

Raddant, Matthias; Kenett, Dror

Conference Paper

Interconnectedness in the global financial market

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel -
Session: Global Financial Markets, No. B16-V1

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Raddant, Matthias; Kenett, Dror (2016) : Interconnectedness in the global financial market, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel - Session: Global Financial Markets, No. B16-V1, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg

This Version is available at:

<https://hdl.handle.net/10419/145560>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Interconnectedness in the global financial market

xxx^{1,1}, xxx^{1,1},

Abstract

The global financial system is highly complex, with cross border interconnections and interdependencies. As such, financial shocks and events can easily spillover and propagate throughout the entire system. In this highly interconnected environment, local events can be easily amplified and turned into global events. Thus, new models are needed to capture the structure of the global financial village and uncover channels of spillover and contagion. In this paper we analyze the dependencies between almost 4.000 stocks from 15 different countries. We normalize the returns by the estimated volatility using a GARCH model and then use a robust regression process to estimate pairwise dependencies between stocks from different markets. The estimation results are then used to derive network representations, both on the individual and sectoral level. We show that countries like the US and Germany are in the core of this global stock market. Furthermore, we find that the energy, materials and financial sector play an important role in connecting markets, and that this role has been increasing in time for the two former sectors, versus the latter. Thus, the presented framework provides the means to monitor interconnectedness in the global financial system on different aggregation levels, and how they evolve in time.

Keywords: asset markets, comovement, financial networks

JEL: G15, G11, C58

1. Introduction

The last two decades have been characterized by an enormous increase in political and economic openness, mostly accompanied or followed by an increase in financial integration. Investment and risk management can no longer be done in a regional context, but have to acknowledge the global nature of financial markets. The sheer size and number of trading products available in this global market necessitates models that can provide a hierarchical or topological simplification of this system. Analyzing and managing macro financial risks have become increasingly important over time as global markets have become increasingly more connected. For this reason we propose a mapping of the global stock market. We will show that the comovement of stocks can be summarized by country- and sector-wise grouping of stocks, and that this approximation provides significant information for risk management and strategic portfolio analysis. Furthermore, we provide a framework to monitor interconnectedness across the global financial system, identify vulnerabilities and transmission channels of shocks.

Among the many factors contributing to the financial crisis of 2008-09, the increase in the interconnectedness of the global financial system is perhaps the least well understood. The crisis exposed the fact that regulators and market participants had very limited information on the risks that firms indirect exposures to one another might pose. It also revealed that there was little theoretical understanding of the relationship between interconnectedness, risk-taking and financial stability. This limited information made it difficult to estimate the impact and importance of financial entities, and how the stress on a given bank or financial firm might propagate throughout the rest of the system. This resulted in an environment of speculative policy making and made it difficult to navigate the crisis.

Interconnections between financial markets play a dual role. On the one hand, they can serve shock absorbing and as a mean of diversifying risk, thus leading to greater robustness. On the other hand, they can serve as a mechanism for propagating shocks, and thus create greater fragility. Supervisors have traditionally focused mostly on interconnectedness as measured through direct exposures, which is constrained on the availability of highly reliable granular data. As the events of the past years have shown, there is a great need to redefine our understanding and knowledge of interconnectedness in the financial system, where they stem from and how they can be evaluated and monitored.

Turning to analytic approaches for considering interconnectedness, networks are a critical tool in the description of the financial system, its systemic structure, analysis and evaluation of contagious effects. Studying the network provides important insights into system level effects, which add to those observed when studying bilateral exposures or interactions. Investigating financial networks provides the means to identify risk both at the individual and the system level. Furthermore, monitoring financial networks can help uncover changes in market microstructure, bubble formation, and changes in business models, where certain market participants start withdrawing from certain activities and other participants take their place.

This paper is related to the literature in several ways. First of all it is related to the general literature that discusses the implications of market openness on business cycles (see, e.g., Brooks and Del Negro, 2004; Beine and Candelon, 2011). One implication of openness is that business cycles can become more synchronized. This however depends also 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 spill-overs can change to what we observe in normal times. See for example Fratzscher (2012) for an analysis of the 2008 crisis and Kaminsky and Reinhart (2000) for an analysis of crisis in the 90s.

The latter note that financial channels have long been neglected in the analysis of contagion. The last decade has then seen a large amount of literature where not the fundamental reasons of spill-overs but the mere financial aspect of it has been analyzed. Analogous to the debate on openness and business cycles, the effect of openness on financial markets has been analyzed. The transmission mechanisms of these seem to be more stable over time (Rigobon, 2003). However, structural similarity of countries explains only partially the level of comovement between them. This resulted in debate about the influence of (global) sectoral factors. The results hint at an increase in the

importance of these factors (Dutt and Mihov, 2013; Bekaert et al., 2009). Forbes and Chinn (2004) find 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.

While in the analysis of comovement within a market (see, e.g., Barberis et al., 2005; Green and Hwang, 2009) one tries to explain the behavior of individual stocks, this is mostly not the case for the analysis of comovement across markets. Most of the approaches to 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; Ahlgren and Antell, 2010), causality tests (Billio et al., 2012), as well as different GARCH-based models (Engle, 2002; Engle et al., 2008). The general problem that all of these approaches deal with are the special statistical features of the asset returns that have to be analyzed. The volatility of the returns is clustered and its distribution follows a power-law. From this it follows that similarities in stocks' returns are difficult to disentangle from similarities in the volatility patterns.

