UNIVERSITY OF TARTU
Faculty of Social Sciences
School of Economics and Business Administration

Samuel Acquaah Arhin
Gabriela Claros

SPILLOVER TRANSMISSION AND THE EFFECTS OF INNOVATION & FDI ON SYSTEMIC RISK

Master's Thesis

Supervisor: Mustafa Hakan Eratalay (Lecturer, Ph.D.)

Tartu, 2020

Name and signature of supervisor …………………………………

Allowed for defence on ....

(date)

I have written this master's thesis independently. All viewpoints of other authors, literary sources, and data from elsewhere used for writing this paper have been referenced. …………………………………..

(signature of author)

Acknowledgments

We will like to thank the University of Tartu for the opportunity given to us to complete our master's program in Quantitative Economics. Special gratitude to our program manager Jaan Masso for his support and endless help during our studies.

We also like to express our sincere gratitude to our supervisor Mustafa Hakan Eratalay whose guidance helped us complete this thesis. We would also like to thank the thesis committee and our opponent Kaspar Oja for taking the time to review and constructively critique this paper.

Finally, and most importantly, we are grateful to the Almighty God for His grace toward us and to our families for their love and support during this journey.

Abstract

This paper investigates volatility spillovers transmission amongst selected companies within the STOXX Europe Diversification Select 50 Index and thereby highlighted systemically important companies that might transfer risk to other firms within a similar sector in the event of substantial external shock. Further, the study assessed the effects of innovation and foreign direct investment on systemic risk. The invariant forecast error variance decompositions for total and directional volatility spillovers by Diebold and Yilmaz (2012) and ΔCoVaR by Adrian and Brunnermeier (2016) were adopted as the spillover and systemic risk measure respectively.

Our results show high volatility amongst some companies; however, volatility levels do not seem to correlate with spillover transmission. We also find a negative relationship between innovation and systemic risk. However, for the variables representing FDI, we find that foreign control decreases systemic risk, while firms with foreign subsidiaries increased systemic risk contribution.

Table of Contents

1. Introduction

Over the past two decades, there have been several global level shocks arising from different adverse situations with palpable effects on both financial markets and the real economy. Noticeable amongst them are the global financial crisis, the Chinese market turbulence, Brexit, the Greek government-debt crisis, and the early onslaught of the Covid-19 pandemic. An undeniable characteristic of these shocks is that it usually starts from one country, but its effects gradually spread across the globe over a period of time. Globalization and financial integration are important factors contributing to the spurt of such shocks across the world (Bruno and Shin (2015), Moshirian (2015)).

Although advancements made toward globalization have resulted in several advantages including international trade, transfer of investment from one part of the globe to another as well as promoting industrialization. Its affinity towards internationalization makes it a perfect channel for the transmission of systemic risk (Van Cauwenberge, Vancauteren, Braekers, and Vandemaele, 2019).

The intensity and concentration of each crisis may be unique, however, the reaction from policy advisors and governments targeted at ameliorating the negative economic impacts have largely been monotonous. Bailouts, stimulus packages, and enhanced regulatory frameworks have been the preferred tools in this regard. For instance, during the global financial crisis, it is estimated that the United States government made commitments of about US$16.8 trillion (Collins, 2015) in addition to regulatory reforms such as the Dodd-Frank Wall Street Reform and Consumer Protection Act. Currently, a US$2 trillion stimulus package has been earmarked for the ongoing health pandemic (Covid-19). Similar interventions have been introduced by governments around the world.

Often, the ensuing debate after the implementation of these strategies focuses on whether these measures constitute an efficient use of public funds and why the signs of an imminent crisis were not noticed and examined in time. Certainly, a more proactive approach could be properly tailored regulation in response to systemically important firms irrespective of their sector of operation because of their potential to negatively impact the stability of other firms and even the entire economy depending on the magnitude of spillovers emitted.

Considering a different context, the European Central Bank (ECB) introduced interventions at the end of the third quarter of 2019 to help stimulate growth within the economy of the Eurozone. The aggressive nature of these measures was as a result of consistently low inflation levels and slow growth rates experienced in the Eurozone. The situation was projected to worsen due to the USA-China trade war, Brexit, and the slowdown of the Chinese economy, therefore, affirming the possibility of spillover transmission and systemic risk from different situations.

These considerations make the study of systemic risk and spillover transmission imperative. A scan through literature shows more studies have been carried out on the financial sector probably because most devastating crisis' are related to the financial sector (Rossi and Malavasi (2016), Acharya Philippon, Richardson, and Roubini (2009)), even though firms in both the financial and non-financial sectors have the potential to influence systemic risk (Van Cauwenberge et al., 2019). The effects of crises on the real sectors of the economy can be equally devastating. Initially, individual consumers defer spending on durable goods while businesses shun capital investments, this strategy results in declining sales and price reductions within both local and international markets (Eaton, Kortum, Neiman, and Romalis (2016), Bems, Johnson and Yi (2013)) which then culminates into job losses and even economic recessions.

Accordingly, this research seeks to identify systemically important companies by evaluating the volume of volatility spillover received and transmitted and also ascertain the effects of innovation and FDI on systemic risk amongst blue-chip companies in the STOXX Europe Diversification Select 50 Index. A common characteristic of blue-chip companies is that they lend themselves to innovation and internationalization which are components of the OLI framework (Dunning, 1979) used to explain why companies seek new markets. It will be interesting to find their impacts on systemic risk.

This study adopts the definition of systemic risk proposed by Adrian and Brunnermeier (2016). It simply denotes the risk that an entire system's (industry or even economy) capacity becomes compromised or unstable as a result of activities at the individual firm level. In this case, the impaired state of the system could be caused by global shocks that increase the potential to transmit high volatility spillovers to other firms in the sector and thereby trigger systemic risk incidents. By extension, we define systemically important firms as firms with high positive net volatility spillovers.

The rest of this research is constituted into five additional sections: Section 2 reviews literature about financial spillovers and systemic risk, Section 3 describes the data and data sources used, Section 4 elaborates on the selected methodology for the study, Section 5 provides a summary of empirical results and findings, and Section 6 highlights conclusions and recommendations from the research.

2. Literature Review

2.1 Financial Spillover

In the time of crisis, the interdependence between various financial markets is highly discussed among investors, academics, and regulatory authorities. There are several reasons for this interest. First, the possibility of diversifying risk depends on the degree of interactions between these markets. Second, if there is a causal relationship between the returns from different aspects of the financial market, investors can exploit investment strategies to obtain benefits in periods of high uncertainty. Third, knowledge about the connections between markets is useful in optimizing portfolios and asset pricing. Finally, it also helps financial authorities control contagion between markets by implementing effective regulations to stabilize the financial system and capital flows.

Financial crises frequently transcend its epicenter due to the existence of channels that allow vulnerability transmission. The nature of spillover effects observed could be considered as a warning post for a possible crisis that manifests itself through signals emitted by the market such as the direction of capital flows, drop in share indexes, depreciation of the national currency, etc. Generally, spillovers connote events, policies, or a phenomenon that occurs in a country, sector, firms, stock market, or any similar entity that impacts the structure of other entities. The spillover effect as it is known has become relevant as a result of the increasing integration of the markets, financial institutions, factors such as deregulation, globalization, and the advances in information technology.

Evidence indicates that information plays a critical role in most markets and these markets continue to strive for integration. Advantages attained from integration are well known (Kose et al., (2009), Prasad et al., (2010)). For instance, investors have the freedom to allocate their risk in a more efficient way which reduces the cost of capital of firms. However, studying the consequences from the recent financial crisis, some authors (Mendoza et al. (2009), (2010); Caballero et al. (2008); Milesi-Ferretti and Tille (2011) Cetorelli and Goldberg, (2012); Bruno and Shin (2015); Moshirian (2015)) found that the integration of markets with some retrenchment in capital inflows intensified contagion effect causing a severe loss to the global economy, enormous collapse in international trade, and a reduction in capital flow to and from advanced economies.

There is vast literature on volatility spillovers across developed markets (Beirne and Fratzscher, (2013), Beirne et al., (2013), Cho et al., (2015), Diebold and Yilmaz (2009) (2012), Singh et al., (2010), Syriopoulos (2007), Worthington and Higgs (2004)) show that countries usually experience significant spillover effects when there is a slowdown in the biggest economies within the integrated system, for example, the USA or China. These examples are often useful in understanding contagion, stock market integration, and the possible role of some countries or regions as sources of systemic shock.

The global financial crisis of 2008/2009 confirmed the importance of measuring contagious effects, especially for highly connected economies. The shocks from stock market downturns in the United States spread rapidly across the globe and impacted distinct economies at different levels. Apostolakis and Papadopoulos (2014) examined the financial stress co-movements and the results showed a positive relationship between crisis periods and uncertainty, with the USA being the principal transmitter of the financial stress spillovers through financial markets during stressful periods. To have a holistic discussion concerning global financial interconnectedness, it is important to know the volatility spillovers within different regions as it helps provide better appreciation of the channels of intra-regional and inter-regional transmission of volatility spillover across developed countries and emerging markets such as Asia, Latin-American, Europe and Africa (Yarovaya, Brzeszczyński, Lau, and Keung, 2016).

More so, increasing economic integration of emerging markets during the last two decades - with the help of globalization and new technologies - has many implications for the rest of the world. According to Huidrom et al., (2016) the key channels for transmitting spillovers from emerging markets are usually through its increasing share in global economic activity, global trade, and financial linkages. On average, the fluctuations in asset prices from major emerging markets such as Brazil, China, India, and South Africa to equity prices and exchange rates of other economies have increased by 28% (Gelos & Surti, 2016). Apostolou, Beirne, and John (2019) opined that changes in the monetary policies of the Federal Reserve (FED) and European Central Bank (ECB) had impacts on emerging economies in terms of market volatilities since the financial crisis.

In recent times, the European financial market has reacted to uncertainty over Brexit, and countries within the region have been affected. Nishimura and Sun (2018) adopted a new approach by using intraday data to examine the spillover effect in most important European markets. The results of this study reveal that the spillover effects increase in the first month after the vote but diminished afterward. Also, the dynamics of volatility spillovers from Credit Default Swaps (CDSs) around the Brexit pronouncement show that there was an increase with respect to previous prices and undermine creditworthiness in both the UK and Europe (Bouoiyour and Selmi, 2018). From this, it was concluded that the UK is a net transmitter of volatility while countries like France and Germany that are more likely to be "stress receivers".

Li, Ahmedy, and Chevapatraku (2016) analyzed four of the most important European financial markets to uncover the characteristics of volatility spillovers and the interdependence among them. The authors made use of four types of measures: total (non-directional) spillovers, gross directional spillovers, net directional spillovers, and net pairwise spillovers. They employed the measure designed by Diebold and Yilmaz (2012) based on a generalized vector autoregression (VAR). The results highlight considerable interdependence between these markets where Germany and France before the Brexit referendum were found the net volatilities transmitters to others but after the referendum, France and the United Kingdom appear to be net transmitters of volatilities spillovers to Germany and Switzerland.

2.2 Relationship Between Financial Spillovers and Systemic risk

Recent investigations into risk within financial systems are beginning to unravel the relationships between financial connectedness or spillover effects and systemic risk. Systemic risk thrives on the integration and connectedness of markets (Diebold and Yilmaz, 2014). Let us focus on our choice of systemic risk measure ΔCoVaR, similar to aggregated spillover transmissions from a company to a sector, ΔCoVaR also captures effects or systemic risk contributions from an entity to the entire system. Both measures gauge risk contributions from an individual entity to the overall risk of a system. The various spillover measures as well as systemic risk measure have been explained in detail under the methodology section of this research.

