Sectorial connectedness of the United States of America

Analysis of volatility and skewness connectedness between the apex of the financial crisis and present day based on the Diebold - Yilmaz framework

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„Én, Sugár Miklós teljes felelősségem tudatában kijelentem, hogy a jelenszakdolgozatban szereplő minden szövegrész, ábra és táblázat - az előírt szabályoknak megfelelően hivatkozott részek kivételével - eredeti és kizárólag a saját munkám eredménye, más dokumentumra vagy közreműködőre nem támaszkodik."
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1 Introduction

According to the Global Industry Classification Standard ("GICS"), companies can be classified into eleven sectors based on their principal business activity (MSCI and S&P, 2018). These sectors however, are not entirely separated from each other as there are countless ties between the corporations whether through supply chains, trading activity, legal contracts or competition. When firms interact with each other, connectedness arises. As the world becomes more globalized the connectedness across the globe increases and the impact of a sizeable shock becomes greater, as evidenced most recently by the financial crisis in 2008.

An important aspect of crisis is the weakening of diversification in the financial markets due to the contagion effect, i.e. the spreading of shocks in the system (Gai and Kapadia, 2010). Furthermore, recent studies about the financialization of commodities, such as Gross (2017), Creti et al. (2013), Silvennoinen and Thorp (2013) and Büyüksahin and Robe (2014) show that commodities, which were previously considered as great additions to a portfolio because of their low correlation with other elements, are losing their diversification efficiency. Ironically, this phenomenon is due to investors who choose commodities as portfolio elements while they seek shelter against losses through diversification. This is because they increase connectedness among different markets while making and adjusting their portfolio. Owing to this effect, investors faced significant additional losses during the crisis, spurring the need to achieve a better understanding of the dynamics of the markets we conduct business on.

Researchers applied several approaches focusing on the topic of connectedness, such as the study of pairwise Granger casualties by Billio et al. (2012). However, this method would be quite challenging due to the high dimensionality of data and would also spawn efficiency concerns as it would only consider pairwise relations. Maziarz (2015) also criticizes the Granger causality because one can easily misinterpret the results without having adequate background knowledge on the researched topic. An alternative could be the investigation of correlations between the timeseries of the underlying stocks as in Engle and Kelly (2012) or the lagged correlations as in Curme et al. (2015) but these approaches would also neglect the multilateral effects arising between firms.

The approach I prefer to use is a method developed by Diebold and Yilmaz in a series of papers (Diebold - Yilmaz, 2009, 2012, 2014). They advocate a framework based on the variance decompositions of a vector autoregression, enabling the measurement of spillovers generated between market participants. Their method doesn’t rely on pairwise effects and is applicable to
high dimensional data, thus it overcomes the constraints of the previously described techniques. *Bostanci and Yilmaz* highlight some other appealing features of the framework and analyze its relationship with network theory, which enables the effective visualization and interpretation of results. They also praise the frameworks ability to “adapt to the changes in data relatively faster”, because the “predictive power of these measures are among the highest (*Arsov et al.*, 2013) of the existing indicators” (*Bostanci - Yilmaz*, 2015, p. 6)

This framework was mostly used so far to analyze the relationship between either individual stocks, sovereigns or asset classes but there has been little to any focus on sectorial connectedness (please see Section 2 for the literature review). Based on the few articles with this underlying interest (*Sita, 2012*, *Nguyen, 2015*, *Barunik et al., 2016*) we know that there is a strong, but time-varying relationship between the sectors. These articles provide a benchmark for my results however, I wish to add to this topic from a slightly different perspective.

Given the recent findings on weakening diversification and the room for additional sectorial studies, my main interest is to examine the sectors of the United States of America (“U.S.”) by applying the Diebold-Yilmaz (“DY”) framework for the eleven GICS sector tracking sub-indices of the S&P 500 index, to gain a better understanding on how they are connected. The question I’m aiming to answer is: Can investors turn to any sector in times of market distress, in order to avoid or decrease correlated losses?

After analyzing volatility and skewness connectedness respectively, between late 2008 and late 2018, I find that the most appealing portfolio additions are telecommunications followed by utilities sector if an investor seeks to increase the efficiency of diversification. Given the time-varying nature of connectedness real estate sector should also be considered but mostly after the settlement of the crisis. Moreover, I find that the consumer discretionary, industrials and health care sectors should be avoided as they heavily spread shocks to others.

The rest of the paper is structured as follows: Section 2 is a literature review, Section 3 is the introduction of the applied methodology, Section 4 is the presentation of underlying data, Section 5 is the static (full sample) analysis, Section 6 is the dynamic (rolling sample) analysis, Section 7 is the robustness check of results and Section 8 is the conclusion.
2 Literature review

My paper expands the literature on the study of connectedness based on the Diebold - Yilmaz framework. Please find a summary of the papers presented in this section in Table 1. The original idea was proposed by Diebold and Yilmaz – please find the detailed methodology in Section 3.1 – they conducted a study on nineteen global equity markets, analyzing both return and volatility connectedness. They found that while return connectedness has a clear upward trend – associated with globalization – volatility connectedness has outbursts related to times of market distress (Diebold - Yilmaz, 2009). In their subsequent work they improved the framework with a generalized version of variance decompositions (“GVD”) of the VAR model. In this paper they applied the methodology to investigate volatility connectedness between U.S. stock, bond, FX and commodity markets. They found evidence of cross-market volatility spillovers from equities to the other asset classes due to the crisis (Diebold - Yilmaz, 2012).

In their 2014 paper, they discovered the relation of the framework to network theory and systemic risk measurement. With the network representation, they were able to effectively visualize and interpret their results obtained from the framework and found it comforting, that the spillover measures (described in Section 3.1) are related to CoVaR and MES measures. Because of these relationships, their framework is applicable extensively. The conducted analysis focused on fifteen U.S. financial institutions with findings of strong connectedness (Diebold - Yilmaz, 2014). These three articles contain the methodology I’ll apply in this study.

In later papers Diebold and Yilmaz examined the volatility connectedness between the European and U.S. financial institutions (Diebold - Yilmaz, 2016). Partnered with Liu they studied commodity connectedness (Diebold et al., 2017) and joined by Demirer also, they investigated global bank connectedness (Demirer et al., 2015). Yilmaz together with Bostanci researched the global sovereign credit risk network using CDS connectedness (Bostanci - Yilmaz, 2015).

While Diebold and Yilmaz mostly concentrated on financial institutions with their analysis, other authors applied the framework for other market participants, asset classes and for a broader analysis. Greenwood-Nimmo et al. measure global connectedness, while they also provide an extension of the framework. They show that the shocks to the financial markets quickly spread over to the real economy (Greenwood-Nimmo et al., 2015). A similar paper, albeit with tighter scope, searches for linkages between oil shocks and equity markets and finds that financial markets influence oil markets, but vice versa the effect is limited (Zhang, 2017).
There has also been extensive research on FX connectedness, starting with the article of McMillan and Speight. The authors put the return and volatility connectedness of the USD, JPY and GBP against the EUR under the microscope, while concentrating on different trader types, by considering different time horizons. They find that news is incorporated to prices in half a day (McMillan - Speight, 2010). Barunik et al. study good and bad volatility connectedness on six FX pairs against the USD, showing that there is asymmetry in the measure (Barunik et al., 2017). Greenwood-Nimmo et al. show that cross currency volatility and skewness spillovers increase among G10 currencies during market distress (Greenwood-Nimmo et al., 2016).

Gross applies the framework for eighteen non-energy commodities and finds evidence of financialization of commodities (Gross, 2017). The same phenomenon was also described by Diebold et al. (2017) and Barunik et al. (2014) by applying the framework and many other authors who used different methodologies. The term structure of interest rates was examined by Sowmya et al. They considered the level, slope and curvature factors respectively and were measuring the connectedness arising between sovereign bond markets (Sowmya et al., 2016).

My goal is to gain a better understanding on how sectors in the U.S. are connected, which have been studied by only a small number of papers using the same framework, while applying a different approach. Sita chose an undisclosed amount of companies classified into thirty U.S. industries (not according to GICS) and conducted his research by calculating the value-weighted returns of stocks in the respective industries. He applied the original (2009) framework for these quasi industry indices and found that the spillover index for volatilities between 1963 and 2010 ranges from 60% to 70%, implying strong connectedness (Sita, 2012).

An alternative approach was presented by Nguyen who applied the framework containing the generalized variance decompositions to analyze sectorial volatility connectedness of the U.S. – which is also the scope of my paper – but the author applied the framework for ten iShares sector ETF’s and didn’t follow the GICS. Since this paper lies closest to mine both regarding its topic and the framework, I’m able to utilize its results as a benchmark. The findings indicate that the energy and materials sectors have the strongest impact on other sectors, while the overall shocks influence the consumer staples, consumer discretionary and health care sectors the most (noting that I’ve reclassified the results to align them with the GICS). The author also highlights the time-varying nature of connectedness and that specific events can change the strongest contributors and receivers of spillovers e.g. the burst of the dotcom bubble or the 2008 crisis (Nguyen, 2015).
The paper which also has a similar focus to mine was written by Barunik et al. This article studies asymmetric volatility spillovers, while also using the generalized variance decomposition framework. They apply the methodology to analyze twenty-one U.S. stocks, divided into seven GICS sectors (Barunik et al., 2016). Although the authors arrive at conclusions which I can compare my results to, I believe the small number of stocks do not represent the respective sectors well enough. Furthermore, they leave out four sectors from their analysis, thus the connectedness between sectors might be distorted and can show a different pattern when we add the lacking sectors to the investigation.

The analysis presented in my paper adds to these studies by applying the enhanced Diebold-Yilmaz framework, examining eleven GICS sectors and researching the effect of skewness and volatility connectedness among these sectors. As per my thesis question I wish to identify sectors which are less connected during market distress and my hypothesis is that the consumer staples sector acts as a safe haven for investors during a financial crisis.

