, 2016). To capture the state of the economy a dummy variable, that measures whether the country where the companies included in the analysis are situated experiences an economic recession or an economic expansion, is added.

There are eight economic sectors examined; the basic materials sector, the oil & gas sector, the health care sector, the personal & household goods sector, the technology sector, the telecommunications sector, the utility sector, and as a comparison the financial sector to see whether there is a same trend in the systemic risk across the financial institutions and institutions within other sectors. The companies examined are all included in the STOXX Europe 600 stock index and situated in Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

This thesis undertakes four different steps to examine the systemic risk in the different sectors of the European economy. In the first step the systemic risk in the sectors is examined. The $CoVaR$ measure reveals that systemic risk is present in all sectors except for the technology and telecom sectors.

Secondly, a state variable, that indicates whether the economy of the country where the company is situated is in a recession, is added to the analysis to see whether systemic risk comes forward, hence increases, in times of financial distress. The results show that systemic risk increases during times of economic recession for all the sectors except for the technology and telecom sector. More specifically, systemic risk starts increasing in the period previous to an economic recession, shows a peak during times of economic recession and then decreases. This results from the third step of this thesis, where is examined whether systemic risk in the different sectors varies annually for the years included in the study.

The increase in systemic risk during the most recent financial crisis holds for all sectors except the basic materials and oil & gas sectors. However, there are ambiguous results for the growth or decline of systemic risk among the different sectors in the other years included in the sample. The telecom and technology sectors show a very large increase in systemic risk in the years after the internet bubble burst. Furthermore, in the years after the financial crisis, systemic risk seems to increase for the financials, health care, telecom and utilities sectors.

Lastly, the co-movement of systemic risk in the different sectors and the financial sector is highlighted. It is shown that the systemic risk in the basic materials, oil & gas, health care, personal & household goods and utilities sector changes in the same direction as the financial sector. All these sectors are positively correlated with the financial sector. The technology and telecom sector show the opposite movement, although not significantly. The significantly positive effects raise the suspicion of spill-over effects from the sectors on systemic risk in the financial sector.

The paper is organized as follows; in section 2 relevant existing literature is reviewed. Section 3 describes the data needed and collected for the analysis and section 4 describes the methodology used to conduct the analysis on systemic risk. Section 5 describes the empirical results. Finally, in section 6 the conclusions are summed up and some points of discussion will be provided, as well as recommendations for future research.

2. Related Literature

In this section, relevant literature on systemic risk is discussed, with a focus on the definition of systemic risk and different systemic risk measures used in previous work.

2.1 Systemic Risk

There is a large amount of research on systemic risk, mostly focused on the existence, development and monitoring of this risk as it can have severe consequences for the financial sector as well as the real economy. Smaga (2014) has studied the concept of systemic risk and the systemic risk in existing literature extensively. The paper concludes that there is no consensus on the precise definition of systemic risk (Smaga, 2014). The core concept of systemic risk is the dependence among all individual (financial) organizations, as well as the interdependence between the financial sector and the economy (Pierret, 2012). Most of the systemic risk definitions in previous (empirical) work highlight that systemic risk has negative spill-over effects on the real economy. Therefore, when studying systemic risk, it is important to consider the effects flowing from macroeconomic conditions (Brownlees and Engle, 2017). This is also mentioned previously in the study of De Bandth and Hartmann (2000)[1]. They already point out that when conducting an empirical analysis on systemic risk, it is important to control for macroeconomic factors that might influence problems that occur to banks simultaneously (De Bandt and Hartmann, 2000). Systemic risk should not be confused with systematic or idiosyncratic risk. Where systematic risk comes from macro-economic factors that affect all stock prices, idiosyncratic risk (i.e. unsystematic risk) includes risk that comes from one asset and can be reduced by portfolio diversification. Systematic risk is build up in times of economic expansion and comes forward in times of economic distress, which is the same for systemic risk.

Systemic risk has a wide scope of features. Systemic risk arises from excessive risk taking of an individually systemic firm or several smaller institutions that are systemic as a herd (Smaga, 2014). De Bandt and Hartmann mention three features that show the strong interconnectedness of the financial sector which can clarify why systemic risk can have a larger impact in the financial sector than other economic sectors. Summed up these features are: the structure of balance sheets of banks, the interdependency and related exposures among financial institutions and the fact that financial contracts are intertemporal and have large credibility risks (De Bandt and Hartmann, 2000). A systemic shock affects the entire financial system simultaneously. Generally, this includes not only financial markets and institutions, as this risk affects the real economy (i.e. the economic growth) as well (Patro, Qi, Sun, 2013).
De Bandt and Hartmann (2000) developed a broad concept of systemic risk, evaluating the existing literature to contribute to understand the basic economic concepts of financial crises. By the time their survey was executed, the paper argued that “a general theoretical paradigm is still missing” (De Bandt and Hartmann, 2000). Furthermore, they mention that the core cause of systemic risk is captured by contagion effects, which can be defined as several forms of externalities and is in line with the finding of Smaga (2014).

[1] By the time of the survey of De Bandt and Hartmann (2000), most empirical studies were limited to analysis on the financial sector in the United States.

2.1.1 Contagion

There are two ways an economic shock can be transferred among companies. The first one is real contagion, which captures the economic exposure companies have towards each other. The second channel is referred to as information contagion. This is the risk that bad news about a certain company may reveal information about companies that are similar or also operate in that economic sector. Systemic risk is the risk of spill-overs through these two channels of contagion, where a shock to one company spills over towards other companies or even the whole sector (Bühler and Prokopczuk, 2007). These transmission mechanisms can change over time or during periods of extreme distress. The change in transition mechanisms is dependent on causality, externalities and spill-over effects (Pierret 2013).

In other words, the approach of systemic risk covers both contagion effects and negative impact on the real economy (Bisias et al., 2012). This short summary of possible definitions and features of systemic risk suggests that only one risk measure is not enough to capture all factors that influence the systemic risk. Bisias et al. (2012) state that the various definitions highlight different aspects of systemic risk, which makes measurement, and therewith regulation, very difficult. They question whether it is desirable to focus on creating one definition, as several aspects may be omitted when doing so. Moreover, they say that the framework for monitoring a stable financial system should cover the diverse perspectives and features of systemic risk (Bisias et al., 2012).

In this thesis, the definition of systemic risk is based on the approach introduced by Martínez-Jaramillo et al. (2010) and is adjusted to be applicable to different sectors next to the financial sector. In this thesis, the interpretation of systemic risk will be the following: systemic risk is the risk of negative externalities to the institutions in a sector if one institution in that sector has excessive losses. These externalities can have severe consequences for all other companies in that sector. These contagion mechanisms are conditional on the dependency and interconnectedness of that sector. This is in line with the definition of Adrian and Brunnermeier (2016) who define systemic risk as "the risk that the capacity of the entire financial system is impaired, with potentially adverse consequences for the real economy".

Spill-overs across institutions can occur directly and indirectly. Directly through companies that have stake in each other's businesses, in other words, have contractual links (Adrian & Brunnermeier, 2011). For the financial sector this direct interconnection is for example through interbank deposits and loans. In addition, as many financial institutions operate internationally this can spread across borders (Kaufmanm & Scott, 2003). Companies in other sectors are directly in contact with each other as they sell and buy each other's products or services. Indirect effects come from the possibility that failure of one company can weaken the market and raise instability in the sector. For example, indirect spill-over effects could arise when one company suffers from bad performance or, for example, a scandal, this might draw a shadow over other companies that operate in the same field (Lori et al., 2006).

2.2 Different Systemic Risk Measures

2.2.1 Two dimensions of systemic risk

There are two dimensions of systemic risk: The cross-sectional dimension and the time-dimension of systemic risk. The cross-sectional dimension of systemic risk shows the structure of the (financial) system and how the system responds to shocks. The time-dimension of systemic risk shows the build-up over time and how this build-up interacts with the macroeconomic business cycle. Caruana (2010) argues that financial fragility and aggregate risk increases in times of economic booms, hence build up, implying that underlying systemic risk is unseen until the financial circumstances worsen. This is where the difficulty lies for policy makers to limit the damage of a shock to the financial system, as the financial system moves pro-cyclical (Caruana, 2010).

2.2.2 How to measure systemic risk?

In the existing literature, systemic risk is defined and measured in various ways. As described by Adrian and Brunnermeier (2011), a measure for systemic risk has two components. First, it should identify the risk of the individual firm, as well as the systemic risk of financial institutions that are highly interconnected and their individual or combined influence on the entire sector. Secondly, their paper argues, in line with Caruana (2010), that systemic risk builds up in times of economic booms, which implies that a systemic risk measure should capture this build-up, as this form of risk does exist during periods of economic expansion (Adrian & Brunnermeier, 2011).

Several studies have investigated whether market-based data can be used to determine and predict the contribution of financial systems towards financial crises. De Bandt & Hartmann (2000) sum up different possibilities to measure risk contagion in securities and currency markets. For example, they find empirical evidence on risk contagion by analyses on, among others, correlation of returns across markets, correlation of stock price movements or co-movement in exchange rate returns. Rodríguez-Moreno and Peña (2012) compare interbank rates, stock prices and credit derivatives as systemic risk measurements. They find that Credit Default Swaps (CDS's) are the best to measure systemic risk in a financial environment. This is explained by the fact that CDS's carry information on individual and joint default probability (Rodríguez-Moreno and Peña, 2012). However, they also argue that there is a variation of mechanisms that can possibly influence systemic risk, which is why it is necessary to have more than one risk measure to capture these various mechanisms.

2.2.3 Stock prices as an indicator for systemic risk

To measure risk of a company, the two widely used firm-level risk measures are: *Value-at-Risk (VaR)* and the *Expected Shortfall (ES). VaR* is the maximum loss of a firm given a certain confidence level and the *ES* is the average of returns that exceed the *VaR* value. These risk measures can both be used for time series and cross-sectional analyses of systemic risk. Yamai and Yoshiba (2002) show that for the same degree of accuracy, the *ES* measure needs a larger sample size than the *VaR*. This is an important property to keep in mind when deciding an appropriate risk measure (Yamai & Yoshiba, 2002).

Measures on tail dependence between an individual organization and the whole sector are, among others, the Conditional Value at Risk (*CoVaR)* of Adrian and Brunnermeier (2011) and the Systemic Expected Shortfall *(SES)* of Acharya et al. (2016). Adrian and Brunnermeier (2011) suggest using *CoVar* as a measure of systemic risk. *CoVar* shows the contribution of each institution to the risk in the system and captures spill-overs to the whole financial network using return losses on market equity to determine the *CoVaR*. They argue that *CoVar* could be used to monitor the build-up of systemic risk by indicating firms that are expected to contribute most to a systemic crisis (based on current firm characteristics). They find that in times of financial instability, extremely high losses tend to spread across financial institutions after the risk has built up in a previous economically booming phase.

The analysis of Acharya et al. (2016) focusses on the capital shortfall of financial firms when the financial sector is undercapitalized, which results in negative externalities to the real economy. The Systemic Expected Shortfall (SES) is defined as the sum of expected losses when in default and the expected contribution to a systemic crisis (Acharya et al. 2016). Thus, they examine the stress of a financial firm conditional on the system's stress and find that market data from equity and CDS's, when using *SES* as a systemic risk measure, can predict the contribution of each financial firm to a systemic crisis (Acharya et al. 2016) [2].

In line with the *CoVaR* and *SES* methods, Brownlees and Engle (2017) introduce another measure of systemic risk, SRISK. This measure captures the capital shortfall of a firm conditional on a severe market decline. The SRISK is a function of the size of the financial firm, the degree of leverage and the expected loss in case of a market decline. The authors argue that the sum of the SRISK is the total amount of capital that the authorities would have to provide in times of crisis, to prevent the economy from collapsing. They conducted an empirical study on the conditional capital shortfall of the largest financial institutions in the United States in the most recent financial crisis. The results of the analysis indicate that an increase in SRISK predicts lower industrial productions and a higher unemployment rate. Again, this research is based on returns, book value of equity and debt and, in addition, market capitalization.

The investigation of systemic risk relates to the field of extreme value theory (EVT)[3] and can also be applied to identify systemic risk. Chan-Lau et al. (2012) use EVT approaches on market data to identify systemic risk and the largest contributors to systemic risk in the (global) financial system. Another study that focusses on financial contagion of the financial sector by examining the extreme stock returns finds that contagion is predictable and is depending on conditional stock return volatility (Bae et al. 2003).

Patro et al. (2013) find that measuring daily stock return correlations among financial institutions is a simple and effective systemic risk indicator. They argue that correlation among stock returns is a necessary requirement for systemic failure. They state that an individual event is unlikely to trigger broad-based disturbance over a relatively short period of time if correlations are low (Patro et al., 2013). Besides that, they argue that the correlation of stock returns can give an insight in bank's individual and aggregate risk[4]. This measurement gives insight in the cross-sectional dimension of systemic risk and investigates how the system is expected to respond to shocks.

Patro et al. (2013) argue that the focus on stock market returns has advantages over other financial risk indicators. In the first place, stock market returns are forward-looking. When high correlation is detected, this could help to prevent systemic failure in the future as it can act as an early warning for systemic crises in the system. Secondly, they state that correlation in stock risk explains variation in asset returns better than fundamental variables do and therefore, stock prices can be an effective indicator of default risk. Lastly, they argue that stock return correlations are simple and robust and are widely available, which makes the chance of measurement error very low (Patro et al., 2013). With the measure of Patro et al. (2013) alone, only the existence of systemic risk is measured, but not the causality or directions of systemic risk.

The study of Patro et al. (2013) lies in the same strand of literature as the study of Huang et al. (2009). The latter assesses the vulnerability of a financial system by estimating the asset return correlations. They also address the advantages of market-based analysis, which are that

[2] In their framework, Acharya et al. (2016) assume the financial system to be affected by a single firm, as the firms take the costs from externalities not into account when deciding on financial risk. Acharya et al. suggest regulators to monitor this, by imposing a tax on the financial firms as large as the costs of the externalities imposed on the real economy by that firm (Acharya et al. 2016).

[3] Extreme Value Theory (EVT) is used in studies where the focus lies on tail behavior in distribution functions, and for that reason provides a better estimation of risk. In addition, EVT is very useful to model for quantiles that are higher than the greatest value in the distribution (Lin, Ko, 2009).

[4] Patro et al. (2013) use three different correlation measures to control for non-linear dependencies between stock returns in their analysis.

the measures are forward looking and the data is available on a daily basis, implying it can be updated easily (Huang, Zhou, & Zhu, 2009).

To get more insight in the systemic risk among investment portfolios, Gualdi et al (2016) study the common asset holding by financial institutions. They study the overlaps within these portfolios and find that these are a potential contagion channel and contribute to systemic risk. Gualdi et al. (2016) propose to address the significance in overlaps between portfolios in an attempt to recognize the overlaps that bear high liquidation risk. However, data necessary for an analysis like this is very difficult to obtain (Gualdi et al., 2016).

