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Interconnectedness in the Global Financial Market

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INTERCONNECTEDNESS IN THE GLOBAL FINANCIAL MARKET

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ABSTRACT

The global financial system is highly complex, with cross-border interconnections and interdependencies. In this highly interconnected environment, local financial shocks and events can be easily amplified and turned into global events. This paper analyzes the dependencies among nearly 4,000 stocks from 15 countries. The returns are normalized by the estimated volatility using a GARCH model and a robust regression process estimates pairwise statistical relationships between stocks from different markets. The estimation results are used as a measure of statistical interconnectedness, and to derive network representations, both by country and by sector. The results show that countries like the United States and Germany are in the core of the global stock market. The energy, materials, and financial sectors play an important role in connecting markets, and this role has increased over time for the energy and materials sectors. Our results confirm the role of global sectoral factors in stock market dependence. Moreover, our results show that the dependencies are rather volatile and that heterogeneity among stocks is a non-negligible aspect of this volatility.

Keywords: Asset markets, Comovement, Financial networks, Interconnectedness

JEL classification: G15, G11, C58

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1. Introduction

The last two decades saw an increase in political and economic openness, mostly accompanied by an increase in financial integration. Analyzing and managing macroeconomic financial risks have become increasingly important as global markets have become increasingly connected. The sheer size of these markets and the number of products available require models that can provide a hierarchical or topological simplification of this system.

This paper proposes a mapping of interconnectedness in the global stock market. We use a measure of statistical interconnectedness, based on econometric analysis of comovement patterns (see also Billio et al., 2012; Diebold and Yilmaz, 2014). The comovement of stocks can be summarized by a country- and sector-wise grouping of stocks, and this approximation provides significant information for strategic portfolio decisions and risk management. The paper also presents a framework to monitor the changes in interconnectedness within and between markets, and to identify transmission channels and vulnerabilities.

This paper contributes to efforts to redefine our understanding and knowledge of interconnections in the financial system, where they stem from, and how they can be evaluated and monitored. Interconnections between financial markets play a dual role. On the one hand, they can absorb shocks and lead to greater robustness. They can also propagate shocks and create greater fragility. Supervisors have traditionally focused on interconnectedness as measured through direct exposures, which is constrained by the availability of reliable granular data. A more intuitive way is to investigate the empirical correlation of assets and the resulting implied network structure. This network helps describe the financial system, its systemic structure, and possible contagious effects.

This paper builds on existing literature in several ways. First, it is related to the macroeconomics literature that discusses the effects of market openness on business cycle synchronization (see, e.g., Brooks and Del Negro, 2004; Buch et al., 2005). These effects depend on similarities in industry structure, although this is often overshadowed by country-specific effects (Imbs, 2004). There are also studies on the transmission of shocks in a crisis situation. In such a situation, the determinants for spillovers can change relative to what is observed in normal times. See, for example, Fratzscher (2012) for an analysis of the 2008 crisis and Kaminsky and Reinhart (2000) for an analysis of crisises in the 1990s.

The financial and economic crisis of the 1990s have shown that contagion can often not be explained by dependencies in the real part of the economy. Distress of financial activity can by itself create contagion which consequences then go beyond the financial sphere. Numerous studies have therefore looked at dependencies of financial markets, especially if they amplify shocks in times of crisis. The transmission mechanisms in financial markets have been claimed to be relatively stable over time (Rigobon, 2003; Bracker et al., 1999), but this claim is debated (Corsetti et al., 2005). Studies that examine determinants of comovement find that structural similarity of countries explains only partially the level of comovement of their financial markets. This resulted in a debate about the influence of global sectoral factors (Dutt and Mihov, 2013; Bekaert et al., 2009, 2011). Previous results hint at an increase in the importance of these factors. Forbes and Chinn (2004) finds that cross-country factors and global sectoral

factors both are important determinants of stock returns. They also note that changes in global linkages over time might make it difficult to disentangle different influences on asset market comovement. The results from our study confirm the doubts about the stability of dependencies of financial markets and show a picture of rather volatile relationships. We do find sectoral effects and observe that these are in fact not stable (eventhough we use a different methodology) confirming the problems described by Forbes and Chinn (2004).

For the following, it is important to note that the analysis of comovement across markets differs from the well understood properties of comovement within markets (see, e.g., Barberis et al., 2005; Green and Hwang, 2009). In the latter, one describes the behavior of individual stocks. This is not the case in the analysis of comovement across markets. Most approaches to studying comovement on the global level have focused on the analysis of stock market indices (see, e.g., Baur and Jung, 2006) or other smaller samples of sectoral indices. A wide range of methods has been applied, among these unit root and cointegration tests, vector autoregression models, correlation-based tests (Forbes and Rigobon, 2002; Fry et al., 2010), causality tests (Billio et al., 2012), as well as different GARCH-based models (Engle, 2002). Most of these models deal well with the statistical features of asset returns, but their application to large data sets like ours is very limited. In this respect our paper is also a methodological contribution since it describes a method to analyze dependencies in a setting that can in principle be applied to systems with any size without the need of an apriori dimensional reduction. This is important since we also find that the dependencies of stocks between markets are heterogenous and that the analysis of index comovement might therefore tend to show us stable relationships while in fact the factors for dependence are moving.

This paper is also related to the literature of network based analysis of financial markets. Several studies exist that have mainly focused on dependencies and possible cascading effects in the financial sector, especially interbank markets (see Battiston et al., 2016; Summer, 2013; Gai et al., 2011; Levy-Carciente et al., 2015; Glasserman and Young, 2015). But even the comovement of stocks has already been analyzed as a network phenomenon. In these approaches, the similarity of stock performance is interpreted as information about linkages between stocks (Song et al., 2011; Gopikrishnan et al., 2001; Kenett et al., 2012). These approaches deal well with the complexity of financial markets and it is possible to analyze problems where the dimensionality is high. A weakness of some of these studies is that they are of a more exploratory nature and that statistical significance is often difficult to assess. We contribute to this literature by developing the methodology of stock market networks to a point where each of the connections in this network can be quantified by strength and significance, and could thus serve as a foundation for applications in portfolio and risk management.

This paper investigates a set of nearly 4,000 stocks from 15 countries. We analyze the dependencies of these stocks by assessing significant dependencies on the stock level, then aggregate hierarchically by sectoral and regional dependencies. Findings are first analyzed for the entire sample of 2006-13, then examined for dependencies in 13 overlapping time windows.

The remainder of the paper is organized as follows: Sections 2 and 3 describe the stock market dataset, the methodology to measure interconnectedness in terms of dependencies between stocks, and how this information can be used to derive networks.

Static and dynamic results are presented in Sections 4 and 5, respectively. In Section 6 we study the structure of the derived networks, and investigate the presence of geographic or sectoral factors.

2. Data

The data used in this study consist of the daily closing prices of stocks listed on exchanges in Australia, Brazil, China, Spain, France, the United Kingdom, Hong Kong, India, Japan, South Korea, the Netherlands, Singapore, United States, Canada, and Germany. We chose stocks that were components of the individual country benchmark index, and were continuously traded with sufficient volume throughout the sample period.[1] Excluded were stocks with price behavior or market capitalization similar to penny stocks. Also excluded were stocks that were exempt from trading or traded with negligible volumes for more than 10 days, and stocks with negligible trading volume for more than 8 percent of the total trading days. Some countries had a large number of stocks that met our criteria. For this reason, we selected the 500 stocks with the highest market capitalization from exchanges in India, Japan, China, and Korea. We chose U.S. stocks that are in the S&P 500 index. For the UK, we selected stocks in the FTSE 350. The Global Industry Classification Standard (GICS) sector designation for each stock was used, when available. When GICS was not available, we used the TRBC classification from Thomson Reuters. The number of stocks by country and sector is summarized in Table 1.

Country	Energy	Material.	Indus.	Cons.D.	Cons.S.	Health	Finan.	IT	Telec.	Util.
AUS	12	21	25	17	7	8	29	5	2	3
BRA	2	11	10	13	5	1	5	3	2	14
CHN	10	95	134	90	36	42	36	40	0	17
ESP	1	9	15	6	4	4	11	3	1	6
FRA	6	15	47	53	16	18	42	47	4	9
GBR	17	19	69	54	21	10	68	26	3	8
HKG	1	2	16	8	2	1	37	3	2	6
IND	7	125	105	116	37	28	21	51	4	6
JPN	3	35	125	115	20	17	24	157	3	1
KOR	2	91	101	102	27	35	11	125	4	2
NLD	2	3	17	8	9	0	12	9	1	0
SGP	0	0	11	3	1	1	18	2	2	1
USA	38	26	65	73	43	43	81	55	6	31
CAN	50	43	19	13	11	3	40	6	6	8
GER	6	11	50	29	8	22	15	33	5	4

Table 1: Number of stocks by sector and country. Sectors are: Energy, Materials, Industrials (Indus.), Consumer Discretionary (Cons. D.), Consumer Staples (Cons. S.), Health Care (Health), Financials, Information Technology (IT), Telecommunication Services (Telec.), and Utilities (Util.). Countries are: Austria (AUS), Brazil (BRA), China (CHN), Spain (ESP), France (FRA), United Kingdom (GBR), Hong Kong (HKG), India (IND), Japan (JPN), South Korea (KOR), Holland (NLD), Singapore (SGP), United States (USA), Canada (CAN), and Germany (GER). Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

Our observation period starts on 1 July 2006 and ends on 30 June 2013. The eight

[1] Data were obtained from Standard & Poor's Compustat and Thomson Reuters Corp.

years of data results in $T = 1329$ trading days and $N = 3828$ stocks. For stocks in all countries, we use data from trading days when the stock markets in London and New York are both open. Because the stocks are traded in different time zones there are limitations in the synchronization of the returns. The international date line in the Pacific necessitates that Asian countries finish trading first in the day, while the Americas finish last. The correlation of daily returns will naturally under-represent the amount of comovement between the most distant countries because trading takes place without an overlap in time. To address this issue, we use two approaches: To analyze the long-run effects, we calculated weekly returns for all time series, which leaves us with $T' = 365$ observations. To analyze short-run effects, we calculate a correction factor to use with the daily data; details are explained in Section 3.2.