Several studies have been done to measure systemic risk within the financial sector. Billio et al., (2012) presents one of the first studies conducted to capture casual relationships across some of the largest financial institutions including the connectedness between hedge funds, banks, broker/dealers and insurance companies using econometric measures such as principal component analysis and Granger-causality networks on monthly return data.

Their approach was to measure Granger-causality among sectors that have diversified their portfolios by moving into non-core activities thereby increasing the potential to influence systemic risk. The study focuses more on direct and unconditional measures of connectedness to detect new links within the financial system. This is something lacking in conditional loss probability measures like COVAR and SES, which in non-crisis periods play a modest role in systemic risk buildup. Granger-causality includes this missing conditional loss probability since it uses predicted future values.

The results show that in both of the sample periods October 2002-September 2005 and July 2004–June 2007, Granger-causality and principal components analysis seem to be predictive of the Financial Crisis of 2007–2009. Also, the results suggest that the banking and insurance sectors could be a more important source of spillovers to other financial institutions rather than brokers/dealers and hedge funds. This is consistent with evidence from the recent financial crisis. Although banks play the main role in transmitting shocks in comparison with other financial institutions, all four sectors selected for the study have become highly interrelated over the past decade and thereby impact the level of systemic risk in financial industries.

In the case of Europe, some studies quantify systemic risk exposures within the financial sector. Andries, Nistor and Sprincean (2017) analyze the influence of Central Bank transparency on systemic risk for 34 banks operating on 9 Central and Eastern Europe

(CEE) countries, employing CoVaR and SRISK measures. The results revealed that high transparency from Central Banks, guide commercial banks to individually improve their expectations and decisions thereby decreasing their idiosyncratic risk. However, this transparency can also be harmful to the system from a macroprudential perspective. This is because individual financial institutions can increase their contribution to the risk of the banking system while engaging in risky activities. For emerging markets like the CEE, the spread of contagion spillover through the system will most likely depend on the degree of interconnectedness within interbank markets and how many of them are controlled by large international groups.

Similarly, Karimalis and Nomikos (2018) use CoVaR as well, but with a new methodology. They use Copula CoVaR and CoES for 46 large European Banks as a representation of the European financial system, finding that banks from Spain and France contribute the most to systemic risk. The asymmetric behavior during the pre-crisis period and afterwards seem to be connected to the harmonized intervention of central banks in response to the financial crisis. Also, the major determinants with the greatest impact on systemic risk are size and leverage, which means that bigger and/or highly leveraged financial institutions contribute to the increase of systemic risk in the economy in comparison to smaller less leveraged banks.

Buch, Krause and Tonzer (2019) investigate whether there is a difference in the marginal contribution of the banking system to systemic risk by assessing whether banks adopt measures dictated from the European Central Bank (ECB) or measures from their respective national central banks. Their results show that banks with cross border externality have a higher contribution to systemic risk in the Euro area compared to the national level. In other words, banks with higher regional interconnectedness tend to contribute more to systemic risk.

There are not enough empirical studies on systemic risk transmission in the non-financial sector. Some studies addressing this topic have recently emerged. For instance, Van Cauwenberge et al., (2018) consider stock data of 67 publicly listed Dutch companies, using ΔCoVaR suggested by Adrian and Brunnermeier (2016) capturing the marginal contribution of individual firms to overall systemic risk. To examine the impact of globalization, the authors conducted panel data analysis which measured three variables: firm trade intensity, the existence (or not) of foreign subsidiaries, and the presence (or not) of foreign control. The findings suggest that firms within the financial sector recover quickly from the effects of crisis in comparison with non-financial firms (Trapp and Wewell 2013) a reason why the non-financial sector deserves extra attention. Regarding the link between globalization and systemic risk, we find that foreign direct investment increases contribution to systemic risk spread. The result also highlights the importance of considering the effect of globalization not only on all sectors.

With a different objective, Dungey et al., (2015) investigate the degree of systemic risk amongst different sectors in Australia before, during, and after the Global Financial Crisis by calculating a daily index of systemic risk from 2004 to 2013. The results demonstrate that the financial sector is the most consistently systemically risky sector, but there have been periods since 2008 where the mining sector has contributed to equivalent levels of systemic risk or even exceed the financial sector firms when combining the risk of all mining sector firms.

A more specific study made by Kerste et al., (2015) highlighted the contagion risk within the energy sector and from the energy sector towards the banking sector which can be compared to other non-financial sectors. They made special emphasis on systemic risk in Over The Counter (OTC) derivative trading, which are private contracts traded between two parties without going through an exchange or other intermediaries. OTC derivatives could be negotiated and customized to suit the exact risk and return needed by each party. Although this type of derivative offers flexibility, it carries credit risk. For this reason, strict regulations are needed for these kinds of contracts, which are highly used within the non-financial sector (for instance, the energy sector) and the banking sector as highlighted in this study.

Wu (2018) found similar results from the energy sector by analyzing Marginal Expected Shortfall (MES) and Component Expected Shortfall (CES) using post 2008 financial crisis data for the Chinese Market. The results based on MES found that the information technology sector contributes the most to systemic risk. However, the CES analysis presents different results. It showed that the financial sector is the most important sector for systemic risk, followed by the industrial sector and energy sector. This again indicate the need to pay more attention to sectoral contributions to systemic risk and impose specific regulations to effectively monitor risk or contagion.

3. Data

The study focuses on companies within the STOXX Europe Diversification Select 50 EUR Index. The firms within the Select 50 index better suits our purpose since it is a condensed version of the comprehensive STOXX Europe 600 Index which contains 600 high performing companies across over 18 countries in the Euro area (including Finland, Switzerland, France, Spain, Netherlands, Germany, Denmark, Italy, Belgium, Austria, Sweden, Great Britain, Norway, and Portugal).

The index is controlled for correlated and volatile stocks before the top 50 companies in terms of dividend yield are selected to make up the index. Another advantage of using the index is that the companies therein are not concentrated in a few sectors of the economy but are rather spread across 13 essential sectors.

However, due to data inconsistencies, the study was restricted to a sample of 37 companies for volatility spillover analysis and 33 companies for the systemic risk analysis. Consequently, share prices of the selected companies for the period spanning January 01, 2010, and December 31, 2018, were retrieved from the Yahoo Finance website. The iShares Core Euro STOXX 50 UCITS ETF a different index was employed as a representation of the system in order to avoid overemphasizing potential relationships in estimating systemic risk measures. The index serving as a proxy is also controlled for sectorial concentration.

For the time horizon analysed, there are about four main shocks that had palpable effects on stock markets across the globe and therefore are expected to be visible in time series plots of the systemic risk and spillover measures. These shocks include the aftermath of the Global Financial Crisis, the Greek currency crisis, Chinese Market Turbulence (August 2015), and Brexit (June 2016).

Figure 1: Plot of Price (STOXX Europe Diversification Select 50 EUR Index)

Source: www.stoxx.com/index-details?symbol=SXXDSGR

In addition to the above, firm characteristics obtained from the Amadeus Database and regional variables (including 3-month spot yield rate, 1-year forward rate, 5-year forward rate, 10-year forward rate, and credit spread) were used for the computation of the chosen systemic risk measure and other idiosyncratic metrics required for further analysis. Access to credit and the price thereof are important to systemic risk transmission as seen in Karimalis and Nomikos (2018) as well as the real sector, the focus of this research.

In the case of panel data sources, annual firm characteristics retrieved from the Amadeus Database which includes total current assets, total liabilities, common equity, shareholding structure, spending on research as well as information on ownership and subsidiaries were added to the calculated systemic risk measure and other relevant metrics.

4. Methodology

4.1 Calculation of Stock Returns and Volatility

Financial return is described as a percentage expressing the difference in prices between two consecutive periods as a ratio of the earlier price. Often, studies into financial returns (for instance see Politi, Millot, and Chakraborti (2012), Han (2019), Pernagallo and Torrisi, (2019)) select the log-return definition out of the assorted formulae for financial return because of its unique characteristics which are amenable to statistical estimations. These characteristics according to Fryzlewicz (2005) include the log-return series exhibiting clustered volatility, having a sample mean approaching zero, approximately symmetric marginal distribution with heavy tails and a maximum value of zero, as well as insignificant sample autocorrelations of the series for nearly all lags but sample autocorrelations derived from absolute values and squares of the series remain large for the majority of lags.

These characteristics go beyond the stationary requirement needed to take care of seasonal and deterministic trends found in time-series data such as stock prices. As a result, this study also adopts the log-returns definition as exhibited below. Here, P_t and P_{t-1} represent the current period's closing price and the preceding period's closing price, respectively.

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right)$$

For volatility, the study modifies Garman and Klass (1980) "best analytic scale invariant estimator" as a proxy because of the challenges involved in calculating volatility directly.

$$\begin{aligned}\tilde{\sigma}_{it}^2 = 0.511(logH_{it} - logL_{it})^2 \\ - 0.019[(logC_{it} - logO_{it})(logH_{it} + logL_{it} - 2logO_{it}) - 2(logH_{it} \\ - logO_{it})(logL_{it} - logO_{it})] - 0.383(logC_{it} - logO_{it})^2\end{aligned}$$

From the above formula, O_{it}, C_{it}, H_{it}, and L_{it} represent open, close, high, and low stock prices of a particular firm (i) at time (t) respectively. A similar estimate was adopted by Lebedeva (2018) when a normalized volatility series was required as a prerequisite for generalized variance decomposition.

4.2 Spillover Measure

To ascertain information on spillover dynamics amongst top companies within the STOXX Europe Diversification Select 50 Index, the study employs the spillover index developed by Diebold and Yilmaz (2012). Their estimation is hinged on a generalized vector autoregressive (VAR) framework which include directional volatility spillovers and its forecast-error variance decompositions are not susceptible to permutations of the variables being examined. This is achieved by further developing the framework by Pesaran and Shin (1998) and Koop, Pesaran, and Potter (1996). The approach does not orthogonalize shocks, therefore the sum of contributions towards variances in forecast errors is not expected to be equal to one in all instances.

The main distinction which provides this framework an edge over other traditional approaches is that it provides information on the scale, direction and intensity of spillovers which are vital to various participants in the money markets, capital markets, foreign exchange markets amongst others. It also depicts time-varying spillover attributes between entities by means of a rolling window analysis of sample intervals (Yin et al., 2020). Another important characteristic in relation to its application in this study is that the framework allows for return or volatility spillover measure of assets, portfolios and markets across and within countries providing information on important trend events (Diebold and Yilmaz, 2009).

Its building block is a covariance stationary vector autoregression process VAR(p) where ε_t is independent and identically distributed to $\varepsilon_i \sim (0, \Sigma)$, Σ is a covariance matrix and t = 1, 2, 3…., T

$$x_t = \sum_{i=1}^{p} \Phi_i \, x_{t-1} + \varepsilon_t$$

In the context of our research x_t represents volatilities of N companies, it is an N-dimensional column vector. Usually the moving average representation of the above VAR model is preferred because it is easier to understand and consequently explain. The main complexities with the VAR model include too many parameters, difficult parameter estimators and convoluted interactions between variables. The variance decompositions or impulse response function of the moving average version of the estimated parameters is critical to unravelling the complexities of the system. The variance decomposition approach calculates the proportion variance in forecast errors of all endogenous variables by diverse shocks within the VAR model. See below the moving average form, where A_i follows a recursive process $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots. + \Phi_p A_{i-p}$ and $A_i = 0$ for $i < 0$.

$$x_t = \sum_{t=0}^{\infty} A_i \, \varepsilon_{t-1}$$

Relying on the moving average transformation, Diebold and Yilmaz (2012) proceed to define own variance shares "as ratios of H-step error variances in estimating x_i resulting from shocks to x_i for i = 1, 2, 3, ….N" and cross variance shares (spillover) "as ratios of H-step error variances in estimating x_i resulting from shocks to x_i for i = 1, 2, 3, ….N for $i \neq j$". This can be computed as.