2.2.4 Single banks vs. the financial system

The estimation of the risk of the banking system recently received more attention from regulators than only the risk at the level of individual banks. The mentioned portfolio approach can be a good measure to define whether a simultaneous failure of several banks would result in a severe economic crisis (Lehar, 2005). Lehar (2005) argues that correlation between the asset portfolio value of banks is the most important factor that can contribute to systemic risk. When the values of the portfolios are highly correlated, there is a high probability of simultaneous defaults. This is in line with the previously mentioned study of Patro et al. (2013). Secondly, Lehar (2005) states that when banks are sufficiently capitalized they will not experience severe consequences from larger negative shocks. This factor captures the stability of a bank and when aggregated the ability of the banking system to absorb losses. Lastly, when a bank has more volatile assets, the probability of default of the bank will be higher (Lehar, 2005).

2.3 Real Sectors and Systemic Risk

The work discussed in the previous section is evaluating the systemic risk in the financial sector. Existing work on systemic risk in other sectors than the financial sector is limited. However, there is some literature that focusses on the existence of systemic risk in other sectors than the financial sector in the United States and Germany. Muns & Bijlsma (2011) investigate the systemic risk in the United States in the insurance sector, the construction sector and the food sector, and compare this with the systemic risk in the banking sector. They find that the systemic risk in the banking sector is significantly larger compared to the other sectors investigated. The systemic risk of the other sectors is the highest in the insurance sector, followed by the construction sector and it is the lowest in the food sector.

Generally, the banking sector is more fragile than the other sectors. This is due to the maturity mismatch on the balance sheet, which makes them vulnerable to bank runs. Another cause of the fragile banking sector is that contagion can easily spread problems from one bank to another through the large interaction between financial institutions (Muns and Bijlsma, 2011). These findings on the banking sector confirm the previously mentioned systemic risk features of de Bandt and Hartman (2000). When Muns and Bijlsma (2011) correct for the general effects of the economy, only the systemic risk in the financial sector remains significant. This means that the extreme negative returns for the other sectors is caused by the economy as a whole (Muns and Bijlsma, 2011).

Mechanisms that show the dependency among companies in other sectors than the financial sector can be, for example, cooperation in research and development (R&D). Companies use combined R&D to complement internal resources, to strengthen innovation on products and to increase expertise that is only accessible through collaboration (Becker & Dietz, 2004). This means that the risk and costs of innovation will be spread out over the collaborating companies. This is mostly relevant for the basic materials, oil & gas, technology and telecom sector. Albalate et al. (2015) show that, in the transportation sector, high-speed rail lines and airlines benefit from cooperation especially in hub airports as their supply of transport can be complementary for their customers (Albalate et al., 2015).

These cooperation examples for companies in the other sectors than the financial sector are optional mechanisms of direct spill-overs of risk. Simultaneous exposure to the same risk factors in the market can be seen as an indirect potential contagion channel for risk (Allenspach & Monnin, 2009).

The systemic risk indicator of Muns and Bijlsma (2011) is the stock price movement over time, which is used in most of the previously discussed literature. They argue this is an appropriate measure as it contains all publicly available information on individual asset and liability side risk and dependency between the different risks that companies face. Their approach is in line with the *CoVaR* approach, as they measure the expected number of institutions at an abnormal risk level given that at least one institution experiences an extreme event. This thesis follows on the examination of Muns and Bijlsma (2011). However, it distinguishes itself from their work as it is done on more sectors, with more recent and European data and the application of a different methodical approach, namely the *CoVaR* model.

2.3.1 Energy markets and systemic risk

An investigation on the German energy market suggests that the energy market is a sector that has a large impact on the economy (Pierret, 2012). The paper argues that energy markets are highly connected, directly and indirectly, to all other sectors, through the dependence of energy. Pierret (2012) studies the systemic risk in the energy market by using the method of Brownlees and Engle (2011), to see whether the risk of an energy crisis, i.e. rising energy prices, affects the real economy. They do this by measuring the tail dependence between the asset and the energy market factor, as a function of the Marginal Expected Shortfall. In their definition, systemic risk in the energy sector comes from the co-movement of energy prices, together with an economic environment that is continuously more dependent on energy[5] and the fact that there are low available energy reserves (Pierret, 2012). After investigating the impact from several market events in Europe, such as the gas crisis or the BP oil spill etc., the findings show that changes in energy prices highly influence the each other. The results of the paper suggest that when the economy is strongly dependent on energy sources, the systemic risk for the real economy coming from the energy market will increase.

2.3.2 Real estate sector

Allen and Carletti (2013) state that real estate prices play an important role in systemic risk build-up and develop a model that estimates how real estate bubbles can arise. They argue that the real estate sector has the tendency to end up in a bubble of housing prices in times of economic booms. They state that this sector has an agency problem, as there is an inequality in the risk that investors face when borrowing from banks and the real risk that the bank carries resulting from issuing this loan. This results in risk shifting and substitution for assets, which leads to the bubble in real estate prices, which rise faster than the rents paid by normal consumers (Allen and Carletti, 2013).

[5] As demand on energy markets is quite inelastic the author assumes that the real economy strongly depends on prices of energy (Pierret, 2012).

This thesis contributes to existing literature as it not only examines systemic risk in the financial sectors but also includes seven other real sectors. To extend the existing analyses focused on German and US data, the data used in this thesis is from large companies situated in Europe. According to the findings from previously mentioned literature I expect to find the systemic risk to be the highest in the financial sector. I also expect that systemic risk is present in the oil & gas sector, the utilities sector, the basic materials sector and the technology sector, taking previous findings into account. These findings also suggest that the results of this thesis will show that there will be lower or no systemic risk in the personal & household goods sector. Expected results for the health care and telecom sector are difficult to predict as I did not find existing literature that investigates these sectors linking them to systemic risk.

In addition, this thesis looks into the correspondence of the systemic risk build-up between the financial sector and the other seven sectors included in this thesis.

3. Data Description

This section introduces the data used for the analysis conducted in this thesis. It also elaborates on the calculation of the market value of the assets, which is the main research variable used in the estimation of the contribution of the individual companies to systemic risk in the sector. Additionally, the Value at Risk calculation and the descriptive statistics of the data used are discussed.

3.1 Data

The data used for the research on this topic is from publicly traded institutions of the largest economic sectors in the European economy. The period covered is from 1998-2016, as this includes several periods of systemic build-up, as well as crises[6] and the periods where the economy recovered from these financial shocks. The market value of the assets is daily data, as this allows for short time horizon as well as longer time horizon investigation (Patro et al., 2013).

Adrian and Brunnermeier (2016) analyze the *CoVaR* while using the growth rates of market-value total assets, as this is closely related to the supply of credit in the real economy. Data necessary for this analysis is equity data and balance sheet data, to capture the daily equity returns as well as the book and market value of equity and the total debt to capture the size of the firm. As this thesis investigates the European financial environment, the equity and balance sheet data are retrieved from the database Datastream. The data to measure the state of the economy is retrieved from the database of the Federal Reserve Bank of St. Louis.

3.1.1 Sector Classification

The companies used in this study are categorized among industries by similar primary revenue resources and other publicly available information according to the Industry Classification Benchmark (ICB)[7]. The eight sectors examined in the analysis are the basic materials sector, the oil & gas sector, the healthcare sector, the personal & household goods sector, the technology sector, the telecommunications sector, the utility sector, and as a comparison the financial sector to see whether there is a same trend in the systemic risk among the financial institutions and the institutions in other sectors. This comes to a total of 281 companies in the sample[8]. An aspect that could influence the interdependency and systemic

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[6] The internet bubble crisis starting in 2002 and the financial crisis starting in 2008.

[7] The companies in the STOXX Europe 600 are divided in 10 industries. When the classification is taken more narrowly, there are 19 supersectors, 41 sectors and 114 subsectors. https://www.stoxx.com/sector-classification-icb
The sectors and respectively subsectors used in this analysis are:
Basic materials; Chemicals, Mining, Industrial Metals, Forestry and Paper.
Oil & gas; Oil and Gas Producers, Alternative Energy and Oil Equipment and services.
Financials; Banks, Nonlife Insurance, Real Estate Investment Trusts, Financial Services, Life Insurance.
Health Care; Pharmaceuticals and Biotechnology, Health Care Equipment and Services.
Personal & Household Goods; Tobacco, Personal Goods, Household Goods and Home Construction, Leisure Goods.
Technology; Software and Computer Services, Technology Hardware and Equipment.
Telecom; Mobile Telecommunications, Fixed Line Telecommunications.
Utilities; Electricity, Gas, Water and Multiutilities

[8] A full list of companies included in this thesis is summarized in the appendix.

risk in a sector is the amount of institutions that are active in the sector. Size of the sector is therefore important to notice when conducting the analysis.

The companies selected are all included in the STOXX Europe 600 stock index[9], which is an index of European stocks. The index represents Europe's most advanced markets and companies. The amount of companies in the analysis varies over time. The European countries where the companies are situated according to the country classification used in the Stoxx Europe are: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

Using the market value of assets as an indicator of risk, constraints the analysis to use data for publicly traded companies only. However, these are mostly the largest firms in an economy and therefore, if systemic risk is detected, it can be important to reduce this risk, or consider this in policy making. The stock based approach is not only of interest for research, but for investors as well, as they can take the results into account when trying to reduce risk through diversifying their portfolio. Another advantage of the use of market value of the assets as an indicator for risk, pointed out by Muns and Bijlsma (2011) and by Partro et al. (2013), is that it is forward-looking. The systemic risk indicator that uses the stock based approach can warn for a systemic crisis as it is assumed that the stock prices, and therewith returns, reflect all publicly available information about the risk of the assets (Muns and Bijlsma, 2011, Patro et al., 2013).

3.2 Market Return on Total Assets

As mentioned by Lehar (2005), more profitable and larger banks are not as risky as smaller less profitable banks in terms of systemic risk (Lehar, 2005). This is one of the reasons why it is important to control for the size of the company when measuring systemic risk in the sector. The study of Muns and Bijlsma (2011) determines a firm's size by its market capitalization (Muns & Bijlsma, 2011).

To correct for company specific factors, such as size, Adrian and Brunnermeier (2011) introduce a calculation to determine the return per company as a function of the market value of the assets of the company. As in their analysis, X_t^i represents the growth rate of the market value of the total assets of company *i* at day *t*. As the dataset contains daily data, each lag consists of one day.

To determine the return X_t^i per company the following equation will be used:

$$X_t^i = \frac{MVE_t^i\left(\frac{BVA_t^i}{BVE_t^i}\right) - ME_{t-1}^i\left(\frac{BVA_{t-1}^i}{BVE_{t-1}^i}\right)}{MVE_{t-1}^i\left(\frac{BVA_{t-1}^i}{BVE_{t-1}^i}\right)} = \frac{MVE_t^i LEV_t^i - MVE_{t-1}^i LEV_{t-1}^i}{MVE_{t-1}^i LEV_{t-1}^i}$$
$$= \frac{MVA_t^i - MVA_{t-1}^i}{MVA_{t-1}^i} \qquad (1)$$

[9] The STOXX Global 1800 Index includes 600 European region stocks (the STOXX Europe 600 Index), 600 American region stocks (the STOXX North America 600 Index) and 600 Asia/Pacific region stocks (the STOXX Asia/Pacific 600 Index).

Where BVA_t^i and BVE_t^i are respectively the book value of total assets and the book value of total equity of company *i* at day *t*. MVE_t^i is the market value of total equity of company *i* at day *t*, which is the stock price times the number of shares outstanding. LEV_t^i is the leverage of the company (total assets over total equity) of company i at day t and MVA_t^i the market value of the total assets of company *i* at day *t* (Fullenkamp, 2013).

The return of a sector is defined as the sum of the market value of the total assets of all institutions in the sample denoted by *n*, and mathematically this looks like:

$$X_t^{sector} = \frac{\sum_{i=1}^{n}(MVA_t^i - MVA_{t-1}^i)}{\sum_{i=1}^{n}(MVA_{t-1}^i)} \tag{2}$$

The definition of return on assets is the growth rate of the market value of the total assets between day *t* and day *t* -1 (Fullenkamp, 2013). The term 'return' will be used further on in this thesis to indicate this growth rate.

3.3 Value at Risk

The return of the companies per sector is used to determine the *Value at Risk*, on which the systemic risk measure of Adrian and Brunnermeier (2011) is based. Hull (2015) defines *Value at Risk (VaR)* as the probability that the loss will not be larger than a certain amount over a given time period (Hull, 2015). The value of loss that will not be exceeded with this probability equals the *VaR*. *VaR* tries to capture the risk of a certain asset, or the risk in a portfolio, in a single number and this method is widely used in setting capital requirements for financial institutions (Hull, 2015). Following this definition, as Adrian and Brunnermeier (2011) state, the quantile where the loss is larger than the *VaR* equals probability that the return loss on the market value of the assets, X^i for institution *i*, is below a certain value;

$$PR\left(X^i \leq VaR_q^i\right) = q\% \tag{3}$$

In this thesis the probability that the return will not be lower than the *VaR* loss is measured at 5%. When *X* is defined as the return loss, following Adrian and Brunnermeier (2016), *VaR* is typically a positive number indicating that greater risk is associated with a higher positive *VaR*. For consistency with previous literature where *VaR* is usually measured as return losses, this will be further on indicated as the 95% *VaR* level.

3.4 Descriptive Statistics

Table 1a shows the summary statistics of the main variables used in the analysis. *Mean Xi* displays the average return of the total market value of the assets of all 281 companies, summarized per sector over the period 1998 until 2016. *St. Dev Xi* is the average standard deviation of the average returns of the companies. The *VaRi* shows the average 95% *VaR* level of all companies per sector. For each the average, standard deviation, minimum and maximum value is displayed.

It is visible from table 1a that, for the data used in this thesis, the financial sector contains the most companies and therewith observations. This is followed by the basic materials and the health care sector, with respectively 60, 45 and 44 constituents. The two sectors with the fewest companies and therewith observations used in this thesis are the oil & gas and telecom sector with only 20 and 21 constituents.

The mean of all returns is slightly positive for all sectors, which means that the market value of the assets of the companies has grown in the period from 1998-2016. For $Mean\ Xi$ the mean indicates the average return of all companies in the sector, the standard deviation of the average return of all companies, the minimum is the average return of the company that has the lowest return on average and vice versa for the maximum.

The financial sector has highest average daily return of 0.2%, and the utilities sector has had the slowest growth with an average return of 0.05% followed by the oil & gas sector with an average growth rate of 0.07%. The standard deviation of this growth is also the highest in the financial sector, with a level of 0.009. This is high compared to the other sectors, as none of the average returns has a standard deviation above 0.002. When looking at the mean returns of all sectors more extensively, there are only 16 companies that have a negative average daily return, of which six are in the utilities sector.