This paper is also related to the literature which applies methods of network science to financial economics. For example, the comovement of stocks has been analyzed as a network phenomenon. In these approaches the similarity on stock performance is interpreted as information about linkages between stocks (Mantegna and Stanley, 1999; Song et al., 2011; Gopikrishnan et al., 2001). These approaches deal well with the complexity of financial markets. They typically tend to analyze not only indices and indicators but also larger sets of stocks. One weakness of these studies might be that they are mostly of a more exploratory nature and that statistical significance is often difficult to assess (see for example Curme et al., 2015; Tumminello et al., 2011). However, Kenett et al. (2012) shows that network approaches have the potential to describe the dynamics of market couplings on the global and regional level. Recent work have also emphasized the role of interconnectedness in the financial system as channels of contagion (Summer, 2013; Gajurel and Dungey, 2015; Diebold and Yılmaz, 2014; Levy-Carciente et al., 2015; Glasserman and Young, 2015a,b), and the added insights provided when investigating the financial system using network science tools.

The methodological framework presented here provides a way to quantify the evolution of interconnectedness in the global market, evaluate a world financial network and quantify changes in the world inter market relations. Such changes can be used as precursors to the agitation of the global financial village. In this paper we explore comovement not on the basis of indices, but on the basis of individual stocks. Hence, we study the global stock market from the viewpoint of an investor or strategic portfolio manager. For this reason we investigate a set of almost 4,000 stocks from 15 countries. We analyze the dependencies of these stocks by assessing significant dependencies, and uncovering significant forms of interconnectedness amongst the investigated markets. The remainder of the paper is organized as follows: In section 2 we describe our data set as well as the methodology to measure dependencies between stocks and how this information can be used to derive networks. The results are presented in sections 3 and 4. We will first show our findings for the entire sample, before analyzing the de-

dependencies in 13 overlapping time windows. We will see that the market is segmented into regions for most of the time, but that in times of economic stress this segmentation fades. Further we show that sectoral effects are present, but rather volatile. The financial sector has for some time played a role in connecting markets, but in general sectoral influences mainly stem from the energy and materials sectors.

2. Estimating inter and intra market interconnectedness

2.1. Data selection

The data used in this study consists of the daily closing prices of stocks listed on the stock exchanges in Australia, Brazil, China, Spain, France, UK, Hong Kong, India, Japan, South Korea, The Netherlands, Singapore, USA, Canada and Germany. For our analysis we use data from Compustat and Thompson Reuters. We choose those stocks which were continuously traded with sufficient volume throughout the sample period and had a meaningful market capitalization. We excluded stocks which price behavior or market capitalization showed similarities to penny stocks, or which were exempt from trading or traded with negligible amounts for more than 10 days, or for which the trading volume was negligible for more than 8% of the total trading days. For some countries the number of stocks that fulfilled this criteria is rather high. For this reason we choose the 500 stocks with the highest market capitalization for the markets in India, Japan, China and Korea. For the US we use stocks that are part of the S&P500 index, for the UK we selected those stocks which are part of the FTSE350. For all stocks we make use of the GICS sector classification. Where this is not available we use the (for our purposes practically identical) TRBC classification used by Thompson Reuters. The number of stocks by country and sector is summarized in table A.1 in the appendix.

Our observation period starts on 1 July 2006 and ends on 30 June 2013. Hence we have 8 years of data, which results in $T = 1329$ trading days and $N = 3828$ stocks. For the stocks from all countries we use those trading days where the stock markets in London and New York are both open. The fact that the countries under investigation lie in different time zones leads to limitations in the synchronization of the returns. The data barrier in the Pacific necessitates that Asian countries finish trading first in the day, while the Americas finish last. Hence, the correlation of daily returns will naturally underrepresented the amount of comovement between very distant countries due to the fact that trading takes place without overlap in time. In order to cope with this issue we employ two approaches: For the analysis of the long-run effects we calculated weekly returns for all time series, which leaves us with $T' = 365$ observations. For the analysis of short-run effects we calculate a correction factor for use with the daily data which details are explained in section 2.3.

In the remainder of this paper we mostly use 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 up to 500 for the larger countries, see the summary statistics presented in table 1. 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%. The distributions of the returns time series for

	N	caps	var(r)	kurt.	tail exp.	corr sec	corr all
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	YES	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	YES	0.00114	8.5		0.31	0.25
JPN	500		0.00120	15.1	2.99	0.37	0.31
KOR	500	YES	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 1: 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 two rightmost columns show that the average correlation of stocks within a given sector is always larger than the average correlation of all stocks within a given country.

these countries are thus truncated. Interestingly, this does not mean that the volatility is necessarily lower, see the sample variances in the table. As all time series of asset returns they are heavy-tailed, as the values for the Kurtosis indicated. We have also calculated the tail exponent by using the Hill-estimator, the values are mostly slightly greater than 3.

In order to uncover dependencies between stocks in different countries by a sector-wise analysis, it is also necessary to test if stocks within a specific sector are actually more correlated than stocks from random sectors. In the right-most columns in table 1 we 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 than the within-correlation (see also figure A.1 in the appendix).