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' \, e_i)}$$

From the above equation σ_{jj} represents ith diagonal feature of the variance-covariance matrix (Σ) and e_i stands for the selection vector. Normalizing individual entries within the variance decomposition matrix by the corresponding row sum helps to ascertain useful values required in estimating the spillover index.

$$\widetilde{\theta_{ij}^{g}} = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}$$

Consequently, total volatility spillover index which quantifies volatility shock contributions of all entities under consideration to overall forecast variance error is calculated as.

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \breve{\theta}_{ij}^{g}\,(H)}{\sum_{i,j=1}^{N} \breve{\theta}_{ij}^{g}(H)} \cdot 100$$

To enrich our understanding of each entity's risk level, total volatility spillover is disaggregated to account for volatility spillover received by entity i from all other entities under consideration j and volatility spillover spread by entity i to all other entities under consideration j as follows.

$$S_{i\cdot}^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \breve{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \breve{\theta}_{ij}^{g}(H)} \cdot 100$$

$$S_{\cdot i}^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \breve{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \breve{\theta}_{ij}^{g}(H)} \cdot 100$$

Now net volatility spillover which is the difference between volatility shocks transmitted by entity i and received from all other entities j is computed as.

$$S_{i}^{g}(H) = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H)$$

Finally, we calculate net pairwise volatility spillover which is the difference in volatility shocks transmitted from entity i to entity j and volatility shocks transmitted from entity j to entity i. This differs completely from net volatility spillover which deduct transmission from an entity and that by all other entities.

$$S_{ij}^{g}(H) = (\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \breve{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \breve{\theta}_{jk}^{g}(H)}) \cdot 100$$

4.3 Systemic Risk Measure

In current literature there are a variety of systemic risk measures. Notable amongst them are Marginal Expected Shortfall (MES) and its variant Systemic Expected Shortfall (SES), the Systemic Risk Measure (SRISK) and Conditional Value at Risk (CoVaR), a variant of Value at Risk (VaR).

This study selects the risk measure developed by Adrian and Brunnermeier (2016), ΔCoVaR. ΔCoVaR is preferred because of its characteristics which makes it a suitable risk measure for the real economy. CoVaR is conditional and directional, thus, CoVaR of a system is conditional on entity i which is not the same as CoVaR of entity i conditional on a system. This differentiates the interpretation of CoVaR from other measures (MES and SRISK) which are conditional on a system. Similarly, we model the systemic risk of a system (group of firms within the real sector) conditional on the state of one of these firms. Additionally, Sedunov (2016) found CoVaR to be better at estimating systemic risk in his comparative study.

To fully understand ΔCoVaR we need to explain its building blocks VaR and CoVaR. VaR represents an entity's standalone risk, it is the maximum expected loss of an entity at a specified confidence level. CoVaR denotes the VaR of a system conditional on entities within the system experiencing distress. Adrian and Brunnermeier (2016) relying on CoVaR then defined ΔCoVaR as "the difference between CoVaR conditional on an entity experiencing distress and CoVaR conditional on an entity at its median or normal state". This then represents a firm's contribution to the system's systemic risk.

Assuming entity i with return r^i_t and confidence level q, $VaR^i_{q,t}$ can be defined as the q-quantile of the distribution if returns.

$$q = \Pr\,(r_t^i \leq VaR_{q,t}^i)$$

Based on the above $CoVaR^{j|i}_{q,t}$ as the VaR of system j condition on entity i's state.

$$q = \Pr\,(r_t^s \leq CoVaR_{q,t}^{j|r_t^i < VaR_{q,t}} | r_t^i VaR_{q,t})$$

Finally, we have entity i's contribution to system j's systemic risk as.

$$\Delta CoVaR_{q,t}^{j|i} = CoVaR_{q,t}^{j|r_t^i = VaR_{q,t}^i} - CoVaR_{q,t}^{j|r_t^i = Median^i}$$

Following Adrian and Brunnermeier (2016) we begin the estimation of ΔCoVaR with a quantile regression of daily stock prices of entity i. it displays a joint distribution between entity i (X^i) and the system (X^{system}) estimated through a conditional distribution. Considering the importance of credit to the real economy, a function of lagged state variables (M_{t-1}) was inculcated into the quantile regression. State variable used include the 3-month spot yield rate, 1 year forward rate, 5 year forward rate, 10 year forward rate and credit spread.

$$X_t^{system} = \alpha^{system|i} + \hat{\beta}^{system|i} X_t + \gamma^{system|i} M_{t-1} + \varepsilon_t^{system|i}$$

From the quantile regression, predicted values for $VaR^i_t(q)$ and $CoVaR^i_t(q)$ are estimated.

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}$$

$$CoVaR_t^i(q) = \hat{\alpha}^{system|i} + \beta^{system|i} VaR_t^i(q) + \gamma^{system|i} M_{t-1}$$

$\Delta CoVaR^i_t$ is then computed for each entity.

$$\Delta CoVaR_t^i(q) = \hat{\beta}^{system|i}(VaR_t^i(q) - VaR_t^i(50\%))$$

4.4 Panel Regression

Systemic risk measures in themselves only communicate an entity's contribution to the risk of a system. It is more beneficial to ascertain contributory factors affecting systemic risk in order to formulate appropriate strategies in an attempt to manage it. As a result, a panel regression equation has been formulated to identify unobserved effects of innovation and FDI – expected characteristics of blue-chip companies - on systemic risk (ΔCoVaR). The selection of independent variables for the panel regression equation were based on the author's hypothesis and contributions from previous studies on the subject such as Van Cauernberge et al. (2019), Karimalis and Nomikos (2018), Adrian and Brunnermeier (2016) as well as Karimalis and Nomikos, (2018).

Consequently, the equation below tries to find the impact of innovation, FDI and other firm characteristics on systemic risk.

$$\Delta CoVaR_{i,t} = \alpha_i + \partial' Inno_{i,t} + \delta' FDI_{i,t} + \beta' x_{i,t} + \mu_{i,t}$$

$\Delta CoVaR_{i,t}$ in this case is the measure of systemic. $Inno_{i,t}$ is a variable representing innovation. $FDI_{i,t}$ represents a vector of two dummy variables indicating whether a firm has foreign subsidiaries (FornSub) or has foreign owners (FornCon). $x_{i,t}$ represents a vector of firm level data used as control variables. These consist of variables such as firm beta, leverage, size, VaR, and a dummy for each sector. The dummies for each sector are expected to capture sectoral heterogeneity.

All the studies mentioned in the first paragraph of section 4.4 found a positive association between beta, size and VaR on one side and systemic risk on the other. This study hypothesises a significant negative relationship between innovation and systemic risk. However, FDI is expected to show significant positive relationship with systemic. Such postulation is derived from the assumption that firms that usually invest in research and development are able to gain competitive advantages which translates into superior profits and are therefore not likely to contribute to systemic risk. On the other hand, foreign companies face certain peculiar disadvantages in their host countries which could contribute to their instability or possible failure and thereby increases its potential to contribute to systemic risk.

Four estimations were done in an attempt to uncover the impact each of the selected variables has on systemic risk. The models employed include a pooled OLS model, a fixed effects model, a first difference model and a random effects model. These models treat data differently thereby exhibiting different size effects for each variable. Pooled OLS regard each observation in the dataset as independent, fixed effects model eliminates individual effects by relying on deviations from individual means, the first difference model also gets rid of individual effects using first differences with respect to time and as such nine (9) were lost. Random effects model estimates variable effects notwithstanding its variability overtime or otherwise.

Theoretically, estimates from a pooled OLS model are inconsistent in situations where there is evidence of heterogeneity. Fixed effects models generate unbiased and consistent estimates when observations and time period of the panel data are large enough. Estimates from first difference models are based on lesser observations depending on the groups and missing values in the dataset. With the right assumptions, estimates from a random effects model are efficient and consistent. Due to the disadvantages associated with each model, various statistical tests (Lagrange Multiplier Test, Hausman Test, Breusch-Pagan Test, coeftest etc.) are conducted to ascertain the best estimates for our dataset.

5. Results and Empirical Analysis

5.1 Spillover Effects

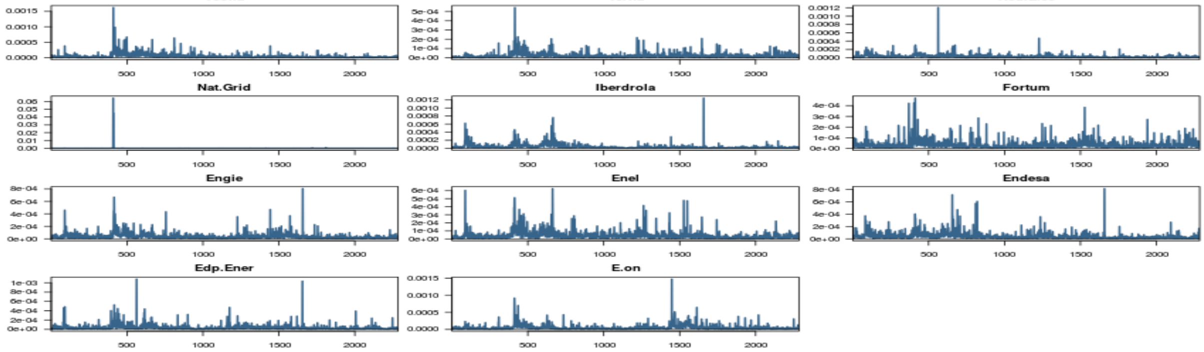
Under this section we examine volatility spillovers of selected companies according to their various sectors of operation. The goal for this section is to observe volatility interactions amongst these companies in response to crises situations and thereby identify unstable companies that are likely to pose systemic risk.

5.1.1 Utilities

The utilities sector is important to the development of any economy or region since it is a major backbone to the industrial and manufacturing sector. Volatility within the utilities industry mostly reflects the European debt crisis, the Chinese stock market turbulence and Brexit. This is expected as governments during these crises were quick to cut subsidies to the utilities (European Commission, 2013).

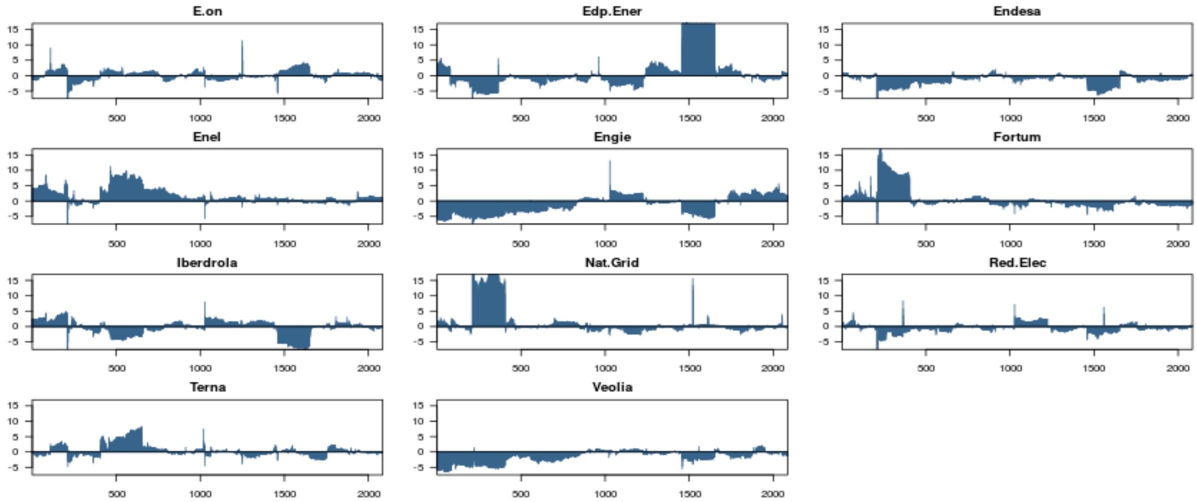
An interesting case is National Grid Plc which shows no volatility in response to various shocks but exhibits a sharp spike in August 2011 when there were fears of a contagion European debt crisis affecting Italy and Spain. The shock from the European debt crisis was evident in all companies within this sector. The most volatile companies within the utilities industry were Fortum, Engie, Terna, Enel, Endesa, EDP Energias and Eon. These companies demonstrate subsequent volatile moments after the European debt crisis corresponding with the Chinese stock market turbulence and Brexit. They also provide an indication of moderate correlation amongst themselves in terms of the erratic nature of their volatility.