The standard deviation differs across the different sectors and table 1a shows that the average standard deviation of the return on assets is particularly larger in the financial sector compared to the other sectors in this analysis with a value of 0.11. This high deviation of the average return is caused by one outlier that has a very high standard deviation (Spanish company Bankia with a standard deviation of 2.112) and when left out the average standard deviation of the Financial sector equals 0.076, which is more in line with the average standard deviation of the other sectors. However, as this standard deviation remains the highest disregarding the outlier, systemic risk is expected to be the highest in the financial sector.

The average *VaR* level of each sector, indicated with *VaRi* is also summarized in table 1a. The mean indicates the average *VaR* of all companies in the sector, the minimum is the *VaR* of the company that has the lowest *VaR* on average and vice versa for the maximum. The average *VaR* level lies around -0.03 for all sectors. This means that when the company is at its *VaR* level the average daily decrease of the market value of the assets of the sector equals -3%. The average loss at the *VaR* level is the highest in the technology sector with an average negative return value of -0.041 (-4.1%) and the lowest for the utilities sector with an average negative return value of -0.028 (-2.8%). Remarkably also the lowest negative return value is from a company in the utilities sector, -0.069 (-6.9%), coming from the Italian company Italgas.

When looking at the skewness of the average returns of all companies, the table indicates that these are not normally distributed, but are highly positively skewed. This means that that there are a lot of extreme high returns in the sample, as there are substantially more outliers in the positive tail. The financial sector shows the highest value for skewness, indicating that in the financial sector the returns are the least normally distributed. This would suggest that systemic risk is the strongest for this sector. The distribution of the other sectors is slightly less skewed than the financial sector. Skewness is, following the financial sector, the highest for the health care, basic materials and personal and household goods sector. This again suggests that there are some extremely high returns for companies in these sectors in the sample period used in this analysis.

Table 1a. Summary Statistics Main Variables

Sectors	Companies	Mean	Std. Dev.	Min.	Max.	Skewness	Observations
Basic Materials							
Mean Xi	45	0.001	0.002	0.000	0.003	3.516	178,626
St. Dev Xi	45	0.058	0.105	0.016	0.614	4.416	178,626
$VaRi$	45	-0.034	0.007	-0.052	-0.020	-0.133	178,626
Energy							
Mean Xi	20	0.001	0.001	-1.935	2.490	1.810	89,077
St. Dev Xi	20	0.032	0.012	0.020	0.068	1.746	89,077
$VaRi$	20	-0.036	0.007	-0.051	-0.025	-0.481	89,077
Financial							
Mean Xi	61	0.002	0.009	0.000	0.068	7.110	234,922
St. Dev Xi	61	0.110	0.303	0.014	2.112	4.718	234,922
$VaRi$	61	-0.034	0.008	-0.059	-0.017	-0.228	234,922
Health Care							
Mean Xi	44	0.001	0.002	-0.953	10.843	5.312	182,289
St. Dev Xi	44	0.052	0.054	0.015	0.359	4.516	182,289
$VaRi$	44	-0.031	0.006	-0.047	-0.021	-0.726	182,289
Personal & Household Goods							
Mean Xi	36	0.001	0.002	-0.001	0.012	3.199	147,968
St. Dev Xi	36	0.074	0.137	0.018	0.578	3.314	147,968
$VaRi$	36	-0.031	0.005	-0.042	-0.023	-0.292	147,968
Technology							
Mean Xi	24	0.001	0.001	0.000	0.005	2.501	108,790
St. Dev Xi	24	0.056	0.064	0.022	0.315	3.443	108,790
$VaRi$	24	-0.041	0.008	-0.061	-0.028	-0.450	108,790
Telecom							
Mean Xi	21	0.001	0.002	-0.001	0.008	2.658	76,847
St. Dev Xi	21	0.083	0.133	0.017	0.506	2.628	76,847
$VaRi$	21	-0.033	0.008	-0.051	-0.021	-0.553	76,847
Utilities							
Mean Xi	30	0.000	0.001	-0.001	0.003	1.287	114,544
St. Dev Xi	30	0.035	0.038	0.015	0.214	3.971	114,544
$VaRi$	30	-0.028	0.009	-0.069	-0.019	-3.697	114,544

Table 1a. displays the summary of descriptive statistics of the main variables used in the regression analysis. The table includes the daily returns of the market values of the assets in 8 different sectors of the European economy. The period analyzed is from the 1st of January 1998 till the 31st of December 2016. The appendix contains a constituent list of all firms per sector used in the analysis. *Mean Xi* displays the average return of all companies in the sector. *St. Dev Xi* is the average standard deviation of the mean the returns of the companies on average. The *VaRi* shows the average 95% *VaR* level of all companies in the sector. For each of the summarized statistics the mean displays the average return of all companies, the average standard deviation and the average *VaR* of all companies.

To elaborate further on the extreme values of the returns of the different companies in the different sectors, table 1b displays the summary statistics of the minimum and maximum returns observed per sector and which company had these extreme returns. Something to note from table 1b is that the minimum and maximum values differ largely across sectors, and the extreme positive returns are much higher than the extreme negative returns. This means there are more outliers in the upper tail than in the lower tail of the distribution of the return observations, as already stated when looking at the skewness of the company returns. Especially the positive returns of the financial sector are very high compared to the other sectors. The largest return losses are visible for the average and sector returns of the telecom sector and the sector returns of the health care sector. Something to point out here is that in the oil & gas, personal & household goods and telecom sectors, the same company has the highest, but also the lowest return. This indicates that these companies have relatively more volatile returns than the other companies in the sector concerned.

Table 1b. Summary Statistics: Minimum and Maximum Returns per Company

Sectors	Return	Companies
Basic Materials		
Min	-0.999	Randgold Resources
Max	43.167	Norsk Hydro
Oil & gas		
Min	-1.935	Lundin Petroleum
Max	2.490	Lundin Petroleum
Financial		
Min	-0.973	Fonciere Des Reg
Max	75.563	Bankia
Health Care		
Min	-0.953	BTG
Max	10.843	Medclinic International
Personal & Household Goods		
Min	-4.080	Imperial Brands
Max	40.491	Imperial Brands
Technology		
Min	-4.641	Micro Focus Intl
Max	22.049	Ericsson
Telecom		
Min	-13.464	BT Group
Max	32.261	BT Group
Utilities		
Min	-6.924	EON
Max	14.975	CEZ

Table 1b. displays the companies of the 8 different sectors that experienced the highest positive and most negative return in the period from the 1st of January 1998 till the 31st of December 2016. These are the smallest and highest daily returns observed in the dataset used for the quantile regression analysis.

4. Methodology

In this section, the *CoVaR* model is introduced and explained, followed by a brief overview of the use of quantile regression models. The application of the model to the data used in this thesis and the results are presented in section 5.

4.1 The CoVaR model

The idea behind the *CoVaR* model of Adrian and Brunnermeier (2016), here adjusted for all different sectors in an economy, is that the distribution of assets of a particular sector depends on the financial circumstances of the individual companies in that sector and the effects they have on each other. When one of the institutions in a particular sector is under financial stress, the distribution of asset values will change in the sector. *CoVaR* estimates the tail of the distribution of asset values in the sector and the change that comes from the stress of one particular asset.

4.1.1 Conditional Value at Risk

CoVaR is a statistical approach for systemic risk, developed by Adrian and Brunnermeier, that is used to analyze the tail co-movements of stock return distributions (Adrian and Brunnermeier, 2016). In other words, this measure tells whether the sector is at its *VaR* level when one company is at its *VaR* level.

Following this methodology, the $CoVaR_q^{sector}$ indicates the *q*-percent probability that the sector is at its *VaR* level conditional on company *i* being at or above its *VaR* level;

$$PR\left(X^{sector} \leq CoVaR_q^{sector} | X^i = VaR_q^i\right) \;=\; q\% \qquad (4)$$

Where X^{sector} and X^i represent the return of the entire sector and the return of company *i*, and *q* is the quantile of which the value is at the sectors' *VaR* level. In other words, *CoVaR* simply displays the probability of a loss above a certain value for the sector, conditional on the companies in the sector being at their *VaR* level. Estimates can be used to calculate the magnitude of losses of the sector which are coming from one company in that sector.

A way to measure the contribution of one company to the systemic risk in a sector, is to investigate what happens to the sector when the situation of the company changes from the normal (median) state to the financial stressed *(VaR)* state. The systemic risk in the sector that comes from company *i* is defined as *ΔCoVaR,* which equals the difference between the *CoVaR* of the sector conditional on company *i* being at its median level and on company *i* being at its *VaR* level. Formally this is defined as:

$$\Delta CoVaR_q^{sector} = CoVaR_q^{sector|X^i=VaR_q^i} - CoVaR_q^{sector|X^i=Median^i} \qquad (5)$$

$\Delta CoVaR_q^{sector}$ captures the marginal contribution of a company to sector wide risk[10]. This is the contribution of risk to the sector coming from company *i*, conditional on firm *i* being at its *VaR* level (Adrian and Brunnermeier, 2016). $CoVaR_q^{sector|X^i=VaR_q^i}$ is the *CoVaR* of the sector

[10] $\Delta CoVaR_q^{sector}$ covers the links between the institutions in a sector and the part of systemic risk of the sector that comes from company *i,* however this risk does not cause the systemic risk in that sector. It measures the tail-dependency of the company and the sector (Adrian and Brunnermeier, 2016).

conditional on company i being at its VaR level and $CoVaR_q^{sector|X^i=Median^i}$ represents the *CoVaR* of the sector conditional on company i being at its median level. Hence, with this measure it is possible to capture the contribution of each institution to the risk in that sector: the systemic risk[11].

The *CoVaR* can be extended to the Conditional Expected Shortfall (*CoES*), to get more insight in the observations above the VaR level. However, as this concerns the tail estimates they tend to contain noise. This noise can influence the outcomes of the study more severely when there are fewer observations (Kondor, 2014).

4.1.2 Estimating with CoVaR: Quantile Regressions

To capture the effects of the financial situations of the individual companies on the largest 5% returns losses of the sectors' market equity, quantile regressions are used in this analysis. The quantile regression methodology was first introduced by Koenker and Bassett (1978) and provides the estimates of the relationship among variables conditional on the quantiles, not only conditional on the mean. This leads to an advantage of quantile regressions over OLS regressions, as they are more robust to non-normal errors and outliers (Baum, 2013).

While OLS estimates the effect of the predictor variables only on the conditional mean, $E(y|x)$, this might not indicate the effects of the return losses on market equity in the tail of the distribution (beyond the VaR level). The quantile regression model uses the conditional *median* function, $Q_q(y|x)$, where $q = 50$ is the median of the distribution. This can be applied to each quantile q to investigate whether the relation between the dependent and independent variable differs over the quantiles of the distribution of the observations. The standard conditional quantile is specified to be linear and in this case equals:

$$Q_q\left(X^{sector}|X^i\right) = \beta_q^i X^i \tag{6}$$

Where Q represents the conditional quantile function and the regression parameter β_q estimates the change in a specified quantile q of the dependent variable, X^{sector}, produced by a unit change in the independent variable, X^i.

The quantile regression minimizes $\sum_j q\,|e_j| + \sum_j (1-q)\,|e_j|$ which gives asymmetric penalties for under prediction (q) and over prediction $(1-q)$, where e_j is the prediction error for the observation j in quantile q and $0 < q < 1$ (Baum, 2013).

The q^{th} quantile regression estimator $\hat{\beta}_q$ minimizes over β_q the function:

$$Q_q\left(\beta_q\right) = \sum\nolimits_{j:X_j^{sector} \geq \beta_q^i X_j^i}^{n} q\,\left|X_j^{sector} - \beta_q X_j^i\right| + \sum\nolimits_{j:X_j^{sector} \leq \beta_q^i X_j^i}^{n} (1-q)\,\left|X_j^{sector} - \beta_q X_j^i\right| \tag{7}$$

Where X_j^{sector} represents the return of the sector and X_j^i the return of company *i*. *j* is the specific observation in quantile *q* and *n* equals the number of observations in the quantile. In this thesis, the quantile regression estimates the effect of the return of the individual companies on the VaR 95% percentile of the sector return loss. $\hat{\beta}_q$ is estimated for the median and the 95% VaR level in this thesis to see whether it changes substantially over the quantiles.

[11] Some externalities may not be discovered by $\Delta CoVaR_q^{sector}$ as companies can take measures to avoid the impact of the externalities on their returns. Secondly, common factors that affect (some) firms in a sector are also captured by $\Delta CoVaR_q^{sector}$ as systemic risk (Adrian and Brunnermeier, 2016).

5. Regression Models and Results

This section contains the estimation of $CoVaR$ and $\Delta CoVaR$ using quantile regressions. In section 5.1 the estimation of the $CoVaR$ *and* $\Delta CoVaR$ model is summarized. In section 5.2 and 5.3 the model is expanded using a variable that indicates the economic state and section 5.4 examines the $\Delta CoVaR$ over time. Section 5.5 discusses the interaction between the return of the financial sector and other sectors.

5.1 Time-unvarying $CoVaR$ and $\Delta CoVaR$ Estimation

This section describes the contribution to systemic risk of all companies to the return of the total sector. This contribution is measured by the previously introduced *CoVaR* model, using quantile regressions to estimate this contribution.

To give a clear overview, the estimation models are given for the median quantile, the 95% *VaR* quantile, and the difference between the two coefficients of both models. This difference in the coefficients tells whether the effect of company *i* on the 95% *VaR* quantile significantly differs from the effect of company *i* on the median quantile.

From the value at risk definition it follows that the *CoVaR* equals the return of the sector conditional on the return of company *i,* which leads to the following regression models:

Median regression model

$$CoVaR_{q=0.5}^{sector|X^i=VaR^i_{median}} = X^{sector}_{q=0.5} = \alpha^i_{q=0.5} + \beta^i_{q=0.5}X^i + \varepsilon^i \tag{8}$$

The quantile regression model on the 95% VaR level

$$CoVaR_{q=0.05}^{sector|X^i=VaR^i_{q}} = X^{sector}_{q=0.05} = \alpha^i_{q=0.05} + \beta^i_{q=0.05}X^i + \varepsilon^i \tag{9}$$

Where X^{sector} and X^irepresent the returns of the whole sector and the return of the company *i*, $\beta^i_{q=0.5}$ captures the effect of company *i* on the sector in a normal (median) state and $\beta^i_{q=0.05}$ captures whether the return of company *i* is at its 95% *VaR* level when the sector is at its 95% *VaR* level (for the 95% *VaR*, the lowest 5% quantile is used, as the analysis focuses on return losses).

To capture the contribution of each company to the risk in the sector the difference between the median level and the 95% *VaR* level is examined.

The $\Delta CoVaR$ regression model

$$\begin{aligned}\Delta CoVaR_q^{sector} &= CoVaR_{q=0.05}^{sector|X^i=VaR^i_{q}} - CoVaR_{q=0.5}^{sector|X^i=VaR^i_{median}} \\ &= (\beta^i_{q=0.05} - \beta^i_{q=0.5}) = \Delta\beta\end{aligned} \tag{10}$$

which is the estimation of the impact that company *i* has on the risk of the whole sector when company *i* moves from its median state to its 95% *VaR* level.