The remainder of this paper uses the returns time series derived from the log price changes of the stocks, $r_t = log(p_t) - log(p_{t-1})$. The number of stocks per country varies from 39 for Singapore to 500 for the larger countries (see summary statistics presented in Table 2. The markets in China, Korea, and India have imposed limits on the maximum daily price changes. In Korea, for example, the limit for the daily price movement was 15 percent. The distributions of the returns time series for these countries are truncated. This does not mean that the volatility is necessarily lower (see sample variances in the table). All time series of asset returns are heavy-tailed, as the values for the kurtosis indicated. The tail exponent was calculated with the Hill estimator, and the values are mostly slightly greater than 3.

To uncover dependencies between stocks in different countries by sector, it is necessary to test if stocks within a specific sector are more correlated than stocks from random sectors. The far right columns in Table 2 show the results from calculating the average of all within-sector correlations and the average of all between-sector correlations. The average of the first is significantly higher for all countries except for China. The dispersion and level vary by country. In Japan, only two sectors show a higher than average between-sector correlation than the within-correlation (see also Figure A.1 in the appendix).

3. Estimating Inter-market and Intra-market Interconnectedness

3.1. GARCH filtering process

Although an analysis of the correlation of the returns can be informative, changes in volatility in all time series will govern the results. The long memory in volatility also complicates the assessment of significance bounds. Since the volatility in stock markets around the world is synchronized, this prevents inferring information about which stocks show similarities in return on a more general level. There are different approaches to filter returns time series, such as treating the returns within a multivariate GARCH model. This model simultaneously estimates the parameters for conditional variances and the mutual influences of the returns time series.

However, models of this kind are difficult to use with a large number of stocks (see also Engle et al., 2008). A robust and faster filtering method for large datasets is the conditional variance from a univariate GARCH model.

Country	N stocks	$var(r)$	Kurtosis	Tail exponent	Avg. correlation within sector	Avg. correlation all stocks
AUS	129	0.00064	18.7	3.47	0.35	0.18
BRA	66	0.00063	14.4	3.77	0.42	0.22
CHN	500	0.00105	5.0	–	0.27	0.25
ESP	60	0.00057	12.1	3.61	0.38	0.23
FRA	257	0.00059	26.4	3.32	0.22	0.14
GBR	295	0.00064	25.6	3.40	0.22	0.16
HKG	78	0.00082	18.0	3.35	0.44	0.20
IND	500	0.00114	8.5	–	0.31	0.25
JPN	500	0.00120	15.1	2.99	0.37	0.31
KOR	500	0.00124	8.0	–	0.36	0.27
NLD	61	0.00059	25.7	3.38	0.40	0.25
SGP	39	0.00052	38.1	3.37	0.48	0.29
USA	461	0.00065	24.2	3.25	0.24	0.21
CAN	199	0.00070	21.1	3.26	0.23	0.15
GER	183	0.00074	17.1	3.44	0.25	0.15

Table 2: Statistics for the Returns Time Series. We calculated the variance, kurtosis and the tail exponent from all returns in each country. In three of the markets, the maximum daily price change is constrained (caps), which permits the analysis of the tail exponent. The far right columns show the average correlation of stocks within a given sector is always larger than the average correlation of all stocks within a given country. Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

That means that we assume that the returns follow a random process with $\varepsilon_t = v_t \sqrt{h_t}$ where v_t is white noise and

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}. \tag{1}$$

We will make use of the conditional variance h_t to calculate filtered returns[2] such that

$$r_t^f(i) = \frac{r_t(i)}{\sqrt{h_t(i)}}, \tag{2}$$

for all stocks i. We obtain time series with unit volatility.

The parameter h_t is a useful filtration for the given returns time series. Except for a few exceptions for stocks from developing markets, this model fits well and yields the expected coefficients for α and β close to 0.1 and 0.9. Apart from negligible exceptions for some stocks from developing countries, $p, q = 1$ is sufficient to describe the variance process.[3] Figure A.2 (in the appendix) shows the averages of the autocorrelation functions for the raw and filtered returns that result from this procedure.

[2]It should be noted that also the covariances of h_t can be used to analyze interconnections, a short comparison of these two measures can be found in Appendix C.

[3]We checked the robustness of the results by omitting the 83 stocks where the fit of the GARCH model was least satisfactory. We could not find any meaningful effect from this.

3.2. Estimation and correction for non-synchronous trading

By "de-garching" the returns, a time series is obtained that can be treated in an almost standard regression framework. Running a pairwise regression of all the filtered returns generates a measure for the comovement.[4] The only econometric issue of these time series is that the residuals are not normally distributed, which we account for by using a robust regression (Lange et al., 1989) with t-distributed errors. (See also Figure A.3 in the appendix for details on the distributions of returns and residuals).

To measure interconnectedness, we estimate pairwise the dependencies for all pairs of stocks (i, j)

$$r_t^f(i) = \beta_{0,ij} + \beta_{1,ij} r_t^f(j). \tag{3}$$

Next, we focus on stock-to-stock relationships that are significant with respect to a certain threshold. We will use the p-values that can be obtained from this estimation, which we store in a matrix p_{ij}. The rows and columns are ordered by countries.[5]

To test the robustness of these results, which depend on the univariate de-garching, we compare our results with those of a multivariate GARCH model. These models can only be estimated with a limited number of time series. We use the Dynamic Conditional Correlation (DCC) model (Engle, 2002) with pairs of stocks from the sample and compare the correlation implied by the DCC model with the correlation of our filtered returns. The results are indistinguishable for long windows. For windows of 190 days, the results on the stock level differ, but the differences are marginal and unsystematic. (see Appendix B).

A challenging issue is the time difference in trading hours across markets. It leads to problems in determining the true dependencies between stocks from different markets. For stocks from Europe, this is a minor issue because UK trading time differs from other European countries by only one hour. The U.S. market opens before EU markets close, for a difference of six hours. Calculating the dependencies between stocks traded in the Americas and Asia is most problematic. The dependencies are biased downwards because the time series are asynchronous (see also Martens and Poon, 2001). In general, this can be dealt with in two ways: by using tick data and calculation of synchronous pseudo closing prices, or by time aggregation. The first method would require large amounts of data and even then it would be difficult to find a specific time each day when price quotes for all stocks would be available. The second method is easier but limits the time resolution for our analysis.

By aggregating several days of returns, the timing mismatch becomes less important. But daily data are essential in this analysis because financial markets react quickly to new information. To work with daily data, a correction must be applied for the bias described above.

[4] It would, of course, be possible to proceed from here by calculating correlation coefficients. However, due to the non-normality of the returns the standard approach for calculating significance levels would not apply. Generalized approaches that provide estimated of significance levels of correlation coefficients exist, but our calculations suggest that for large amounts of data it is easier to obtain significance levels from a robust regression.

[5] For the time horizons in this study, we do not observe significantly negative correlation.

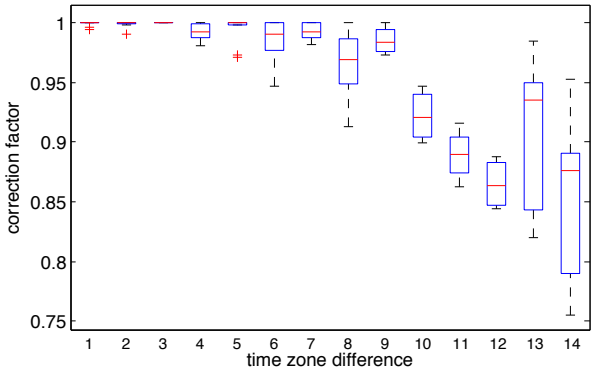


Figure 1: Range of Correction Factors by Time Zone Differences. The plot shows the difference between the average estimated dependency of stocks on the daily level versus the weekly level (see eq. 3.2). Significant differences between the estimated dependencies arise when the markets are more than three time zones apart. Less-developed markets with below average comovement show a lower difference than developed markets (this explain most of the dispersion for the two far right box-plots). Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

The estimated daily dependencies from stocks traded in different stock exchanges and time zones are slightly biased but still informative. A correction factor is calculated on a country-to-country basis by comparing the estimation results from the daily data with the estimation from the weekly data for the same time period. This procedure is related to the works by Christensen et al. (2010) and Hayashi and Yoshida (2008).

We calculate a correction factor for the p-values in the following way: let pr^w and pr^d be $N \times N$ matrices where the elements are the average p-values on a country-to-country level (the matrix contains blocks with identical values resembling all pairs of countries). After adding 1 to each element of these matrices, we can calculate the element-wise (notation: ./) ratio of the p-values of the weekly and daily estimates.

$$pr_{ij} = (1 + p^w_{ij}) \,./\, (1 + p^d_{ij}). \tag{4}$$

Then, the correction factor pc can be calculated as

$$pc_{ij} = min(\, 1 \,,\; pr_{ij} - \langle diag^*(pr) \rangle), \tag{5}$$

where the second term corrects for differences in the p-values that are not due to non-synchronous trading times (we denote by $diag^*$ the diagonal blocks of pr capturing the dependencies between stocks within one country). The *max* and *min* ensure that all p-values stay within the $[0, 1]$ band. The corrected p-values can then be obtained as

$$p_{ij} = max\Big(\, 0 \,,\; \big((1 + p^d_{ij}) \circ pc_{ij}\big) - 1\Big). \tag{6}$$

To summarize, this procedure assumes that overall estimates from the daily and the weekly data are similar and differences are likely to be a result of non-synchronous

data. The ratio of the slightly transformed p-values is used to correct for this issue so interdependencies that were otherwise discarded as, say just below the 10 percent confidence bound, will now be accounted for as significant if the correction factor for this country pair is sufficiently smaller than 1.

The calculated correction factors are presented in Figure 1. As expected, the correction increases with geographical distance, even though this does not fully explain the issue. The correction remains relatively small for distant, less-developed markets where the comovement is low anyway (which explains the wide range of the far right boxplots).