<table>
<thead>
<tr>
<th>Category</th>
<th>Articles</th>
<th>Underlying analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic framework</td>
<td>Diebold and Yilmaz, 2009</td>
<td>Global equity; original framework</td>
</tr>
<tr>
<td></td>
<td>Diebold and Yilmaz, 2012</td>
<td>Stock, bond, FX, commodity; GVD</td>
</tr>
<tr>
<td></td>
<td>Diebold and Yilmaz, 2014</td>
<td>U.S. FIs; Network theory</td>
</tr>
<tr>
<td>Other articles from</td>
<td>Diebold and Yilmaz, 2016</td>
<td>European and U.S. FIs</td>
</tr>
<tr>
<td>Diebold and Yilmaz &amp;</td>
<td>Diebold et al., 2017</td>
<td>Commodities in the U.S.</td>
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<tr>
<td>co.</td>
<td>Demirer et al., 2015</td>
<td>Global bank network</td>
</tr>
<tr>
<td></td>
<td>Bostanci and Yilmaz, 2015</td>
<td>Global sovereign CDS</td>
</tr>
<tr>
<td>Other global scope</td>
<td>Greenwood-Nimmo et al., 2015</td>
<td>Global; DY framework extension</td>
</tr>
<tr>
<td></td>
<td>Zhang, 2017</td>
<td>Global focus, including oil</td>
</tr>
<tr>
<td>FX connectedness</td>
<td>McMillan and Speight, 2010</td>
<td>Different trader types and time horizons</td>
</tr>
<tr>
<td></td>
<td>Barunik et al., 2017</td>
<td>Asymmetric volatility</td>
</tr>
<tr>
<td></td>
<td>Greenwood-Nimmo et al., 2016</td>
<td>Cross currency volatility and skewness</td>
</tr>
<tr>
<td>Commodities</td>
<td>Gross, 2017</td>
<td>18 non-energy commodities</td>
</tr>
<tr>
<td></td>
<td>Barunik et al., 2014</td>
<td>Crude oil, heating oil, gasoline</td>
</tr>
<tr>
<td>Term structure of</td>
<td>Sowmya et al., 2017</td>
<td>Level, slope and curvature factors</td>
</tr>
<tr>
<td>interest rates</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sectorial</td>
<td>Sita, 2012</td>
<td>30 U.S. industries</td>
</tr>
<tr>
<td></td>
<td>Nguyen, 2015</td>
<td>ETF sectorial</td>
</tr>
<tr>
<td></td>
<td>Barunik et al., 2016</td>
<td>21 U.S. stocks in 7 GICS sectors</td>
</tr>
</tbody>
</table>

1. Table: Summary of the literature review. Source: own construction.
3 Methodology

The key aspect of my analysis is financial connectedness, i.e. the relation between the “participants” of the financial markets such as firms, countries and financial assets or even different sub-markets. These relations arise due to the intertwined nature of the financial markets as when different participants sign contracts, trade or transact with each other, they increase the degree of financial connectedness.

To conduct the analysis, we must consider spillovers: i.e. the effects of shocks spreading between financial assets (Engle et al., 1990). This phenomenon became a key interest of economists after the financial crisis in 2008 as a seemingly local crisis quickly became a crippling global distress, although it has been recognized much earlier by Engle et al. Based on this contagion effect Diebold and Yilmaz proposed a framework: utilizing variance decompositions they constructed a spillover index measuring connectedness.

3.1 The Diebold-Yilmaz framework

Following Diebold and Yilmaz (2009) I use variance decompositions of a vector autoregression to produce spillover measures. However, ordinary variance decompositions would not be adequate for our calculations due to the requirement of orthogonal shocks, (even though we have identification schemes readily available to produce such innovations like the Cholesky factorization) because “VAR innovations are generally contemporarily correlated” (Diebold - Yilmaz 2012, p.58). To resolve this discrepancy, Diebold and Yilmaz (2012) propose the usage of generalized variance decompositions, following Koop et al. (1996) and Pesaran and Shin (1998). The approach of these authors lets us use variance decompositions without the orthogonalization of shocks and the result will be order invariant.

Let’s consider an N-variable $p^{th}$ order VAR where $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \epsilon_t$, given that $\epsilon_t \sim (0, \Sigma)$. We can write the moving average representation of this VAR as $x_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i}$ where $A$ represents an $N \times N$ coefficient matrix and can be written as $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$; all elements of the $A_0$ matrix are equal to one and $A_i = 0$ for every $i < 0$. (Demirer et al., 2015).

Utilizing the notation of Demirer et al. (2015, p.5), firm j’s contribution to firm i’s $H$-step-ahead generalized forecast error variance is calculated as:

$$\theta_{ij}^g(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i'H \Sigma^{-1} e_j)^2}{\sum_{h=0}^{H-1} (e_i'H \Sigma^{-1} e_i)^2}, \quad (1)$$
where $\Sigma$ is the covariance matrix of the error vector $\epsilon$, $\sigma_{jj}$ is the $j^{th}$ diagonal element of $\Sigma$, $e_i$ and $e_j$ are the selection vectors containing one as the $i^{th}$ (or $j^{th}$) element and zeros otherwise and $A_h$ is the moving average of the $NxN$ coefficient matrix.

Let’s arrange the calculated values using equation (1) into a matrix called a connectedness table, where the upper left $NxN$ matrix contains the $H$ step ahead forecast error variances:

<table>
<thead>
<tr>
<th></th>
<th>$x_1$</th>
<th>$x_2$</th>
<th>…</th>
<th>$x_N$</th>
<th>From others</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_1$</td>
<td>$\theta_{11}^g(H)$</td>
<td>$\theta_{12}^g(H)$</td>
<td>…</td>
<td>$\theta_{1N}^g(H)$</td>
<td>$\sum_{j=1}^{N} \theta_{1j}^g(H), j \neq 1$</td>
</tr>
<tr>
<td>$x_2$</td>
<td>$\theta_{21}^g(H)$</td>
<td>$\theta_{22}^g(H)$</td>
<td>…</td>
<td>$\theta_{2N}^g(H)$</td>
<td>$\sum_{j=1}^{N} \theta_{2j}^g(H), j \neq 2$</td>
</tr>
<tr>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
</tr>
<tr>
<td>$x_N$</td>
<td>$\theta_{N1}^g(H)$</td>
<td>$\theta_{N2}^g(H)$</td>
<td>…</td>
<td>$\theta_{NN}^g(H)$</td>
<td>$\sum_{j=1}^{N} \theta_{Nj}^g(H), j \neq N$</td>
</tr>
</tbody>
</table>

To others

$\sum_{i=1}^{N} \theta_{1i}^g(H)$ $\sum_{i=1}^{N} \theta_{i2}^g(H)$ … $\sum_{i=1}^{N} \theta_{in}^g(H)$ $\frac{1}{N} \sum_{i,j=1}^{N} \theta_{ij}^g(H)$

$\sum_{i \neq 1} \sum_{i \neq 2} \sum_{i \neq N} \sum_{i \neq j} \sum_{i \neq 1} \sum_{i \neq 2} \sum_{i \neq N} \sum_{i \neq j}$


When we calculate $\theta_{ij}^g(H)$ based on the generalized variance decomposition, the sums of the rows are not necessarily one (like they would be in case of applying the ordinary variance decomposition), so in order to calculate our connectedness measure we normalize by dividing with the sum of each row and define pairwise directional connectedness as:

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

(2)

$C_{i \leftarrow j}^H$ is also denominated as $\tilde{\theta}_{ij}^g(H)$ because it proves useful for calculations, but the $C_{i \leftarrow j}^H$ form helps the better understanding of the measures as it also expresses direction in a straightforward manner. Noting also that by construction $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H) = N$.

Following the logic in the connectedness table (Table 2) but using this new notation from equation (2) we can construct total directional connectedness “To” and “From” any variable.

Total directional connectedness to variable $i$ from all other variables is calculated as:

$$C_{i \leftarrow o}^H = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ij}^g(H)}{N}$$

(3)
And total directional connectedness from variable $i$ to all other variables is calculated as:

$$ C^H_{i\leftarrow i} = \frac{\sum_{j=1}^{N} \bar{\theta}_{ji}^g(H)}{\sum_{i,j=1}^{N} \bar{\theta}_{ij}^g(H)} = \frac{\sum_{j=1}^{N} \bar{\theta}_{ji}^g(H)}{N} $$ \hspace{1cm} (4)

One can easily calculate the effect of a single variable to the entire system by deducting the calculated “From” measure (equation (4)) from the calculated “To” measure (equation (3)). Diebold and Yilmaz call this effect as “Net” total directional connectedness:

$$ C^H_i = C^H_{i\leftarrow i} - C^H_{i\rightarrow i} $$ \hspace{1cm} (5)

“Net” total directional connectedness reveals the role of any variable in the examined system. If a variable $i$ transmits more shocks than it receives, it is considered a net transmitter and if it is the other way around, I classify it as a net receiver (Diebold and Yilmaz, 2014).

The final step is to calculate systemwide connectedness, which is simply the sum of the row sums – or sum of the column sums, as they are the same by construction – of the connectedness table:

$$ C^H = \frac{\sum_{i,j=1}^{N} \bar{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \bar{\theta}_{ij}^g(H)} = \frac{\sum_{i,j=1}^{N} \bar{\theta}_{ij}^g(H)}{N} $$ \hspace{1cm} (6)

The data which I’m conducting my analysis on (described in Section 4) is the timeseries of S&P’s eleven sub-indices tracking their respective GICS sectors, thus I work with 11x11 connectedness matrices.

3.2 Network representation

The relatively high-dimensionality raises another issue: it makes the comprehending of the results extremely difficult. Although our calculated measures can be arranged into connectedness tables (like in Table 2), due to the large number of pairwise connectedness measures some sort of visualization is desired to achieve better understanding of results.

In their earlier papers Diebold and Yilmaz mostly relied on simple charts (which still proves useful e.g. to visualize the evolution of total systemwide connectedness in our full sample), but in their paper published in 2014 they demonstrated the relation between their framework and network theory and introduced visualization utilizing weighted directed graphs. (Diebold - Yilmaz, 2014). It turns out that the connectedness table can easily be converted to a graph, as
we can view the variables of the table as the nodes of the network, where the linkages are the pairwise connectedness measures. We have multiple tools readily available to foster better understanding, such as node size, node location, node color, link arrows and their sizes. Since I examine the sectorial structure of the U.S. economy, I name the nodes with their respective GICS name in the sake of effortless identification.

Node size indicates the total “From” connectedness of a sector. The bigger the node size is, the more spillovers it receives from others. Relative node location should give us some information about the strength of pairwise connectedness. Based on Demirer et al., I use “the ForceAtlas2 algorithm of Jacomy et al. (2014) as implemented in Gephi”, which is the software I utilize for visualization of graphs (Demirer et al., 2015, p. 9).

As I’m interested in the relationship between different groups, I use node colors to show “Net” connectedness, indicating the role of each sector in the economy. Dark red nodes are capable of spreading shocks the most, red nodes in general indicate net spillover transmitters, while green notes mark net spillover recipients and dark green nodes receive the most impulses. Link arrows and their sizes tell us how strongly two nodes are connected. Even though the node location already indicates the strength of the connectedness between the companies, the thicker links with bigger arrows helps to emphasize this effect.

3.3 Calculating volatility and skewness

Connectedness can be calculated for a wide range of timeseries, but I follow in the steps of papers which calculate it for different moments of the stock returns observed. Usually the second and sometimes the third moment is the main interest of the authors (in some relatively rare cases even the fourth moment is under the microscope). I don’t focus on the fourth moment (kurtosis) since it usually proves insignificant (Greenwood-Nimmo et al., 2016 and Rafferty, 2012). I could also be studying return connectedness, but I choose not to because returns of different companies tend to move together in times of crisis and peaceful periods alike (Demirer et al., 2015).