As the models above display the true values of the parameters, the estimated coefficients of the regression models are indicated as $\hat{\beta}^i_{q=0.5}$ and $\hat{\beta}^i_{q=0.05}$ and $\Delta\hat{\beta}$ and are specified per sector and summarized in table 2. The regressions are done for all individual companies, and the weighted average of the coefficients is displayed in the different rows of the table per sector. As the regression is done on all individual firms, the fraction of significant coefficients for the companies on at least a 5% significance level is displayed in the before last column. The significance for the $\Delta\hat{\beta}$ indicates whether the effect of the companies on the return of the sector significantly differs when in different financial circumstances.

5.1.1 Median Regression

The coefficients of the median regression summarized in the top rows per sector in table 2 are significant at the 1% level for all companies except for the health care sector where only 12 out of the 43 companies seem to have a marginally significant impact on the return of the sector when they are in the normal (median) state with at least 10% significance. Moreover, the average individual effect of the companies in the health care sector is remarkably low, relative to average individual effect of the companies in all other sectors. The median regression on the health care sector even exhibits some negative coefficients in the median regression, indicating that when the returns of these companies grow, this has a negative effect on the returns of the other companies in the health care sector. However, none of these negative effects are significant.

The highest average individual effect comes from companies in the oil & gas sector, followed by the financial and utilities sectors. Two companies in the financial sector, Bankia and Unipolsai, show extremely small values of the coefficient in the financial sector. This indicates that these firms have a relatively low effect on the returns of all other companies in the financial sector.

5.1.2 Quantile Regression on the 95% VaR level

When looking at the coefficients that measure the effect of the individual companies in the different sectors on the VaR level, it is visible that most of the companies returns have a significant effect on the sector returns. However, again there are only eight out of 43 companies that are included in the health care sector that have a significant coefficient. Only one company in the financial, telecom and two companies in the utilities sector do not have a significant effect on at least the 10% significance level. When companies have a stronger effect on the sector above the 95% VaR level, hence a larger coefficient than at the median level, this could point at systemic risk to be present in the sector.

5.1.3 $\Delta CoVaR$ Estimation

The most important results are displayed in the rows that contain difference between the beta coefficients for the median and 95% VaR regression, which comes from the $\Delta CoVaR$ estimation indicated with $\Delta\hat{\beta}$. If the effect is significantly higher at the 95% VaR level, that indicates that a company contributes to systemic risk. Whether the coefficients differ significantly from each other is showed in the fifth column of table 2. Even though nearly all individual companies show a significant effect for the median and 95% VaR level regressions, not even half of all companies across the sectors show a difference between these with a significance level of at least 10%. This means that most returns of individual companies have the same effect on the sector returns when their returns are at a medial level or when at the 95% VaR level. Again, the amount of significant different effects of individual companies is relatively the lowest in the health care sector.

Table 2. Summary Statistics of the Beta Coefficients of the Median, 95% Quantile and $\Delta CoVaR$ Regressions per Sector

Sectors	Mean	Std. Dev.	Min	Max	Significant coefficients	Observations
Basic Materials						
$\hat{\beta}^i_{q=0.5}$	0.238	0.231	0.000	1.046	45/45	178,626
$\hat{\beta}^i_{q=0.05}$	0.254	0.241	0.000	1.112	45/45	178,626
$\Delta\hat{\beta}$	0.015	0.050	-0.115	0.139	18/45	178,626
Oil & Gas						
$\hat{\beta}^i_{q=0.5}$	0.332	0.314	0.070	1.450	20/20	89,077
$\hat{\beta}^i_{q=0.05}$	0.365	0.388	0.066	1.780	20/20	89,077
$\Delta\hat{\beta}$	0.033	0.086	-0.128	0.330	9/20	89,077
Financial						
$\hat{\beta}^i_{q=0.5}$	0.284	0.237	0.000	0.992	61/61	234,922
$\hat{\beta}^i_{q=0.05}$	0.288	0.284	0.000	1.080	60/61	234,922
$\Delta\hat{\beta}$	0.005	0.115	-0.431	0.422	20/61	234,922
Health Care						
$\hat{\beta}^i_{q=0.5}$	0.003	0.011	-0.026	0.054	12/43	182,241
$\hat{\beta}^i_{q=0.05}$	0.007	0.027	-0.036	0.145	8/43	182,241
$\Delta\hat{\beta}$	0.004	0.028	-0.167	0.036	2/43	182,241
Personal & Household Goods						
$\hat{\beta}^i_{q=0.5}$	0.238	0.256	0.000	0.955	34/34	147,968
$\hat{\beta}^i_{q=0.05}$	0.260	0.288	0.000	1.062	34/34	147,968
$\Delta\hat{\beta}$	0.022	0.049	-0.166	0.073	12/34	147,968
Technology						
$\hat{\beta}^i_{q=0.5}$	0.315	0.248	0.026	0.896	24/24	108,790
$\hat{\beta}^i_{q=0.05}$	0.269	0.231	0.006	0.877	24/24	108,790
$\Delta\hat{\beta}$	-0.046	0.083	-0.384	0.041	10/24	108,790
Telecom						
$\hat{\beta}^i_{q=0.5}$	0.238	0.205	0.033	0.925	21/21	153,694
$\hat{\beta}^i_{q=0.05}$	0.209	0.204	0.013	0.862	20/21	153,694
$\Delta\hat{\beta}$	-0.029	0.049	-0.060	0.184	6/24	153,694
Utilities						
$\hat{\beta}^i_{q=0.5}$	0.282	0.191	0.035	0.701	28/28	114,544
$\hat{\beta}^i_{q=0.05}$	0.301	0.204	0.021	0.698	26/28	114,544
$\Delta\hat{\beta}$	0.019	0.043	-0.106	0.080	6/28	114,544

Table 2. displays a summary of the coefficients of the models for the median ($\beta^i_{q=0.5}$), quantile ($\beta^i_{q=0.05}$) and interquantile ($\Delta\hat{\beta}$) regressions for the 8 different sectors examined. The Mean, Standard Deviation, Minimum and Maximum values of the beta coefficients are presented in the first four columns, and in the fifth column the fraction of significant coefficients is displayed. For the $\Delta CoVaR$ model this is the significant difference between the coefficients for the median and 95% quantile models. The effect of the companies is significant on at least a 10% significance level. In the last column, the number of observations per model is added.

When looking at the findings of the study of Muns and Bijlsma (2011), it is expected that systemic risk would be present in the financial sector and of greater magnitude compared to other sectors. The results of the $\Delta CoVaR$ estimation, displayed in table 2 show that indeed systemic risk is present in the financial sector, however, not of the largest magnitude.

The average effect of the return of the different individual companies on the return in their respective sectors is the largest for the oil & gas sector, followed by the personal & household goods, utilities, basic materials and the financial sector. This could be interpreted as, when at their VaR level, the companies have, on an average individual level, larger impact on the sector returns than when at their median level. The technology and telecom sectors display an average negative coefficient, indicating that the effect of the individual companies is smaller in the VaR state compared to the normal (median) state. This means that does not point towards systemic risk in periods of distress by using the $\Delta CoVaR$ as a systemic risk measure.

To elaborate on the interpretation of the results, take for example the effect of the basic material sector. In this sector, the mean value of 0.015 indicates that the VaR of the return of the basic materials sector changes on average by 1.5% if one company moves from median return to its 95% VaR level return. For the technology and telecom sector the mean value has a negative average coefficient, indicating that the VaR of the sector decreases when a company moves towards its distressed state. However, these results should be interpreted with care as not all companies have a significantly different effect for the median and 95% VaR level state.

The results suggest that systemic risk is present across most sectors examined in the analysis. However, the results neither confirm nor reject that contribution to risk comes from all companies that operate in the sector. When looking at the significant difference between the median and 95% VaR effect, this differs among the sectors included in the analysis. This indicates that systemic risk differs across sectors in magnitude.

5.2 Adding state variable: Recession

Co-movement of the returns on individual and sector level could also arise from a strong dependency on prices of inputs or the demand on the market. To capture this, the research of Muns and Bijlsma (2011) distinguishes extreme events, which are driven by the economy itself, from systemic events (Muns and Bijlsma, 2011). A dummy variable "recession" is added to the model, which captures the effect of varying economic conditions per country (whether there is an economic expansion or a recession). In the data, the recession begins the first day following an expansionary period in the time series.

The dummy variable is retrieved from the database of the Federal Reserve Bank of St. Louis, which uses the Organization of Economic Development (OECD) indicator for individual countries. This indicator is based on the "growth cycle" approach, where the Gross Domestic Product (GDP) per country is used to identify the turning points[12] from economic expansion to the recession and the other way around in the growth cycle for all countries (OECD, 2017).

5.2.1 Estimation Including Recession to Company Return

The regression models, including the influence of the economic state on the return of the different companies, and respectively the sector, look like:

[12] The turning points of the economies are calculated by a simplified Bry-Boschan routine, an algorithm the National Bureau of Economic Research (NBER) uses to determine an economic expansion or recession (OECD, 2017). The period that is between the expansion and recession is always marked as a recession.

Median regression including recession variable for Xi

$$X^i_{q=0.5,t} = \alpha^i_{q=0.5} + \gamma^i_{q=0.5} M_{t-1} + \varepsilon^i_t \tag{11}$$

Quantile regression on the 95% VaR level including recession variable for Xi

$$X^i_{q=0.05,t} = \alpha^i_{q=0.05} + \gamma^i_{q=0.05} M_{t-1} + \varepsilon^i_t \tag{12}$$

where M_{t-1} represents the NBER lagged economic state variable at day $t-1$, which is 1 if the economy is in a recession an 0 if there is an economic expansion, which is why $\gamma^i_{q=0.5}$ and $\gamma^i_{q=0.05}$ are expected to be negative. The recession variable varies per country where the individual company is situated.

Table 3 displays the average effect of the recession variable on the individual company returns, specified per sector. $\hat{\gamma}^i_{q=0.5}$ indicates the average estimated coefficient of the recession dummy variable when the individual company is in its median state and $\hat{\gamma}^i_{q=0.05}$ the average estimated coefficient of the recession dummy variable when the individual company is at its 95% VaR level.

5.2.2 Median and Quantile Regression Coefficients Including Recession Variable for Xi

The results of table 3 indicate whether the economy being in a recession can clarify the returns of the individual companies when in a normal (median) state and the negative returns at the 95% VaR level. Evaluating these results suggest that the recessionary state of the economy does not explain the median returns of the individual companies. This is indicated by the average coefficients per sector and the number of significant coefficients per company, which are both zero or close to zero for all companies in the different sectors for the median analysis.

On the contrary, the recession significantly affects most of the companies in the sample when they are at their 95% VaR level. The results of the analysis at the 95% VaR level indicate that indeed when the economy is in a recession, the returns of individual companies are negatively influenced. As the effect is the highest for the financial, technology and oil & gas sector, this indicates that the individual companies' returns are most affected by recessionary periods relative to the other sectors where the effect points at the same direction, however is slightly less strong. Even though these coefficients are small, they point at the returns of the individual companies being more negative in times of recession.

These estimations suggest that the extreme negative daily returns result from systematic risk, as all companies are exposed equally to periods of economic recession. However, as Adrian and Brunnermeier (2016) state, the recession variable captures the economic circumstances which affect the average and volatility of the risk measured. When adding this interpretation to the results displayed in table 3, it suggests that the contribution of an individual company to the risk in a sector is larger in times of economic recessions relative to economic expansions. This is further examined in the following section.

Table 3. Coefficients of the Median and 95% *VaR* Quantile Regression for all *Xi* companies per Sector Summarized

Sectors, coefficients	Mean	Std. Dev.	Min	Max	Significant coefficients	Observations
Basic Materials						
$\hat{\gamma}^{i}_{q=0.5}$	0.000	0.000	-0.001	0.002	0/45	173,668
$\hat{\gamma}^{i}_{q=0.05}$	-0.008	0.007	-0.026	0.010	39/45	173,668
Oil & Gas						
$\hat{\gamma}^{i}_{q=0.5}$	0.000	0.218	-0.001	1.000	0/20	89,077
$\hat{\gamma}^{i}_{q=0.05}$	-0.010	0.005	-0.020	0.001	19/20	89,077
Financial						
$\hat{\gamma}^{i}_{q=0.5}$	0.000	0.000	0.000	0.000	2/61	234,922
$\hat{\gamma}^{i}_{q=0.05}$	-0.015	0.007	-0.026	0.002	56/61	234,922
Health Care						
$\hat{\gamma}^{i}_{q=0.5}$	0.000	0.000	0.000	0.001	1/43	182,241
$\hat{\gamma}^{i}_{q=0.05}$	-0.006	0.004	-0.015	0.004	31/43	182,241
Personal & Household Goods						
$\hat{\gamma}^{i}_{q=0.5}$	0.000	0.000	-0.002	0.000	1/34	147,968
$\hat{\gamma}^{i}_{q=0.05}$	-0.009	0.006	-0.022	0.000	29/34	147,968
Technology						
$\hat{\gamma}^{i}_{q=0.5}$	0.000	0.000	0.000	0.001	0/24	108,790
$\hat{\gamma}^{i}_{q=0.05}$	-0.014	0.011	-0.047	0.004	22/24	108,790
Telecom						
$\hat{\gamma}^{i}_{q=0.5}$	0.000	0.001	-0.002	0.001	2/21	76,847
$\hat{\gamma}^{i}_{q=0.05}$	-0.009	0.009	-0.034	0.009	17/21	76,847
Utilities						
$\hat{\gamma}^{i}_{q=0.5}$	0.000	0.000	-0.001	0.000	0/28	114,544
$\hat{\gamma}^{i}_{q=0.05}$	-0.008	0.005	-0.023	-0.001	21/28	114,544

Table 3. shows the average value of all coefficients of the state variable recession per company. $\hat{\gamma}^{i}_{q=0.5}$ indicates the average estimated coefficient of the recession dummy variable when the individual company is in its median state and $\hat{\gamma}^{i}_{q=0.05}$ the average estimated coefficient of the recession dummy variable when the individual company at or above its 95% *VaR* level. In the fifth column, the fraction of significant coefficients on at least a 10% significance level is displayed. In the last column, the number of observations per model is added.

5.3 Estimation Including Recession to Sector Return

The recession variable being explanatory for the returns of the individual companies when at their 95% *VaR* level arouse interest in whether the effect of the individual company return on the sector return is affected by the economy being in a recessionary state. This is why the recession variable is added in the analysis of the effects of the individual company return on the return of the corresponding sector.

The influence of the individual companies in combination with the state variable recession is estimated using the following quantile regression models.