2.2. GARCH filtering process

Although an analysis of the correlation of the returns can already be quite informative, in general it suffers from the fact that 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 all around the world is very synchronized, this issue mostly prohibits to infer information about which stocks show similarities in return on a more general level. There are different approaches for the filtering of returns time series and one very appealing one is of course to treat the returns within a multivariate GARCH model. In this model one would simultaneously estimate the parameters for conditional variances and the mutual influences of the returns time series.

Models of this kind are however difficult to estimate once the number of stocks becomes very large. Since we are interested in an analysis which can easily be implemented with moderate computational effort even for large data sets we choose a robust and much faster filtering method: we use the conditional variance from a univariate GARCH model.

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

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

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

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

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, since, besides very few exceptions for stocks from the developing markets, we find that the fit of this model is good and yields the expected coefficients for α and β close to 0.1 and 0.9. Besides negligible exceptions for some stocks from developing countries, we find that $p, q = 1$ is sufficient to describe the variance process.¹ Figure A.2 (in the appendix) shows the averages of the autocorrelation functions for the raw and filtered returns that result from this procedure.

2.3. Estimation and correction for non-synchronous trading

By “de-garching” the returns we obtain time series which can be treated in an almost standard regression framework. We run a pairwise regression of all the filtered returns and obtain a measure for the comovement.² 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).

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

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

In the following we want to focus on stock-stock relationship that are significant with respect to some threshold. Thus we will make use of the p-values that can be obtained

¹For the following analysis we have 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 of this.

²Note that it would of course be possible to commence 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.

form this estimation which we store in a matrix p_{ij} . The rows and columns are ordered by countries.

To check the robustness of these results, which depend on the univariate de-garching, we compare our results with those of a multivariate GARCH model. Since these models can only be estimated with a limited number of time series, we estimate the DCC model with pairs of stocks from our sample and compare the correlation implied by the DCC model with the correlation of our filtered returns. We find that the results are indistinguishable for long time windows. For time windows of 190 days the results on the stock level differ marginally (see Appendix B).

A challenging issue is to deal with is the difference in trading hours across different markets. Some of the stock exchanges that are relevant for our analysis are located in far apart regions. This leads to problems in determining the true dependencies between stocks from different markets. For stocks from Europe the problem is of relatively minor order since only the UK trading time differs from the other European countries by 1 hour. The US market opens before the EU markets close, here the difference is 6 hours. Calculating the dependencies between the markets 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, one can deal with this problem in two different ways: by using tick data and calculation of synchronous pseudo closing prices - or by time aggregation. The first method would necessitate incredibly large amounts of data, still it would probably be very difficult to find one specific time at a day for which price quotes for all stocks would be available. The second method is much easier but severely limits the time resolution for our analysis. By aggregating several days of returns the timing mismatch becomes less important. Hence, when concerned with long-run correlations, it is instructive to use weekly returns. Since financial markets react very fast to new information any analysis of its dynamics necessitates the use of higher frequency data. Therefore we also have to work with the daily data and apply some correction for the bias described above.

The estimated daily dependencies from those stocks which are traded in different time zones are slightly biased, however, they are not uninformative. By comparing the estimation results from the daily data with the estimation from the weekly data for the same time period it is possible to calculate a correction factor on a country-to-country basis. The idea of 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 (hence, the matrix contains blocks with identical values resembling all pairs of countries). After adding 1 to each of this matrices we can calculate the element-wise (notation: ./) ratio of the p-values of the weekly and daily estimates.

$$pr_{ij} = (1 + p_{ij}^w) ./ (1 + p_{ij}^d) \quad (4)$$

Then, the correction factor pc can be calculated as

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

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

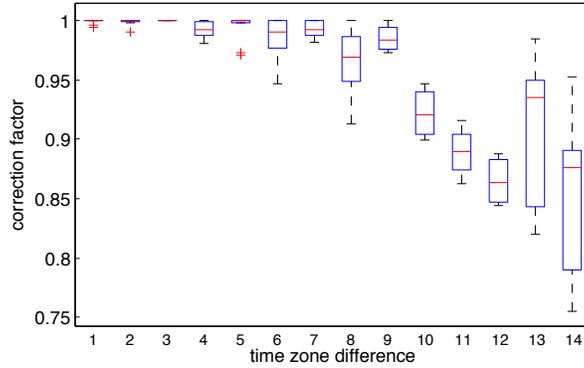


Figure 1: Range of correction factors by time zone differences. The plot shows the difference between the average estimated dependency of stocks on the daily level versus the weekly level (see eq. 2.3). We observe that significant differences between the estimated dependencies arise when the markets are more than 3 time zones apart. We also observe that for less developed markets with below average comovement the difference is much lower than for developed markets (this explain most of the dispersion for the two rightmost boxplots).

the dependencies between stocks within one country). Purely for numerical reasons we remove few entries outside the $[0, 1]$ band (thus the *max* and *min*). The corrected p-values can then be obtained as

$$p_{ij} = \max\left(0, \left((1 + p_{ij}^d) \circ pc_{ij}\right) - 1\right) \quad (6)$$

To summarize, this procedure assumes that overall the estimates from the daily and from the weekly data should be very similar and that 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 that 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 explain the issue fully. Especially for distant less developed markets where the comovement is low anyhow, the correction remains relatively small (which explain the wide range of the rightmost boxplots).