I concentrate on the second and third moment (the volatility and skewness) of my observations. Diebold and Yilmaz state that volatility connectedness is “fear connectedness” as it is associated with the uncertainty on the markets and they prefer to study it because it behaves such differently in times of market turmoil, compared to times of market prosperity (Diebold - Yilmaz, 2016, p. 5). Skewness is associated with crash risk i.e. jumps in the price of the underlying which can bring significant losses to investors (Greenwood-Nimmo et al., 2016).
I chose these two moments because I’m interested in the identification of GICS sectors which are relatively tranquil even in times of economic distress. Skewness also serves as a great addition to volatility when conducting a research, because skewness tends to be high when volatility is low (Hamdan et al., 2016).

There are plenty of papers on how to calculate realized volatility. Some of these develop models which turn out to be more precise than the formers and some only focus on the ideal sampling frequency to achieve the most punctual measures. On the other hand, only a few papers address realized skewness, thus I decided to follow Amaya et al. (2015) as it contains both measures. The authors propagate a method to calculate range-based realized moments from intra-range data then annualize them (i.e. calculate monthly moments from daily log returns). This is especially appealing to me for two reasons: (i) My data (described in Section 4) is eleven timeseries containing ten years of trading days. If I would choose five-minute sampling advocated by e.g. Liu et al. (2015) I wouldn’t be able to obtain the desired data. (ii) Even if I could get the high frequency data, I would lack the necessary computational power required for processing such information.

For the calculation of monthly range-based realized variance of returns, I utilize the following equation:

\[ \sigma_t^2 = \sum_{i=1}^{N} r_{t,i}^2 \]  

(9)

where \( r \) is the log return of any given day \( i \), for any given month \( t \) and \( N \) is the number of trading days (Amaya et al., 2015, p. 6). As the formula estimates monthly realized variance, I take the square root of it to obtain the standard deviation and annualize by multiplying with \( \sqrt{12} \), given there are twelve months annually. I refer to these annualized standard deviations as volatility in my paper. Since volatilities tend to have a right skewed distribution, I take their natural logarithms before I apply the VAR (Bostanci - Yilmaz, 2015).

Monthly realized skewness is also calculated following Amaya et al. (2015, p. 6) as in Equation 10. I create a 21-day rolling-window period (\( N=21 \)) from the log returns \( r \) calculated from closing prices and quantify each data point in the skewness timeseries based on the prior 21 days as there are 21 trading days in a month on average. After obtaining the monthly skewness series, I annualize by multiplying with \( \frac{1}{\sqrt{12}} \) based on the work of Shum (2014). Since skewness timeseries are not skewed, I don’t need to transform them.
\[ S_t = \frac{\sqrt{n} \sum_{i=1}^{N} r_i^3}{\left[ \sum_{i=1}^{N} r_i^2 \right]^{3/2}} \] (10)

These volatility and skewness calculations result in 22 data points shorter periods than the original timeseries (an additional data point is lost at the calculation of log returns), although I still have above 2500 observations for each sector.

In this section I introduced the main methodology I apply in my paper and the related visualization techniques and defined what I mean by volatility and skewness. In the following section I present the data I conduct my analysis on, including the timeframe, description of the sectors and indices, summary statistics of the underlying timeseries as well as some commonly applied statistical tests.
4 Data

I apply the methodology described in *Section 3* to analyze the volatility and skewness connectedness of the eleven U.S. sectors based on GICS. To conduct my research, I downloaded the daily closing prices of the underlying S&P 500 sub-indices. The examined timeframe ranges from September 30th, 2008 to October 19th, 2018 (which marks the day of the download), without U.S. holidays and weekends, adding up to a total of 2533 observations. For volatility and skewness, I only have 2511 data points given the method of calculation, thus the timeframe used ranges from October 30th, 2008 to October 19th, 2018. Data was obtained from Standard & Poor’s (“S&P”) website (*Standard & Poor’s, 2018*).

The described period is long enough to allow the study of market dynamics, has the crisis in the beginning (starts from a month after Lehman’s collapse) so it is possible to compare times during and after, while it is also an opportunity to put the crisis under the microscope. Particularly, I wish to identify sectors which are more resilient to crisis and can act as a safe haven for investors during financial distress or can increase the efficiency of diversification in general. Since I base my analysis on GICS sectors I give a short summary of each based on the most up to date document published by MSCI and S&P. I also briefly share some facts on the indices I used which are constructed and published by S&P. The eleven sectors are as follows:

*Consumer Discretionary:* These companies produce goods directly consumed by customers such as “automotive, household durable goods, leisure equipment and textiles & apparel”, while the services provided include “hotels, restaurants and other leisure facilities, media production and services, and consumer retailing and services” and generally this sector is “the most sensitive to economic cycles” as the goods and services provided are discretionary in their nature, thus consumers cut back on spending in times of distress (*MSCI and S&P, 2018, p. 1*). The index tracking the performance of this sector is composed of 65 companies (as of October 2018) and the three largest market capitalizations companies are Amazon, Home Depot and McDonald’s (*Standard & Poor’s, 2018*).

*Consumer Staples:* “Includes manufacturers and distributors of food, beverages and tobacco and producers of non-durable household goods and personal products. It also includes food & drug retailing companies as well as hypermarkets and consumer super centers” while due to the nature of the goods and services this sector is “less sensitive to economic cycles” (*MSCI and S&P, 2018, p. 1*). The index has 32 companies and the three largest are Wal-Mart, Procter & Gamble and Coca-Cola (*Standard & Poor’s, 2018*).
**Energy:** This sector contains the “companies engaged in exploration & production, refining & marketing, and storage & transportation of oil & gas and coal & consumable fuels. It also includes companies that offer oil & gas equipment and services” (*MSCI and S&P, 2018, p. 1*). The index has 30 companies and the three largest are Exxon Mobil, Chevron and ConocoPhillips (*Standard & Poor’s, 2018*).

**Financials:** “contains companies involved in banking, thrifts & mortgage finance, specialized finance, consumer finance, asset management and custody banks, investment banking and brokerage and insurance. It also includes Financial Exchanges & Data and Mortgage REITs” (*MSCI and S&P, 2018, p. 1*). The index has 67 components with the top three market cap being Berkshire Hathaway, JP Morgan Chase & Co and Bank of America (*Standard & Poor’s, 2018*).

**Health Care:** “includes health care providers & services, companies that manufacture and distribute health care equipment & supplies, and health care technology companies. It also includes companies involved in the research, development, production and marketing of pharmaceuticals and biotechnology products” (*MSCI and S&P, 2018, p. 1*). The index is composed of 63 firms and the three largest are Johnson & Johnson, Pfizer and UnitedHealth Group (*Standard & Poor’s, 2018*).

**Industrials:** “includes manufacturers and distributors of capital goods such as aerospace & defense, building products, electrical equipment and machinery and companies that offer construction & engineering services. It also includes providers of commercial & professional services including printing, environmental and facilities services, office services & supplies, security & alarm services, human resource & employment services, research & consulting services. It also includes companies that provide transportation services” (*MSCI and S&P, 2018, p. 1*). The sub-index of the S&P 500 tracking the performance of the sector has 71 components and the three with the largest market capitalizations are Boeing Company, 3M Company and Union Pacific Corporation (*Standard & Poor’s, 2018*).

**Information Technology:** “comprises companies that offer software and information technology services, manufacturers and distributors of technology hardware & equipment such as communications equipment, cellular phones, computers & peripherals, electronic equipment and related instruments, and semiconductors” (*MSCI and S&P, 2018, p. 1*). The index is composed of 65 corporations with the three largest being Apple, Microsoft and Visa (*Standard & Poor’s, 2018*).
**Materials:** Companies in this sector “manufacture chemicals, construction materials, glass, paper, forest products and related packaging products, and metals, minerals and mining companies, including producers of steel” (MSCI and S&P, 2018, p. 1). The index is tracking 23 firms and the three largest are DowDuPont, Praxair and Ecolab (Standard & Poor’s, 2018).

**Real Estate:** Includes “companies engaged in real estate development and operation” and “companies offering real estate related services and Equity Real Estate Investment Trusts (REITs)” (MSCI and S&P, 2018, p. 2). The sub-index of the S&P 500 tracking the performance of this sector has 32 components and the three with the largest market capitalizations are American Tower Corporation, Simon Property Group and Crown Castle International Group (Standard & Poor’s, 2018).

**Telecommunications:** “companies that facilitate communication and offer related content and information through various mediums. It includes telecom and media & entertainment companies including producers of interactive gaming products and companies engaged in content and information creation or distribution through proprietary platforms” (MSCI and S&P, 2018, p. 2). Noting, that this sector was renamed to “Communication Services” in September 2018 (MSCI, 2018) but since I started my analysis earlier I will continue to use the old name of the sector, i.e. “Telecommunications”. The index tracking the sector is composed of 26 companies and the three largest are Alphabet (noting that this is Google’s holding company and the firm has Class A and Class C stocks issued, taking the first two places on the list but I will count them as one regarding the placing), Facebook and Verizon Communications (Standard & Poor’s, 2018).

**Utilities:** “comprises utility companies such as electric, gas and water utilities. It also includes independent power producers & energy traders and companies that engage in generation and distribution of electricity using renewable sources” (MSCI and S&P, 2018, p. 2). The sub-index of the S&P 500 tracking the performance of this sector has 29 components and the three with the largest market capitalizations are NextEra Energy, Duke Energy Corporation and Dominion Resources (Standard & Poor’s, 2018).

*Table 3 contains descriptive statistics for volatilities (please see Section 3.4 for method of calculation) of the sectors. After applying the Jarque-Bera normality test for each volatility timeseries it is clear that the null hypothesis can be rejected on every usual significance level implying that neither of the sectors have normally distributed volatility timeseries.*

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Since these timeseries are right-skewed, I will normalize by taking the natural logarithm of them before applying the framework. Please see the histogram of the Consumer Discretionary sector as an example of the application of this method in Figure 1. Since skewness timeseries are much less skewed than volatility timeseries, I will run the analysis without similar modifications.

Table 4 contains descriptive statistics of sectorial skewness timeseries. After running the Jarque-Bera normality test for each skewness timeseries I find that on a 1% significance level five sectors can be viewed as normally distributed while we reject the null hypothesis for the other sectors and on a 5% significance level only one sector’s skewness timeseries can be considered as normally distributed.

Table 3. Descriptive statistics of the sectors for volatility timeseries. Source: Standard & Poor’s (2018), own construction.