3.3. Visualizing and quantifying interconnectedness

In a financial network, entities such as banks, financial institutions, central counterparties, and traders are considered nodes. Their relationships in interbank lending, contractual obligations, and counterparty exposures define the links that connect them. Stocks and their relationships can also be expressed as a network. Each stock is a node and its estimated interdependencies show whether, and how strongly, the nodes are connected to each other. This information is stored by using adjacency matrices, where the entries in row i and column j indicate the strength of the connection between the respective nodes (see Figure 2).

Because the p-values contain this required information and their distributional properties allow a useful weighting, it is relatively easy to obtain adjacency matrices. The matrices of p-values are converted to adjacency matrices A by removing all entries where the significance level for the stock-to-stock dependence is below a certain threshold γ. In the following, we use $\gamma > 0.1$ if not stated otherwise. The estimated significance level can be used as a measure of connection strength by defining

$$A_{ij} \propto (\gamma - p_{ij}). \tag{7}$$

This adjacency matrix has a weighted positive entry if stocks i and j are significantly linked, measured by the estimated conditional correlation.

To uncover the dependencies between the markets on a sector level, the stock level dependencies are used to describe the resulting network on a sector to sector basis. The averages of the p-values of the relationships of the stocks in a specific sector in one country are used with stocks in a specific sector in another country to map the sector-by sector dependencies.[6] The translation into this second adjacency matrix is done in the same way but the dimension is reduced to 150×150 (15 countries, 10 sectors). Sectors in countries that consist of fewer than three stocks are excluded from further analysis.

[6]The averages of the p-values are not p-values anymore. However, in this case it makes sense to use these averages because of low dispersion within the groups of stocks. Also note that in Table 3 median values are used for the comparison because the distribution of p-values for all stocks within one country is slightly skewed. On the sector level, however, the difference between the mean and the median is small, the latter value is mostly slightly higher and would tendencially lead to more significant links.

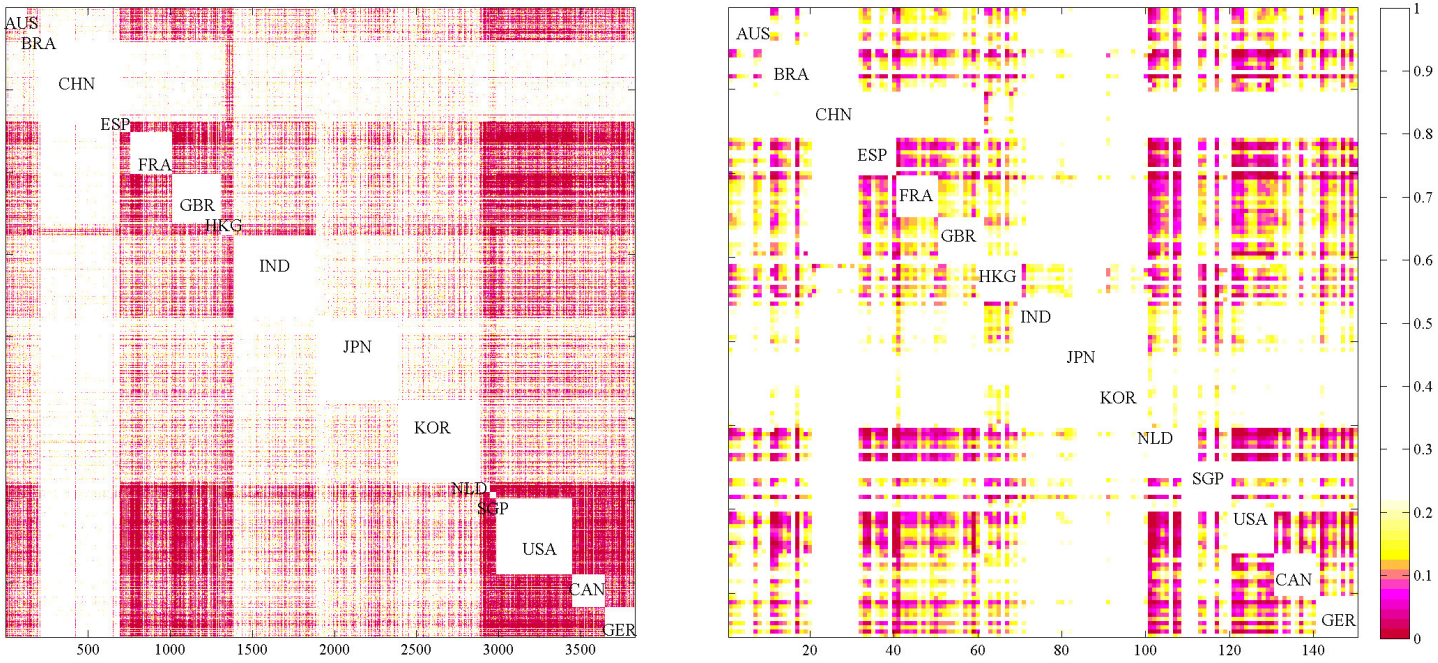


Figure 2: p-Values for the Stock-to-Stock Dependencies (left) and Sector Averages (right). The stocks are arranged by countries and the abbreviated country names are plotted along the main diagonal. Entries for dependencies within countries have been removed. The values are color-coded with dependencies above the 90 percent confidence interval appearing pink to red. In the right panel, the values are averaged on a sector to sector basis, so that for each country we show the average dependency to the 10 sectors in the 14 other countries. This reduces the matrix to 150×150 entries. Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

Finding useful visual representations of adjacency matrices is a complex process and the equivalent of finding a good dimensional reduction of a N-dimensional system, where N is the number of nodes. This process is also related to the problem of community detection in graphs, which is a high-dimensional clustering problem.[7] We graph our networks by applying the widely used algorithm developed by Hu (2005). This algorithm arranges nodes in a two-dimensional space in such a way that the total edge length of the graph is minimized, which shows the most pronounced communities of nodes within a graph. This specific algorithm uses the physics of repulsion to generate a visualization.[8]

Once a visualization of the network is computed, it is a starting point to identify the general structure of the network and groups of stocks from specific markets or sectors that comove most. We can compare the number of links between stocks (nodes) in the same group with the number of links between them as if these were random. This network feature is called modularity, see e.g. Newman (2006). Denote by c the groups of nodes, then the number of links between these groups is given by

$$\sum_{\text{edges}}(c_i, c_j) = \frac{1}{2}\sum_{ij} A_{ij}\delta(c_i, c_j), \tag{8}$$

where δ in Kronecker's delta and A is the adjacency matrix. The expected number of links can be derived from looking at the node and the fraction of links to each node in the other group. If node i has degree k_i and the total number of links is $2m$ the probability that it has a link to j is $k_j/2m$. Hence, the expected number of links between nodes in the same group is

$$\frac{1}{2}\sum_{ij}\frac{k_i k_j}{2m}\delta(c_i, c_j). \tag{9}$$

Taking the difference of these two expressions and normalizing by the number of edges yields the modularity Q of a network

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta(c_i, c_j), \tag{10}$$

which describes in how far nodes of the same group are connected with each other. In order to compare different networks, we also calculate an associativity coefficient which is given by $AC = Q/Q_{max}$.

4. Static analysis of global interconnectedness

The results obtained from analyzing the weekly returns are depicted in Figure 3. Stocks from Western markets form a hairball in the middle of the network, showing

[7] See also the book by Newman (2010) for an in-depth introduction to network science.

[8] We have verified that the qualitative results of the obtained visualizations do not depend on the choice of this specific algorithm.

they are highly interconnected. Within this hairball, the mixing is strongest within the European markets, while otherwise regional structures remain visible. The markets of China, Japan, and India are only loosely connected to the central component of the network. These results can also be compared with those obtained for the stock level interactions (see Figure D.1 in the appendix), to verify that the aggregation procedure does not influence these findings.

Even in the densely connected middle, sectors from the same market are mostly grouped close to each other, which is a sign of remaining regional segmentation. It is more instructive to observe nodes that are separated from others with the same color, such as the German materials sector or the British and French energy sectors. Their surrounding nodes indicate sectoral effects are also at work here, and the underlying stocks from the materials or energy sectors are as well connected to similar stocks in other countries as to stocks in their home markets.

The overall connectivity in this network is shown by countries and by sectors. This can be achieved by summarizing the number of links between them or evaluating how often the average p-value for a sector-to-sector pair is higher than 0.1. This can be aggregated by country and by sector as shown in Figure 4. The left panel confirms the visual impression of a very connected U.S. stock market. Most sectors in European markets comove in a significant manner. The right panel shows clear differences on the sector level. Stocks from the financial, industrials, materials, and energy sectors show more interconnections than stocks from other sectors, and this is consistent for all countries.

An analysis of individual stocks differs from an analysis of stock indices. We illustrate this by applying the same estimation methodology to stock market indices for the 15 countries. The weekly index returns are de-garched and p-values of the pair-wise estimated dependencies are presented in Table 3. The results can be compared with the median of the p-values for the stock-wise analysis and the median when we hierarchically average within sectors and then overall sectors within a country. While the indices are all highly dependent, the stock level shows lower median p-values, indicating pronounced heterogeneity in stock-to-stock dependencies, which are in no way captured by a market index analysis.

5. Dynamic Analysis of Global Interconnectedness

During the eight years covered by the dataset, global economic and political events occurred that are likely to lead to significant fluctuations in comovement across markets. The 2007-09 financial crisis, the euro crisis, and Japan's 2011 tsunami are a few examples. A dynamic analysis is also necessary to show changes in global financial integration. The data resolution can characterize stock market dependencies in the order of months. A perform a rolling window approach that uses 190 days of data in 13 time steps with a 95-day overlap. We apply the same methodology as before now to daily data with a timing corrections for the p-values as described in Section 3.2. Additionally we will look at the development of some measures for the network structure.