Figure 2: Log -volatilities Utilities Sector



As expected, most volatile companies as shown above experienced high levels of volatility spillover transmission in response to specific events. EDP Energias exhibited high positive transmission during the Chinese stock market turbulence and Brexit periods. Enel and Fortum experienced high positive transmission post the global financial crisis and the European debt crisis. National Grid, Enel and Terna experienced high transmission during the period of the Greek currency crisis.

Figure 3: Net Volatility Spillover Utilities Sector



Analysing the decomposition of spillovers transmitted and received within the utilities industry, we find that Iberdrola, Endesa and Engie are the major recipients of spillovers and therefore seem to be at risk. Major transmitters of spillovers Enel, National Grid, Iberdrola, EDP Energias, Fortum and Terna. These are systemically important as their spread of volatility spillovers (instability) are high. Iberdrola is a special case as it had the highest spillover receipts from the sector however, its spillover contribution was quite low resulting in a negative net spillover effect. Other companies in a similar circumstance include Endesa, Veolia, Engie and Red Electrica. Such firms can likely to experience instability in case of a systemic risk event.

Again, we see that for the utilities sector 45.46 percent of variances in volatility forecast error can be attributed to spillovers which is moderate.

Table 1: Volatility Spillover for Utilities Sector

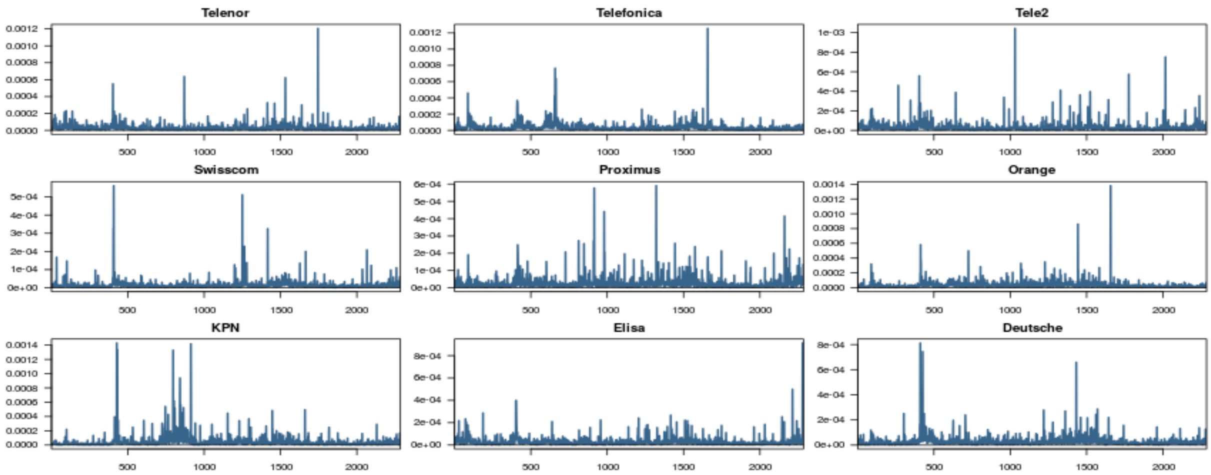
	E.on	Edp Energias	Endesa	Enel	Engie	Fortum	Iberdr.	Nat. Grid	Red Electr.	Terna	Veolia	From
E.on	63.756	2.112	2.560	6.018	2.446	4.643	3.625	3.909	2.584	5.368	2.976	36.241
Edp Energia	3.104	60.469	3.689	3.626	2.946	2.374	4.852	4.205	7.670	3.824	3.232	39.831
Endesa	2.621	8.260	45.451	6.928	4.066	3.335	9.878	4.206	6.339	5.848	3.067	54.549
Enel	6.592	2.266	2.926	53.931	1.902	3.685	3.849	3.956	2.154	17.324	1.413	46.069
Engie	5.432	8.583	3.414	6.705	45.690	2.546	7.969	4.591	5.084	3.962	6.023	54.310
Fortum	3.405	2.384	2.596	3.324	2.471	71.541	2.474	4.481	2.511	2.431	2.382	28.459
Iberdrola	3.132	8.940	7.560	7.528	7.664	3.664	37.935	3.695	9.736	4.695	5.450	62.065
Nat. Grid	2.849	2.094	2.747	3.146	1.979	3.937	2.416	73.150	2.353	2.663	2.666	26.850
Red Electr.	2.054	9.185	5.980	2.789	5.554	3.696	11.181	3.656	47.867	2.879	5.159	52.133
Terna	4.724	2.510	2.749	19.413	2.315	3.144	3.689	4.776	3.175	51.921	1.581	48.079
Veolia	4.125	4.345	4.216	5.417	8.173	3.161	7.946	4.964	5.025	4.355	48.243	51.757
Contribution To others	38.037	50.678	38.448	64.925	39.515	34.185	57.881	42.443	46.634	53.348	33.951	500.044
Contribution including own	101.796	111.147	83.898	118.856	85.206	105.725	95.816	115.593	94.501	105.268	82.193	TCI
Net Spillovers	1.796	11.147	-16.102	18.856	-14.794	5.725	-4.184	15.593	-5.499	5.268	-17.807	45.459

Source: Author's calculation

5.1.2 Telecommunications

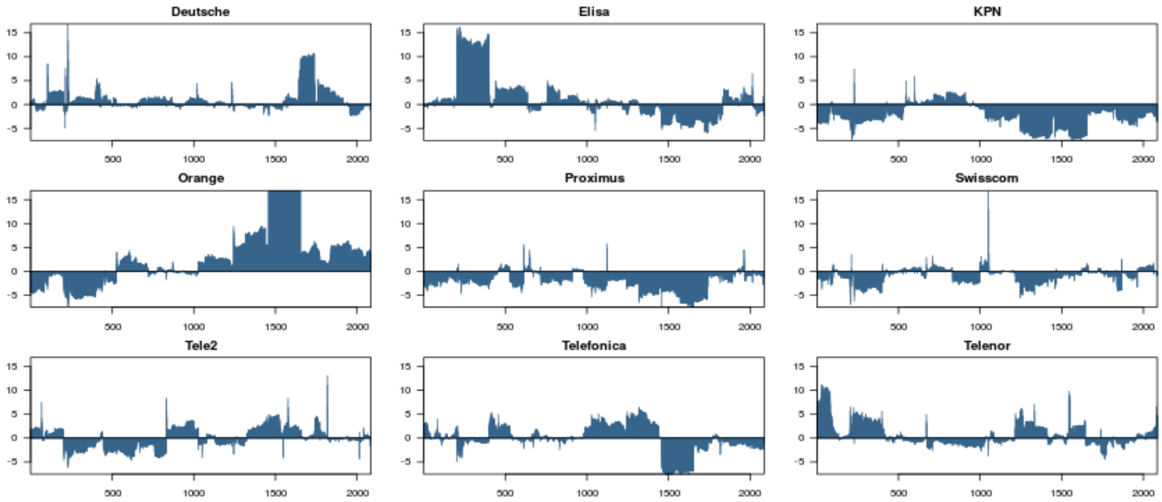
Telecommunication companies have become more important to the global economy and to individual lives in recent decades. They largely focus on disruptive technological developments which often impact their business models and competitive positions in an attempt to keep and possibly increase their market share. In many countries, access to internet connectivity is seen as a basic utility and its consumption has substantial effects on the social, cultural, and economic aspects of a modern society.

Figure 4: Log-volatilities Telecoms Sector



In the telecommunications sector, we find that firms mostly experience higher than normal volatilities for particular periods. Specifically, around the Greek financial crisis, Chinese stock market turbulence and Brexit. Telenor, Telefonica, Swisscom, Orange, Elisa, and Deutsche Telekom were relatively stable with isolated high spikes and short period volatilities. Over the entire period Tele2 B, Proximus, and KPN were more volatile. Some companies show simultaneity in responds to shocks, but magnitude usually differ.

Figure 5: Net Volatility Spillover Telecoms Sector



In terms of which of the companies received or transmitted more spillovers, we see from the graph above that Orange was receiving volatility spillovers post the global financial crisis. However, Orange transformed into a net transmitter with an increasing magnitude. Elisa experienced the opposite, started as a net transmitter but reverted to a net receiver during the Chinese stock market turbulence. KPN, Proximus, Swisscom, Tele2 B and Telenor are most of the time net recipients of volatility spillovers and are therefore at risk.

From the decomposition of the spillovers, Proximus (41.909), KPN (41.355) and Telefonica (40.309) were the highest recipients of volatility spillovers. Unfortunately, the volatility transmissions of these firms are low resulting in negative net spillovers. Major transmitters in the telecoms sector were Orange, Elisa, and Telefonica. These systemically important firms are crucial since their downturn can be a trigger point for systemic risk events.

For the telecoms sector, across our entire sample, 33.92 percent of volatility forecast error variance within the sector comes from spillovers which is lower in comparison to the utilities sector.

Table 2: Volatility Spillover for Telecoms Sector

	Deuts	**Elisa**	**KPN**	**Orange**	**Proxim**	**Swiss**	**Tele2.**	**Telefo**	**Telenor**	**From**
Deutche	74.897	4.208	2.481	2.121	2.078	3.319	3.054	3.429	4.414	25.103
Elisa	4.853	67.252	1.625	2.472	3.206	4.377	6.754	2.062	7.398	32.748
KPN	5.315	2.423	58.645	15.232	4.178	2.218	1.785	7.771	2.524	41.355
Orange	4.599	2.903	2.838	68.195	1.953	2.649	2.061	12.263	2.539	31.805
Proximus	5.075	2.746	4.671	12.126	58.091	2.888	2.401	7.779	4.223	41.909
Swisscom	2.115	8.934	2.182	2.224	2.601	67.166	5.807	1.908	7.062	32.834
Tele2	2.144	10.848	1.372	3.023	2.613	2.137	70.686	2.303	4.872	29.314
Telefonica	4.252	4.206	2.319	18.058	2.328	2.656	2.171	59.691	4.318	40.309
Telenor	5.947	6.176	1.600	2.262	2.923	3.519	5.336	2.638	70.099	29.901
Contribution To others	34.300	42.445	19.089	57.518	21.380	23.673	29.369	40.151	37.353	305.277
Contribution including own	109.197	109.698	77.734	125.713	79.471	90.839	100.055	99.842	107.451	TCI
Net Spillovers	9.197	9.698	-22.266	25.713	-20.529	-9.161	0.055	-0.158	7.451	33.920

Source: Author’s calculation

5.1.3 Industry

From the figure below, we see that OMV and Snam Rete show more volatility in their stock prices during the study period. A similarity shared across companies within the industrial sector is that the volatilities seem to be clustered. Kone B, Enagas and Flughafen exhibited more volatilities. There seem to be a weak positive association between the volatility trends between Snam Rete and Enagas because both operate within the oil and gas sector.