Table 4. Descriptive statistics of the sectors for skewness timeseries. Source: Standard & Poor’s (2018), own construction.
In this section I presented the data I use for my research and some related statistics. In the following section I apply the framework introduced in Section 3 for the volatility and skewness measures and conduct a full sample analysis, including the comparison of the results. I also present the connectedness tables and graphs and describe their traits.

Figure 1. Full sample volatility histogram before and after normalization. Source: Standard & Poor’s (2018), own construction.
5 Static (full sample) analysis

In this section I present the results of the full sample analysis, applying the framework described in Section 3 for the whole timeframe described in Section 4. The period I chose for analysis starts at the peak of the crisis shortly after the collapse of Lehman Brothers (September 2008) and ranges to present day. The static analysis gives us a basic understanding of the sectorial connectedness and the magnitude of the spillover intensity over the last ten years.

For the approximating model I use a VAR order of 1 and a 10-day forecast horizon reflecting a period of two trading weeks. The framework is sensible to the parameters chosen, so I present a robustness check in Section 7 to different forecast periods and rolling window lengths used for the dynamic analysis.

The section is structured as follows: Section 5.1 contains the general introduction of the connectedness table, Section 5.2 is the analysis of volatility connectedness, Section 5.3 describes the skewness connectedness of the sectors and Section 5.4 compares the results of the different moments.

5.1 General introduction of the connectedness table

Our main tool for the static analysis is the connectedness table introduced in Section 3.1 and the connectedness graph based on the table, which is constructed as described in Section 3.2. The connectedness table shows the state of the market for a given time and varies significantly over different historical periods as can be seen from the spillover measure calculated based on the dynamic analysis presented in Section 6. Table 5 contains the volatility connectedness of the eleven GICS sectors for the whole sample and the table is constructed to inform the reader about the following things:

Pairwise connectedness arising between sectors can be seen from the \((i,j)\)-th element of the upper left \(11 \times 11\) matrix, i.e. the percentage of the forecast error variance of variable \(i\) due to variable \(j\)’s contribution. Intuitively, the greater the percentage is, the more effect a sector has on the other. As an example, utilities sector’s greatest contributor (excluding the sector’s own forecast error variance) is the real estate sector as can be seen from element \((11,9)\), accounting for 10% of the sector’s total forecast error variance. A possible explanation for this relatively strong connection is that real estate and utilities have a natural linkage in the real economy and the prosperity or decline of the sectors affect the other.
It is important to note, that this matrix is not symmetric and the (9,11) element describing the effect of utilities on real estate is only 7% as opposed to the 10% described above, as sectors can affect each other differently. This percentage however is still the largest of utilities’ contribution to others, implying a closer connection between these sectors. I present the more in-depth analysis of the results after the general introduction of the table in Section 5.2.

The matrix is constructed so its row sums are equal to one as each sector’s forecast error variance is wholly accounted for by the sectors collectively, but column sums are rarely equal to one as summing these measures vertically doesn’t have such a straightforward interpretation. The last column of the connectedness table is not the row sum, but the row sum less the diagonal elements of the matrix, implying the effect other sectors have on sector \(i\). For example, the first element of the last column is 77%, meaning that the consumer discretionary sector’s forecast error variance derives mostly from other sectors performances and only approximately fifth comes from inner-sector activity.

The first row inserted below the variance decomposition matrix contains the “To” connectedness measures, i.e. the effect of a sector on other sectors (excluding the within sectorial connectedness). The first element of this row is 100% – which is coincidental – meaning that the sum of the forecast error variances of the other ten sectors explained by the consumer discretionary sector is the highest out of all variables.

When we deduct the “From” measure from the “To” measure we get the “Net” connectedness which reveals the role of each variable in the system. The 23% net connectedness for the consumer discretionary sector indicates it gives more shocks to the system than it receives from it and the numeric value can only imply comparability when we see it next to the other sectors’ values. In this specific case, this sector is the highest net transmitter of shocks during the observed period and I believe this is because consumer sentiment (which most directly can be observed from people’s spending on discretionary goods) has a significant effect on each sector.

By construction, the sum of the “From” and “To” values are equal, and one could divide each element with this sum to see which sector accounts for what percent of the total figure. I didn’t include this to the table as I believe that the difference in magnitude and the ordering of the sectors can be mostly seen without these calculations. Instead of this, I decided to show the spillover index in the bottom right corner, which indicates the strength of the connectedness in our sample. The 71.1% implies strongly connected sectors over the full sample.
### Table 5. Full sample volatility connectedness table based on Diebold and Yilmaz (2009). Source: Standard & Poor's (2018), own construction.

| Sector                  | CD  | CS  | E   | F   | HC  | I   | IT  | M   | RE  | T   | U   |
|-------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Consumer Discretionary  | 23% | 7%  | 6%  | 9%  | 10% | 12% | 13% | 9%  | 6%  | 3%  | 2%  | 77% |
| Consumer Staples        | 10% | 26% | 5%  | 7%  | 10% | 9%  | 8%  | 7%  | 6%  | 5%  | 5%  | 74% |
| Energy                  | 8%  | 6%  | 32% | 7%  | 8%  | 9%  | 7%  | 13% | 4%  | 3%  | 3%  | 68% |
| Financials              | 11% | 6%  | 6%  | 24% | 9%  | 13% | 9%  | 10% | 7%  | 4%  | 2%  | 76% |
| Health Care             | 12% | 8%  | 6%  | 8%  | 28% | 10% | 9%  | 8%  | 5%  | 4%  | 3%  | 72% |
| Industrials             | 13% | 7%  | 6%  | 20% | 11% | 12% | 5%  | 5%  | 4%  | 2%  | 76% |
| Information Technology  | 14% | 7%  | 6%  | 9%  | 10% | 12% | 23% | 9%  | 4%  | 4%  | 2%  | 77% |
| Materials               | 11% | 6%  | 10% | 10% | 8%  | 13% | 9%  | 25% | 5%  | 3%  | 2%  | 75% |
| Real Estate             | 9%  | 6%  | 5%  | 8%  | 7%  | 7%  | 5%  | 6%  | 35% | 5%  | 7%  | 65% |
| Telecommunications      | 6%  | 8%  | 5%  | 6%  | 7%  | 5%  | 6%  | 5%  | 6%  | 42% | 4%  | 58% |
| Utilities               | 6%  | 9%  | 6%  | 5%  | 8%  | 5%  | 4%  | 4%  | 10% | 4%  | 39% | 61% |
| From Others             |     |     |     |     |     |     |     |     |     |     |     | 71.1% |
| To Others               | 100%| 69% | 59% | 82% | 86% | 95% | 81% | 82% | 58% | 39% | 32% | 61% |
| Total Net Connectedness | 23% | -4% | -9% | 5%  | -9% | 5%  | -9% | 5%  | -9% | 5%  | -9% | 66.0% |


| Sector                  | CD  | CS  | E   | F   | HC  | I   | IT  | M   | RE  | T   | U   |
|-------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Consumer Discretionary  | 25% | 7%  | 5%  | 10% | 8%  | 14% | 12% | 10% | 5%  | 2%  | 1%  | 75% |
| Consumer Staples        | 9%  | 33% | 4%  | 6%  | 8%  | 9%  | 6%  | 6%  | 6%  | 5%  | 7%  | 67% |
| Energy                  | 8%  | 4%  | 38% | 7%  | 5%  | 10% | 5%  | 13% | 4%  | 2%  | 2%  | 62% |
| Financials              | 12% | 6%  | 5%  | 26% | 8%  | 15% | 10% | 10% | 5%  | 2%  | 1%  | 74% |
| Health Care             | 11% | 10% | 5%  | 9%  | 27% | 11% | 8%  | 9%  | 5%  | 3%  | 2%  | 73% |
| Industrials             | 13% | 7%  | 6%  | 12% | 8%  | 23% | 10% | 12% | 5%  | 3%  | 1%  | 77% |
| Information Technology  | 14% | 6%  | 4%  | 10% | 7%  | 13% | 29% | 10% | 5%  | 2%  | 1%  | 71% |
| Materials               | 10% | 6%  | 8%  | 10% | 7%  | 15% | 9%  | 27% | 5%  | 2%  | 1%  | 73% |
| Real Estate             | 7%  | 9%  | 4%  | 5%  | 5%  | 6%  | 5%  | 5%  | 41% | 4%  | 8%  | 59% |
| Telecommunications      | 5%  | 7%  | 3%  | 5%  | 4%  | 6%  | 4%  | 4%  | 5%  | 53% | 4%  | 47% |
| Utilities               | 4%  | 11% | 4%  | 1%  | 4%  | 3%  | 3%  | 3%  | 10% | 4%  | 53% | 47% |
| From Others             |     |     |     |     |     |     |     |     |     |     |     | 66.0% |
| To Others               | 94% | 73% | 48% | 75% | 64% | 103%| 72% | 83% | 57% | 30% | 29% | 47% |
| Total Net Connectedness | 19% | 5%  | -14%| 0%  | -9% | 26% | 1%  | 10% | -2% | -17%| -19%| 47% |
5.2 Static volatility analysis

After describing the general traits of the connectedness table, I carry on with the analysis of volatility connectedness over the full sample. Table 5 contains the calculated connectedness measures. First let me point out that the diagonal elements of the matrix contain the highest figures, meaning that the strongest connectedness arises within the sectors, rather than between them. The highest observed value is 42%, which is the connectedness inside the telecommunications sector, meaning that internal shocks explain more than forty percent of volatility innovations. The industrials sector has the lowest within sector connectedness with 20% over the last ten years. The 20% to 42% range is fairly low, implying strong relations between the different sectors and high openness of the system. The energy, real estate, telecommunications and utilities sectors have within sector connectedness above 30%, reflecting their slightly more closed nature with less outside connections.

Given there are eleven GICS sectors, the connectedness table contains 121 pairwise connectedness measures, so the analysis of each would exceed the limitations of my paper. As instead, I highlight only a couple of pairwise measures before turning to the analysis of the “To” and “From” measures. The highest spillover (excluding the diagonal of the matrix) is 14% and spills from the consumer discretionary sector to the information technology sector. This is not intuitively interpretable but since the consumer discretionary sector has a significant effect on the other sectors in general with six sectors ranging from 10% to 14%, I believe this is due to consumer sentiment in general and the peak of the information technology sector is coincidental. The lowest pairwise connectedness is between utilities and information technology with just 1.6% (values of Table 5 are rounded to foster visibility). Noting, that the utilities sector has the least amount of “To” connectedness and this low value is not an outlier.