Figures 5 (a–d) display four of the 13 resulting networks. Interestingly these representations show pronounced deviations from the long-run representation presented in figure 3. The number of clusters, its relative position, and also the number of sectors

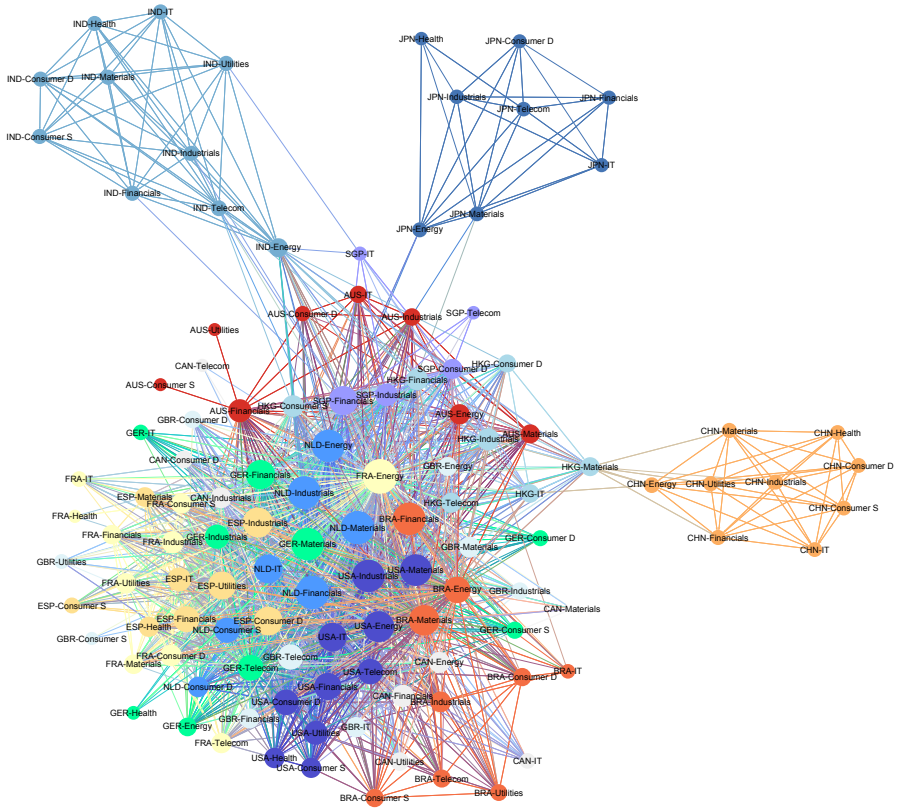


Figure 3: Network Representation Based on Sector-wise Averaged Estimated Dependencies from Weekly Data. Nodes (sectors) from the same country have the same color. The node size is proportional to the degree of the number of significant links/dependencies. The sector network displays features similar to the stock network in Figure 2. Most sectors form a central cluster around the U.S. market. India, China, and Japan form loosely connected cliques. Sectors with few or no links are omitted (South Korea is not present). The layout was performed in Gephi using the Yifan Hu algorithm. Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

Country		AUS	BRA	CHN	ESP	FRA	GBR	HKG	IND	JPN	KOR	NLD	SGP	USA	CAN	GER
	index	0.0000	0.0000	0.0036	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AUS	sector	0.0823	0.2202	0.6162	0.1357	0.1220	0.1869	0.1285	0.3215	0.3196	0.3571	–	–	0.1190	0.2547	0.1285
	stock	0.0303	0.1856	0.5673	0.0858	0.0993	0.1253	0.0718	0.3125	0.2848	0.3297	0.0481	0.0560	0.0861	0.1615	0.1058
	index	0.0000	0.0000	0.0008	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BRA	sector	0.2038	0.0095	0.6370	0.0530	0.0852	0.1048	0.0748	0.2759	0.3910	0.2513	0.0616	–	0.0323	0.1516	0.0746
	stock	0.1774	0.0073	0.6129	0.0524	0.0903	0.0977	0.0635	0.2890	0.3657	0.2749	0.0342	0.0595	0.0284	0.1043	0.0812
	index	0.0018	0.0001	0.0000	0.0390	0.0070	0.0040	0.0000	0.0020	0.0097	0.0006	0.0111	0.0002	0.0118	0.0021	0.0026
CHN	sector	0.5655	0.5435	0.0000	0.7299	0.6068	0.6202	0.1665	0.5258	0.6351	0.4136	0.5710	–	0.6674	0.7197	0.6041
	stock	0.5333	0.5367	0.0000	0.7302	0.6150	0.6415	0.1964	0.5441	0.6586	0.4689	0.6305	0.3510	0.6723	0.6686	0.6219
	index	0.0000	0.0000	0.0826	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ESP	sector	0.1344	0.0570	0.7534	0.0011	0.0163	0.0258	0.1169	0.2566	0.3311	0.2989	0.0097	–	0.0044	0.0968	0.0323
	stock	0.0870	0.0531	0.7557	0.0006	0.0205	0.0243	0.0825	0.2710	0.3163	0.2861	0.0031	0.0554	0.0050	0.0650	0.0275
	index	0.0000	0.0000	0.0094	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
FRA	sector	0.1505	0.1067	0.6852	0.0236	0.0361	0.0697	0.1252	0.2882	0.3002	0.3109	0.0186	–	0.0221	0.1218	0.0552
	stock	0.1173	0.1123	0.6817	0.0287	0.0367	0.0678	0.0983	0.3047	0.2819	0.3147	0.0130	0.0712	0.0335	0.1110	0.0546
	index	0.0000	0.0000	0.0101	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GBR	sector	0.2002	0.1315	0.6983	0.0345	0.0542	0.0526	0.1603	0.3707	0.3379	0.3612	0.0359	–	0.0249	0.1469	0.0658
	stock	0.1310	0.1169	0.6883	0.0304	0.0611	0.0356	0.1199	0.3596	0.3342	0.3490	0.0120	0.0876	0.0189	0.1113	0.0583
	index	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HKG	sector	0.1316	0.0844	0.2054	0.0931	0.0936	0.1179	0.0062	0.1318	0.2378	0.1527	–	–	0.0729	0.2223	0.0956
	stock	0.0648	0.0674	0.2215	0.0718	0.0752	0.1001	0.0007	0.1153	0.2022	0.1495	0.0348	0.0046	0.0632	0.1335	0.0741
	index	0.0000	0.0000	0.0063	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
IND	sector	0.2853	0.2375	0.6172	0.2144	0.2346	0.3141	0.1295	0.0018	0.5052	0.3788	0.1466	–	0.2573	0.3515	0.2297
	stock	0.2767	0.2573	0.6367	0.2370	0.2510	0.3057	0.1181	0.0025	0.5175	0.3890	0.1772	0.0986	0.2663	0.3224	0.2395
	index	0.0000	0.0000	0.0448	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
JPN	sector	0.3659	0.3911	0.7258	0.3404	0.2903	0.3597	0.2810	0.5842	0.0431	0.4657	0.1923	–	0.3135	0.4064	0.3113
	stock	0.3023	0.3790	0.7411	0.3186	0.2822	0.3542	0.2487	0.5825	0.0401	0.4655	0.2137	0.1875	0.3062	0.3477	0.2933
	index	0.0000	0.0000	0.0036	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
KOR	sector	0.3535	0.2897	0.5265	0.2886	0.2962	0.3630	0.1710	0.4299	0.4096	0.1015	0.2323	–	0.3335	0.4360	0.3005
	stock	0.3241	0.3063	0.5342	0.2932	0.2947	0.3392	0.1633	0.4333	0.4096	0.1093	0.2310	0.1574	0.3310	0.3962	0.3028
	index	0.0000	0.0000	0.0211	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
NLD	sector	–	0.0835	0.6929	0.0158	0.0205	0.0318	–	0.2056	0.2055	0.2464	0.0156	–	0.0137	0.0994	0.0309
	stock	0.0625	0.0497	0.7091	0.0049	0.0135	0.0146	0.0531	0.2420	0.2191	0.2671	0.0009	0.0248	0.0045	0.0413	0.0157
	index	0.0000	0.0000	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SGP	sector	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	stock	0.0609	0.0703	0.4812	0.0586	0.0642	0.0842	0.0067	0.1251	0.1564	0.1603	0.0230	0.0007	0.0585	0.1251	0.0582
	index	0.0000	0.0000	0.0297	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
USA	sector	0.1435	0.0329	0.7274	0.0048	0.0158	0.0207	0.0993	0.3015	0.3114	0.3079	0.0099	–	0.0003	0.0559	0.0151
	stock	0.0803	0.0278	0.7221	0.0044	0.0225	0.0145	0.0683	0.3079	0.2900	0.3152	0.0023	0.0482	0.0001	0.0284	0.0168
	index	0.0000	0.0000	0.0056	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
CAN	sector	0.2674	0.1622	0.7475	0.1035	0.1137	0.1428	0.2351	0.4408	0.3898	0.4429	0.0982	–	0.0653	0.1161	0.1157
	stock	0.1646	0.1177	0.7112	0.0755	0.1044	0.1094	0.1468	0.3770	0.3431	0.3966	0.0389	0.1210	0.0368	0.0487	0.0893
	index	0.0000	0.0000	0.0066	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GER	sector	0.1544	0.0955	0.7109	0.0376	0.0618	0.0675	0.1276	0.2914	0.3006	0.3407	0.0301	–	0.0238	0.1304	0.0416
	stock	0.1291	0.1105	0.7107	0.0382	0.0564	0.0667	0.1052	0.3056	0.2916	0.3330	0.0151	0.0657	0.0266	0.1010	0.0423

Table 3: p-values for stock *index* Correlations versus Median of p-Values from Stock Correlations. *Sector* denominate values are obtained by first averaging over stocks within one sector, while *stock* denotes the median p-value of the correlation of all stocks between two countries. For Singapore and the Netherlands, several of the sectors are not populated and therefore do not have sector results. Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