Figure 6: Log-volatilities Industrial Sector

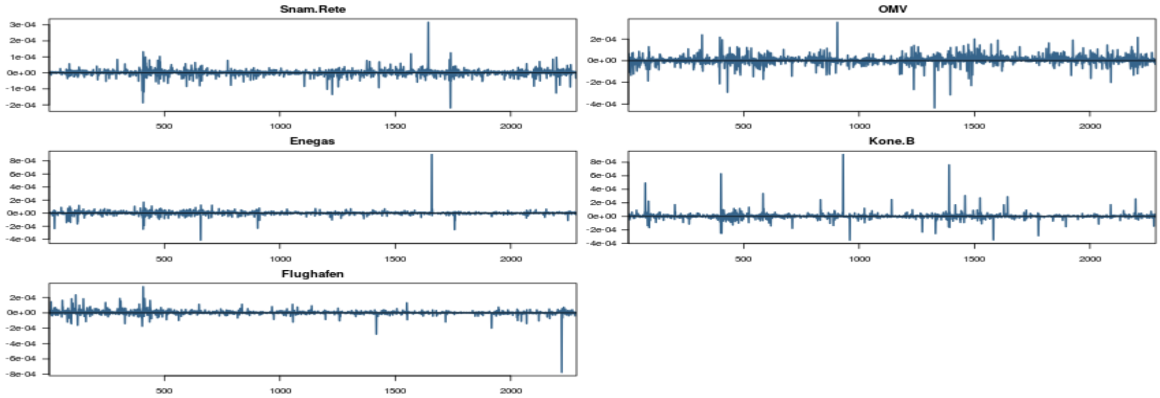
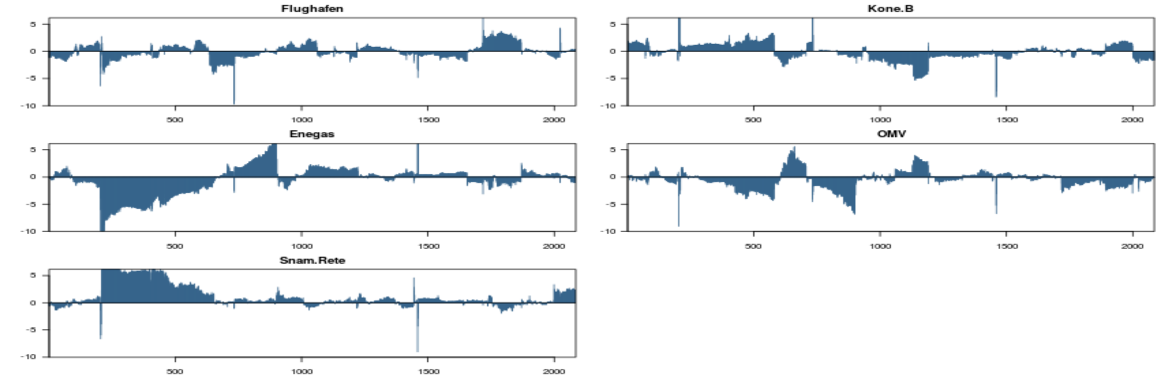


Figure 7: Net Volatility Spillover Industrial Sector



In terms of the decomposition of spillovers transmitted and received within the industrial sector, we find that Enagas (14.672) and OMV (12.544) are the top recipients of spillovers. On the other hand, the major transmitters of spillovers is Snam Rete (17.985) and Enagas (12.017). Enagas is an interesting scenario because the company was both a major receiver and transmitter. It is not surprising that it was one of the companies at risk together with OMV. On the other hand, the major transmitter was Snam Rete, the dominance of Snam Rete is not surprising as from the net volatility spillover chart the company is usually a net transmitter.

We also see that 12.342 percent of variances in volatility forecast error can be attributed to spillovers which is very low for this specific sector, even lower thank the telecoms and utilities but again we have only 5 companies for this analysis.

Table 3: Volatility Spillover for Industrial Sector

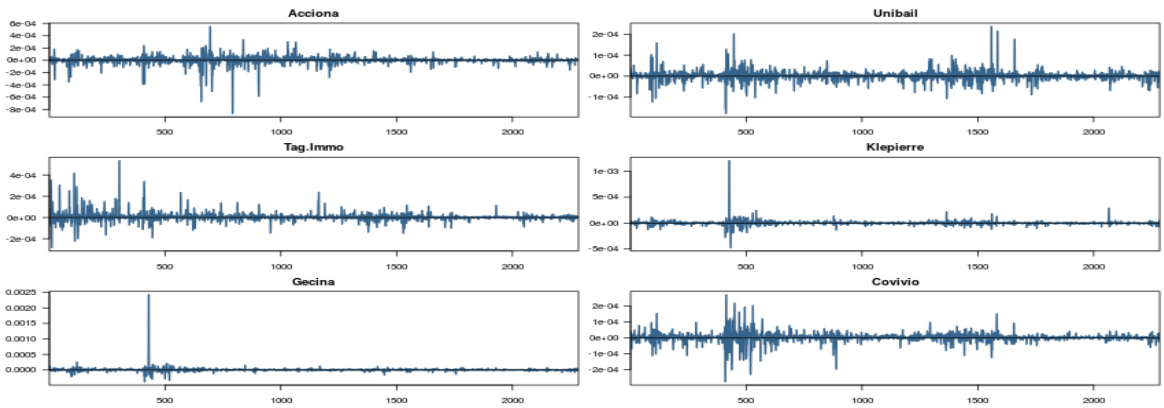
	Flugha	**Kone B**	**Enagas**	**OMV**	**Snam Rete**	**From**
Flughfen	88.802	2.886	2.791	2.603	2.918	11.198
Kone B	2.282	88.552	1.557	3.257	4.352	11.448
Enagas	3.294	1.558	85.328	1.705	8.116	14.672
OMV	2.885	3.446	3.615	87.456	2.599	12.544
Snam Rete	2.546	2.957	4.055	2.288	88.153	11.847
Contribution To others	11.007	10.847	12.017	9.853	17.985	61.709
Contribution including own	99.809	99.399	97.309	97.309	106.138	TCI
Net Spillovers	-0.191	-0.601	-2.655	-2.691	6.138	12.342

Source: Author's calculation

5.1.4 Real Estate & Construction

From the figure displaying volatilities in the real estate and construction sector, we see that apart from Covivio and Unibail, the rest of the companies experience much more volatility within the first part of the period under investigation (thus, post the global financial crisis and the Greek currency crisis). Tag Immobilien was the most volatile in the beginning but overall Unibail was the most volatile overtime. Klepierre and Gecina were the least volatile but generally each of the companies reflected at least one of the major crises enumerated.

Figure 8: Log-volatilities Real Estate & Construction Sector



The net volatility figure shows Unibail as a persistent net receiver of volatility spillovers and Klepierre as a persistent transmitter of volatility spillovers. Although the receipts to

Unibail grew in magnitude overtime, that of Klepierre declined in magnitude with a spike at the later stages. Gecina’s experience was interesting receiving volatility spillovers between 2010 and 2013 but transforming into a transmitter afterwards. The rest of the companies exhibits both transmission and receipt of spillovers at different periods.

Figure 9: Net Volatility Spillover Real Estate & Construction Sector

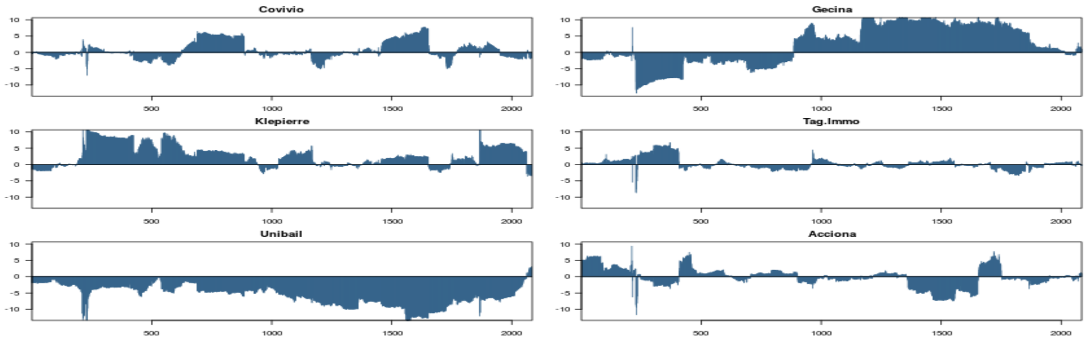


Table 4: Volatility Spillover for Real Estate & Construction Sector

	Coviovio	**Gecina**	**Klepierre**	**Tag Immo**	**Unibail**	**Acciona**	**From**
Coviovio	61.734	12.651	14.141	3.287	4.325	3.862	38.266
Gecina	7.969	70.490	12.053	2.794	2.905	3.788	29.510
Klepierre	12.582	11.134	67.567	2.150	2.797	3.770	32.433
Tag Immo	2.637	3.453	2.583	86.610	2.128	2.589	13.390
Unibail	13.701	10.452	16.788	2.817	51.376	4.865	48.624
Acciona	4.952	4.957	4.298	3.593	2.297	79.903	20.097
Contribution To others	41.842	42.647	49.864	14.641	14.452	18.874	182.320
Contribution including own	103.375	113.137	117.431	101.251	65.828	98.776	TCI
Net Spillovers	3.575	13.137	17.431	1.251	-34.172	-1.224	30.387

Source: Author’s calculation

Analysing which companies were contributing more volatility spillovers to others in the real estate and construction sector as well as those at risk by being major recipients, we find that Unibail with 48.624 percent has the highest spillovers receipts and its net spillovers contribution was the lowest by far in the sector with -34.172. Covivio, Klepierre and Gecina were relatively impacted less by volatility spillovers with 38.266, 32.433 and 29.510 percent, respectively. These three companies are however systemically important being major transmitters of volatility spillovers. Considering net spillover measures, Unibail and Acciona are at high risk in an event of a systemic shock.

The total variances in volatility forecast error that can be attributed to spillovers in this real estate and construction sector was 30.387 percent which is somewhat moderate.

5.1.5 Health & Lifestyle

In the following figure we see that Sanofi is the most volatile company with the highest volatilities recorded post the global financial crisis and the Greek currency crisis. Novartis and Unilever were moderately volatile with periodic clustered volatilities in tandem with movements in Sanofi. It is interesting to see Glaxo - a British company - not being responsive to events during Brexit. Unilever shows more volatilities during the Chinese market turbulence.