The next step in my analysis is the investigation of the “From”, “To” and “Net” measures, as these will aid me to answer the research question, i.e. “Can investors turn to any sector in times of market distress, in order to avoid or decrease correlated losses?”. The “From” measure of the sectors tells us exactly this information as the lower the spillovers received from other sectors, the higher the value added from diversification. Based on my analysis, the 58% of telecommunications sector is the lowest, closely followed by utilities with 61% and the third lowest value is the 65% of the real estate sector. To answer my research question, allocating capital to these sectors could decrease correlated losses, but as I experience in Section 6, the nature of spillovers is time-varying, so further research is desired.
Looking at the distribution of the “From” measures, we can see that they clog in the 58% to 80% range, with most values in the 70’s, implying strong connections between the sectors. Industrials have the highest figure as four other sectors have more than 10% effect on this group: consumer discretionary has 13% as the industrial goods produced are discretionary in nature, financials have 11% deriving from the capital-intensive operations, information technology with 11% as a result of increased automation and materials with 12% due to supply chain.

Turning to the first row below the variance decomposition matrix in Table 5 we have the “To” measures ranging from 32 to 100 (the percentage interpretation is not possible here, so I choose not to confuse the reader with writing it out) which is a much wider range compared to the “From” distribution. Utilities have the lowest figure showing that the shocks spawning here are not likely to contaminate other sectors and telecommunications’ “To” measure is also below 40 implying similar nature. On the other end of the scale we have consumer discretionary with 100 indicating that shocks can easily spread from this sector to others. The second highest transmitters of spillovers are industrials, spreading shocks to the sectors mentioned in the paragraph above.

“Net” connectedness reveals the roles of the sectors in the system and divides them to net recipients and net transmitters as indicated by negative and positive values respectively. Strongest transmitter of shocks is the consumer discretionary sector with 23 (the percentage interpretation is not viable here either) and the industrials and health care sectors are the second and third top contributors. Utilities, telecommunications and energy receive the most compared to their contribution also showing the usefulness of their addition to one’s portfolio. Total connectedness (as measured by the spillover index) is 71.1% over the whole sample, indicating closely linked sectors.

As I described in Section 3.2 the connectedness table can be converted to a weighted and directed graph as in Figure 2. Each node represents a sector and they are labeled accordingly, while the node sizes indicate the amount of spillovers received from others in a way that bigger nodes receive more spillovers from others. The node colors range from dark red to dark green, showing the role of each sector in the system as they indicate total “Net” connectedness. Red nodes spread shocks to others, while green nodes are net recipients. Links between the nodes show the strength of pairwise connectedness and arrow sizes also indicate it: ticker links with bigger arrows represent stronger relationships. Distance between nodes are also indicative as more connected sectors are closer to each other.
The graph can reveal some characteristics of the system which would be hard to see from the connectedness table (especially with the increase of dimensionality). We can observe the clustering of the sectors from Figure 2: namely the consumer discretionary, financials, industrials, information technology and health care sectors are close to each other. When interpreting the connectedness table, I was able to find this cluster, but the graph provides effortless identification.

Outliers are also more visible from the graph and the position of each sector is also informative. For example, an investor who has exposure to the above-mentioned cluster can look to diversify their portfolio with additions from the telecommunications, real estate or utilities sectors. Energy sector can also be a good choice, although it lies closer to industrials, health care and materials, which are some of the strongest net transmitters of spillovers and it has strong links to materials as can be seen from the size of the link connecting them. Materials sector is also
more central than the three peripheral sectors, with strong links to industrials, consumer discretionary and financials. Consumer staples – which is a cycle resilient sector by nature – also lies closer to the five-sector cluster but it has weaker links to other sectors on average than materials. Generally speaking, the smaller and greener nodes are potentially better additions to investor portfolios if the goal is to increase the effect of diversification, although let me emphasize again that the nature of sectorial connectedness is time-varying and can be vastly different for other geographical regions as well.

5.3 Static skewness analysis

I shall continue my investigation of sectorial connectedness with the study of skewness spillovers over the full time period, hoping that the third moment can reveal additional information about the sample. As I highlighted in Section 3.3, skewness is associated with crash risk, indicating jumps in the timeseries of the underlying. Similarly to Section 5.2, I start with the connectedness table then I proceed with the graph.

The skewness connectedness table is presented in Table 6. The diagonal of the table contains the highest values with telecommunications’ and utilities’ figure being the largest at 53%. This indicates, that the shocks with the potential to cause crashes mainly originate from the respective sectors and this effect is especially strong in these two. Lowest amount of the diagonal is 23% of industrials and a total of six sectors are below 30%. Outside of the diagonal, no element is greater than 15%.

Considering pairwise connectedness measures, the lowest is 1% and this figure is observable several times, although always between utilities and another sector. Just by looking at the pairwise measures we can suspect that utilities might be a sector I seek to identify. The highest off-diagonal element of the matrix is 15% spreading from industrials to financials and materials respectively. Industrials seem to be one of the main transmitters of shocks in the system, along with consumer discretionary and financials.

Turning to “From” measures, we observe a 30ppts range between the lowest figure of 47% – both telecommunications and utilities have it – and 77% of industrials, although most measures are above 65%. The 77% of industrials indicate that it is rather vulnerable to external shocks, while telecommunications and utilities seem more resilient. It is interesting to notice, that there is more than 10ppts difference between the two lowest figures compared to the third lowest (i.e. real estate with 59%) indicating a possible cluster of the two sectors. The “middle measures” range from 59% to 67% counting three members, while the other six are above 70%.
“To” measures range from 29 to 103 and after taking a look at the pairwise measures it is not surprising that the two sectors with the minimum and maximum figures are utilities and industrials, respectively. Similarly to “From” measure we have six sectors with higher amounts delivered to others, two sectors with relatively low figures and three somewhere in the middle, although the order is not entirely the same.

Turning to “Net” measures we uncover the roles of each sector and observe an evenly distributed state: five of them are net transmitters, one is neutral and five are net receivers. The neutral sector is financials, which might strike as surprising just ten years after the peak of the crisis, but since my sample ranges to present day the neutral state of financials sector can be justified. This is the sector which serves as an intermediary to others, while it actively seeks to hedge its exposure so by nature it should have a close to neutral role (especially in times of market prosperity, which marks most of my sample). Highest and lowest “Net” measures are again associated with industrials and utilities respectively. Consumer discretionary and materials both actively spread spillovers, telecommunications and energy absorb them.

After analyzing the measures presented above, I finish the study of Table 6 with its bottom-right element: the spillover index. The 66% indicates significant but not too strong connectedness, leaving room for inner-sector effects as well. The magnitude of total spillover shows that the study of connectedness is desired as crashes do spread between sectors.

Now looking at Figure 3, the clustering shows slightly different picture compared to the one I painted based on the connectedness table as the “middle measure” sectors (i.e. consumer staples, energy and real estate) do not form a cluster and neither do utilities and telecommunications. Although the grouping I assumed still holds to some extent as (i) telecommunications and utilities are evidently further away from the rest, (ii) the six sectors form a cluster with industrials in the middle as the strongest transmitter and (iii) the three sectors are somewhere between the two groups.

The cluster has strong links with each other in general, although health care might have some weaker connections than the rest and it is a net receiver of shocks instead of being a transmitter. Financials’ neutral role is indicated by its whiteish-yellow color and the vague red information technology sector has also close to zero “Net” connectedness. Members of this cluster have the biggest nodes, as they have the highest “From” connectedness in the sample.
Telecommunications and utilities have the smallest nodes and they are also the darkest green as they are net recipients with low “From” connectedness. They are on the periphery of the graph so in terms of seeking shelter from crash risk, my recommendation would be investing in one of these sectors. If an investor is more exposed to the consumer staples sector though, I would rather recommend the telecommunications, since it has weaker links with that sector.

Real estate – a traditionally considered portfolio addition increasing diversification – is closer to the cluster but doesn’t have strong links to the sectors within so it could still be a candidate. Consumer staples is also known to be a must have in times of market distress and it isn’t as central as the cluster members but has moderately strong links with the cluster and is relatively close to it, so investors should be cautious. Energy’s strongest links are materials and industrials, although it is also positioned as slightly peripheral, thus it might be considered.
5.4 Comparison of static volatility and skewness connectedness

In this section I present the comparison of the measures analyzed in Section 5.2 and Section 5.3. The structure of the section follows the structure of the previous two, starting with the connectedness tables then moving to the graphs. The aim of this section is to identify the differences between the two moments regarding connectedness and to gain a better understanding on the sectorial connectedness of the U.S. economy over the last ten years.

Comparing Table 5 to Table 6, we can see that the pairwise connectedness measures are different and skewness connectedness table has lower figures in general. Although, the diagonal of the skewness table has higher values with the largest figure considering both tables being 53.1% of telecommunications sector as described in the previous section. The diagonal of the skewness table is also more scattered ranging from 23% to 53% compared to volatility’s 20% to 42%. This implies that crash impulses are more frequently originated within sectors than the volatility impulses.

The volatility “From” connectedness measures are more concentrated than the skewness “From” figures as they range between 58% and 80% as opposed to the 47% to 77%. The volatility values are higher in general, although the highest figure is industrials sectors’ in both cases. On the other hand, the lowest skewness connectedness is 11ppts lower than the lowest volatility counterpart, while they both describe the telecommunications sector.

The “To” distributions are similar, ranging from 32 to 100 for volatility and 29 to 103 for skewness. The highest volatility “To” measure belongs to consumer discretionary sector, while the highest skewness “To” is associated with industrials, although the second highest sector value of each moment belongs to the other’s first sector. Utilities sector has the lowest “To” measure in both cases.

“Net” measures are similarly distributed, with volatility ranging from -29% to 23% and skewness being between -19% and 26%. First and second highest “Net” figures are associated with the same sectors as in case of the “To” measures, while the lowest ones belong to utilities and telecommunications respectively. Considering the results for both moments, it is clear that the consumer discretionary and industrials spread the most shocks, while telecommunications and utilities absorb the most. Consumer staples sector is a net recipient considering volatility spillovers, but it is a net transmitter of skewness shocks, while health care sector is the opposite of this. Energy absorbs shocks in both cases and so does real estate, while information technology and materials are net transmitters of volatility and skewness alike. Financials sector
is neutral regarding skewness but is a transmitter of volatility shocks. Total connectedness is higher in case of volatility with 71%, while the spillover index of skewness is 66%. The difference is not drastic, but it shows us that volatility spreads easier between sectors than jumps do. Most sectors behave the same regarding the two measures, although some turned out to be less open when it comes to skewness.

Comparing the two graphs presented in Figure 2 and Figure 3, we see similar structures but there are some notable differences as well. The cluster of consumer discretionary, financials, materials, industrials, health care and information technology is visible in both cases, although in the volatility graph materials is further away from the rest of the group. Moreover, industrials play a more central role in the skewness graph, while the other sectors have lighter colors indicating “Net” connectedness closer to zero.