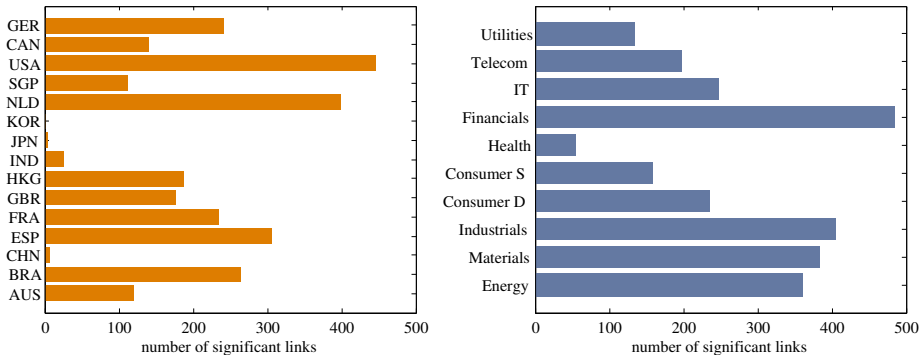


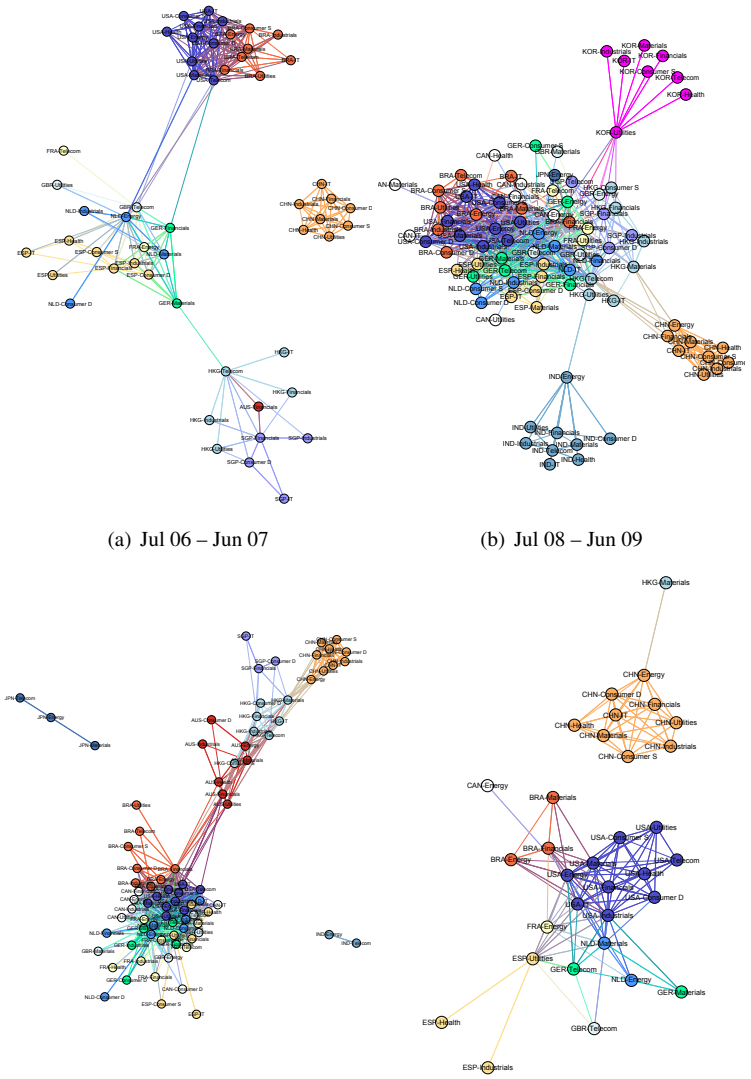
Figure 4: Number of Significant Links by Country (left) and by Sector (right). We count the number of significant links between sectors and aggregate by country and by sector based on the estimation of the weekly data. The United States and European countries (which are slightly favored by their large number) are the most connected ones. The four Asian countries (excluding Singapore) are least connected. When aggregated by sectors, stocks from the financial sector, followed by the materials sector and energy sector, are the most connected stocks. Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

(nodes) vary even in tranquil times. The network in the top left panel of Figure 5 is structurally different from the others. American and European stocks form individual groups within the network, although there are multiple links between them. Some Asian markets are loosely connected to the European market. Chinese stocks show strong internal comovement but are not significantly linked to other markets.

The network changes completely at the end of 2008 with the growing financial crisis. Stocks from all developed markets form one connected component. Some grouping into American, European, and Asian stocks remains, but the borders blur. The markets of South Korea, China, and India appear as weakly connected satellites. In fact, this network looks in many parts similar to the one presented in figure 3, but the connections are more dense and incorporate more sectors and countries. One can argue that this time period shows strong signs of contagion, since the level of dependencies has clearly shifted upwards, compared to both the previous and the long-run state. One could further refer to this period as that of global contagion, since the stock market network is a bloomed up version of its long-run comparison.

The bottom left panel of Figure 5 shows that in 2011 there is stronger comovement within Asia, these markets are almost separated from the European-American component. Some remaining links now run between American and Asian markets, while the comovement between European markets becomes more heterogeneous. Its nodes have drifted apart. This may reflect the Euro crisis, which affected some but not all European countries. This crisis induced shifts in the structure of the network, but does not (at least at this time-scale) lead to clear signs of contagion.

By 2012, the network shows comovement almost back to the pre-2008 levels. Some stock markets are very much connected to U.S. stocks, but many sectors are no longer



(a) Jul 06 – Jun 07

(b) Jul 08 – Jun 09

(c) Jan 11 – Dec 11

(d) Jul 12 – Jun 13

Figure 5: Dynamics of Sector Dependency Networks. We show four networks that are representative of the dynamics in 13 time windows. The dates are the mid-points of 190-day windows. Nodes (sectors) from the same country carry the same color. Links represent an average p-value of 0.1 or higher. The network shows growth and contraction during the peak of the financial crisis. Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

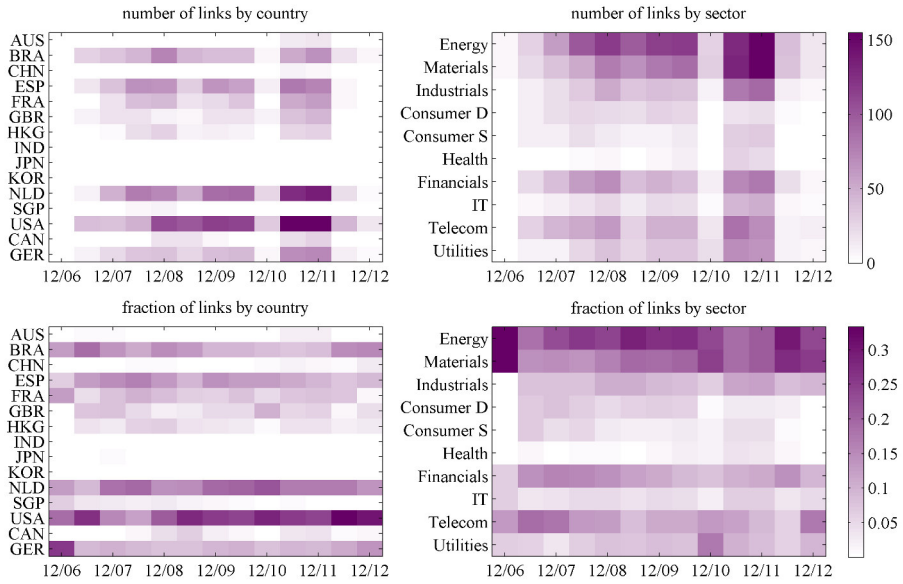


Figure 6: Number of Significant Links Over Time by Country (left) and by Sector (right). We count the number of significant links on the sector level and aggregate by country and by sector. The two top panels show the absolute number of links, the bottom panels show the fraction of links in the respective time window. The numbers are color coded according to the scale on the right. On the country level, we observe an overall wave-like pattern in the number of links with slight increases for the United States, Germany, and the Netherlands over time. The fractions of links by country are in fact relatively stable. Also the breakdown by sectors shows a wave-like pattern. A slight difference to the analysis of the weekly data (see Figure 4) is the daily data shows the energy and materials sectors as the most connected, not the financial sector. Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

part of this connected core.[9]

For a deeper investigation into the origin of this variation, we study the number of links between markets on a country and sector level, similar to Figure 4, but with the addition of the time dimension. The top panels of Figure 6 show that the number of links between stock markets is low at the beginning and at the end of the sample period. It is possible to observe two peaks where many links exist between markets, at the end of 2008 and again around 2010/2011.

There appears to be some synchronization in the dynamics of the number of links, both by country and by sector. It is possible to calculate the fractions of links for each time window, which are presented in the bottom panel of Figure 6. This normalization can help detect shifts in the relative influences of specific countries or sectors. The country-wise view in the left bottom panel shows the relative number of links is stable for most countries. Only the UK and Hong Kong show fluctuating behavior. The number of links for the United States is steadily increasing towards the end of

[9]For comparison, networks with links aggregated on the country level are shown in Figure D.2 in the appendix.

Window	Nodes n	Degree $\langle k \rangle$	Clustering $\langle C \rangle$	p. Length $\langle L \rangle$	Density
Jul 06 – Jun 07	26	3.885	0.018	0.010	0.155
Jan 07 – Dec 07	52	7.077	0.029	0.032	0.139
Jul 07 – Jun 08	66	8	0.034	0.026	0.123
Jan 08 – Dec 08	78	9.743	0.036	0.062	0.126
Jul 08 – Jun 09	84	9.869	0.032	0.052	0.119
Jan 09 – Dec 09	53	10.452	0.035	0.069	0.201
Jul 09 – Jun 10	64	10.297	0.031	0.067	0.163
Jan 10 – Dec 10	60	10.833	0.034	0.053	0.184
Jul 10 – Jun 11	42	7.524	0.034	0.022	0.184
Jan 11 – Dec 11	72	13.569	0.036	0.040	0.191
Jul 11 – Jun 12	75	13.680	0.038	0.045	0.185
Jan 12 – Dec 12	36	8.222	0.037	0.086	0.235
Jul 12 – Jun 13	36	6.361	0.029	0.026	0.182

Table 4: Summary Statistics for Networks Calculated Using Dynamical Analysis. For each window we calculate the number of nodes, n , average degree, $\langle k \rangle$, average clustering coefficient, $\langle C \rangle$, average shortest path for the giant component, $\langle L \rangle$, and density. Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

the sample period. The bottom right panel with a sectoral analysis shows more interesting developments. Only in 2007 and 2008 is the financial sector a driving force for interconnections. Much more dominant are links with the energy and the materials sectors, which gain influence throughout the sample.[10] Stocks related to consumer goods become less important over time and the health industry is not relevant for the entire sample period.