Figure 10: Log-volatilities Health & Lifestyle Sector

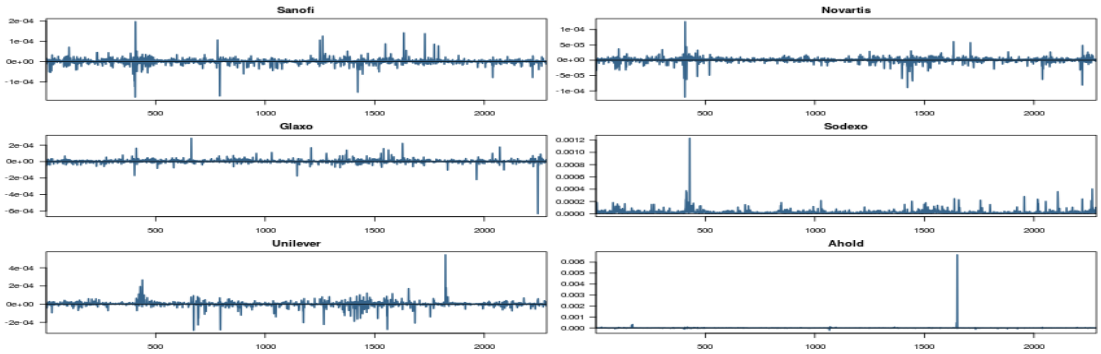
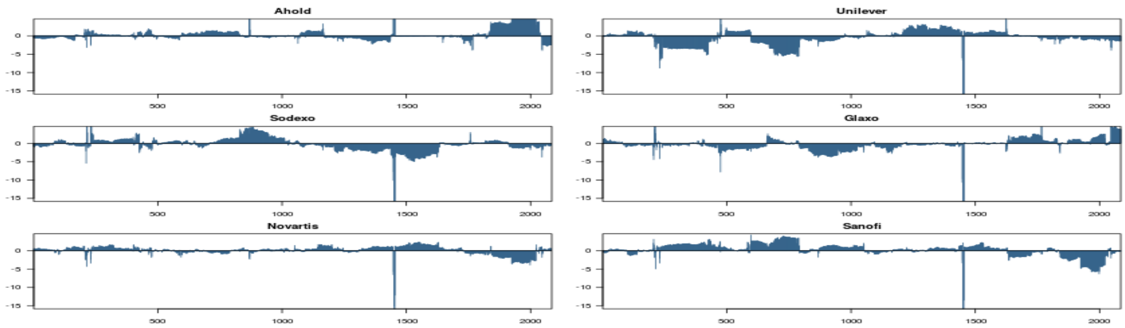


Figure 11: Net Volatility Spillover Health & Lifestyle Sector



The net volatility spillover figure shows unique trends for companies in the health and lifestyle sectors. However, a similar negative net spillover spike is seen during the Chinese market turbulence for all companies with the exception of Ahold. A similar response was seen in most companies within the industrial sector. This could be evidence of complementarities between the two sectors and their integration with the Chinese market or economy. Generally, the companies alternating periods of positive and negative volatility transmissions although the magnitude and cycles differ.

Table 5: Volatility Spillover for Health & Lifestyle Sector

	Ahold	**Unilever**	**Sodexo**	**Glaxo**	**Novartis**	**Sanofi**	**From**
Ahold	77.897	2.204	1.916	2.678	7.442	7.863	22.103
Unilever	2.795	85.375	3.408	1.915	2.020	4.487	14.625
Sodexo	2.760	3.516	85.870	1.872	3.047	2.934	14.130
Glaxo	3.322	1.926	2.370	86.078	3.688	2.590	13.922
Novartis	8.149	1.658	3.016	2.975	64.613	19.588	35.387
Sanofi	9.273	2.291	1.773	2.836	19.780	64.047	35.953
Contribution To others	26.300	11.595	12.508	12.277	35.978	37.462	136.120
Contribution including own	104.197	96.970	98.378	98.355	100.591	101.509	TCI
Net Spillovers	4.197	-3.030	-1.622	-1.645	0.591	1.509	22.687

Source: Author’s calculation

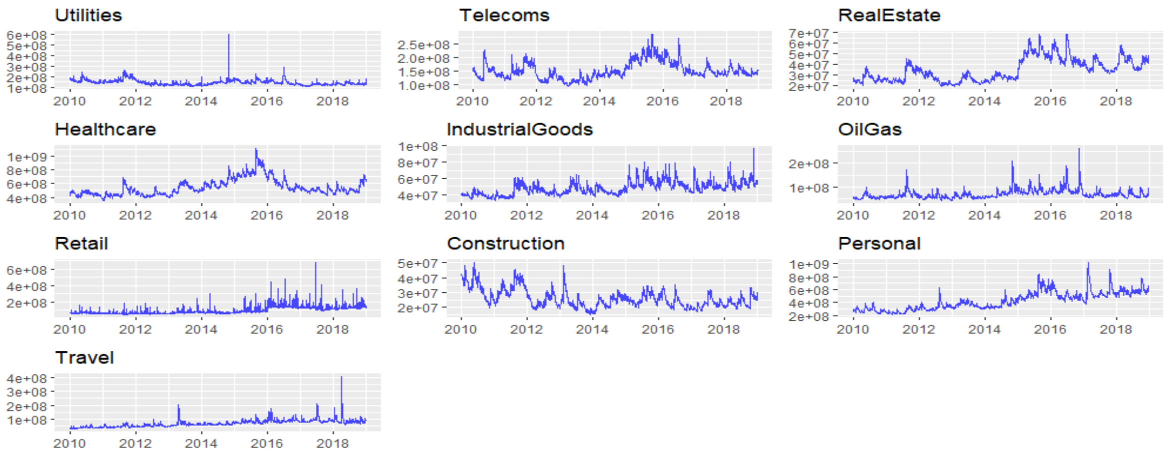
From the analysis of which companies transmitted more volatility spillovers in the health and lifestyle sector, we find that Novartis and Sanofi are the major recipient of spillovers and so both seem to be at risk compared to the rest. On the other hand, both companies in addition to Ahold were the major transmitters of spillovers to the rest of the companies. Thus, these can be considered as systemically important companies that might affect the stability of the industry in case of a systemic shock. Unilever, Sodexo, and Glaxo experience negative net spillovers are more at risk to face instability.

Additionally, across the lifestyle industry, 22.687 percent of volatility forecast error variance in all the companies comes from spillovers.

5.2 Systemic Risk Measure

From our estimations, we find unique dynamics of systemic risk (ΔCoVaR) for sectors within the STOXX Europe Diversification Select 50 EUR Index over the period under consideration. Most prominent for most of these sectors is the build-up of systemic risk between the year 2014 and 2017. As seen in Adrian and Brunnermeier (2016) there is evidence of systemic risk being procyclical, while risk accumulates over the period, adverse effects from unexpected shocks are then magnified. The cycle in this case corresponds with the Chinese stock market turbulence and the Brexit vote. This confirms the integration of Euro market since the selected firms originate from various countries within the region as well as the region's interactions with the Chinese economy.

Figure 12: Average ΔCoVaR per Sector



Distinctively, the construction, real estate, telecoms, and utility sectors experienced varying degrees of spikes during the later stages of the global financial crisis. Perhaps, these sectoral response to unexpected shocks can be analysed as compound effects since some crisis situations overlap. For instance, the later stages of the global financial crisis overlap with the Greek currency crisis just as the later parts of the Chinese stock market turbulence

As expected, the retail sector exhibits stable risk over with very frequent seasonal spikes. Most volatile sectors include industrial, telecoms, construction, real estate, oil and gas as well as healthcare. These effects are expected to translate into significant impacts in the regression results.

5.3 Regression Results

From the results of the panel regression we find the effect of innovation and FDI on systemic risk. A combination of the F-test for individual effects and the Lagrange multiplier test for unbiased panels indicates significant effects, meaning the fixed effects and random effect models are more appropriate in comparison to the pool OLS model. To select the most appropriate models amongst the two, the Hausman test was applied. Results from the test indicates that the fixed effects model is consistent therefore the random effects model is ignored.

However, the Breusch-Pagan test indicate heteroscedasticity in the model therefore the estimate below is generated with corrected standard errors based on the Arellano (1987) method.

Table 6: Fixed Effects Regression Results

	Dependent variable: log(ΔCoVaR)			
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
Beta	1.0647e+00	1.2186e-01	8.7372	2.498e-16 ***
log(VaR)	9.5015e-01	1.2348e-02	76.9452	< 2.2e-16 ***
log(Leverage)	-1.3216e-01	1.8506e-02	-7.1417	8.434e-12 ***
log(Size)	2.1254e-02	6.0485e-03	3.5138	0.0005171 ***
Inno	-5.1240e-05	5.3163e-06	-9.6384	< 2.2e-16 ***
Dummy_FornCon	-1.6388e-01	1.2953e-02	-12.6519	< 2.2e-16 ***
Dummy_FornSub	4.6204e-01	3.2766e-02	14.1013	< 2.2e-16 ***
Dummy_Utilities	-3.0572e-01	9.7211e-03	-31.4492	< 2.2e-16 ***
Dummy_Telecoms	-3.3845e-01	1.6670e-02	-20.3037	< 2.2e-16 ***
Dummy_RealEst	3.6605e-02	3.9336e-02	0.9306	0.3529060
Dummy_Health	7.7450e-02	3.3408e-02	2.3183	0.0211751 *
Dummy_Indust	-4.7010e-01	1.4852e-02	-31.6511	< 2.2e-16 ***
Dummy_Oil	9.5432e-03	1.2646e-02	0.7547	0.4511107
Dummy_Retail	-1.9183e-01	2.8196e-02	-6.8036	6.483e-11 ***
Dummy_Const	-6.2695e-01	4.0479e-02	-15.4883	< 2.2e-16 ***
Dummy_Pers	2.7392e-02	2.2301e-02	1.2283	0.2203933

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Source: Author's calculation

The estimates show a significant negative relationship between innovation and systemic risk. Specifically, other things being equal, every Euro spent on innovation reduces log of ΔCoVaR by 0.00005124 percent. Contrary to our hypothesis, variables for FDI show mixed effects. Ceteris paribus, firms with foreign shareholders (FornCon) exhibit log of ΔCoVaR which is 0.6388 percent less in comparison to firms without foreign owners. However, firms with foreign subsidiaries (FornSub) had log of ΔCoVaR being 0.46204 percent higher in relation to companies without foreign subsidiaries. This suggest that foreign direct investments through the establishment of foreign subsidiaries serve as channels for transferring systemic risk.

In terms of sectoral activities, firms in the health sector increase log of ΔCoVaR by 0.07745 percent. On the other hand, firms in the utilities sector, telecom sector, industrial sector, retail sector and construction sector decrease log of ΔCoVaR by 0.30572 percent, 0.33845 percent, 0.4701 percent, 0.19183 percent, and 0.62695 percent. The health sector increases systemic risk, and this is understandable considering its direct impact on all sectors. In contradiction to the findings of Van Cauernberge et al. (2019) sectors that provide support services such as telecoms and utilities rather reduce systemic risk.

Now focusing on other firm characteristics, an increase in firm beta by a percentage point increases log of ΔCoVaR by 1.0647 percent. An increase in log of VaR and log of Size by one percent increases log of ΔCoVaR by 0.95015 percent and 0.02125 percent. Also, an increase in Log of leverage by one percent reduces log of ΔCoVaR by 0.13216 percent. These results are not surprising as beta and VaR are measures of a firm volatility and standalone risk. It is expected that risk measures correlate with systemic risk. Again, firms with large current asset values can have larger adverse effects through its interactions with debtors and creditors.

6. Conclusions

This study endeavored to identify systemically important companies by evaluating the volume of volatility spillover received and transmitted between blue-chip these companies in the STOXX Europe diversification select 50 Index. Further, it investigated the effects of innovation and FDI on systemic risk amongst these companies.

Our findings from the spillovers analysis provide some insights into the interactions between companies within a specific sector. We identify systemically important companies that are likely to contribute to the instability of others as a result of the magnitude of spillover volatilities they transmit. Transfer of instability could serve as a spark for a systemic risk event. The results show that the utility sector presents the highest percentage of variances in volatility forecast error due to spillovers of 45.46 percent, followed by the telecommunication and Real estate and construction with 33.92 and 30.387 percent, respectively. Interestingly, there seems not to be a link between volatility levels and the volume of spillover emitted.

With regards to the impacts of innovation and FDI on systemic risk, the results confirm that there is a negative relationship between innovation and systemic risk which means that firms who are more innovative can decrease their contribution to systemic risk. This result agrees with our hypothesis since innovative firms tend to gain competitive advantages and are often more profitable in comparison with their competitors and therefore are likely to undergo stress or be impacted by the failure of related companies.