Energy is further away from the other non-clustered sectors in both cases, although it is more separated when it comes to volatility and is also differently connected to the cluster. Telecommunications and utilities are the furthest away from the cluster in both cases and they are my candidates to answer my research question with. Real estate produced one of the most notable changes between the two cases, as it moved closer to the cluster when analyzing skewness connectedness. Consumer staples sector is somewhere in the middle between the cluster and the outliers, changing the direction of transmitting shocks between graphs.

In the following section I present the dynamic analysis by applying a rolling window estimation. I identify the main events which happened during my sample and show their effect on the spillover measures. Similarly to this section, I present a separate volatility and skewness study then I compare the results.
6 Dynamic (rolling sample) analysis

In this section I present the results of the dynamic analysis, i.e. instead of looking at my sample as a whole and researching the full time period all at once like in Section 5, I create a rolling window period of 252 trading days (or one trading year) and estimate the connectedness tables and related measures numerous times. This estimation method will shorten my observed period by one year and the new timeframe will range from October 29th, 2009 to October 19th, 2018. Since each day’s results are estimated from the previous year, the peak of the crisis is still reflected in the beginning of my sample. This analysis highlights an important feature of connectedness, which can’t be seen from the static one: spillovers have a time-varying nature.

The research presented in this section is also based on the measures introduced in the previous sections, but since for each day in my shortened sample I calculated them, I’m able to treat each measure as a timeseries. Due the high number of pairwise connectedness measures (121 in my case), I do not focus on them in this section, but I present the “To”, “From” and “Net” measures along with the total spillover measures for each moment.

The rest of this section is structured the following way: Section 6.1 presents the results of the dynamic volatility connectedness analysis, Section 6.2 contains the study of the dynamic skewness connectedness and Section 6.3 compares the two former section’s results.

6.1 Dynamic volatility analysis

As opposed to the logic in Section 5, I will not present the results from the micro to the macro level given I can’t show the results of the pairwise measures. Instead, I start with the presentation of the total spillover measure’s dynamics then I continue with each sector’s “To”, “From” and “Net” measures focusing on the time-varying nature of the sectors’ roles. Since my research question focuses on identifying the sectors investors can turn to during market distress, I break down my timeframe to periods during and after the crisis.

I present the spillover plot for volatility in Figure 4. The time-varying nature of the measure can be seen instantaneously as it gradually decreases from its highest levels around the crisis to a normalized level but with significant volatility over the years. The measure was ranging from 38.8% to 86.1% over the last nine years, reaching its lowest value recently in January 2018 and the highest in January 2012. The volatility of the measure can be radically different in times of market prosperity compared to market turmoil as we can see from the higher levels of connectedness in the first one third of the graph compared to the other two-third, while steep jumps indicate some of the events happened in the past.
Going forward I present the main events that are visible from the graph in a historical order:

**European sovereign debt crisis:** The first notable event happened in April 2010 when Greece turned to the IMF and to the EU to receive a loan as it was unable to refinance its piling sovereign debt from the market (Reuters, 2010). As a result, S&P downgraded Greece to BB+ which is the highest rating for junk bonds from BBB+ which is a decent investment grade rating. The line between investment grade and non-investment grade (BBB- to BB+ at S&P) is critical for obligors as most institutions can’t invest in non-investment grade assets due to their strict financial policies. Moreover, this was the start of the European sovereign debt crisis and due to this event stock markets worldwide took a hit and volatility began to rise gradually as we can see from the chart.

**U.S. debt crisis:** A couple of months passed after the first signs of the European sovereign debt crisis and connectedness started to settle a little bit. But the U.S. had to deal with its own debt crisis: Congress had to accept the raising of the country’s debt ceiling to avoid defaulting, but the republican party wanted to reduce the deficit and didn’t want to accept the new ceiling until their request was settled. To resolve this issue, Congress accepted the Budget Control Act of 2011 and successfully raised the debt ceiling avoiding the default. However, S&P downgraded
the sovereign rating of the U.S. to AA+ from AAA for the first time ever and assigned a Negative Outlook reflecting its concerns about the high levels of debt. Investors became concerned about the U.S. raising the volatility on the markets (Standard & Poor’s, 2011).

Fed quantitative easing and Bernanke speech: Volatility connectedness was the highest in my sample during 2012 and only started to lower when the Fed announced the third round of quantitative easing in September 2012. During the program the Fed purchased “agency mortgage-backed securities at a pace of $40 billion per month” which later was increased to $85 billion per month (Fed, 2012, p. 1). This program boosted the economy of the U.S. (and it also had a favorable effect on many countries worldwide) as investors were provided with ample liquidity and the markets started to settle, while the economy started to become stronger.

This did come at a price of course; the balance sheet of the Fed has expanded significantly, and the amounts purchased until the end of the program on 29th October 2014 totaled to $4.5 trillion putting a heavy burden on the U.S. (The New York Times, 2014). Since the economy started to get back on track, Ben Bernanke, the Chairman of the Fed at the time announced the tapering of the purchases in June 2013, causing a market turmoil with his speech but markets were relieved shortly after (Fed, 2013). However, during the fall tensions have risen again when the specifics of the end of the quantitative easing were announced.

U.S. economy flourishes: Starting from April 2014 and lasting almost a year (marked by an ellipse in Figure 4) volatility began to decrease significantly on the markets as there were no unsettling major news, while the economy was flourishing. Unemployment rate has gradually decreased in the U.S. and real GDP growth was extremely high with 5.1% in 2Q14, 4.9% in 3Q14 and strong results were published for the next few quarters as well (Statista, 2018).

Chinese GDP growth slows down: After enjoying some tranquility, tensions have started to increase once again due to the announcement of the Chinese economy’s slowdown in early 2015. Investors were worried about the global effect it will bring and this news combined with the end of the quantitative easing caused the U.S. GDP growth to also slow down (Statista, 2018). Furthermore, in June 2015, the possibility of Greece’s default was high again and it has set a negative market sentiment in the Eurozone (The Guardian, 2015).

Chinese Black Monday: Couple of months after the Chinese GDP slowdown was announced a huge market crash happened in China. On August 24th, 2015 the Chinese “Black Monday” occurred wiping out billions of dollars as the market plummeted and sparked significant volatility (The New York Times, 2015). The correction continued on the following day as well
and huge losses were accounted for again. Due to the connected nature of the global economy shocks rippled through quickly to other markets across the globe and caused a fall in every region (Greenwood-Nimmo et al., 2015). Volatility connectedness has stayed high at above 70% for the next year after this event.

**Brexit:** In June 2016 the UK held its Brexit referendum and they decided to leave the European Union (UK Government, 2016). This event caught the market by surprise as the opinion polls showed a slight advantage towards staying in the EU. Volatility connectedness jumped to 77% but has decreased steeply after as the Brexit would not take effect for approximately two and a half years and the global economy was in a relatively good shape.

**Trump gets elected:** In November 2016 the U.S. had general elections and Donald John Trump got elected. He became the 45th president of the U.S. and assumed office on January 20th, 2017 (White House, 2016). After some initial panic on the stock markets due to the unexpectedly one-sided election results in favor of Trump, investors calmed down and started to focus on the new president’s policies affecting the economy such as a potential tax cut and other economy boosting initiatives he shared during the electoral campaign.

As a result of the market-friendly approach of Trump, and also due to the strong state of the U.S. economy, volatility started to decrease radically, bringing down volatility connectedness to its lowest of 38.8% in January 2018. This period was the steepest decline of connectedness over my sample and it was also due to the stock market rally during 2017 fostered by stable economic growth, low unemployment rates, low inflation and “unusually low volatility” (Financial Engines, 2018, p. 1).

**First Trump tariffs:** After several months of market prosperity, the biggest volatility connectedness jump in my sample occurred because president Trump announced that the U.S. would impose tariffs on solar panels and washing machines (Time, 2018). This was just the first of the announced tariffs during 2018 and every similar action was met with reactionary tariffs imposed on U.S. exports. The potential further escalation of the trade war radically increased volatility on the markets.

The graph ends with some additional volatility as connectedness settled a little in September continuing the general decreasing trend but jumped back in October as the Fed increased interest rates and investors were still concerned about the trade war’s escalation. As a final note let me highlight that during the last nine years volatility connectedness decreased substantially from 79% to 62%, indicating more relaxed times as of October 2018 compared to October 2009.
After analysing the total volatility spillover measure’s evolution, I shall continue with the sectorial “To” volatility connectedness as presented in Figure 5. These measures also show strong time-varying nature with significant volatility over the years. The ranges are vastly different for each sector and neither figure has an observable trend.

During the crisis, health care sector was the strongest transmitter with its “To” connectedness peaking above 1.6 then returning to moderate 0.6 levels rather quickly. Energy, financials and materials behave quite similarly during the crisis period with their “To” connectedness decreasing sharply at the beginning then gradually returning to higher levels. To a lesser extent, information technology and consumer discretionary sectors behave similarly but their elevation following the initial decrease was much faster.

Consumer staples were the most tranquil during the crisis, the “To” connectedness decreased to 0.4 from 0.7 during the first two years so its crisis resistant reputation seems justified. Industrials’ “To” connectedness is slowly increasing but this sector doesn’t transfer much more volatility during the crisis compared to other periods. However, this doesn’t mean it is a peaceful sector as its average measure is one of the highest as it could be seen in Section 5. Real estate and utilities increase the volatility connectedness spread during the first three years but utilities doesn’t reach above 0.8. Telecommunications quickly decrease back to lower levels after some initial climb.

After the crisis has settled and the U.S. economy started to grow again, some sectors’ “To” connectedness returned to lower levels, although at different paces, while there are a couple of sectors which stayed at their average amount observed during the crisis. The first group consists of energy, real estate, telecommunications and utilities as they decreased their “To” connectedness after the crisis. Telecommunications were the first to do so, followed by utilities and real estate, while energy showed a gradually decreasing trend. The rest of the sectors were more in-line with their distressed measures although consumer discretionary, consumer staples, financials and information technology showed a decreasing phase in the recent three years.

Materials and industrials were moving in a rather tight range through the last nine years and one wouldn’t be able to tell peaceful and turbulent periods apart just by their line chart. They react to some market events I described earlier as can be seen e.g. from industrials’s chart when the measure decreases after the announcement of the third round of quantitative easing or when it jumps after the Chinese “Black Monday”. Health care moved in the widest range and it was the biggest transmitter during the crisis, so investors should be careful with the sector.
Figure 5. Sectorial volatility “To” connectedness. Source: Standard & Poor’s (2018), own construction.
Turning to “From” volatility measures in Figure 6, we can see that these measures are much less volatile compared to the “To” amounts. This is not surprising given that “From” connectedness can only range between zero and one as it is the percentage of the variance decomposition explained by other variables. On the other hand, most of the “From” figures are flat or flat during at least half of the last nine years indicating less variability. The lowest amount is just 7.5% associated with consumer staples, while the highest is 90.6% observed also in the consumer staples sector.