The ranking of the most-connected sectors varies with the data frequency. For example, the analysis based on weekly data showed financial stocks had the most links, followed by industrial stocks. When daily data and shorter time windows are used, stocks from energy and materials sectors dominate the linkages. That indicates fast-moving energy and raw materials markets influence stocks in these sectors more than the factors responsible for comovement with the financial and industrial sectors

The results demonstrate the existence of sectoral influences. While the extent of comovement fluctuates, their relative influence is relatively stable. The frequency of the data has a significant influence on the visibility of these sectoral influences. The speed and degree of stock comovements across sectors and across borders varies across time horizons.

The general structure of the network can change over time. Table 4 illustrates that the number of nodes with statistically significant relationships fluctuates between 26 and 84. The average number of links of each node, the degree, is related to the number of nodes. This relationship is only linear and indicates that the network is undergoing

[10]Due to the low overall number of links, the values (fractions) for the first time window are noisy and discarded from our discussion.

more changes than just size. A qualitative proof of this is the clustering coefficient presented in the middle column. Clustering measures how often two nodes B and C, which are both connected to node A, will also be connected to each other. The values for clustering in these networks are low and relatively constant. This shows that the networks do have some meaningful structure; not everything is always connected to everything else. This is confirmed by the changes in the average path length, which do simply vary with the network size. Their changes are caused by the contractions and diversions of single components of the network over time. The density describes the fraction of existing versus possible links between nodes. These values are high because of many links between sectors within countries that are rather stable. We see the highest values during the financial crisis, when the network is large and very connected, and in 2012, when the network is smaller and dense. These findings indicate fundamental changes in the network structure which cannot be fully explained by the sectoral influences described above or by changes within countries.

6. Mapping the Network Structure of the Global Market

A visualization of the network of stock market interconnections mostly shows stocks from specific regions forming connected groups. We want to quantify this and calculate the assortativity coefficient for different hypotheses. In this case, hypotheses are formed by assuming that certain countries or sectors are part of specific groups. We can then check if the classification of these groups explains the connectivity between the nodes in our network better than the assumption of random connections (given the degree of each node). The result is the assortativity coefficient. It takes the value 1 if the actual distribution of links is perfectly described by the assumed grouping, and 0 if the actual distribution of links is random and thus not explained at all by the grouping (see also Section 3.3).

We consider several hypotheses for regional groups in the network.[11] One hypothesis proposes the network consists of a group that contains all Western countries and another group with all Eastern countries. An alternative hypothesis explains network structure by dividing the network into three groups – America, Europe and Asia. The assortativity coefficients over time for the two hypotheses are in the two left columns of Table 5. The latter hypothesis, which divided the network into three groups, results in the best description of the network. This structural grouping is also better than a grouping into developed and developing stock markets (middle column). The segmentation into three regions explains the network imperfectly. This observed segmentation of the network structure is higher in times without severe crisis, that is until 2008 and after 2012. From 2009 to 2011, the network structure is weakened and more volatile.

For comparison, we also calculate the assortativity coefficient for assuming that the most connected sectors of energy, materials, and financial stocks form connected

[11] Note that, instead of testing some hypothesis, a different approach to discuss network structure would be to determine clusters endogenously using methods from community detection or graph partitioning. Own experiments however showed that robust results only partition the network up to the structure presented already in section 4, without giving much insights into the interplay of regional and sectoral effects.

Number of groups	West vs East[A] 2	America Europe Asia[B] 3	Developing vs Developing[C] 2	energy/materials/utility financial rest[D] 3	Sectors and regions[E] 4
window					
Jul 06 – Jun 07	0.30	0.38	0.29	0.06	0.06
Jan 07 – Dec 07	0.21	0.38	0.19	0.03	0.04
Jul 07 – Jun 08	0.22	0.36	0.20	0.04	0.04
Jan 08 – Dec 08	0.25	0.36	0.21	0.02	0.03
Jul 08 – Jun 09	0.20	0.29	0.17	0.01	0.01
Jan 09 – Dec 09	0.20	0.23	0.16	0.01	0.00
Jul 09 – Jun 10	0.20	0.23	0.16	0.00	0.00
Jan 10 – Dec 10	0.16	0.19	0.15	0.00	-0.02
Jul 10 – Jun 11	0.27	0.28	0.26	0.02	0.02
Jan 11 – Dec 11	0.22	0.20	0.13	0.00	0.00
Jul 11 – Jun 12	0.20	0.18	0.11	0.00	0.00
Jan 12 – Dec 12	0.24	0.26	0.22	0.01	0.00
Jul 12 – Jun 13	0.27	0.31	0.26	0.03	0.03

Table 5: Modularity of the Network Over Time. We calculate the assortativity coefficient for five hypotheses for all 13 time windows. The results show that the network structure partly resembles a regional clustering (left columns) while international sectoral structures do not explain the observed networks (far right columns). The different hypotheses correspond to the following groups: (A) 1: BRA ESP FRA GBR USA CAN GER, 2: CHN HKG IND KOR SGP JPN (B) 1: BRA USA CAN, 2: ESP FRA GBR GER NDL, 3: CHN HKG IND JPN SGP KOR AUS (C) 1: AUS ESP FRA GBR JPN NLD USA CAN GER HKG, 2: BRA CHN IND KOR SGP (D) 1: energy, materials, util., financials 2: other sectors (E) 1-3: sectors from *D* in countries like *B* 4: all other. Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

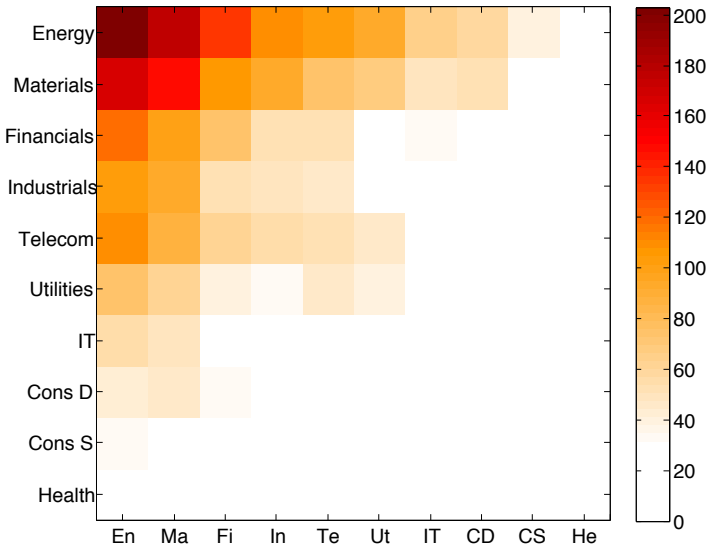


Figure 7: Number of Significant Links for all Time Windows, Sector to Sector, Sorted. The figure shows a color-coded count of the number of links between all combinations of sectors, regardless of the country. The sector names on the horizontal axis are the same as on the vertical in an abbreviated form. The row and column number of each sector has been arranged such that the sum over rows (or columns) is descending. We observe that we do not have significant structures (cliques) composed of combinations of specific sectors, but that the distribution of links on the sector to sector level is roughly the product of the distributions of links on the sector level. Sources: Standard & Poor's Compustat, Thomson Reuters Datastream, author's analysis.

groups. This is not a good description of the network, and the results are equally poor if links within countries are discarded. A grouping that combines sector with country characteristics, shown in the far right column, does not lead to better results (we assume that the financials, energy, and materials form one group in each region and that all other stocks are in group 4).

In the case of the static analysis, countries show heterogeneous patterns in the amount of comovement. A similar heterogeneity is observed on the sectoral level, but has almost no explanatory power in our analysis of group structure. This indicates the links on the sector level are not as assortative as on the country level. We have to look at the 10×10 matrix of sector to sector links to find out the structure of these links.

Figure 7 is a color-coded representation of these relationships. We counted the number of significant links between the sectors in each country and aggregate for all 13 time windows. Next, the sectors are sorted by the total number of links from top to bottom (and/or left to right). This process shows there is no grouping on the sectoral level. A core of very connected sectors is observed, namely the energy sector, materials sector, and to a slightly lesser extent, financial sector. The underlying stocks, however, do not only comove with stocks from the same sector, they often also comove with

stocks from related sectors. This core is emanating comovement onto other sectors. This means the connections between stock markets heavily rely on these three sectors, but the connection is not necessarily most intense within one sector, but between related sectors. Visualizations on the previous pages (e.g. Figure 3) show many cases where the links between different groups are characterized by such kind of dependencies.

The dynamics of the stock market network are the result of a complex mix of changes in market comovement that are visualized by the contraction and separation of regional components of the network and by sectoral effects, which are more stable. The regional aspects are most visible in the network but they explain the network structure only in part and less in times of market stress. It is important to look at interdependencies on a lower level of aggregation, namely sectors, which are heterogeneous in their ability to connect markets.

7. Conclusions

This paper presents an empirical investigation of comovement, as a statistical measure of interconnectedness, across 15 representative stock markets. The analysis shows that for asset markets, a global financial market, in terms of cross-country statistical interconnectedness, exists only within certain limits. We observe a mixture of regional and global sectoral effects, with the balance between the two fluctuating over time. For most of the time, regional segregation remains visible, even though in times of stress markets contract to a unisonous behavior. During such contraction periods, some countries still retain a high level of autonomous behavior.

Previous research has focused on factors that determine the level of stock market comovement for various countries. The results, however, were not always as convincing as similar studies on the synchronization of business cycles. Our findings shed some light on this debate: the fine structure of stock market comovement shows significant time variation. Sectoral effects do exist, but they influence only parts of markets. These effects are also overshadowed by sectoral bubbles or collapses such as the financial crisis. Tracking the sectoral interconnections over time, we find a shift from the financial sector, to the materials and energy sectors. A similar effect has been found during the dot-com bubble of 1997-2000 (see also Imbs, 2004; Raddant and Wagner, 2017). These help explain why identifying stable country-specific determinants for asset market comovement is difficult. In fact, for the Western markets, country determinants are probably at best secondary effects.

Our results also hint that the dimensional reduction on the level of sectors preserves qualitative features of the global stock market, like sectoral shifts, that can be lost in an analysis that is based on market indices. While indices' comovement is high and persistent, stock and sector-based comovement show more heterogeneity, which is not averaged out in the aggregate.