In the case of FDI, we find results that are different from our initial hypothesis. On one hand, we find that firms with foreign control decreased systemic risk in comparison with firms without foreign control. This could be as a result of the effects of diversification and a common currency system. Our findings contradict that of Van Cauwenberge et al., (2019) who found a positive relationship between foreign control and systemic risk in the Netherlands.

On the other hand, firms with foreign subsidiaries increase systemic risk contribution. This suggests that FDI through the establishment of foreign subsidiaries serve as channels to spread systemic risk through the firm's operations in other countries. Therefore, Multinational companies can contribute to the spread of systemic risk through international networks to domestic or host economies. This confirms the findings of Goldin and Mariathasan (2014) as well as Battiston et al. (2007) who find that due to transactions between subsidiaries such as outsourcing and subcontracting, the failure of a firm most likely will transmit negative externalities to its subsidiaries and thereby trigger systemic risk.

Several important recommendations can be made for future studies. With the availability of adequate firm-level data, our research can be expanded to examine such effects within countries (a single market), regions, as well as other asset classes across different sectors. We recommend further exploration of volatility spillovers as an early warning system for impending crises. Also, a comparison of systemic risk in specific sectors of the real economy within developing economies could be investigated and contrasted with findings from developed economies.

7. References

Acharya, V., Pedersen, L. H., Philippon, T., & Richardson, M. (2010). Measuring systemic risk. AFA 2011 Denver Meetings Paper. In *Available at Social Science Research Network (SSRN): http://ssrn. com/abstract* (Vol. 1573171).

Acharya, V., Pedersen, L. H., Philippon, T., & Richardson, M. (2010). Measuring systemic risk. AFA 2011 Denver Meetings Paper. In *Available at Social Science Research Network (SSRN): http://ssrn. com/abstract* (Vol. 1573171).

Acharya, V., Philippon, T., Richardson, M., & Roubini, N. (2009). The financial crisis of 2007-2009: Causes and remedies. *Financial markets, institutions & instruments*, *18*(2), 89-137.

Adrian, T., & Brunnermeier, M. K. (2009). CoVar: a method for macroprudential regulation. *Federal Reserve Bank of New York Staff Report*, *348*.

Adrian, T., & Brunnermeier, M. K. (2016). CoVar. Am. Econ. Rev. 106 (7), 1705–1741.

Andrieş, A. M., Nistor, S., & Sprincean, N. (2017). The impact of central bank transparency on systemic risk: Evidence from Central and Eastern Europe. Research in International Business and Finance 51 (2020) 100921.

Apostolakis, G., & Papadopoulos, A. P. (2014). Financial stress spillovers in advanced economies. *Journal of International Financial Markets, Institutions and Money*, *32*, 128-149.

Apostolou, A., Beirne, & John. (2019). Volatility spillovers of unconventional monetary policy to emerging market economies. Economic Modelling. Volume 79, Pages 118-129.

Arellano, M. (1987) Computing robust standard errors for within-group estimators, *Oxford Bulletin of Economics and Statistics*, 49(4), pp. 431--434.

Battiston, S., Gatti, D. D., Gallegati, M., Greenwald, B., & Stiglitz, J. E. (2007). Credit chains and bankruptcy propagation in production networks. *Journal of Economic Dynamics and Control*, *31*(6), 2061-2084.

Beirne, J., Caporale, J., Schulze-Ghattas, M., & Spagnolo, N. (2013). Volatility spillovers and contagion from mature to emerging stock markets. Review of International Economics, 21 (5) (2013), pp. 1060-1075.

Bems, R., Johnson, R. C., & Yi, K. M. (2013). The great trade collapse. *Annu. Rev. Econ.*, *5*(1), 375-400.

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of financial economics*, *104*(3), 535-559.

Bruno, V., & Shin, H. S. (2015). Capital flows and the risk-taking channel of monetary policy. Journal of Monetary Economics, 71, 119-132.

Bruno, V., & Shin, H. S. (2015). Cross-border banking and global liquidity. *The Review of Economic Studies*, *82*(2), 535-564.

Buch, C. M., Krause, T., & Tonzer, L. (2019). Drivers of systemic risk: Do national and European perspectives differ? *Journal of International Money and Finance, 91*, 160-176.

Caballero, R. J., Farhi, E., & Gourinchas, P.-O. (2008). An Equilibrium Model of 'Global Imbalances' and Low Interest Rates. American Economic Review 98 (1): 358–93.

Cetorelli, N., & Goldberg, L. S. (2012). Liquidity management of US global banks: Internal capital markets in the great recession. *Journal of International Economics*, *88*(2), 299-311.

Cho, S., Hyde, S., & Nguyen, N. (2015). Time-varying regional and global integration and contagion: Evidence from style portfolios. *International Review of Financial Analysis*, *42*, 109-131.

Collins, M (2015). The big bank bailout [https://www.forbes.com/sites/mikecollins/2015/07/14/the-big-bank-bailout/#2e8687222d83] Retrieved on [30 May, 2020]

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. Economic Journal, 119 (2009), pp. 158-171.

Diebold, F. X., & Yilmaz, K. (2012). Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers. International Journal of Forecasting, 28 (2012), pp. 57-66.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119-134.

Dungey, M., Luciani, M., Matei, M., & Veredas, D. (2015). Surfing through the GFC: Systemic risk in Australia. Tasmanian School of Business and Economics, University of Tasmania.

Dunning (1979) Toward an Eclectic Theory of International Production: Some Empirical Tests. Journal of International Business Studies.

Eaton, J., Kortum, S., Neiman, B., & Romalis, J. (2016). Trade and the global recession. *American Economic Review*, *106*(11), 3401-38.

European Commission (2013). Is European debt crisis undermining interest in low-carbon energy? [https://setis.ec.europa.eu/publications/setis-magazine/wind-energy/european-debt-crisis-undermining-interest-low-carbon-energy] Retrieved on [17 July, 2020]

Fryzlewicz, P. (2005). Modelling and forecasting financial log-returns as locally stationary wavelet processes. *Journal of Applied Statistics*, *32*(5), 503.

Garman, M. B., & Klass, M. J. (1980). On the estimation of security price volatilities from historical data. *Journal of business*, 67-78.

Gelos, G., & Surti, J. (2016). The growing importance of financial spillovers from emerging market economies. VOX. CEPR Policy Portal.

Goldin, I., & Mariathasan, M. (2015). *The butterfly defect: How globalization creates systemic risks, and what to do about it*. Princeton University Press.

Han, D. (2019). Network analysis of the Chinese stock market during the turbulence of 2015–2016 using log-returns, volumes, and mutual information. *Physica A: Statistical Mechanics and its Applications*, *523*, 1091-1109.

Huidrom, R., Kose, A., & Ohnsorge, F. (2016). Painful spillovers from slowing BRICS growth.*The VoxEU*, 17.

Karimalis, E. N., & Nomikos, N. K. (2018). Measuring systemic risk in the European banking sector: A Copula CoVaR approach. *The European Journal of Finance*, *24*(11), 944-975.

Kerste, M., Gerritsen, M., Weda, J., & Tieben, B. (2015). Systemic risk in the energy sector—Is there need for financial regulation?

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of econometrics*, *74*(1), 119-147.

Kose, A. M., Prasad, E., Rogoff, K., & Wei, S.-J. (2009). Financial Globalization: A Reappraisal. International Monetary Fund. Staff Papers, 8-62.

Lebedeva, E. (2018). Spillovers between cryptocurrencies. Network map of cryptocurrencies, *Master Thesis*. University of Tartu.

Mendoza, E. G., & Quadrini, V. (2010). Financial globalization, financial crises and contagion. Journal of Monetary Economics, Volume 57, Issue 1, Pages 24-39.

Mendoza, E. G., Quadrini, V., & Rios-Rull, J.-V. (2009). Financial Integration, Financial Development, and global imbalances. J. Political Econ. 117 (3), 371–416.

Milesi-Ferretti, G.-M., & Tille, C. (2011). The great retrenchment: International capital flows during the global financial crisis. Economic Policy pp. 289–346.

Moshirian, F. (2015). Global governance and financial stability. *Journal of Banking and Finance*, (55), 358-360.

Nishimura, Y., Sun, & Bianxia. (2018). The intraday volatility spillover index approach and an application in the Brexit vote. Volume 55, Pages 241-253: Journal of International Financial Markets, Institutions and Money.

Pernagallo, G., & Torrisi, B. (2019). An empirical analysis on the degree of Gaussianity and long memory of financial returns in emerging economies. *Physica A: Statistical Mechanics and its Applications*, *527*, 121296.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, *58*(1), 17-29.

Politi, M., Millot, N., & Chakraborti, A. (2012). The near-extreme density of intraday log-returns. *Physica A: Statistical Mechanics and its Applications*, *391*(1-2), 147-155.

Prasad, E., Rogoff, K., Wei, S. J., & Kose, M. A. (2010). Financial Globalization and Macroeconomic Policies. *Handbook of Development Economics*.

Rossi, S. & Malavasi, R. (2016) Financial Crisis, Bank Behaviour and Credit Crunch, vol. 1, Springer International Publishing, Switzerland.

Sedunov, J. (2016). What is the systemic risk exposure of financial institutions? *Journal of Financial Stability*, *24*, 71-87.

Singh, P., & Kumar, A. P. (2010). Price and volatility spillovers across North American, European, and Asian stock markets. International Review of Financial Analysis, 19 (2010), pp. 55-64.

Syriopoulos, T. (2007). Dynamic linkages between emerging European and developed stock markets: Has the EMU any impact? International Review of Financial Analysis, 16 (1) (2007), pp. 41-60.

Trapp, M., & Wewel, C. (2013). Transatlantic systemic risk. *Journal of Banking & Finance*, *37*(11), 4241-4255.

Van Cauwenberge, A., Vancauteren, M., Braekers, R., & Vandemaele, S. (2019). International trade, foreign direct investments, and firms' systemic risk: Evidence from the Netherlands. *Economic Modelling*, *81*, 361-386.

Worthington, A., & Higgs, H. (2004). Transmission of equity returns and volatility in Asian developed and emerging markets: a multivariate GARCH analysis. *International Journal of Finance & Economics*, *9*(1), 71-80.

Wu, F. (2018). Sectoral contributions to systemic risk in the Chinese stock market. Finance Research Letters 31 (2019) 386–390.

Yarovaya, L., Brzeszczyński, J., Lau, M., & Keung, C. (2016). Intra- and inter-regional return and volatility spillovers across emerging and developed markets: Evidence from stock indices and stock index futures. International Review of Financial Analysis. Volume 43, Pages 96-114.

Yin, K., Liu, Z., & Jin, X. (2020). Interindustry volatility spillover effects in China's stock market. *Physica A: Statistical Mechanics and its Applications*, *539*, 122936.