Apart from the telecommunications, health care, consumer staples and utilities all other sectors are flat in the first two to three years during the crisis. Consumer staples and utilities increase to some extent then become linear at their respective levels, while health care almost does the same but with a jump during 2010 leaving only telecommunications as a transmitter of real volatility during the crisis. Telecommunications decrease steeply to 40% from just below 80% in the first year then it increases back to 70% before decreasing below 65% and jumping to 80% again in the first three years of my sample.

In general, the telecommunications sector seems to be the most volatile throughout the nine years observed, which is surprising given it was one of my recommendations in Section 5. However, it reaches quite low “From” connectedness and generally has lower figures, thus can serve as a good portfolio addition. Real estate and utilities tend to be rather volatile as well, although these two mostly started to become volatile after the crisis and they also have generally lower amounts of “From” connectedness.

Consumer discretionary, financials, industrials, information technology and materials are basically horizontal over the observed period and they only present a jump at the announcement of tariffs which I described in the first part of this section. Moreover, they all have “From” connectedness of around 80%, which is also the amount almost every sector had during the crisis. Consumer staples, energy and health care also behave quite similarly but they turn more volatile in the second part of my observed period, while their connectedness also decreases. These sectors also react strongly to the announcement of tariffs.

Utilities didn’t have the tariff jump and it seems like that the announcement had the lowest effect on this sector. On the other hand, the “From” connectedness of utilities showed a steep decline while the U.S. economy flourished and only climbed back when China announced the slow down of its GDP growth.
Figure 6. Sectorial volatility “From” connectedness. Source: Standard & Poor’s (2018), own construction.
Lastly, I present the “Net” volatility connectedness in Figure 7. Highest value observed was 1.02 and belonged to health care sector during the crisis, as its “From” measure decreased while its “To” measure increased drastically at the same time. Lowest “Net” volatility connectedness figure was -0.67 and belonged to telecommunications as its “From” connectedness peaked after the Chinese “Black Monday” while its “To” connectedness was fairly low due to the sector’s place in the real economy.

From the sectorial connectedness figures we can see that the role of a sector is also time-varying as all sectors were net recipients and net transmitters at some point during the past nine years. Moreover, it is clear that most sectors changed their roles multiple times and don’t have a primary role. However, some sectors assume predominantly one specific role and have it through most of my sample. The predominantly net transmitters are consumer discretionary, health care and industrials, while the net recipients are telecommunications and utilities.

Consumer staples was a net recipient during the crisis but after the economy started to boom it changed its role and was mostly a net transmitter for the rest of the time. Real estate was a net recipient at the start of the crisis then transferred into the role of shock spreader for four years but returned to its original role after the end of 2014. The rest of the sectors didn’t have longer periods when they assumed a specific role.

Regarding my thesis question, I would recommend investors to add utility companies to their portfolios as they are capable of absorbing shocks during crisis and tranquil periods alike, although it is worth noting that during market turmoil every sector – except telecommunications for a while – had around 80% of “From” connectedness. Telecommunications is also a good choice as the sector’s net transmitter role derived from the decrease of “From” connectedness which is desirable for investors.
Figure 7. Sectorial volatility “Net” connectedness. Source: Standard & Poor’s (2018), own construction.
6.2 Dynamic skewness analysis

In this section I analyze the sectorial “To”, “From” and “Net” skewness connectedness of my sample but I chose not to present the total skewness connectedness on a spillover plot in this section as I show the comparison to volatility connectedness in Figure 11 in Section 6.3. The reason behind my decision is that I already identified the main events during my sample in Section 6.1 and the same notable events are responsible for the movements of the two measures.

Starting the study of skewness connectedness with the sectorial “To” measures, I present the results in Figure 8. Most sectors sidle through my sample in an 0.84 wide range on average and they don’t show an observable trend. However, these ranges are mostly different for the sectors: energy had an 0.99 range between 0.09 and 1.08 while financials had a much narrower range of 0.64 between 0.53 and 1.17. The lowest amount observed was utilities’ 0.07 and the highest was industrials’ 1.50. Some sectors have trends in their timeseries but even those with such trends tend to sidle for years as well before they start their decreasing trend. Neither sector had an increasing trend after the crisis has finished.

In the first third of my sample the health care, industrials and utilities sectors had an increasing trend while other sectors waved around their starting level. A notable exception is the information technology sector as it actually decreased its “To” connectedness during the crisis and it shows a decreasing trend throughout my whole sample with a few jumps associated with some notable events. During the crisis, industrials sector was the strongest transmitter with its “To” connectedness averaging around 1.2. The telecommunications sector has the lowest levels during crisis averaging just above 0.4 and this sector has similar amount of “To” connectedness throughout my sample.

After the settling of the crisis, consumer staples, energy, health care, real estate and utilities present a decreasing trend, while other sectors mostly stagnate (except for the prior mentioned information technology). Most sectors finished below their initial “To” connectedness measure, although there are a few exceptions. Financials finished the observed period with a higher “To” measure but it was the sector with the narrowest range and it was mostly sidling through the sample. Health care also finished above its initial value but it had the second lowest value at the beginning of my observations. Materials is the only sector which started from one of the highest “To” measure and finished above it, with a steep jump after president Trump announced the tariffs in January 2018. This is quite worrying as we saw in Section 5.2 that materials is strongly connected to other sectors.
Figure 8. Sectorial skewness “To” connectedness. Source: Standard & Poor’s (2018), own construction.
Skewness “From” measures present less fluctuations compared to the “To” measures partly due to the tighter range given the variance decomposition interpretation and partly because these measures are less volatile. Telecommunications have the lowest amount during the observed timeframe with just 11% while consumer staples have the highest with 87%. The widest range belongs to telecommunications with 68ppts and the tightest span is associated with the industrials sector with just 19ppts.

During the crisis, almost every sectorial “From” measure is stuck at the 80% mark for years. Consumer staples and health care started from lower levels, but they also elevate quickly to 80% leaving only one exception to this rule of thumb: telecommunications. This sector is exceptional because it’s “From” measure is more volatile and never reaches 80% not even during the crisis as the highest amount it produces is 79%. After some sidling in the 60% to 80% range for the first two years its “From” connectedness gradually decreases throughout the whole sample. Judging by this behavior, the telecommunications sector could be recommended during crisis for investors as it is mostly responsible for its own crash risk (and even after the crisis as the measure is decreasing).

All of the sectorial “From” connectedness start to decrease eventually but we can see that the consumer discretionary, consumer staples, energy, health care, industrials, information technology and materials sectors mostly start to decrease during 2014 while the U.S. economy flourished. The observed decrease can be vastly different in magnitude as e.g. the energy sector radically drops, while the others decrease more gradually. Industrials and materials return to their crisis levels after the Chinese “Black Monday” and only start to decrease again in the outer parts of my sample. I left out financials sector from this group because it didn’t really decrease during 2014 and mostly started to do so in 2017.

The other three sectors I left out from the prior listing are real estate, telecommunications and utilities and they were excluded because their “From” measures started to decrease much faster, indicating that in these sectors the crisis might have been shorter than in the others. These sectors responded to the third round of the quantitative easing indicating that investors were not that concerned about crash risk originating from outside of these sectors. Due to this behavior and factoring that these sectors reach the lowest average “From” connectedness in the second half of my timeframe I would recommend investing in them.
Figure 9. Sectorial skewness “From” connectedness. Source: Standard & Poor’s (2018), own construction.
The line charts revealing the roles of each sector is presented in Figure 11. The “Net” skewness connectedness is time-varying mostly due to the “To” measures volatile nature as we could saw that the “From” figures are rather flat. As a result, the ranges of the “Net” figures are comparable to the “To” domains with the widest being 0.99 wide (belonging to materials) and the tightest being 0.65 narrow (referring to telecommunications). The highest value of 0.74 was observed at industrials while the lowest value of -0.60 was detected at utilities.

Starting with the analysis of the crisis we can see that most sectors assumed a specific role during the crisis. Consumer discretionary, consumer staples, industrials, information technology and materials were net transmitters during the market turmoil, although consumer staples changed its role much faster compared to the others. On the other hand, energy, health care and telecommunications were net recipients during the first two to three years.

There are three exceptional sectors which changed their roles even during the crisis – not considering extremely short-term roles changes for now. Financials is one of them as they spread skewness until early 2010 then started to receive it for a year before changing its role back to net transmitter again. The second is real estate, which produced a similar burst to financials but remained a net recipient until the end of 2013. The third sector is utilities which was one of the heaviest absorbers of crash risk throughout my sample but changed its role for almost a year during the crisis.

During my observations every sector switched character at least for very short periods but I can classify consumer discretionary, industrials and materials as transmitters while health care, real estate, telecommunications and utilities were predominantly recipients. Consumer staples was mostly a transmitter but during the crisis the sector turned to be a recipient for a year, and financials acted similarly. Both were on the receiving end twice for at least a year each time.

Energy was a collector during the crisis and after the Chinese “Black Monday” as well so it seems that this sector turns to be a receiver during market distress but is a transmitter otherwise. If this really is the case, then the drop in the last half year of my sample is a bad sign for the economy. Although I must highlight that the sector produced much lower “Net” connectedness during the late 2015 to early 2018 period than during the financial crisis so we can take comfort from that. Lastly, information technology is also an interesting case because it was a neutral sector for two years between October 2010 and October 2012 while it changed its role five times (including the change to neutral and from neutral).
Figure 10. Sectorial skewness “Net” connectedness. Source: Standard & Poor’s (2018), own construction.
6.3 Comparison of dynamic volatility and skewness connectedness

In this section I compare the results of Section 6.1 to Section 6.2 and identify the main differences and similarities. I also conclude and answer my thesis question based on the two measures and I reflect on some of the results others found (as presented in Section 2).

I present the evolution of the two spillover indexes in Figure 11. Since I talked about the main events that happened during my timeframe in Section 6.1, now I will only focus on the main characteristics of the spillover measures. The first thing to note is that both indexes present a very similar course, although the volatility figure moves in a wider range. Moreover, the volatility spillover index has more severe and fast paced reactions to main news as we can see from the steeper jumps in its timeseries, noting that in a few cases the skewness has a stronger reaction (e.g. at the announcement of the third round of the quantitative easing in 2012).