Median regression model including recession variable for the sector

$$CoVaR_{q=0.5,t}^{sector|X^i=VaR_{median}^i} = X_{q=0.5,t}^{Sector} = \alpha_{q=0.5}^i + \beta_{q=0.5}^i X^i + \gamma_{q=0.5}^i M_{t-1} + \varepsilon_t^i \quad (13)$$

Quantile regression model on the 95% VaR level including recession variable for the sector

$$CoVaR_{q=0.05,t}^{sector|X^i=VaR_q^i} = X_{q=0.05,t}^{Sector} = \alpha_{q=0.05}^i + \beta_{q=0.05}^i X_t^i + \gamma_{q=0.05}^i M_{t-1} + \varepsilon_t^i \quad (14)$$

The differences between the coefficients indicate the effect of the individual company and the effect of the recession variable when switching from normal to the VaR state. This is captured in model (16).

The $\Delta CoVaR$ regression model including recession variable for the sector

$$\begin{aligned} \Delta CoVaR_{q,t}^{sector} &= CoVaR_{q=0,05,t}^{sector|X^i=VaR_q^i} - CoVaR_{q=0,5,t}^{sector|X^i=VaR_{median}^i} \\ &= \left(\beta_{q=0.05}^i - \beta_{q=0.5}^i\right) + \left(\gamma_{q=0.05}^i - \gamma_{q=0.5}^i\right) = \Delta\beta + \Delta\gamma \end{aligned} \quad (15)$$

The results of the estimated coefficients are displayed in table 4. The table shows the average effect of all individual company per sector. The estimated values of the coefficients of the model, respectively (14), (15) and (16) are presented per sector. $\hat{\beta}_{q=0.5}^i$ and $\hat{\gamma}_{q=0.5}^i$ show the average estimated coefficients of the individual companies and the economy being in a recession when the sector is at its median state. $\hat{\beta}_{q=0.05}^i$ and $\hat{\gamma}_{q=0.05}^i$ show the average estimated coefficients of the individual companies and the economy being in a recession when the sector is at its 95% VaR level. $\Delta\hat{\beta}$ and $\Delta\hat{\gamma}$ show the estimated difference between the coefficients of the two models, which indicate the difference between the sector being at its median state and being at its 95% VaR level. The fifth column shows how many of the coefficients are significant at least with a 10% significance level and the last column contains the number of observations per sector.

Table 4. Summary Statistics of Median, 95% VaR Quantile and $\Delta CoVaR$ Regression Coefficients per Sector including Recession Variable

Sectors	Coefficient	Mean	Std. Dev.	Min	Max	Significant coefficients	Observations
Basic Materials							
$CoVaR_{q=0.5,t}^{sector}$	$\hat{\beta}_{q=0.5}^{i}$	0.264	0.252	0.000	1.044	45/45	173,668
	$\hat{\gamma}_{q=0.5}^{i}$	-0.001	0.001	-0.005	0.000	45/45	173,668
$CoVaR_{q=0.05,t}^{sector}$	$\hat{\beta}_{q=0.05}^{i}$	0.275	0.262	0.000	1.146	45/45	173,668
	$\hat{\gamma}_{q=0.05}^{i}$	-0.004	0.006	-0.026	0.004	45/45	173,668
$\Delta CoVaR_{q,t}^{sector}$	$\Delta\hat{\beta}$	0.011	0.056	-0.128	0.143	18/45	173,668
	$\Delta\hat{\gamma}$	-0.004	0.006	-0.004	0.026	39/45	173,668
Oil & Gas							
$CoVaR_{q=0.5,t}^{sector}$	$\hat{\beta}_{q=0.5}^{i}$	0.332	0.314	0.070	1.453	20/20	89,077
	$\hat{\gamma}_{q=0.5}^{i}$	0.000	0.000	-0.002	0.000	1/20	89,077
$CoVaR_{q=0.05,t}^{sector}$	$\hat{\beta}_{q=0.05}^{i}$	0.362	0.379	0.063	1.727	20/20	89,077
	$\hat{\gamma}_{q=0.05}^{i}$	-0.004	0.006	-0.024	-0.001	19/20	89,077
$\Delta CoVaR_{q,t}^{sector}$	$\Delta\hat{\beta}$	0.030	0.075	-0.274	0.124	9/20	89,077
	$\Delta\hat{\gamma}$	-0.004	0.005	-0.022	-0.001	19/20	89,077
Financial							
$CoVaR_{q=0.5,t}^{sector}$	$\hat{\beta}_{q=0.5}^{i}$	0.302	0.274	0.011	0.992	61/61	234,922
	$\hat{\gamma}_{q=0.5}^{i}$	0.000	0.000	-0.002	0.001	19/61	234,922
$CoVaR_{q=0.05,t}^{sector}$	$\hat{\beta}_{q=0.05}^{i}$	0.309	0.327	0.011	1.111	60/61	234,922
	$\hat{\gamma}_{q=0.05}^{i}$	-0.007	0.013	-0.061	0.002	54/61	234,922
$\Delta CoVaR_{q,t}^{sector}$	$\Delta\hat{\beta}$	0.008	0.094	-0.210	0.252	18/61	234,922
	$\Delta\hat{\gamma}$	-0.007	0.011	-0.060	0.002	52/61	234,922
Health Care							
$CoVaR_{q=0.5,t}^{sector}$	$\hat{\beta}_{q=0.5}^{i}$	0.001	0.012	-0.065	0.028	9/43	182,241
	$\hat{\gamma}_{q=0.5}^{i}$	0.000	0.001	0.000	0.002	29/43	182,241
$CoVaR_{q=0.05,t}^{sector}$	$\hat{\beta}_{q=0.05}^{i}$	0.003	0.015	-0.040	0.042	6/43	182,241
	$\hat{\gamma}_{q=0.05}^{i}$	-0.003	0.004	-0.021	0.001	39/43	182,241
$\Delta CoVaR_{q,t}^{sector}$	$\Delta\hat{\beta}$	-0.002	0.036	-0.027	0.224	2/43	182,241
	$\Delta\hat{\gamma}$	-0.004	0.005	-0.022	0.001	39/43	182,241
Personal & Household Goods							
$CoVaR_{q=0.5,t}^{sector}$	$\hat{\beta}_{q=0.5}^{i}$	0.261	0.257	0.023	0.961	34/34	147,968
	$\hat{\gamma}_{q=0.5}^{i}$	0.000	0.000	-0.001	0.000	10/43	147,968
$CoVaR_{q=0.05,t}^{sector}$	$\hat{\beta}_{q=0.05}^{i}$	0.282	0.288	0.011	1.086	43/43	147,968
	$\hat{\gamma}_{q=0.05}^{i}$	-0.004	0.003	-0.014	0.000	39/43	147,968
$\Delta CoVaR_{q,t}^{sector}$	$\Delta\hat{\beta}$	0.021	0.048	-0.125	0.076	12/43	147,968
	$\Delta\hat{\gamma}$	-0.004	0.003	-0.013	0.000	38/43	147,968

Technology							
$CoVaR^{sector}_{q=0.5,t}$	$\hat{\beta}^i_{q=0.5}$	0.315	0.248	0.026	0.891	24/24	108,790
	$\hat{\gamma}^i_{q=0.5}$	-0.001	0.001	-0.002	0.000	16/24	108,790
$CoVaR^{sector}_{q=0.05,t}$	$\hat{\beta}^i_{q=0.05}$	0.261	0.222	0.006	0.856	24/24	108,790
	$\hat{\gamma}^i_{q=0.05}$	-0.008	0.006	-0.021	-0.001	23/24	108,790
$\Delta CoVaR^{sector}_{q,t}$	$\Delta\hat{\beta}$	-0.054	0.085	-0.383	0.031	12/24	108,790
	$\Delta\hat{\gamma}$	-0.007	0.006	-0.020	0.000	24/24	108,790
Telecom							
$CoVaR^{sector}_{q=0.5,t}$	$\hat{\beta}^i_{q=0.5}$	0.238	0.203	0.033	0.919	21/21	76,847
	$\hat{\gamma}^i_{q=0.5}$	0.000	0.001	-0.001	0.002	2/21	76,847
$CoVaR^{sector}_{q=0.05,t}$	$\hat{\beta}^i_{q=0.05}$	0.204	0.202	0.013	0.858	20/21	76,847
	$\hat{\gamma}^i_{q=0.05}$	-0.003	0.007	-0.015	0.018	17/21	76,847
$\Delta CoVaR^{sector}_{q,t}$	$\Delta\hat{\beta}$	-0.034	0.053	-0.037	0.184	9/21	76,847
	$\Delta\hat{\gamma}$	-0.003	0.007	-0.016	0.015	19/21	76,847
Utilities							
$CoVaR^{sector}_{q=0.5,t}$	$\hat{\beta}^i_{q=0.5}$	0.268	0.160	0.040	0.596	28/28	114,544
	$\hat{\gamma}^i_{q=0.5}$	0.000	0.000	-0.001	0.000	12/28	114,544
$CoVaR^{sector}_{q=0.05,t}$	$\hat{\beta}^i_{q=0.05}$	0.280	0.173	0.019	0.684	26/28	114,544
	$\hat{\gamma}^i_{q=0.05}$	-0.003	0.002	-0.007	0.000	22/28	114,544
$\Delta CoVaR^{sector}_{q,t}$	$\Delta\hat{\beta}$	0.013	0.045	-0.107	0.086	5/28	114,544
	$\Delta\hat{\gamma}$	-0.002	0.002	-0.006	0.001	22/28	114,544

Table 4. displays the summary of the coefficients of the independent variables used in the regression models (13), (14) and (15). $\hat{\beta}^i_{q=0.5}$ and $\hat{\gamma}^i_{q=0.5}$ show the average coefficients of the individual companies and the economy being in a recession when the sector is at its median state. $\hat{\beta}^i_{q=0.05}$ and $\hat{\gamma}^i_{q=0.05}$ show the average coefficients of the individual companies and the economy being in a recession when the sector is at its 95% *VaR* level. $\Delta\hat{\beta}$ and $\Delta\hat{\gamma}$ show the coefficients of the interquantile model, which indicate the difference between the sector being at its median state and being at its 95% *VaR* level. In the fifth column, the fraction of significant coefficients on at least a 10% significance level is displayed. In the last column, the number of observations per model is displayed.

5.3.1 Median Regression Including Recession

From table 4 it is visible that the coefficients of the regression on the median level returns for each sector are positive and significant at least at a 10% significance level, indicating that the return of the individual companies influences the return of the sectors. Whereas most of the coefficients that measure the effect of a depressed economic state are equal to zero or have a small negative effect, only a small fraction of these have a significant effect on the returns across the different sectors. This means than a recession does not explain the median returns of the sector. However, an exception to this is the health care sector which shows a very small coefficient for the individual company influence on average. Moreover, there are just nine out of the total 43 companies where the individual return has a significant effect on the return of the health care sector in the median state.

The results show that the highest average individual company effect is measured in the oil & gas sector, for the median state, followed by the technology and financial sector. In the utilities, basic materials, and the personal and household goods sector the average effect on the median return of the sector is slightly lower, followed by the telecom sector.

When comparing the effects of the individual companies in combination with the recession variable with the earlier results, the effects do not differ too much with the average effects of the individual companies without the recession variable, displayed in table 2.

5.3.2 95% VaR Level Quantile Regression Including Recession

Nearly all individual companies in all sectors have a positive significant effect at the 5% significance level on the returns of the sector when at its 95% VaR level. The health care sector again shows, in contrast with all other sectors examined, that just a small fraction of the individual companies can explain the returns of the sector, and the recession variable is more explanatory for the health care sector returns at the 95% VaR level when added to the model.

The magnitude of the effect of the individual companies is smaller at the 95% VaR quantile than in the median state of the technology and telecom sector. This indicates that in these sectors the companies have a smaller effect on an individual level on average when the sector is at its VaR level. This could be due to the effect of the recession variable added to the model, which explains the sector returns better than the returns of the individual companies in those sectors. However, when comparing this to the effect of the individual companies in these sectors with the earlier results, the coefficients do not differ much.

The recession coefficient is more negative than when in the median state in all of the sectors and has a slightly lower fraction of significant coefficients than the beta coefficients of the company returns at the sectors being at their 95% VaR level. The effect of the recession is the highest in the financial and technology sector and the smallest in the health care, telecom and utilities sector. This means that the recession has the largest impact on the returns of the technology and financial sector on average and the smallest effect on average in the telecom and utilities sector when at the 95% VaR level.

5.3.3 $\Delta CoVaR$ Estimation

The average contribution of the individual firms to systemic risk is displayed per sector in the before last row per sector of table 4. This contribution is measured by comparing the median returns with the returns at the 95% VaR level in combination with the economic state variable that indicates the effect of a recession. The interpretation of the $\Delta\hat{\beta}$ is the difference of the estimated effect of a company when the sector moves from the median state to the 95% VaR level on average, controlling for the effect of the state of the economy. This means that $\Delta\hat{\beta}$ can be interpreted as the average contribution from company i to the sector wide systemic risk. In most sectors and for most companies, the beta coefficients differ significantly when comparing the median and 95% VaR level coefficient estimates, hence the most companies significantly contribute individually to the sector wide systemic risk. The coefficient for the economic state being a recession displayed in table 4 as $\Delta\hat{\gamma}$, captures the difference in effect of the economic environment on the returns of the sector. For all sectors, the effect of the recession is larger when the sector returns are at their 95% VaR level compared to their median level.

Comparing the number of significantly different beta coefficients in table 4 with the results of the analysis on the effect of the individual companies without controlling for the economic state (table 2), there is no difference or a slight increase in the proportion of companies that has a significantly different effect on the sector returns in median state or at 95% VaR level.

When examining this in more detail, the same companies have this significantly different effect regardless whether the recession variable is added. This could reveal that some individual companies have a large impact on the returns of the whole sector unconditional on the state of the economy. In the basic material sector for example, the company Polymetal has the highest significant coefficient indicating that when this company makes large losses, it is expected to influence the whole sector, regardless whether the economy is in a good or bad state. For policy making this could indicate that those companies need to be watched closely as these can influence the market returns of most of the other companies in the sector. In addition to that, there is not just one individual company that explains the returns of the sector it operates in, but there are several companies that influence the sector returns simultaneously.

The contribution of the individual company on average is the largest in the oil & gas and personal & household goods sector (the companies with the largest difference in coefficients for these sectors are respectively BP and Persimmon). This is followed by the utilities, basic materials, financial and health care sector. The technology and telecom sector still have a negative coefficient, which does not point at the individual companies significantly contributing to systemic risk in these sectors. A possible explanation for this result regarding the telecom sector can be that the European telecom market is has become very fragmented, especially compared to about a decade ago (Marinello and Salemi, 2015). They find that some of the companies in this market have a wider operation span, however, none covers the whole European market. Bell et al. (2016) argue that the technology sector in Europe is developing rapidly and it has to improve in operating in the region as a whole.