2.4. Visualizing interconnectedness

In a financial network, financial entities (such as banks, financial institutions, CCPs, traders) are considered as nodes, and their relationships (such as interbank lending, contractual obligations, counterparty exposures) define the links that connect them together. Also the relationships between the stocks can be expressed as a network. Every stock can be interpreted as a node in a network and the estimated interdependencies deliver the information whether and with what strength these nodes are connected to

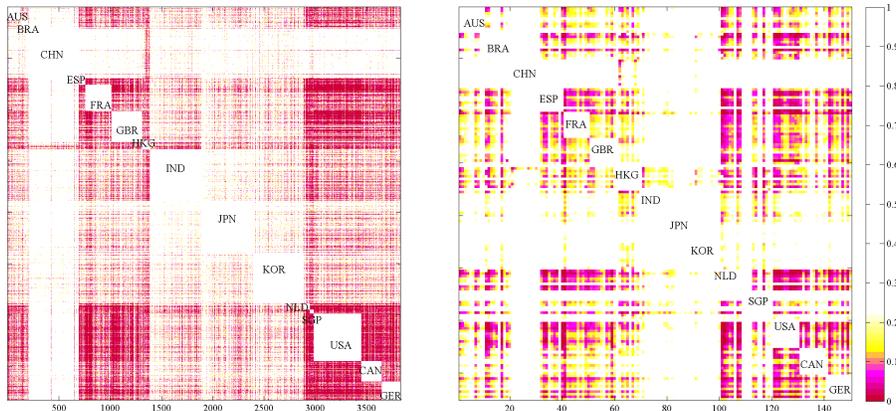


Figure 2: p-values for the stock-stock dependencies (left) and its sector averages (right). The stocks are arranged by countries and the abbreviated country names are plotted along the main diagonal. Entries for dependencies within countries have been removed. The values are color-coded such that dependencies above the 90 percent confidence interval appear 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.

each other. To store this information one uses adjacency matrices, where the entries in row i and column j indicate the strength of the connection between the respective nodes (see figure 2).

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

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

This adjacency matrix then 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 investigated markets on a mesoscopic level, the stock level dependencies are used to describe the resulting network on a sector to sector basis. To this end, we use the averages of the p-values of the relationships of the stocks in a specific sector in one country with all the stocks in a specific sector in another country to map out the sector-by-sector dependencies.³ The translation into

³Note that the averages of the p-values are of course itself not p-values anymore. However, we argue that in this case it makes sense to use these averages, since the dispersion within the groups of stocks that we are interested in is rather low.

this second adjacency matrix is done in the same way as stated above, the dimension however is reduced to 150×150 (15 countries, 10 sectors). Sectors in countries which consists of less then 3 stocks are excluded from further analysis.

Finding useful graphical representations of these adjacency matrices is a very complex process, since this is equivalent of finding the best 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.⁴ In the following we will graph our networks by applying the widely used algorithm developed by Hu (2005). This algorithm arranges nodes in a 2-dimensional space in such a way that the total edge length of the graph is minimized, which naturally leads to a layout that shows the most pronounced communities of nodes within a graph. In fact this specific algorithm uses the physics of repulsion to generate a visualization (it should be noted that other algorithms lead to very similar results).

Once a visualization of the network is computed, one can use it as a starting point to investigate what the most general structure of the network resembles, for example if there are regional groups of stock markets that comove most. Hence, we compare the number of links between stocks (nodes) in the same group (region) with the number of links between them as if these were random. This feature of a network 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

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

where δ is 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

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

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

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

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 $AC = Q/Q_{max}$.

⁴See also the book by Newman (2010) for an in-depth introduction to Network Science.