Appendix

Composition of Stoxx Europe diversification select 50 as at April 29, 2020

Sector	Firm	Country of Origin
Utilities	Red Electrica Corporation	Spain
	Naturgy Energy Group	Spain
	Veolia Environment	France
	Endesa	Spain
	Terna	Italy
	Enel	Italy
	E. On	Germany
	Engie	France
	National Grid	United Kingdom
	EDP Energias De Portugal	Portugal
	Fortum	Finland
	Uniper	Germany
	Terna	Italy
	Iberdrola	Spain
Telecoms	Elisa Corporation	Finland
	Orange	France
	Deutsche Telekom	Germany
	Proximus	Belgium
	Tele2 B	Sweden
	Telenor	Norway
	Swisscom	Switzerland
	Sunrise	Switzerland
	KPN	Netherlands
	Telefonica Deutschland	Germany
Real Estate	Klepeirre	France
	Gecina	France
	Tag Immoblien AG	Germany
	Covivio	Real Estate
	Leg Immobilien	Germany
	Grand City Properties	Germany
	Immofinanz	Austria
	Aroundtown (FRA)	Germany
	Unibail-Rodamco-Westfield	France
Healthcare	Novartis	Switzerland
	Glaxosmithkline	United Kingdom
	Sanofi	France
Industrial Goods & Services	Kone B	Finland
	Flughafen Zurich	Switzerland
	Alstom	France
Oil & Gas	Snam Rete Gas	Italy
	Enagas	Spain
	OMV	Austria
Retail	Ahold Delhaize	Netherlands
	Metro AG	Germany
Construction & Materials	Acciona S. A	Spain
Personal & Household	Uniliver	Netherlands
Travel & Leisure	Sodexo	France
Insurance	TRYG	Denmark
	Topdanmark	Denmark
Bank	Bawag Group AG	Austria
Food & Beverage	Coca Cola HBC	United Kingdom

Selected Companies, 37 out of 50 For Spillover Analysis

Sector	Firm	Country of Origin
Utilities	Red Electrica Corporation	Spain
	Naturgy Energy Group	Spain
	Veolia Environment	France
	Endesa	Spain
	Terna	Italy
	Enel	Italy
	E. On	Germany
	Engie	France
	National Grid	United Kingdom
	EDP Energias De Portugal	Portugal
	Fortum	Finland
Telecoms	Elisa Corporation	Finland
	Orange	France
	Deutsche Telekom	Germany
	Proximus	Belgium
	Tele2 B	Sweden
	Telenor	Norway
	Swisscom	Switzerland
	Telefonica Deutschland	Germany
Real Estate & Construction	Klepeirre	France
	Gecina	France
	Tag Immoblien	Germany
	Covivio	Real Estate
	Unibail Rodem	
	Acciona S. A	Spain
Industrial Goods & Services	Kone B	Finland
	Flughafen	Switzerland
	Enagas	Spain
	Snam Rete Gas	Italy
	OMV	Austria
Lifestyle	Ahold Delhaize	Netherlands
	Unilever	Netherlands
	Sodexo	France
	Novartis	Switzerland
	Glaxosmithkline	United Kingdom
	Sanofi	France

Selected Companies, 33 out of 50 For Systemic Risk Analysis

Sector	Firm	Country of Origin
Utilities	Red Electrica Corporation	Spain
	Naturgy Energy Group	Spain
	Veolia Environment	France
	Endesa	Spain
	Terna	Italy
	Enel	Italy
	E. On	Germany
	Engie	France
	National Grid	United Kingdom
	EDP Energias De Portugal	Portugal
	Fortum	Finland
Telecoms	Elisa Corporation	Finland
	Orange	France
	Deutsche Telekom	Germany
	Proximus	Belgium
	Tele2 B	Sweden
	Telenor	Norway
Real Estate	Klepeirre	France
	Gecina	France
	Tag Immoblien	Germany
	Covivio	Real Estate
Healthcare	Novartis	Switzerland
	Glaxosmithkline	United Kingdom
	Sanofi	France
Industrial Goods & Services	Kone B	Finland
	Flughafen	Switzerland
	Alstom	France
Oil & Gas	Snam Rete	Italy
	Enagas	Spain
Retail	Ahold Delhaize	Netherlands
Construction & Materials	Acciona S. A	Spain
Personal & Household	Uniliver	Netherlands
Travel & Leisure	Sodexo	France

Panel data for regression and their sources

Variable	**Definition**	**Source**
VaR	Largest loss a firm can expect at 95% confidence interval	Author's calculation
Delta_CoVaR	A measure of a firm's contribution to general systemic risk	Author's calculation
Beta	A measure of a firm's responsiveness to the market	Author's calculation
Leverage	Ratio of firm total debt to common equity	Author's calculation
Size	Firm's total value of current assets	Amadeus Database
Inno	Spending on research and development	Author's calculation
Dummy Foreign Control	Assign 1 to firms with 10% or more foreign owners and 0 otherwise	Amadeus Database
Dummy Foreign Subsidiary	Assign 1 to firms with foreign subsidiaries and 0 otherwise	Amadeus Database
Dummy - Sectors	Assign 1 to the sector a firm belongs to and 0 otherwise	Amadeus Database

Panel Regression Results

	Dependent variable:			
	log(Delta_CoVaR)			
	Pooled OLS	Fixed effects	First difference	Random effects
	(1)	(2)	(3)	(4)
Beta	0.470***	1.065***	1.149***	0.470***
	(0.086)	(0.118)	(0.129)	(0.086)
log(VaR)	0.974***	0.950***	0.936***	0.974***
	(0.026)	(0.025)	(0.027)	(0.026)
log(Leverage)	-0.121***	-0.132***	-0.216***	-0.121***
	(0.033)	(0.031)	(0.030)	(0.033)
log(Size)	0.021	0.021	0.039*	0.021
	(0.014)	(0.013)	(0.016)	(0.014)
Inno	-0.00005**	-0.0001**	-0.0001***	-0.00005**
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Dummy_FornCon	-0.157*	-0.164*	-0.208**	-0.157*
	(0.070)	(0.065)	(0.074)	(0.070)
Dummy_FornSub	0.503***	0.462***	0.552***	0.503***
	(0.057)	(0.054)	(0.058)	(0.057)
Dummy_Utilities	-0.246**	-0.306***	-0.737	-0.246**
	(0.083)	(0.078)	(0.389)	(0.083)
Dummy_Telecoms	-0.320***	-0.338***	-0.382	-0.320***
	(0.087)	(0.082)	(0.365)	(0.087)
Dummy_RealEst	0.115	0.037	0.088	0.115
	(0.098)	(0.093)	(0.345)	(0.098)
Dummy_Health	0.028	0.077	-0.129	0.028
	(0.123)	(0.116)	(0.302)	(0.123)
Dummy_Indust	-0.425***	-0.470***	-0.687**	-0.425***
	(0.091)	(0.086)	(0.256)	(0.091)
Dummy_Oil	0.057	0.010	-0.068	0.057
	(0.096)	(0.090)	(0.224)	(0.096)
Dummy_Retail	-0.177	-0.192	-0.316	-0.177
	(0.113)	(0.106)	(0.190)	(0.113)
Dummy_Const	-0.465***	-0.627***	-0.701***	-0.465***
	(0.114)	(0.109)	(0.157)	(0.114)
Dummy_Pers	0.041	0.027	-0.020	0.041
	(0.116)	(0.109)	(0.111)	(0.116)
Constant	-1.393***		-0.020	-1.393***
	(0.138)		(0.022)	(0.138)
Observations	297	297	288	297
R2	0.965	0.970	0.964	0.965
Adjusted R2	0.963	0.968	0.962	0.963
Note:			*p<0.05; **p<0.01; ***p<0.001	

Other Statistical Tests

F test for individual effects

data: f1

F = 5.8496, df1 = 8, df2 = 272, p-value = 6.627e-07

alternative hypothesis: significant effects

Lagrange Multiplier Test - (Breusch-Pagan) for balanced panels

data: f1

chisq = 6.4875, df = 1, p-value = 0.01086

alternative hypothesis: significant effects

Hausman Test

data: f1

chisq = 52.667, df = 16, p-value = 8.546e-06

alternative hypothesis: one model is inconsistent

Durbin-Watson test for serial correlation in panel models

data: f1

DW = 2.7978, p-value = 0.3653

alternative hypothesis: serial correlation in idiosyncratic errors

Breusch-Pagan LM test for cross-sectional dependence in panels

data: log(Delta_CoVaR) ~ Beta + log(VaR) + log(Leverage) + log(Size) + Inno + Dummy_FornCon + Dummy_FornSub + Dummy_Utilities + Dummy_Telecoms + Dummy_RealEst + Dummy_Health + Dummy_Indust + Dummy_Oil + Dummy_Retail + Dummy_Const + Dummy_Pers + Dummy_Trav

chisq = 743.47, df = 36, p-value < 2.2e-16

alternative hypothesis: cross-sectional dependence

Pesaran CD test for cross-sectional dependence in panels

data: log(Delta_CoVaR) ~ Beta + log(VaR) + log(Leverage) + log(Size) + Inno + Dummy_FornCon + Dummy_FornSub + Dummy_Utilities + Dummy_Telecoms + Dummy_RealEst + Dummy_Health + Dummy_Indust + Dummy_Oil + Dummy_Retail + Dummy_Const + Dummy_Pers + Dummy_Trav

z = 27.096, p-value < 2.2e-16

alternative hypothesis: cross-sectional dependence

t test of coefficients:

```
                   Estimate  Std. Error  t value  Pr(>|t|)    
Beta             1.0647e+00  1.2186e-01   8.7372 2.498e-16 ***
log(VaR)         9.5015e-01  1.2348e-02  76.9452 < 2.2e-16 ***
log(Leverage)   -1.3216e-01  1.8506e-02  -7.1417 8.434e-12 ***
log(Size)        2.1254e-02  6.0485e-03   3.5138 0.0005171 ***
Inno            -5.1240e-05  5.3163e-06  -9.6384 < 2.2e-16 ***
Dummy_FornCon   -1.6388e-01  1.2953e-02 -12.6519 < 2.2e-16 ***
Dummy_FornSub    4.6204e-01  3.2766e-02  14.1013 < 2.2e-16 ***
Dummy_Utilities -3.0572e-01  9.7211e-03 -31.4492 < 2.2e-16 ***
Dummy_Telecoms  -3.3845e-01  1.6670e-02 -20.3037 < 2.2e-16 ***
Dummy_RealEst    3.6605e-02  3.9336e-02   0.9306 0.3529060    
Dummy_Health     7.7450e-02  3.3408e-02   2.3183 0.0211751 *  
Dummy_Indust    -4.7010e-01  1.4852e-02 -31.6511 < 2.2e-16 ***
Dummy_Oil        9.5432e-03  1.2646e-02   0.7547 0.4511107    
Dummy_Retail    -1.9183e-01  2.8196e-02  -6.8036 6.483e-11 ***
Dummy_Const     -6.2695e-01  4.0479e-02 -15.4883 < 2.2e-16 ***
Dummy_Pers       2.7392e-02  2.2301e-02   1.2283 0.2203933    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Non-exclusive licence to reproduce thesis and make thesis public

I, Samuel Acquaah Arhin,
(date of birth: 17.02.1993)

1. herewith grant the University of Tartu a free permit (non-exclusive licence) to:

1.1. reproduce, for the purpose of preservation and making available to the public, including for addition to the DSpace digital archives until expiry of the term of validity of the copyright, and
1.2. make available to the public via the web environment of the University of Tartu, including via the DSpace digital archives until expiry of the term of validity of the copyright,

SPILLOVER TRANSMISSION AND THE EFFECTS OF INNOVATION & FDI ON SYSTEMIC RISK

supervised by Hakan Eratalay,

2. I am aware of the fact that the author retains these rights.

3. I certify that granting the non-exclusive licence does not infringe the intellectual property rights or rights arising from the Personal Data Protection Act.

Tartu, 11.08.2020

Non-exclusive licence to reproduce thesis and make thesis public

I, Gabriela Claros,
(date of birth: 04.02.1993)

1. herewith grant the University of Tartu a free permit (non-exclusive licence) to:

1.1. reproduce, for the purpose of preservation and making available to the public, including for addition to the DSpace digital archives until expiry of the term of validity of the copyright, and

1.2. make available to the public via the web environment of the University of Tartu, including via the DSpace digital archives until expiry of the term of validity of the copyright,

SPILLOVER TRANSMISSION AND THE EFFECTS OF INNOVATION & FDI ON SYSTEMIC RISK

supervised by Hakan Eratalay,

2. I am aware of the fact that the author retains these rights.

3. I certify that granting the non-exclusive licence does not infringe the intellectual property rights or rights arising from the Personal Data Protection Act.

Tartu, 11.08.2020