This order of relative individual contribution to systemic risk in the sectors does not differ from the results of the estimation without controlling for the economic state. Only now the health care sector has a lower individual contribution to systemic risk than the financial sector. When comparing the coefficients with the results displayed in table 2, the average effect of the individual companies on the systemic risk for the financial sector increases. For the personal & household goods sector the effect stayed more or less the same and for the basic materials, oil & gas, health care and utilities the effect has decreased. This shows that the contribution of the individual firms to the sector wide systemic risk, when controlling for times of recession, is even higher for the financial sector, and slightly lower, but still present for these other sectors when controlling for relatively bad economic circumstances.

The results of the $\Delta CoVaR$ estimation suggest that systemic risk is present in the real sectors of the economy and the effect is not explained only by relatively bad economic circumstances. The size of the effect differs among the different sectors, and is not largest in the financial sector, as was expected out of the results of the study of Muns and Bijlsma (2011).

5.4 Variance Over Time

The previous section measures $CoVaR$ and $\Delta CoVaR$ which is constant over time. To capture the variance over time, the analysis is repeated annually[13]. This is executed to capture the movement of the difference in the beta coefficient over the period analyzed per sector using again equation 15. As in the previous section when coefficients are positive, this indicates that the effect of company i is larger when it is at its 95% VaR level than when in its normal state. Hence, if the dependence of the sector on the individual company is on average higher at the 95% VaR level in a recession, this suggests that systemic risk is relatively higher in periods of financial distress.

5.4.1 Annual $\Delta CoVaR$ Analysis including Recession

To visualize the results, table 5 shows the annually weighted average effect of the companies on the returns of the eight different sectors. When the beta coefficient at the 95%

[13] 1998 is not displayed in the table as there are insufficient observations in the sample to individually measure the weighted average individual contribution to systemic risk in the sectors.

VaR level is higher than when in the normal state, contribution to sector wide risk is larger, which is indicated with the green background in the cell. The darker color indicates a larger the deviation from zero. The magnitude and significance contribution to systemic risk of the individual companies differ between the sectors and years observed. The red cells indicate that the difference between the effect on the returns at the 95% *VaR* level are smaller than at the median level. This means that the effect of the companies on the sector wide returns is higher in normal times than in when the individual company is in financial distress.

When the economy is in a period of recession (1999, 2001-2003 and 2007-2013) the effect of one company switching from its median state to the 95% *VaR* level differs highly among the different sectors. The systemic risk of the individual companies varies over time and is larger in the last three economically bad periods for the companies in the oil & gas, health care and utilities sector. The differences between the median and the 95% *VaR* effect on the average annual returns is the highest for the technology, telecom and utilities sector either positively or negatively.

The financial sector shows that the contribution to systemic risk is larger in the most recent financial crisis (2008-2012). Additionally, the contribution to systemic risk is remarkably high in the telecom and technology sector after the burst of the internet bubble in the recessionary period of 2001-2003. This shows that systemic risk indeed comes forward when there was a recessionary period related to these sectors. However, the magnitude for the average contribution to systemic risk is higher in the telecom and technology sector compared to the financial sector during the recessionary periods included in the analysis.

5.4.2 Time Varying Analysis per Sector

Basic Materials - As for the basic material sector, most of the significant different effects are visible in the period 2007, 2008, 2009. However, these effects are mostly negative, indicating the effect of the individual companies on the sector being higher in normal times than in times of economic downturn. The results of the sector displayed in table 5 show positive average coefficients at for the years 1999 and 2001, indicating when companies move from the normal to distressed state they affect the sector negatively. The basic material sector has negative differences between the coefficients of the normal and 95% *VaR* state for the other years, what indicates that the effect is weaker in the period of economic downturn. These annual results suggest that systemic risk does come somewhat forward in the basic materials sector in times of economic distress for the first two years of recessions, but not in the financial crisis in the years 2007-2013.

Oil & Gas - The oil & gas sector shows that in nearly all years the individual companies contribute to systemic risk. However, in the period 2008-2011 the average effect at the 95% *VaR* level was lower than when in the normal state, indicating that in this most recent crisis systemic risk did not increase.

Financials - The results of the annual analysis of the financial sector shows that all companies contributed significantly to systemic risk in the sector in multiple years. The period 1999 till 2001 in particular shows significantly different coefficients which are for most of the companies negative. In the period from 2007 till 2011 however, the average coefficients are positive. This is in favor of the *CoVaR* model, indicating that systemic risk is present in the financial sector and is higher in times of economic recession for this sector.

Health Care - In 1999, 2004, 2005 and 2006 the companies affect the sector wide returns negatively when moving to the distressed state. While in the other time periods the effect of the companies moving from the normal to distressed state influence the sector wide returns positively. This points at systemic risk being present in the health care sector but does not indicate whether it is particularly higher in times of economic distress.

Personal & Household Goods - In the personal & household goods sector, most companies seem to have a significant positive different effect on the returns of the sector when moving from the normal to distressed state at the start of the large economic recession in 2008. Over the years in the other periods of economic downturn, most of the differences are negative. This does not indicate that the effect of an individual company on the risk of the personal & household goods sector is larger in times of distress than when in a financially normal state.

Technology - The technology sector shows some outstanding results regarding a few companies. Dialog Semicon., Infineon Techs. and Simcorp, have nearly all years of the sample period a significant positive difference between the effects at the distressed and normal state. This means that these companies seem to contribute to risk in the sector when moving from normal to distressed state. Furthermore, the technology sector has very large differences between the effects of the individual companies when in the normal state compared to the distressed state. The contribution to risk is much stronger in the years after the internet bubble burst and at the beginning of the severe financial crisis in 2008 – 2009. However, in the years after the financial crisis, the difference switches to be much more negative, indicating that systemic risk in the sector has decreased very much relative to the preceding years.

Telecom - Telefonica, Telenor and Telia Company are the only three companies in the telecom sector that show significant positive coefficients, indicating the companies to have a significant effect on the returns of the sector. The other significantly different beta coefficients are not designated to a particular period or year, nor are they positive or negative. This indicates that most of the companies do not have a significant individual effect on the sector wide returns, when moving from the normal state to the 95% *VaR* level. The average coefficients that are displayed in table 5 and figure 1 show that in most of the cases the effect is larger after the internet bubble burst, suggesting systemic risk increased during these years.

Utilities - The companies in the utilities sector seem to individually contribute to systemic risk more compared to other sectors, indicating that systemic risk is present in this sector. The effects of most companies are large during the financial crisis from 2007-2011, but this high contribution to risk holds in the period that follows. This indicates that the economically distressed firms have higher impact on all other companies in the sectors in distressed periods as well as in times of good economic circumstances.

These results do indicate that the build-up of systemic risk differs highly among the different sectors in the European economy. The interdependence among firms in the technology, telecom and utilities sectors seems to be higher in recessionary periods than in the other sectors examined. The contribution to systemic risk seems to come forward in times of economic distress for some sectors, but not for all. Also, the magnitude of the contribution of the individual companies to systemic risk in the sectors differs and is not the highest in the financial sector. This contradicts to the results of the study of Muns and Bijlsma (2011), which finds that systemic risk is the highest in the financial sector compared to three other sectors in their dataset.

Table 5. Yearly Weighted Average Individual Contribution to the Sector Returns when Moving from Normal to 95% *VaR* State

Yearly $\Delta\hat{\beta}$	Basic Materials	Oil & Gas	Financials	Health Care	Personal & Household Goods	Technology	Telecom	Utilities
1999	0.001	0.004	-0.004	-0.001	-0.002	-0.014	-0.001	0.013
2000	-0.001	0.004	-0.004	0.002	0.000	0.179	0.098	0.031
2001	0.002	0.008	-0.009	0.002	0.000	0.098	0.072	-0.033
2002	-0.002	0.005	-0.003	0.006	0.000	0.050	0.048	0.012
2003	-0.001	0.007	-0.005	0.001	-0.004	-0.080	-0.022	-0.041
2004	0.000	0.007	-0.007	-0.002	-0.006	-0.089	-0.045	-0.060
2005	-0.002	0.003	-0.006	-0.003	-0.006	-0.156	-0.059	-0.019
2006	-0.005	-0.002	-0.001	-0.001	-0.003	-0.014	-0.034	0.038
2007	-0.007	0.002	0.000	0.002	-0.001	-0.077	-0.039	0.056
2008	-0.021	-0.019	0.009	0.007	0.009	0.172	0.061	0.327
2009	-0.013	-0.003	0.009	0.002	0.003	0.033	-0.016	0.103
2010	-0.010	-0.001	0.004	0.003	0.001	-0.039	-0.033	0.102
2011	-0.012	-0.004	0.007	0.004	0.003	0.003	-0.013	0.176
2012	-0.004	0.003	0.001	0.000	-0.003	-0.108	-0.054	0.042
2013	-0.001	0.005	0.000	0.000	-0.003	-0.177	-0.026	0.054
2014	-0.001	0.003	-0.001	0.001	-0.004	-0.130	-0.017	0.065
2015	-0.006	-0.001	0.003	0.007	0.001	-0.134	0.061	0.109
2016	-0.006	-0.001	0.007	0.010	-0.001	-0.106	0.060	0.175
Observations	178626	89077	227357	182241	144043	108790	73250	114220

Table 5. displays the average effect of the individual companies on the sector when moving from median to 95% *VaR* state on the returns on the sector. The green cells indicate that the average effect of the companies on the sector returns is higher when at their 95% *VaR* level, pointing at systemic risk. The darker the shade, the larger this contribution to risk. The red cells display the opposite effect and the darker red shade indicates that the interdependence among the different firms is lower.

5.5 Connection of Systemic Risk in the Real Sectors and the Financial Sector

5.5.1 Time Varying Comparison of Real Sectors to the Financial Sector

To elaborate further on the systemic risk in economically bad times, the evaluation of the $\Delta\hat{\beta}$ of equation 15 that introduced the $\Delta CoVaR$ model over time including the recession variable is displayed in figure 1. The top two panes display the sectors that have systemic risk development with the same magnitude as the financial sector's development of systemic risk, whereas the bottom two panes display the sectors with more volatile systemic risk development. On the left-hand side vertical axes, the values of the systemic risk in the sectors are displayed. For the financial sector, this is displayed at the right-hand side vertical axes. The shaded areas indicate recessionary periods.

Panel A displays the systemic risk development of the basic materials and oil & gas sectors compared to the financial sector. The systemic risk in the basic material and the oil & gas sector moves together and in the opposite direction of the financial sector. Panel B shows the development of systemic risk in the health care and personal & household goods sectors in comparison to the financial sector. When looking at the development of the systemic risk coefficient, the results in figure 1 panel B show that the coefficients move in the opposite direction from the financial sector from 1999 to 2002 and after this period they move together. This points at the sectors having a same development of systemic risk in the years after 2002.

Panel C and D display the sectors that differ highly in magnitude of systemic risk development in relation to the financial sector. Therefore, the values of the y-axis differ more from zero when comparing them with the graphs in panel A and B. The technology and telecom sector displayed in panel C show the same development of systemic risk as the sectors displayed in panel B. Compared to the financial sector it shows the same development after 2002. However, the magnitude of the dependency among firms is larger for the technology and telecom sectors than the sectors displayed in panel A and B. This highly volatile path of the systemic risk could be a possible explanation for why in the time un-varying analysis these two sectors did not show systemic risk over the whole period. Panel D displays the development of systemic risk in the utilities sector, which moves together with the financial sector, only again the magnitude is much larger than in the financial sector.

As seen in table 5 and in figure 1, the systemic risk coefficient is positive for nearly all sectors except for the basic materials and oil & gas sectors during the most recent financial crisis. However, this is not the case when looking at the earlier recessionary period, from 2000-2003. Another outstanding result is the growth in systemic risk in the period 2015-2016 for the financials, health care and in particular the telecom and utilities sectors. This is a development that should be watched closely by policymakers as well as investors. The fact that the systemic risk does not show in all sectors in the first economically bad period examined, and is present in the later years as well as the years after the financial crisis, might come from the integration of the European economy (The Council of Foreign Relations, 2017). This interconnection between all European countries has grown over the years and this could be an explanation for the increase in the effects of the individual companies on the different sectors in the European economy.

Figure 1. Annual $\Delta CoVaR$ for the Real Sectors in the European Economy Relative to the $\Delta CoVaR$ of the Financial Sector

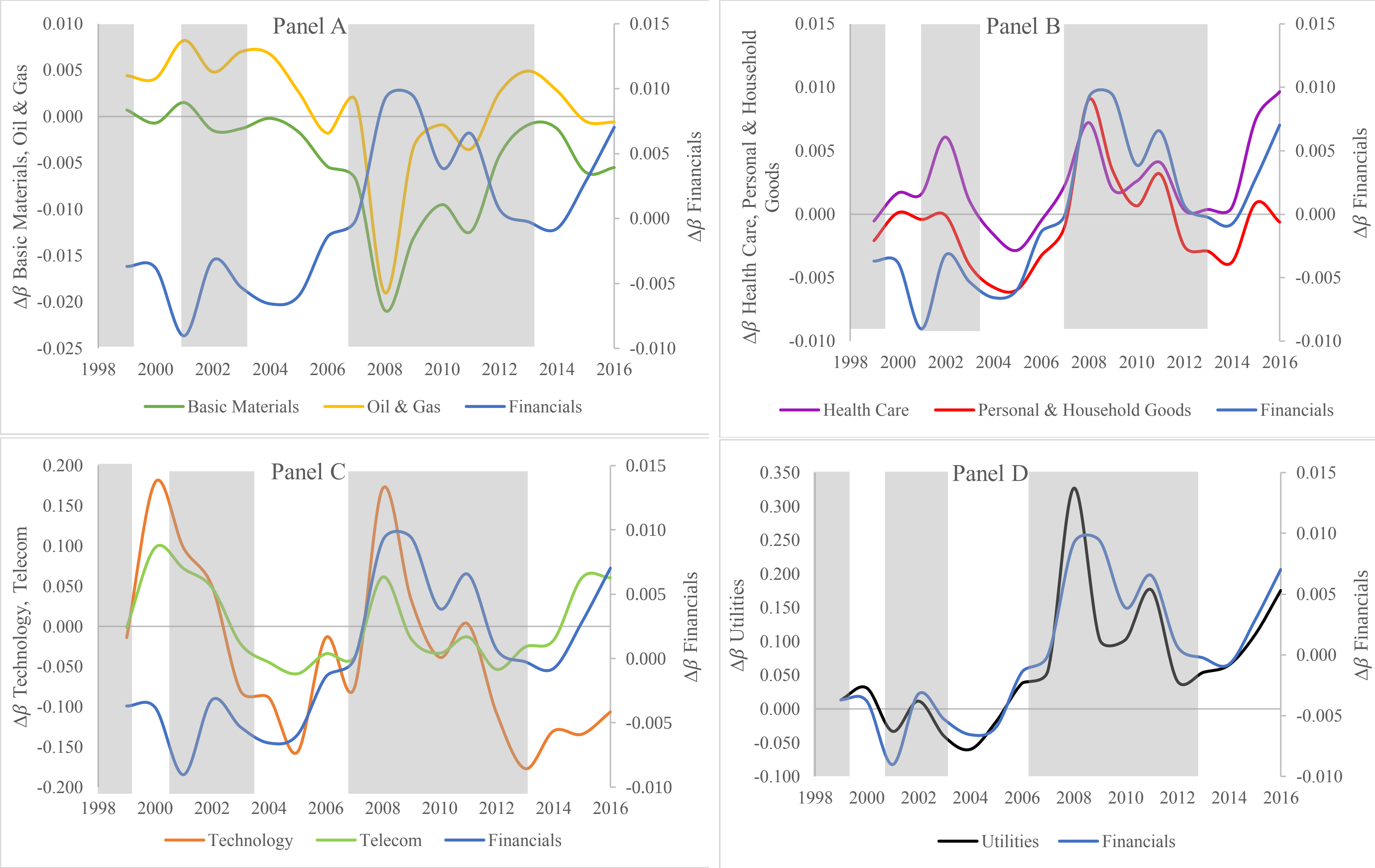

Figure 1 displays the yearly $\Delta\hat{\beta}$ coefficient of the $\Delta CoVaR$ regressions including a recession dummy over the period 1998-2016 for the financial, technology and telecom sector. On the left-hand side vertical axes the values of $\Delta\hat{\beta}$ for the sectors is added, as for the financial sector the values of $\Delta\hat{\beta}$ are added on the right-hand side vertical axes. The shaded area displays the years in which the European economy was in a recession and is added to display the difference in the $\Delta CoVaR$ coefficients in times of economic booms and downturns.