In Section 3.3 I state that one of the reasons why I chose to study skewness amongst volatility is due to the work of Hamdan et. al (2016) as the authors argue that skewness tends to be high when volatility is low. From a spillover perspective this doesn’t seem to be the case as both measures have similar values, move together and present a downward trend throughout my sample. This doesn’t mean that the authors’ statement is incorrect as connectedness can still be high or low even when the underlying measure is the opposite.
I present the summary of the sectorial results in Table 7. I break down my sample to periods during and after the crisis for each moment as can be seen from the column headers, while I focus on the “To”, “From” and “Net” connectedness measures as shown in the row titles. Based on the analysis presented in Sections 6.1 and 6.2, I distinguish “Bad” sectors from “Good” sectors in the sense that the latter group could be an optimal choice for investors who seek to avoid or decrease correlated losses during the given time period, while the sectors in the former group are ought to be avoided.

Before concluding based on Table 7, I would like to highlight the reason why I shaded a couple of cells. I was unable to classify any sectors as “Bad” regarding “From” connectedness because almost all the measures present a similar behavior regardless of the underlying moment or period. Instead of classifying most sectors as “Bad” I chose to label those sectors as “Good” which showed a more desirable performance. I opted for the shading of the cell described by “Bad” “To” skewness connectedness after the crisis for similar reasons. The other notable item is a star next to the telecommunications sector at the “Good” “Net” volatility connectedness during the crisis. I put a star next to this sector as it has a positive “Net” connectedness during the first year of the crisis, which indicates that it is a net transmitter and probably should be avoided, but this is only because a drop in its “From” measure, which is desirable.
Looking at *Table 7* we can see that telecommunications sector shows up in every cell labeled as “Good”, indicating that no matter the period or the measure it should be considered as a portfolio addition if we seek to decrease the effects of connectedness. I would like to emphasize that investing in telecommunications was an optimal choice only regarding sectorial connectedness in the U.S. during my timeframe and these findings don’t automatically mean that one would have achieved the best returns by investing in this sector. As instead, my results solely mean that the effect of diversification could have been mostly increased by some additions from the telecommunications sector, while this doesn’t necessarily imply that this sector will behave in a similar way in the future.

Continuing to interpret the results of *Table 7* with the prior precautions in mind we can see that besides telecommunications utilities appear the most times in the “Good” cells followed by real estate while neither sector was listed as “Bad”. Generally speaking these sectors can also be good choices for investors, although real estate should mostly be considered after the crisis as during the crisis it was only labeled as “Good” (along with telecommunications) in connection with skewness “To” connectedness. Utilities is halfway between the other two sectors regarding my recommendation as it should absolutely be considered during tranquil times while it shows up three times as “Good” during crisis out of the six possible occasions. I must admit that despite my several warnings of connectedness having a time-varying nature the sectors I ultimately recommend are also the ones I recommend in Section 5 based on the static analysis.

While my thesis question was seeking to identify the “Good” sectors, during my analysis I was also able to gather some “Bad” ones which should be treated with caution when allocating capital between assets. The sector appearing the most as “Bad” in *Table 7* is consumer discretionary followed by industrials and health care. The first two ones are not surprising if we take a look at *Figure 2 and Figure 3* as they were the strongest transmitters of spillovers in both static connectedness graphs and neither of them was listed as “Good” in *Table 7*. Health care sector on the other hand was listed twice as “Good” and three times as “Bad” and it seems that this sector should be avoided during crisis due to its ability to transmit volatility, but it might be considered after the crisis is over as it doesn’t spread crash risk during market prosperity.

Out of the eleven GICS sectors two doesn’t appear in *Table 7*, namely financials and information technology. These two belong in the cluster identified in *Figure 2 and Figure 3* and I wouldn’t recommend them from a connectedness perspective, but they don’t have a strongly characteristic nature and wouldn’t label them as must be avoided.
Materials was also part of the cluster observed in Section 5 and it appears twice in Table 7 as “Bad” while it doesn’t appear as “Good”. The reason why I opted to classify it as “Bad” twice is the net transmitter role it assumes throughout my observations regarding skewness connectedness. Since skewness is an indicator of crash risk and materials spread it during and after the crisis alike, I wouldn’t recommend including this sector when diversifying. Energy on the other hand should be considered as an addition to investor portfolios because it appears four times in Table 7 as “Good”, although only during market prosperity. I also recommend it due to the fact that it is never labeled as “Bad”.

The last sector to talk about is consumer staples which has an ambivalent nature as it scores twice as “Good” and once as “Bad” in Table 7. Moreover, it was mentioned three times regarding volatility while it never appears in connection with skewness. When I introduce the GICS sectors in Section 4, I quote the authors of the standard, stating that this sector is “less sensitive to economic cycles” (MSCI and S&P, 2018, p. 1). Based on my findings this is justified and I do recommend investing in the consumer staples sector during crisis as it doesn’t spread volatility connectedness. However, after the crisis it became a net volatility transmitter, hence I don’t recommend it after the market turmoil is over. My hypothesis presented in the end of Section 2 stated that consumer staples is the sector investors can turn to when they seek shelter from correlated losses, which turns out to be true for volatility during a financial crisis.

After presenting the answer to my thesis question I have two final things to do: reflect on the findings of others (collected in Section 2) and appoint the possible future studies of my topic. The paper with the subject closest to mine is the work of Nguyen (2015) who studied the sectorial connectedness of the U.S., found that energy and materials sectors have the strongest impact on other sectors. My findings indicate that the two sectors with such roles in my sample are the consumer discretionary and industrials sectors. Given the application for a different timeframe (he studied the period between 2001 and 2015) and the time-varying nature of connectedness (also emphasized by the author) the difference is not extraordinary or surprising.

Since my paper is a study of the sectorial connectedness of the U.S., a logical next step of this research would be to reveal how other regional sectors are connected e.g. in Europe or in Asia. Furthermore, the analysis of the linkages between different geographies could also be interesting as the shocks quickly spread across the globe during global crises.
7 Robustness check

In this section I present a robustness check for the results by re-estimating the spillover measures using different rolling window sizes and forecast periods. My benchmark is the setup presented in Section 6, i.e. a 252-day window length and a 10-day forecast horizon. Diebold and Yilmaz argue that the results shouldn’t be robust to the forecast horizon, but it can still be interesting to include the parameter in this study (Diebold - Yilmaz, 2014).

I study the volatility and skewness spillover plots for three different window lengths: 126-day, 252-day and 504-day long periods. The 126-day long rolling window is half of a trading year, while the 504-day wide window manifests a two trading year long period. For forecast horizons I focus on 5-day, 10-day and 20-day horizons as the former is one trading week while the latter is a trading month long. As I mentioned above, the window length and forecast horizon in the middle of the respective listings is the benchmark.

Figure 12 contains the results of the robustness check. The chart in the middle is a smaller version of Figure 11 which is presented in Section 6.3 and I compare my results to this diagram. Generally speaking the results appear to be robust for window length and forecast horizon alike as we can observe the same downward trend in all of the cases and the figures present similar amounts of total connectedness. The change of the rolling window size has a more distorting effect as the wider we set the estimation window, the smoother the charts appear. The forecast period doesn’t seem to have as strong effect as the rolling window size but if we choose a narrower period the volatility of the line chart increases.

I believe my settings were optimal as I could identify the main events during my timeframe with the chosen benchmark window length and forecast horizon. Moreover, it is clear that volatility and skewness connectedness present very similar behavior regardless of the model specification. The next section is the last of my paper, where I summarize my findings.
Figure 12. Robustness check: spillover plots for different window lengths (w) and forecast horizons (H). Source: Standard & Poor’s (2018), own construction.
8 Conclusion

In this paper I present the study of the sectorial connectedness of the U.S. from the apex of the financial crisis in 2008 to ten years later (at almost present day) in October 2018. I seek the answer to the following thesis question: Can investors turn to any sector in times of market distress, in order to avoid or decrease correlated losses? To obtain the answer I utilize the framework of Diebold and Yilmaz which they developed in a series of papers as presented in Section 2 and Section 3. This method builds on the variance decompositions of a vector autoregression to capture the spillovers arising between the underlying timeseries. I apply the framework for the eleven S&P 500 sub-indices tracking their respective GICS sector’s.

First, I present a static (full sample) analysis in Section 5 for volatility and skewness connectedness respectively then I compare the findings. The results of the variance decompositions are presented in spillover tables and connectedness graphs. I find that the sectors are strongly connected with spillover indexes of 71.1% and 66% for volatility and skewness respectively, representing significant average connectedness. Six sectors form a cluster with even stronger relations within and they spread considerable amount of shocks to the rest of the sectors. There are three outlier sectors located further away from this cluster: telecommunications, utilities and real estate. Since these three are less affected by the shocks spreading from others, I identify them as the potential answer to my thesis question.

Due to the time-varying nature of connectedness, I continue my study with the dynamic (rolling window) analysis in Section 6, as my main interest is the identification of crisis-resistant sectors. Instead of looking at my timeframe as a whole I apply a rolling window estimation to capture the evolution of the spillover index over time and present the results in spillover plots. I identify the main events which happened during the last ten years that had a significant impact on the U.S. economy and show that these events also change the magnitude of connectedness. I find that these changes can happen rapidly or gradually as well, while the main trend I observe on the spillover plots is a constant decrease of connectedness from crisis levels.

During the dynamic analysis I break down my timeframe to crisis period and after crisis period to seek the answer for my thesis question. I utilize the “To”, “From” and “Net” connectedness measures and find that during the crisis the best choice for investors is the telecommunications sector followed by utilities. During tranquil times real estate should also be considered. Moreover, I advise that the consumer discretionary, industrials and health care sectors should be avoided due to their spillover spreading intensity.
My hypothesis was that the consumer staples sector could be a potential choice for investors as by its nature people buy the sectors’ goods and services even during economic downturns. Comparing my findings to my hypothesis it is clear that during the crisis the consumer staples sector was a good choice, although the telecommunications and utilities were even better. After the crisis the consumer staples sector became a net shock transmitter, so I wouldn’t recommend it during market prosperity from a diversification perspective.

It is important to highlight that my findings can’t be generalized to any given time period or geographic location as my results are strictly applicable to the eleven GICS sectors of the U.S. as represented by the S&P 500 sub-indices between late 2008 and late 2018. This doesn’t mean that the lessons from my findings can’t be applied for upcoming time periods, but investors ought to be careful when doing so and it should be mostly applied for the U.S. sectors. An appealing aspect of the framework I used is that the spillover measures can be calculated on a daily basis and the current state of the economy can be seen from the results.

I present a robustness check in Section 7 and find that my results are mostly robust to the rolling window size and forecast horizon used. The flexibility of the framework makes room for plenty of further studies and since my paper’s scope is the sectorial connectedness of the U.S. economy, I find it logical to apply the methodology for the sectors in Europe or in Asia. One can even analyze the connectedness between different geographical sectors to gain a better understanding of the global system.
9 References


https://www.federalreserve.gov/newsevents/pressreleases/monetary20120913a.htm

(Latest download: 11.02.2018.)

(Latest download: 11.02.2018.)