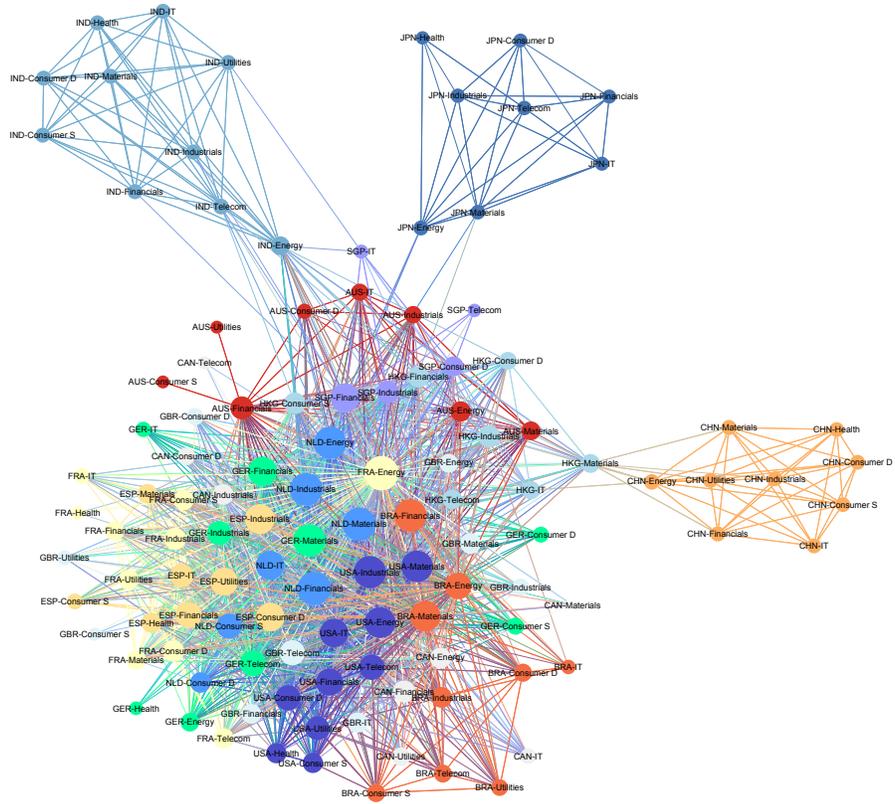


Figure 3: Network representation based on the sector-wise averaged estimated dependencies from the weekly data. Nodes (sectors) from the same country have the same color. The node size is proportional to the degree (the number of significant links/dependencies). The sector network displays features similar to the stock network in figure 2. Most sectors form a central cluster around the US market. India, China, and Japan form loosely connected cliques. Sectors with no or very few links are omitted (which leads to the fact that South Korea is not present). The layout was performed in Gephi using the Yifan Hu algorithm.

3. Static analysis of global interconnectedness

We will start explaining the results that we get from analyzing the weekly returns. Figure 3 the network representation that we obtain. We can see that the stocks from the Western markets form a hairball in the middle of the network. Within this hairball 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 (figure C.1 in the appendix) to verify that the averaging does not influence these findings. Within the densely connected core most sectors of the US stock market are in the middle, they connect with sectors from European stock markets on the left, with the Asian markets to the top, and with markets from the Americas to the bottom-right. It should be emphasized that this layout is not forced but is the result of an optimization algorithm.

Even in the densely connected component in the middle, sectors from the same market are mostly grouped close to each other, which is a sign of remaining regional segmentation. It is however even more instructive to observe those nodes that are a little bit separated from the rest of nodes with the same color, for example the German materials sector or the British and French energy sectors. Their surrounding nodes hint at the fact that also sectoral effects are at work here, namely that the underlying stocks from the material or energy sector are at least as well connected to similar stocks in other countries than to stocks in their home markets.

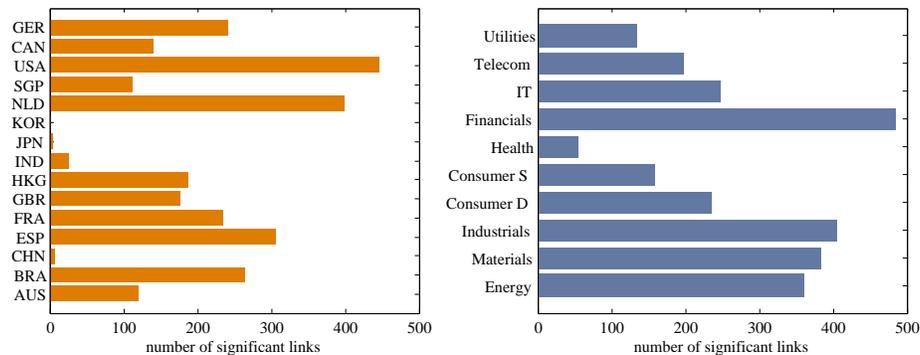


Figure 4: Number of significant links on the country (left) and sector level (right). We count the number of significant links between sectors and aggregate by country and by sector (based on the estimation of the weekly data). The US and the European countries (which are slightly favored by their large number) are the most connected ones. The four Asian countries (excluding Singapore) are least connected. When we aggregate by sectors we see that stocks from the financial sector, followed by materials and energy are the most connected stocks.

A first step to quantify the comovement in this network is to count the number of links between sectors. This means checking how often the average p-value for a sector-sector pair is better than 0.1. We can then aggregate this on the country or on the sector level. The results are shown in figure 4. The left panel confirms the visual impression