5.5.2 Co-movement of Systemic Risk in the Real Sectors and Financial Sector

As an addition to the previous estimations the connection between the returns of the real sectors and the financial sector is looked into. This is done to see whether the performance of the companies in other sectors have spill-overs to the financial sector when the returns move from the normal state to the 95% VaR level. Capital needed for investments are regularly funded with external finance due to capital constraints. When a company with debt to financial institutions becomes distressed, this can spill over to other companies in the sector as well as the financial sector (Canton, 2014). The results in table 5 and figure 1 show that contribution of individual companies to systemic risk differs among the different sectors over the years investigated as well as the magnitude of the contribution.

This regression shows if there is significant co-movement between systemic risk of the individual companies of the real sectors of the European economy and of the average systemic risk of the financial sector for the whole sample period.

This analysis is done by the OLS regression on the average $\Delta\hat{\beta}$ coefficient of the financial sector as dependent variable of the $\Delta\hat{\beta}$ coefficients of the individual companies in the other sectors in the analysis. These coefficients are the estimates of equation 15 that determines the $\Delta CoVaR$.

The model for the estimation of the relation between systemic risk in the financial sector and the other sectors looks like:

$$\begin{aligned}\Delta\beta_t^{Sector=Financial} &= \alpha_t + \delta_1\Delta\beta_t^{i,Sector=Basic\ Materials} + \delta_2\Delta\beta_t^{i,Sector=Oil\ Gas} \\ &+ \delta_3\Delta\beta_t^{i,Sector=Health\ Care} + \delta_4\Delta\beta_t^{i,Sector=PHHG} + \delta_5\Delta\beta_t^{i,Sector=Technology} \\ &+ \delta_6\Delta\beta_t^{i,Sector=Telecom} + \delta_7\Delta\beta_t^{i,Sector=Utilities} + \varepsilon_t\end{aligned} \tag{16}$$

The results of the estimation are summarized in table 6 and indicate whether there exists a relationship between systemic risk in the financial sector and other real sectors of the European economy. When looking at the results in table 6, the individual companies of the basic materials, oil & gas, health care, personal & household goods and utilities sector show a positive significant effect on the returns of the financial sector when moving from their median state towards their 95% VaR level, indicating that the companies in these sectors have systemic risk movement in the same direction as the financial sector over the time period investigated. This effect is the highest for the utilities sector. On the other hand, the technology and telecom sector have a negative but not significant effect, indicating that the systemic risk in these sectors is lower when the systemic risk in the financial sector is higher.

The results of the co-movement of the basic materials, oil & gas and the financial sector are not in line with the expectations that were raised when looking at the average systemic risk development in the previous time-varying analysis, which compares the systemic risk development of the real sectors with systemic risk development in the financial sector. This correlation between the basic materials, oil & gas sector and financial sector could be due to the large differences between the companies' individual contribution to risk in their sector compared to the systemic risk in the financial sector. Another more distinct measure should be applied to detect significant systemic risk co-movement between these sectors and the financial sector. The health care and personal & household goods sector show higher coefficients which indicates more co-movement, and this is also visible in the graphs shown of the average systemic risk in figure 1. The highest significant coefficient of the utilities sector is also in line with the average systemic risk development displayed in the previous section.

The positive significant effects could point at spill-over effects from companies in these sectors to the financial sector. However, further investigation is needed to detect if the $\Delta CoVaR$ of these sectors show explanatory power for the systemic risk in the financial sector or possibly reversed causality. Even though the evidence that confirms systemic risk co-movement among the different sectors here should be interpreted with care, it could be of interest for investors and policy makers to consider the possible co-movement of risk in the real sectors of the economy and the financial sector when making decisions regarding investments or policy making. If the mechanism of the contagion between the other sectors and financial sector is revealed, it can be used to detect the potential contagion effects timely and prevent harm to the whole economy.

Table 6. Connection of Systemic Risk in the Real Sectors and the Financial Sector

	Financial Sector
Basic Materials	0.044***
	(0.011)
Oil & Gas	0.056**
	(0.026)
Health Care	0.203***
	(0.039)
Personal & Household Goods	0.136***
	(0.038)
Technology	-0.005
	(0.035)
Telecom	-0.049
	(0.050)
Utilities	0.422***
	(0.053)
Constant	-0.000**
	(0.000)
Observations	203
R-squared	0.551

Table 6. displays the effect of the different sectors on the returns of the individual sector.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Conclusion

This thesis analyzes the presence and development of systemic risk in eight different sectors of the European economy using the *CoVaR* approach introduced by Adrian and Brunnermeier (2016). This thesis shows that systemic risk in real sectors of the European economy does not show the same build-up and size as the financial sector. The results suggest that there is a possible spill-over of systemic risk in the utilities sector, followed by the health care, personal & household goods, oil & gas and basic materials sector, to systemic risk in the financial sector or the other way around, however this should be interpreted with care. Possible reasons for the interconnection among sectors can be stakes in each other's businesses, contractual links, companies selling and buying each other's products and companies are connected to the financial sector as investments are often funded with external finance (Adrian & Brunnermeier, 2011, Canton, 2014).

Firstly, the research provided in this thesis shows whether systemic risk in the different sectors of the European economy exists and to what extend it is expected to influence the real European economy. It is shown that systemic risk is present in most of the sectors, except for the technology and telecom sector. The results however, neither confirm nor reject that contribution to risk comes from all companies that operate in the sectors. Secondly, the research finds systemic risk that is present in the real sectors of the economy is not explained only by relatively bad economic circumstances. The size of the effect differs among the different sectors, and is not largest in the financial sector, as was expected out of the results of the study of Muns and Bijlsma (2011). Thirdly, this thesis uses the *CoVaR* approach to determine the development of systemic risk in the different sectors. It is shown that the systemic risk build-up in some sectors follow the same path as the systemic risk build-up of the financial sector. However, this is not the case for all sectors. The results indicate that the systemic risk is present in the period after the internet bubble burst for the technology and telecom sector. In this period, there was lower systemic risk visible in the financial sector. For the financial sector, systemic risk was the highest in the most recent financial crisis. Lastly, to measure the importance of systemic risk in other sectors, it is studied whether real sectors influence systemic risk in the financial sector. All sectors except the technology and telecom sectors, show a significant positive result, indicating that systemic risk in the real sectors and the financial sector moves in the same direction over the period investigated. However, this result should be interpreted with care as the analysis only shows the co-movement and not the causality of systemic risk. To determine whether there exists causality, another method should be applied.

A limitation of this thesis is that the time varying estimation of systemic risk has only yearly observations, while this could vary also within years. This thesis only uses a recession variable to determine the economic state, whereas the study of Adrian and Brunnermeier (2016) uses other variables to determine the economic circumstances. These other state variables could replace the recession variable in the model to see the effects on the sector returns more frequently than only annual.

The investigation conducted in this thesis is an attempt to discover systemic risk in other sectors of the real economy in Europe in addition to research on systemic risk in the financial sector. Further research on this topic can be valuable for regulation policy on excessive risk taking or the approach of controlling risk spill-overs in different economic circumstances. This thesis could be extended by investigating whether there are interdependencies between the real sectors in the European economy other than the connection with the financial sector.

Furthermore, following the systemic risk in the technology and telecom sectors after the internet bubble burst and in the financial sector in the most recent financial crisis, it would be interesting for further research to analyze if certain characteristics of a crisis influence the extent of sector specific systemic risk. This could be valuable for policy making. If there exists a connection between crisis characteristics and systemic risk, prevention can be targeted towards sectors to minimize the negative externalities for these sectors and the whole economy.

As mentioned previously, there is a range of mechanisms that can possibly influence systemic risk (Rodríguez-Moreno and Peña, 2012). As systemic risk has these different dimensions, this means that the *CoVaR* method applied in this thesis is not the only way to determine whether systemic risk is present in the different sectors of the real economy. The *CoVaR* approach is used to determine the tail dependency and not necessarily the causality of the spill-over (Adrian and Brunnermeier, 2016). To elaborate on the systemic risk in the different sectors of the European economy, other risk measures could be used to evaluate the results of this thesis further.

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Appendix

List of Companies per Sector

BASIC MATERIALS STOXX EUROPE 600

Company Name	*Year*	*Market*	*Subsector*
BAYER (XET)	1991	Germany	Chemicals
BASF (XET)	1991	Germany	Chemicals
GLENCORE	2011	United Kingdom	Mining
RIO TINTO	1964	United Kingdom	Mining
AIR LIQUIDE	1973	France	Chemicals
BHP BILLITON	1997	United Kingdom	Mining
LINDE (XET)	1991	Germany	Chemicals
ANGLO AMERICAN	1990	United Kingdom	Mining
ARCELORMITTAL	1997	Netherlands	Industrial Metals and Mining
AKZO NOBEL	1973	Netherlands	Chemicals
GIVAUDAN 'N'	2000	Switzerland	Chemicals
NORSK HYDRO	1973	Norway	Industrial Metals and Mining
SOLVAY	1973	Belgium	Chemicals
ANTOFAGASTA	1982	United Kingdom	Mining
COVESTRO (XET)	2015	Germany	Chemicals
DSM KONINKLIJKE	1989	Netherlands	Chemicals
EMS-CHEMIE 'N'	1978	Switzerland	Chemicals
TENARIS	2002	Luxembourg	Industrial Metals and Mining
UPM-KYMMENE	1991	Finland	Forestry and Paper
EVONIK INDUSTRIES (XET)	2013	Germany	Chemicals
MONDI	2007	United Kingdom	Forestry and Paper
FRESNILLO	2008	United Kingdom	Mining
YARA INTERNATIONAL	2004	Norway	Chemicals
BOLIDEN	1999	Sweden	Mining
RANDGOLD RESOURCES	1997	United Kingdom	Mining
STORA ENSO 'R'	1988	Finland	Forestry and Paper
JOHNSON MATTHEY	1964	United Kingdom	Chemicals
CLARIANT	1995	Switzerland	Chemicals
CRODA INTERNATIONAL	1964	United Kingdom	Chemicals
SYMRISE (XET)	2006	Germany	Chemicals
UMICORE	1973	Belgium	Chemicals
ARKEMA	2006	France	Chemicals
BRENNTAG (XET)	2010	Germany	Chemicals
VOESTALPINE	1995	Austria	Industrial Metals and Mining
BILLERUD KORSNAS	2001	Sweden	Forestry and Paper
IMERYS	1973	France	Mining
LANXESS (XET)	2005	Germany	Chemicals
OUTOKUMPU 'A'	1989	Finland	Industrial Metals and Mining
POLYMETAL INTERNATIONAL	2011	United Kingdom	Mining
HEXPOL 'B'	2008	Sweden	Chemicals
IMCD GROUP	2014	Netherlands	Chemicals
K + S (XET)	1998	Germany	Chemicals

VICTREX	1995	United Kingdom	Chemicals
CENTAMIN	2001	United Kingdom	Mining
FUCHS PETROLUB PF. (XET)	1998	Germany	Chemicals

OIL & GAS STOXX EUROPE 600 (ENERGY)

Company Name	*Year*	*Market*	*Subsector*
TOTAL	1973	France	Oil and Gas Producers
ROYAL DUTCH SHELL A	1973	Netherlands	Oil and Gas Producers
BP	1964	United Kingdom	Oil and Gas Producers
STATOIL	2001	Norway	Oil and Gas Producers
ENI	1995	Italy	Oil and Gas Producers
REPSOL YPF	1989	Spain	Oil and Gas Producers
VESTAS WINDSYSTEMS	1998	Denmark	Alternative Energy
OMV	1987	Austria	Oil and Gas Producers
GALP ENERGIA SGPS	2006	Portugal	Oil and Gas Producers
NESTE	2005	Finland	Oil and Gas Producers
SIEMENS GAMESA RENEWABLE ENERGY	2000	Spain	Alternative Energy
LUNDIN PETROLEUM	2001	Sweden	Oil and Gas Producers
SAIPEM	1984	Italy	Oil Equipment and Services
WOOD GROUP (JOHN)	2002	United Kingdom	Oil Equipment and Services
PETROFAC	2005	United Kingdom	Oil Equipment and Services
SBM OFFSHORE	1973	Netherlands	Oil Equipment and Services
SUBSEA 7	1997	Norway	Oil Equipment and Services
AMEC FOSTER WHEELER	1982	United Kingdom	Oil Equipment and Services
TULLOW OIL	1989	United Kingdom	Oil and Gas Producers
TGS-NOPEC GEOPHS.	1997	Norway	Oil Equipment and Services

FINANCIALS STOXX EUROPE 600

Company Name	*Year*	*Market*	*Subsector*
BANCO SANTANDER	1987	Spain	Banks
BNP PARIBAS	1993	France	Banks
ALLIANZ (XET)	1991	Germany	Nonlife Insurance
AXA	1977	France	Nonlife Insurance
ING GROEP	1991	Netherlands	Banks
BBV.ARGENTARIA	1988	Spain	Banks
INTESA SANPAOLO	1973	Italy	Banks
CREDIT AGRICOLE	2001	France	Banks
UNICREDIT	1973	Italy	Banks
SOCIETE GENERALE	1987	France	Banks
KBC GROUP	1973	Belgium	Banks
CAIXABANK	2007	Spain	Banks
DEUTSCHE BANK (XET)	1991	Germany	Banks
ABN AMRO GROUP	2015	Netherlands	Banks
ASSICURAZIONI GENERALI	1973	Italy	Nonlife Insurance
MUENCHENER RUCK. (XET)	1996	Germany	Nonlife Insurance
SAMPO 'A'	1989	Finland	Nonlife Insurance
UNIBAIL-RODAMCO SE REIT	1974	France	Real Estate Investment Trusts
NATIXIS	1989	France	Banks
ERSTE GROUP BANK	1997	Austria	Banks
VONOVIA (XET)	2013	Germany	Real Estate Investment and Services