In general, the methodology presented here can be used to quantify statistical interconnectedness among a large number of assets in many markets. We quantify within and between market interconnectedness, and use network theory to present, quantify, and monitor these relationships and how they change in time. The model presented here is a way to quantify company-specific risks. First-order risks arise from direct interactions on the company level. Second-order risks arise from direct interactions on

the sector level. Both risk channels must be considered when analyzing the risks of a given company based on regional, global or systemic factors.

While in this paper we have focused on the macroscopic features of the markets, future work could apply and extend this framework to portfolio decisions for specific stocks. This would necessitate the estimation of covariances at a much higher frequency, which could be achieved by using high-frequency data and/or the estimation of dynamic correlations similar to those of multivariate GARCH models. Such a framework could then also be used for financial stress-testing on the company specific, sector specific, and country specific level, or all three as a whole.

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Appendix A. Statistical Properties of the Data

For most markets, the correlation of stocks within a sector is much higher than the overall correlation. Figure A.1 shows details for seven countries. The overall correlations are shown as a fitted normal distribution and the single sector averages are shown as histogram bars. The dispersion of measured correlations is smallest for the United States and highest for Japan. The latter, together with China and Korea, are the only countries where the sector effects are weak.

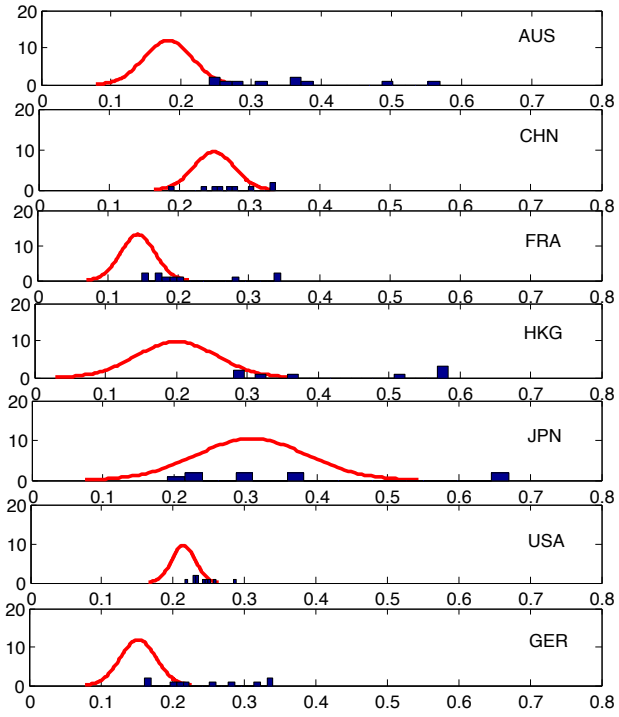


Figure A.1: Distribution of Between-Sector Correlations of Stocks (red curve) versus Average Correlations Within the Same Sector (bars) for Seven Countries. The correlation of stocks within sectors is mostly significantly higher than the average correlation and show higher dispersion. The remaining eight markets behave similarly. Only China and most of the Japanese market demonstrated a different behavior. Sources: Standard & Poor's Compustat, Thompson Reuters Datastream, author's analysis.

Figure A.2 illustrates the ACF of the raw and the filtered returns. For all countries the GARCH(1,1) produces filtered returns without significant auto-correlation.

Figure A.3 sheds some light on the distributional properties of the raw and filtered data. Not surprisingly the raw returns have very pronounced tails. After normalizing everything with the estimated volatilities the filtered returns are rather well described by the fitted t-distribution (middle panel). The analysis of the residuals (right panel)

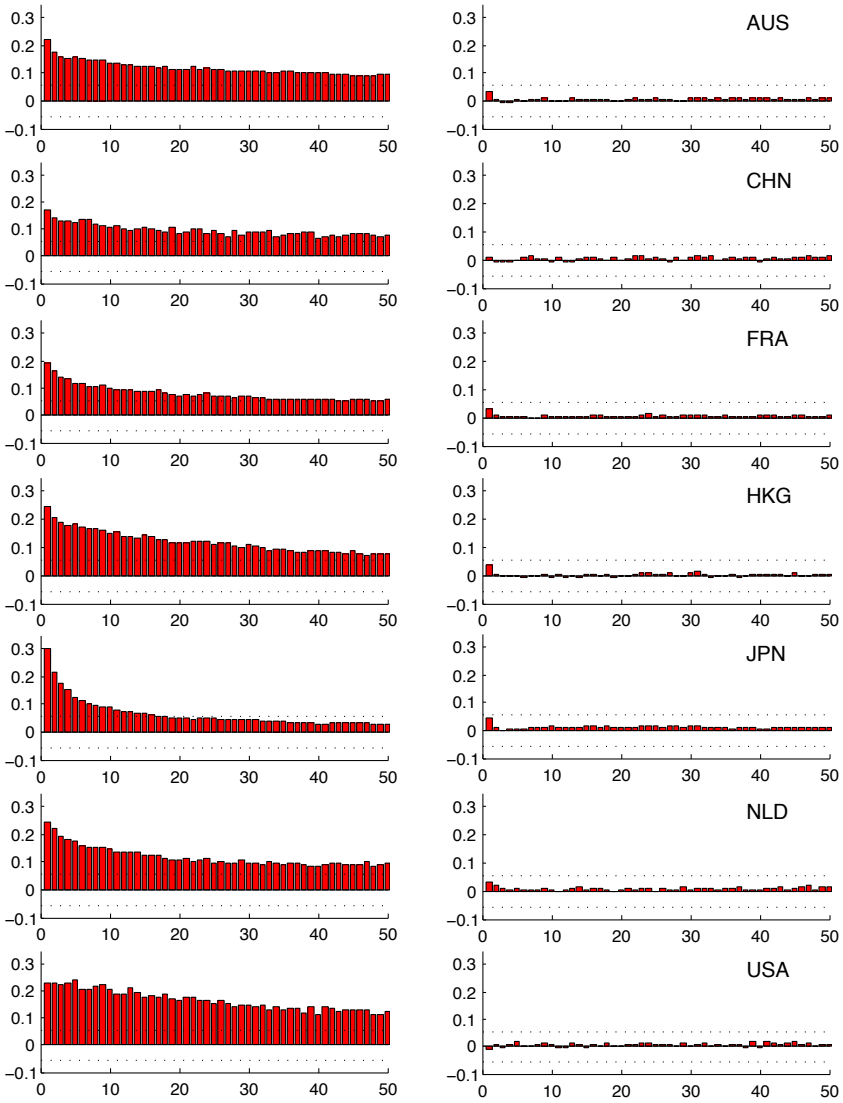


Figure A.2: Average Auto-correlation Functions for the Absolute Raw (left) and Filtered Returns (right) up to Lag 50 for Seven Countries. Although the markets show different levels of autocorrelation and different speed of decay, the GARCH(1,1) is able to produce de-garched time series which sufficient (insignificant) levels of auto-correlation. The results of the other eight markets are very similar. Sources: Standard & Poor's Compustat, Thompson Reuters Datastream, author's analysis.

reveals few observations in the tails that are slightly off, but these are already present in the raw data. Given the large number of observations, these do not pose any problem.

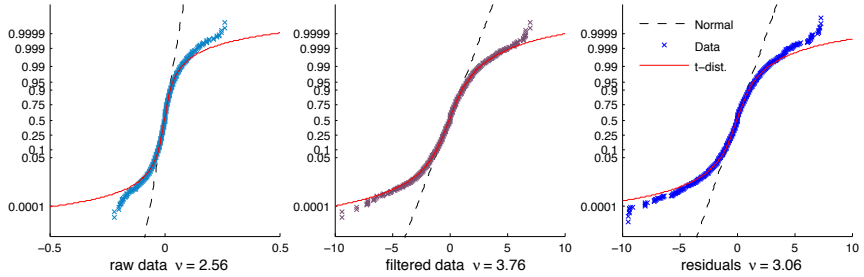


Figure A.3: Distributions of the Raw Returns (left panel), Filtered Returns (middle panel) and Residuals (right panel) and Fitted t-distributions. Sub-sample of roughly 20,000 observations. The degrees of freedom for the fitted t-distribution are given below each plot. Sources: Standard & Poor's Compustat, Thompson Reuters Datastream, author's analysis.

Appendix B. Robustness Analysis

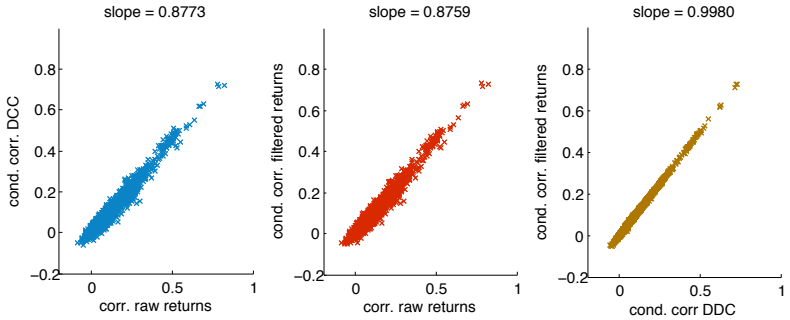


Figure B.1: The left panel shows the correlation of raw returns vs. the correlation conditional on the volatility estimated by the DCC model. The middle panel shows the same for the correlation vs. the correlation of the GARCH filtered returns. The right panel compares the correlation coefficients from the simple GARCH and DCC model. Both models correct the correlation to about 87 percent of the one that one would get from the raw returns. Sources: Standard & Poor's Compustat, Thompson Reuters Datastream, author's analysis.