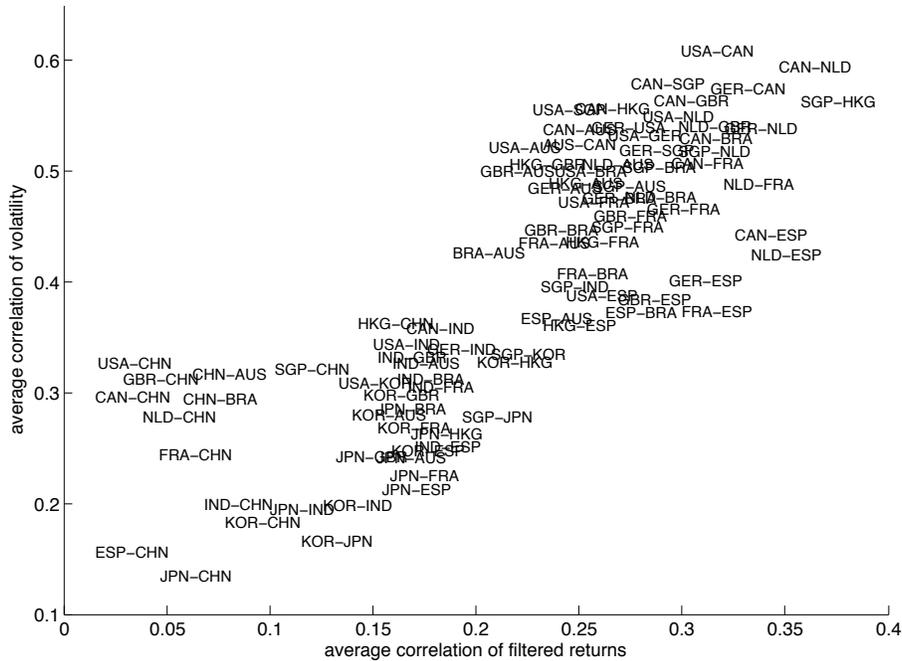


Figure 5: Correlation of returns and correlation of volatility. We compare the averages of the correlations of the estimated (GARCH) volatilities and the averages of the correlation of the filtered returns. Hence, each plotted label represents the averages of the correlation of all stocks in the first 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, the ration is below average for many pairs that involve European countries.

of a very connected US stock market. However, also most sectors in European markets co-move heavily. Of course these figures are also influenced by the selection of the countries in the sample. The right panel shows that there are clear differences on the sector level. Stocks from the financial sector, industrials, materials, and the energy sector show more interconnections than stocks from other sectors – and this is rather consistent for all countries.

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 volatilities of stocks and check if these are simply proportional to the correlation of normalized stock returns or not. Interestingly, we find that when we average the volatility on a country to country level there is actually some structure in the behavior of these two measures. Figure 5 presents a scatter plot of the average correlations of filtered returns versus the average correlations of estimated volatility. At a first glance there seems to be a lot of noise around some imaginary positive sloped line, but

an inspection of the printed labels reveals some structure. Chinas' stocks for example 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 most others in the left part of the figure. Similar findings are observed for many very 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. The important message from this analysis is that comovement cannot be synonymously analyzed by either volatility or returns comovement. They are linked but merely the same. For the case of 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.

4. Dynamic analysis of global interconnectedness

Within the 8 years covered by the dataset the world has seen a number of economic and political events that are likely to lead to significant fluctuations in co-movement. The 2008 financial crisis, the Euro crisis and the tsunami crisis that took place in Japan in 2011 are just a few examples. For this reason also a dynamic analysis is necessary. The resolution of the data allows for a characterization of stock market dependencies in the medium run, say months. Thus we use a rolling window approach that uses 190 days of data in 13 time steps with a 95 day overlap. We use the same methodology as before but now employ daily data with timing correction for the p-values as described in section 2.3.

Figures 6 (a–d) display four of the thirteen resulting networks. These networks resemble the general dynamics very well. The network in the top left panel of figure 6 is very different from all the following ones. It is possible to observe that the American and the European stocks form individual cliques within the network, although there are multiple links between them. Some Asian markets are more loosely connected to the European market. China shows very strong internal comovement but is not significantly linked to other markets.

The picture changes completely at the end of 2008 with the onset of the financial crisis. Stocks from all important developed markets form one connected component. Some grouping into American, European and Asian stocks remains, but the borders seems to blur. The markets of South Korea, China and India appear as weakly connected satellites. The bottom left panel of figure 6 shows that in 2011 there is stronger comovement with Asia, which markets separate from the European-American component. Links now run between American and Asian markets, while comovement between European markets becomes more heterogeneous, which is very likely an effect of the Euro crisis, which has affected some but not all European countries. Finally, we investigate the structure of the network in 2012, where comovement is almost back down to pre-2008 levels. We see stock markets which are very much connected around