DEUTSCHE BOERSE (XET)	2001	Germany	Financial Services (Sector)
BANCO DE SABADELL	2001	Spain	Banks
AMUNDI (WI)	2015	France	Financial Services (Sector)
BANKIA	2011	Spain	Banks
COMMERZBANK (XET)	1991	Germany	Banks
GBL NEW	1973	Belgium	Financial Services (Sector)
NN GROUP	2014	Netherlands	Life Insurance
CNP ASSURANCES	1998	France	Life Insurance
EXOR ORD	2009	Italy	Financial Services (Sector)
HANNOVER RUCK. (XET)	1997	Germany	Nonlife Insurance
KLEPIERRE	1989	France	Real Estate Investment Trusts
AEGON	1973	Netherlands	Life Insurance
DEUTSCHE WOHNEN (XET) BR.SHS.	2006	Germany	Real Estate Investment and Services
MAPFRE	1987	Spain	Nonlife Insurance
BANK OF IRELAND GROUP	1964	Ireland	Banks
BANKINTER 'R'	1987	Spain	Banks
MEDIOBANCA BC.FIN	1973	Italy	Banks
AGEAS (EX-FORTIS)	1973	Belgium	Life Insurance
GECINA REIT	1989	France	Real Estate Investment Trusts
POSTE ITALIANE	2015	Italy	Life Insurance
RAIFFEISEN BANK INTL.	2005	Austria	Banks
SCOR SE	1989	France	Nonlife Insurance
BANCO BPM	1998	Italy	Banks
ICADE REIT	1989	France	Real Estate Investment Trusts
UNIONE DI BANCHE ITALIAN	2003	Italy	Banks
ACKERMANS & VAN HAAREN	1986	Belgium	Financial Services (Sector)
AZIMUT HOLDING	2004	Italy	Financial Services (Sector)
FINECOBANK SPA	2014	Italy	Banks
FONCIERE DES REGIONS	1988	France	Real Estate Investment Trusts
LEG IMMOBILIEN (XET)	2013	Germany	Real Estate Investment and Services
MERLIN PROPERTIES REIT	2014	Spain	Real Estate Investment Trusts
UNIPOLSAI	1973	Italy	Nonlife Insurance
WENDEL	1989	France	Financial Services (Sector)
BOLSAS Y MERCADOS ESPANOLES	2006	Spain	Financial Services (Sector)
BPER BANCA	1991	Italy	Banks
BUWOG	2014	Austria	Real Estate Investment and Services
EURONEXT	2014	France	Financial Services (Sector)
AAREAL BANK (XET)	2002	Germany	Financial Services (Sector)
COFINIMMO	1994	Belgium	Real Estate Investment Trusts
DEUTSCHE EUROSHOP (XET)	2000	Germany	Real Estate Investment and Serv
HEALTH CARE STOXX EUROPE 600			
Company Name	*Year*	*Market*	*Subsector*
ASTRAZENECA	1993	United Kingdom	Pharmaceuticals and Biotechnology
BB BIOTECH N	1993	Switzerland	Pharmaceuticals and Biotechnology
BTG	1995	United Kingdom	Pharmaceuticals and Biotechnology
CHR HANSEN HOLDING	2010	Denmark	Pharmaceuticals and Biotechnology

COLOPLAST	1983	Denmark	Health Care Equipment and Services
CONVATEC GROUP	2016	United Kingdom	Health Care Equipment and Services
ELEKTA	1994	Sweden	Health Care Equipment and Services
ESSILOR INTL.	1975	France	Health Care Equipment and Services
EUROFINS SCIENTIFIC	1997	France	Health Care Equipment and Services
FRESENIUS	1999	Germany	Health Care Equipment and Services
FRESENIUS MED.CARE	1996	Germany	Health Care Equipment and Services
GALAPAGOS	2005	Belgium	Pharmaceuticals and Biotechnology
GENMAB	2000	Denmark	Pharmaceuticals and Biotechnology
GERRESHEIMER	2007	Germany	Health Care Equipment and Services
GETINGE	1993	Sweden	Health Care Equipment and Services
GLAXOSMITHKLINE	1964	United Kingdom	Pharmaceuticals and Biotechnology
GN STORE NORD	1973	Denmark	Health Care Equipment and Services
GRIFOLS ORD CL	2006	Spain	Pharmaceuticals and Biotechnology
H LUNDBECK	1999	Denmark	Pharmaceuticals and Biotechnology
HIKMA PHARMACEUTICALS	2005	United Kingdom	Pharmaceuticals and Biotechnology
INDIVIOR	2014	United Kingdom	Pharmaceuticals and Biotechnology
IPSEN	2005	France	Pharmaceuticals and Biotechnology
LONZA GROUP	1999	Switzerland	Pharmaceuticals and Biotechnology
MEDICLINIC INTERNATIONAL	2013	United Kingdom	Health Care Equipment and Services
MERCK KGAA	1996	Germany	Pharmaceuticals and Biotechnology
NOVARTIS	1973	Switzerland	Pharmaceuticals and Biotechnology
NOVO NORDISK	1974	Denmark	Pharmaceuticals and Biotechnology
NOVOZYMES	2000	Denmark	Pharmaceuticals and Biotechnology
ORION	1993	Finland	Pharmaceuticals and Biotechnology
ORPEA	2002	France	Health Care Equipment and Services
PHILIPS ELTN.KONINKLIJKE	1973	Netherlands	Health Care Equipment and Services
QIAGEN	1998	Germany	Pharmaceuticals and Biotechnology
RECORDATI INDUA.CHIMICA	1986	Italy	Pharmaceuticals and Biotechnology
ROCHE HOLDING	1973	Switzerland	Pharmaceuticals and Biotechnology
SANOFI	1980	France	Pharmaceuticals and Biotechnology
SHIRE	1996	United Kingdom	Pharmaceuticals and Biotechnology
SMITH & NEPHEW	1964	United Kingdom	Health Care Equipment and Services
SONOVA	1994	Switzerland	Health Care Equipment and Services
STADA ARZNEIMITTEL	1998	Germany	Pharmaceuticals and Biotechnology
STRAUMANN HLDG.	1998	Switzerland	Health Care Equipment and Services
SWEDISH ORPHAN BIOVITRUM	2006	Sweden	Pharmaceuticals and Biotechnology
UCB	1973	Belgium	Pharmaceuticals and Biotechnology
UDG HEALTHCARE PUBLIC	1992	Ireland	Health Care Equipment and Services
WILLIAM DEMANT HLDG.	1995	Denmark	Health Care Equipment and Services

PERSONAL & HOUSEHOLD GOODS STOXX EUROPE 600

Company Name	*Year*	*Market*	*Subsector*
BRITISH AMERICAN TOBACCO	1964	United Kingdom	Tobacco
LVMH	1973	France	Personal Goods
L'OREAL	1973	France	Personal Goods
UNILEVER DR	1973	Netherlands	Personal Goods

UNILEVER (UK)	1964	United Kingdom	Personal Goods
RECKITT BENCKISER GROUP	1964	United Kingdom	Household Goods and Home Construction
HERMES INTL.	1993	France	Personal Goods
CHRISTIAN DIOR	1991	France	Personal Goods
ADIDAS (XET)	1996	Germany	Personal Goods
RICHEMONT N	1988	Switzerland	Personal Goods
IMPERIAL BRANDS	1996	United Kingdom	Tobacco
LUXOTTICA	2000	Italy	Personal Goods
BEIERSDORF (XET)	1996	Germany	Personal Goods
THE SWATCH GROUP 'B'	1993	Switzerland	Personal Goods
BURBERRY GROUP	2002	United Kingdom	Personal Goods
ELECTROLUX 'B'	1982	Sweden	Household Goods and Home Construction
PERSIMMON	1985	United Kingdom	Household Goods and Home Construction
PANDORA	2010	Denmark	Personal Goods
TAYLOR WIMPEY	1964	United Kingdom	Household Goods and Home Construction
BARRATT DEVELOPMENTS	1969	United Kingdom	Household Goods and Home Construction
SEB	1975	France	Household Goods and Home Construction
UBISOFT ENTM.	1996	France	Leisure Goods
MONCLER	2013	Italy	Personal Goods
OSRAM LICHT (XET)	2013	Germany	Household Goods and Home Construction
SCA 'B'	1982	Sweden	Forestry and Paper
BELLWAY	1979	United Kingdom	Household Goods and Home Construction
BERKELEY GROUP HDG.(THE)	1984	United Kingdom	Household Goods and Home Construction
BOSS (HUGO) (XET)	1999	Germany	Personal Goods
SWEDISH MATCH	1996	Sweden	Tobacco
AMER SPORTS	1988	Finland	Leisure Goods
BIC	1973	France	Household Goods and Home Construction
HUSQVARNA 'B'	2006	Sweden	Household Goods and Home Construction
ONTEX GROUP	2014	Belgium	Personal Goods
STEINHOFF INTL.HDG.(XET)	2006	South Africa	Household Goods and Home Construction
ESSITY B	2017	Sweden	Personal Goods
HENKEL PREF. (XET)	1991	Germany	

TECHNOLOGY STOXX EUROPE 600

Company Name	*Year*	*Market*	*Subsector*
SAP (XET)	1996	Germany	Software and Computer Services
ASML HOLDING	1995	Netherlands	Technology Hardware and Equipment
NOKIA	1988	Finland	Technology Hardware and Equipment
DASSAULT SYSTEMES	1996	France	Software and Computer Services
INFINEON TECHS. (XET)	2000	Germany	Technology Hardware and Equipment
CAPGEMINI	1985	France	Software and Computer Services
ERICSSON 'B'	1982	Sweden	Technology Hardware and Equipment
ATOS	1989	France	Software and Computer Services
HEXAGON 'B'	1988	Sweden	Software and Computer Services
ILIAD	2004	France	Software and Computer Services
SAGE GROUP	1989	United Kingdom	Software and Computer Services
UNITED INTERNET (XET)	1998	Germany	Software and Computer Services
MICRO FOCUS INTL.	2005	United Kingdom	Software and Computer Services
LOGITECH 'R'	1988	Switzerland	Technology Hardware and Equipment

ASM INTERNATIONAL	1996	Netherlands	Technology Hardware and Equipment
GEMALTO	2004	Netherlands	Software and Computer Services
INGENICO GROUP	1988	France	Technology Hardware and Equipment
TEMENOS GROUP	2001	Switzerland	Software and Computer Services
AUSTRIAMICROSYSTEMS	2004	Switzerland	Technology Hardware and Equipment
DIALOG SEMICON. (XET)	1999	Germany	Technology Hardware and Equipment
SOFTWARE (XET)	1999	Germany	Software and Computer Services
SOPRA STERIA GROUP	1990	France	Software and Computer Services
SIMCORP	2000	Denmark	Software and Computer Services
STMICROELECTRONICS (MIL)	1998	France	

TELECOM STOXX EUROPE 600

Company Name	*Year*	*Market*	*Subsector*
VODAFONE GROUP	1988	United Kingdom	Mobile Telecommunications
DEUTSCHE TELEKOM (XET)	1996	Germany	Mobile Telecommunications
TELEFONICA	1987	Spain	Fixed Line Telecommunications
ORANGE	1997	France	Fixed Line Telecommunications
BT GROUP	1984	United Kingdom	Fixed Line Telecommunications
TELENOR	2000	Norway	Mobile Telecommunications
ALTICE A	2014	Netherlands	Fixed Line Telecommunications
SWISSCOM 'R'	1998	Switzerland	Fixed Line Telecommunications
TELIA COMPANY	2000	Sweden	Mobile Telecommunications
SFR GROUP	2013	France	Mobile Telecommunications
KPN KON	1994	Netherlands	Fixed Line Telecommunications
TELECOM ITALIA	1973	Italy	Fixed Line Telecommunications
PROXIMUS	2004	Belgium	Fixed Line Telecommunications
TELEFONICA DTL. (XET) HLDG.	2012	Germany	Mobile Telecommunications
ELISA	1999	Finland	Fixed Line Telecommunications
CELLNEX TELECOM	2015	Spain	Mobile Telecommunications
INMARSAT	2005	United Kingdom	Mobile Telecommunications
TDC	1994	Denmark	Fixed Line Telecommunications
TELE2 'B'	1996	Sweden	Mobile Telecommunications
FREENET (XET)	1999	Germany	Mobile Telecommunications
SUNRISE COMMUNICATIONS	2015	Switzerland	Fixed Line Telecommunications

UTILITIES STOXX EUROPE 600

Company Name	*Year*	*Market*	*Subsector*
ENEL	1999	Italy	Electricity
IBERDROLA	1987	Spain	Electricity
ENGIE	2005	France	Gas, Water and Multiutilities
NATIONAL GRID	1995	United Kingdom	Gas, Water and Multiutilities
EDF	2005	France	Electricity
E ON (XET)	1991	Germany	Gas, Water and Multiutilities
ENDESA	1987	Spain	Electricity
GAS NATURAL SDG	1987	Spain	Gas, Water and Multiutilities
INNOGY (XET)	2016	Germany	Gas, Water and Multiutilities
DONG ENERGY AS	2016	Denmark	Gas, Water and Multiutilities
SSE	1991	United Kingdom	Electricity
SNAM	2001	Italy	Gas, Water and Multiutilities

CENTRICA	1997	United Kingdom	Gas, Water and Multiutilities
EDP ENERGIAS DE PORTUGAL	1997	Portugal	Electricity
FORTUM	1998	Finland	Electricity
RWE (XET)	1991	Germany	Gas, Water and Multiutilities
TERNA RETE ELETTRICA NAZ	2004	Italy	Electricity
VEOLIA ENVIRONNEMENT	2000	France	Gas, Water and Multiutilities
RED ELECTRICA	1999	Spain	Electricity
SUEZ	2008	France	Gas, Water and Multiutilities
UNIPER SE (XET)	2016	Germany	Gas, Water and Multiutilities
UNITED UTILITIES GROUP	1989	United Kingdom	Gas, Water and Multiutilities
CEZ	1993	Czech Republic	Electricity
SEVERN TRENT	1989	United Kingdom	Gas, Water and Multiutilities
A2A	1998	Italy	Electricity
ENAGAS	2002	Spain	Gas, Water and Multiutilities
PENNON GROUP	1989	United Kingdom	Gas, Water and Multiutilities
ITALGAS	2016	Italy	Gas, Water and Multiutilities
RUBIS	1989	France	Gas, Water and Multiutilities
DRAX GROUP	2005	United Kingdom	Electricity