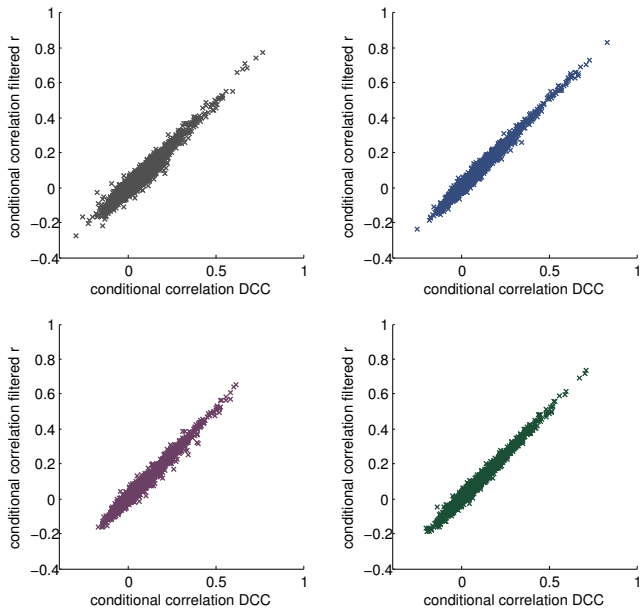


Figure B.2: Scatter Plots of the Correlations of the Filtered Returns versus the Average of the DCC Model Correlation for Four Random Time Windows. Sources: Standard & Poor's Compustat, Thompson Reuters Datastream, author's analysis.

Appendix C. Relationship of Covariances and Correlation of De-garched Returns

Throughout the previous analysis, we have used the estimated volatility from the GARCH model to normalize the returns. It can also be useful to consider the correlation of this estimated volatilizes of stocks and check if these are simply proportional to the correlation of normalized stock returns or not. Interestingly, when we average the volatility on a country to country level there is some structure in the behavior of these two measures. Figure C.3 presents a scatter plot of the average correlations of filtered returns versus the average correlations of estimated volatility.

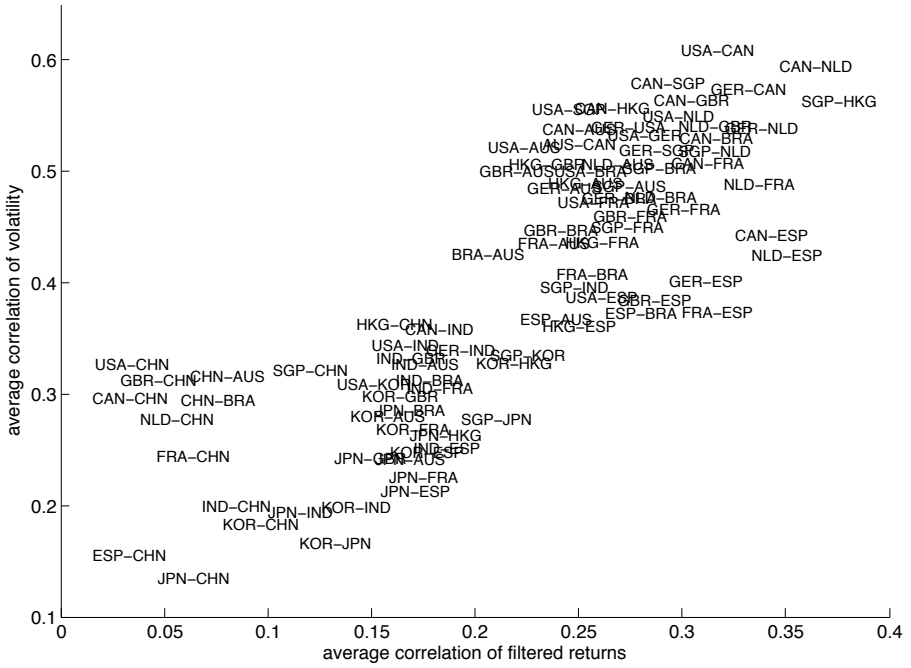


Figure C.3: Correlation of Returns and Correlation of Volatility. We compare the averages of the correlations of the estimated (GARCH) volatilities and the averages of the correlation of the correlation of the filtered returns. Hence, each plotted label represents the averages of the correlation of all stocks in the first with all the stocks in the second country. Although there is a clear positive relationship between correlation of volatility and correlation of filtered returns, some country specific differences in the ratio of the two measures can be observed. The ration is above average for pairs of countries that involve China, and the ration is below average for many pairs that involve European countries. Sources: Standard & Poor's Compustat, Thompson Reuters Datastream, author's analysis.

At a first glance, there seems to be a lot of noise around some imaginary positive-sloped line, but the printed labels reveal some structure. Chinas stocks are, as discussed above, only weakly correlated with those of the rest of the world, but the correlation of volatility is relatively large, making most of the CHN labels appear above others in the left part of the figure. This is also true for many distant countries, which appear on the

top edge of the scatter cloud in the right half. On the other end of the spectrum, we have pairs of mainly European countries, where the ratio of volatility- to returns-correlation is low, which appear a bit below the bulk of the scatter cloud in the right half of the figure. Comovement cannot be synonymously analyzed by either volatility or returns comovement. For China, it seems that financial market restrictions can limit volatility spillovers much less than comovement in returns. For the European markets, we see high levels of comovement in returns but relatively less volatility spillovers than for distant countries.

Appendix D. Dependencies on the Stock and Country Level

In Figure D.1 we show the network representation based on the estimated dependencies from the weekly data, on a stock-stock interaction level. Within the densely-connected core, most sectors of the U.S. stock market are in the middle. They connect with sectors from European stock markets on the left, with the Asian markets at the top, and with markets from the Americas on the bottomright. This layout is the result of an optimization algorithm and other algorithms deliver similar qualitative results.

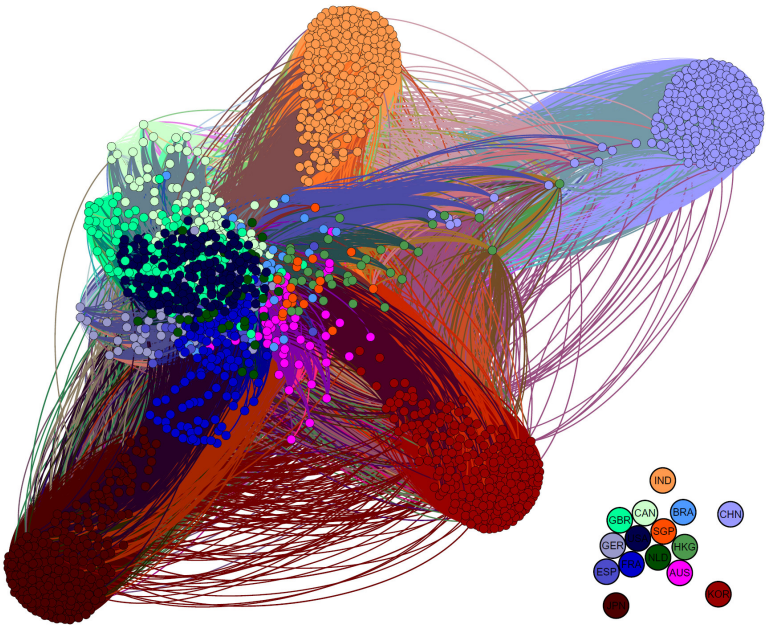
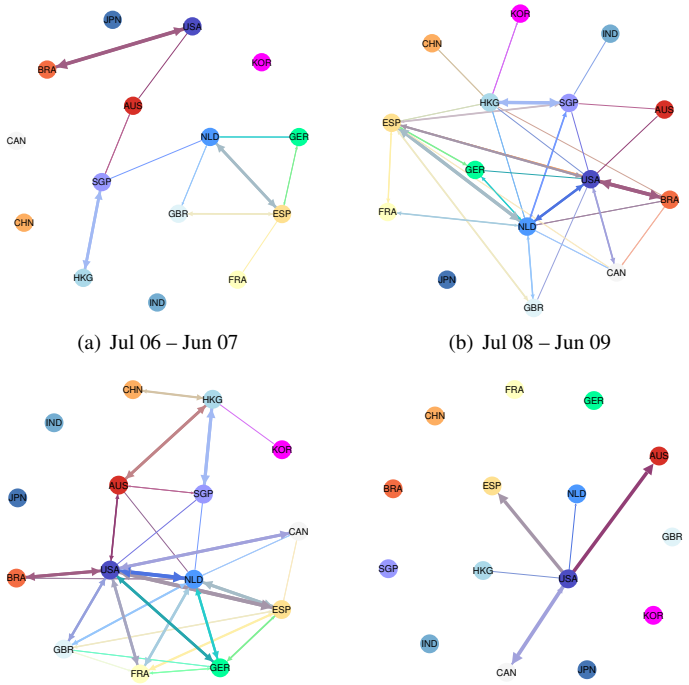


Figure D.1: Network Representation Based on the Estimated Dependencies from Weekly Data. The figure shows a visualization of the network of stocks where the weighted links correspond to stock dependencies that at least satisfy the 90 percent confidence interval. Stocks from the same country have the same color and a legend of the color coding is at the bottom right. Stocks of most countries form a mixed cluster in the center of the figure. Regional structures and parts of national stock markets are at the periphery of the mixed cluster. Stocks from India, China, Japan, and South Korea are not part of the central cluster and these countries show different levels of connectedness. While parts of the Japanese market seem to form a bridge toward the center, the connections of Chinese stocks are weaker and less diverse. The visualization was performed in Gephi using the Yifan Hu multilevel algorithm. Sources: Standard & Poor's Compustat, Thompson Reuters Datastream, author's analysis.

In Figure D.2 we present the dynamics of the country-level dependency networks. We present four networks that are representative for the dynamics within the total of 13 time windows. The weighted links represent an average p-value equal or smaller than 0.25. This low threshold is necessary since the heterogeneity on the stock-to-stock interdependency level is large. This indicates that there is a noticeable difference



(a) Jul 06 – Jun 07

(b) Jul 08 – Jun 09

(c) Jan 11 – Dec 11

(d) Jul 12 – Jun 13

Figure D.2: Dynamics of Country Dependency Networks. We show four networks that are representative for the dynamics within the 13 time windows. The weighted links represent an average p-value of 0.25 or better. This low threshold is necessary since the heterogeneity on the stock-stock interdependency level is large. This indicates a noticeable difference between a comovement analysis on the basis of market indices versus single stocks. It also shows that a large part of this inhomogeneity is captured by the sector-wise grouping. Sources: Standard & Poor's Compustat, Thompson Reuters Datastream, author's analysis.

between a comovement analysis on the basis of market indices versus single stocks. It also shows that a large part of this inhomogeneity is captured by the sector-wise grouping.