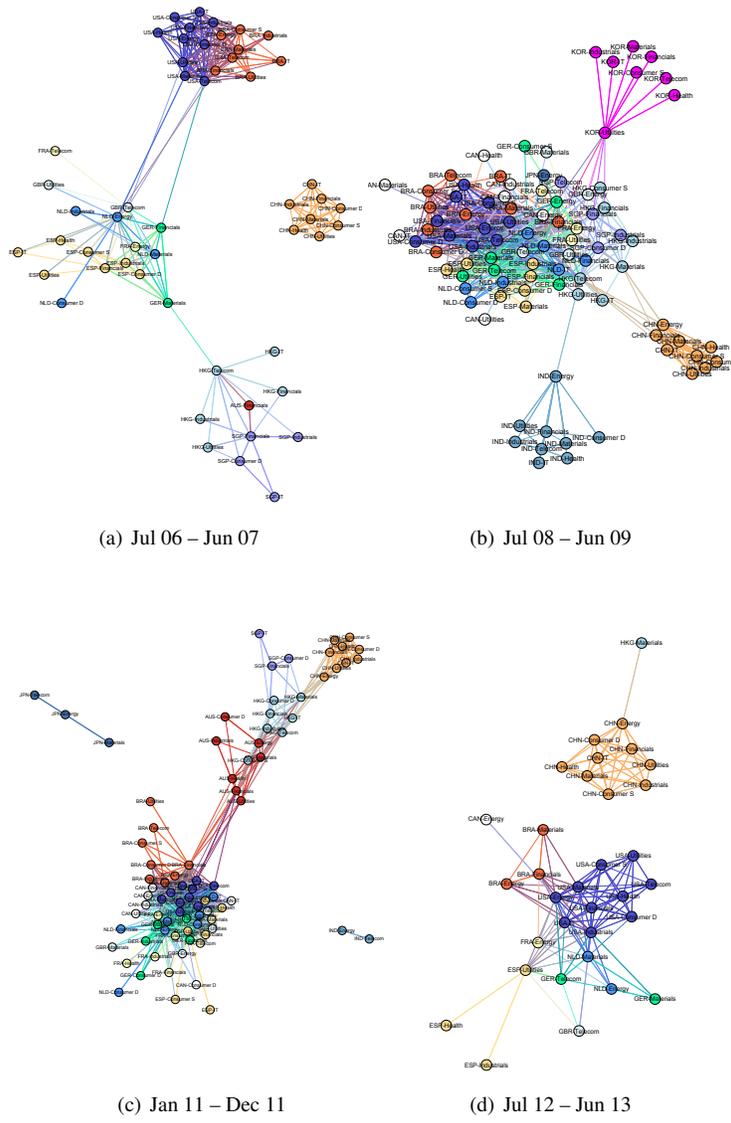


Figure 6: Dynamics of sector dependency networks. We show 4 networks that are representative for the dynamics within the total of 13 time windows. The dates given are the mid-points of the 190-day long time windows. Nodes (sectors) from the same country carry the same color. Links represent an average p-value of 0.1 or better. The network shows growth and contraction during the peak of the financial crisis.

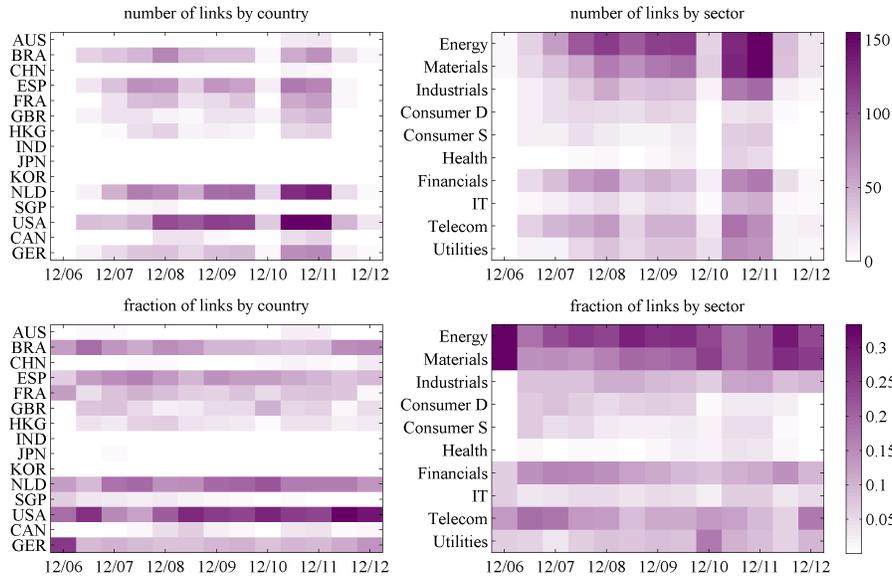


Figure 7: Number of significant links over time by country (left) and by sector (right). We count the number of significant links on the sector level and aggregate by country and by sector. The two top panels show the absolute number of links, the bottom panels show the fraction of links in the respective 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 US, 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 that the daily data shows the sectors energy and materials clearly as the most connected (and not financials).

US stocks, but we also see that many sectors are no longer part of this connected core.⁵

The previous illustrations show that the network of stock market interconnections shows quite some variation. For a deeper look at the origin of this variation we look at the number of links between markets on a country and sector level, similar as shown in figure 4, but adding the time dimension. The top panels of figure 7 show that the number of links between stock markets is low in the beginning and at the end of our sample period. It is possible to observe two peaks where a lot of links exist between markets, one at the end of 2008 and one around 2010/2011.

There seems to be some synchronization in the dynamics of the number of links, both on the country and on the sectoral level. Hence, it is possible to calculate the fractions of links for each time window, which are presented in the bottom panel of figure 7. This normalization allows to detect shifts in the relative influences of specific countries or sectors. The country-wise view in the left bottom panel reveals that the relative number of links is rather stable for most countries, only the UK and Hong Kong show

⁵For comparison networks with links aggregated on the country level are shown in figure C.2 in the appendix. The large heterogeneity in the level of stock-stock dependencies however leads to a huge loss of information in the aggregation process.

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 2: Summary statistics for networks calculated using the 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.

a fluctuating behavior. The number of links for the US is steadily increasing towards the end of the sample period. The bottom right panel with the sectoral analysis shows more interesting developments. Only in 2007 and 2008 is the financial sector a driving force for interconnections. Much more dominant is the number of links that concern the energy and the materials sectors, which are both gaining influence throughout the sample.⁶ Stocks related to consumer goods become less and less important over time, the health industry is not very relevant for the entire sample period.

An interesting observation is that the ranking of most connected sectors is obviously slightly different at different time horizons. Remember that for the analysis based on the weekly data financial stocks had most links, followed by industrials. When we use the daily data and shorter time windows, stocks from energy and materials appear as strongly dominating the statistics, indicating that fast moving energy and raw material markets influence stocks in these sectors more immediate than the factors that are responsible for comovement that involves financials and industrials.

Finally, it is possible to study the general structure of the network and its change over time. Therefore we make use of some common measures from network science to describe the networks. Table 2 illustrates that the number of nodes is fluctuating between 26 and 84. The average number of links of each node, the degree, is related to the number of nodes. We observe that this relationship is only linear. We can take this as a hint that we do not simply observe a grow and decay of a fixed structure, but that the network is undergoing 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 figures that we observe for clustering in these networks are low

⁶Due to the low overall number of links the values (fractions) for the very first time window are a bit noisy and thus we discard them from our discussion.

no. of groups	West vs East ^A 2	America Eur. Asia ^B 3	dev. vs developing ^C 2	en/mat/util fin. 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 3: Modularity of the network over time. We calculate the assortativity coefficient for 5 different hypotheses for all 13 time windows. The results show that the network structure partly resembles a regional clustering (three leftmost columns) while international sectoral structures do not explain the observed networks (two rightmost 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

and they are relatively constant. This shows that the networks have some structure and that we are not talking about structures where everything is always connected to everything else. This is confirmed by the changes in the average path length, which are not simply varying with the network size. Their changes are caused by the contractions and diversions of single components of the network over time. At last, the density describes the fraction of existing versus possible links between nodes. These values are rather constant, because the links between sectors within countries lead to relatively high values for the density. It should be noted that if one would only look at links between different countries this impression would be change.

5. Mapping the network structure of the global market

In the previous section we have seen that a visualization of the network of stock market interconnections mostly leads to a layout where stocks from specific regions form connected cliques. We want to quantify this impression and therefore 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, which takes the value 1 if the actual distribution of links is perfectly described by the assumed grouping, and 0 if the

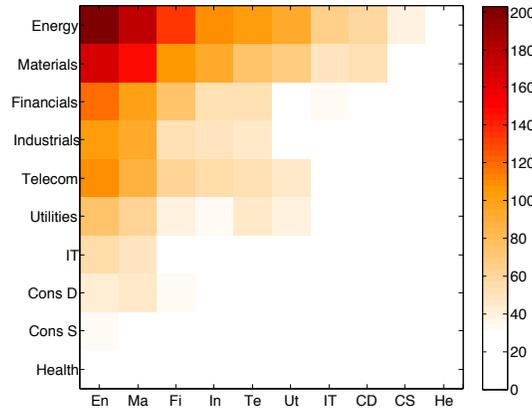


Figure 8: Number of significant links for all time windows, sector to sector, sorted. The figure shows the color coded count for the number of links between all combinations of sectors (regardless of the country). The sector names on the horizontal axis are the same as on the vertical in an abbreviated 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.

actual distribution of links is random and thus not explained at all by the grouping (see also section 2.4).

We check different hypotheses for a regional grouping. For example, it is possible to assume that the network consists of one group that contains all Western countries and another group that contains all Eastern countries. Alternatively we check if a division into America, Europe and Asia explains the network structure better. The assortativity coefficients for these two hypotheses are given by the two leftmost columns of table 3. The latter hypotheses results in the best description of the network. It is also better than a grouping into developed and developing stock markets (middle column). The segmentation into three regions does not explain the network perfectly, but it has some explanatory power. It is higher in times without severe crisis, that is until 2008 and in 2012, from 2009 until 2011 these traces of network structure are weakened and more volatile.

For comparison, we also calculate the assortativity coefficient for assuming that the most connected sectors that have been previously identified (energy, materials, financials) form connected cliques. It is however very notable that this is not a good description of the network, and the results are equally poor if one would discard links within countries. Also a grouping that combines sector with country characteristics, shown in the rightmost column does not lead to much better results (we assume that the financials, energy and materials form one clique in each region and that all other stocks are in group 4).

In the case of the static analysis, it was found that countries show a very heterogeneous patterns when it comes to 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 is a hint that the links on the sector level are not as assortative as on the country level. Thus we have to look at the 10×10 matrix of sector to sector links to find out what the structure of these links is.

Figure 8 is a color-coded representation of these relationships. We have 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). The result of this process uncovers that there is no grouping on the sectoral level. A core of very connected sectors is observed, namely the energy, materials and to slightly lesser extend the 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 that the connections between different stock markets heavily rely on these three sectors, but the connection is not necessarily most intense within one sector, but between related sectors. And in fact if one goes back to the visualizations on the previous pages (e.g. fig. 3) one can easily find many cases where the links between the different cliques are characterized by such kind of dependencies.

6. Conclusions

This paper presents an empirical investigation of interconnectedness and comovement across 15 different representative markets. Our empirical analysis shows that for the case of asset markets, a global financial market exists only within certain limits. We observe a mixture of regional and global 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. Even during such contraction periods, it is still possible to observe that some countries retain a high level of autonomous behavior.

A dimensional reduction of the dependencies in the global financial markets can be achieved by describing the markets in terms of sectors. This can be extremely useful for applications where one has to monitor a large number of assets, for example for strategic portfolio decisions or for the monitoring of macroprudential financial stability. Furthermore, the model presented here provides the means to quantify company specific risks. The first order risks arise from direct interactions on the individual company level, where the second order risks arise from direct interactions on the sector level. Thus, when determining the risk level of a given company - be it company-specific, regional, global or systemic - both risk channels must be considered.

Previous research has aimed at finding 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, like in our case, 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 IT bubble (see also Imbs, 2004; Raddant and Wagner, 2014). Furthermore, the ratio of volatility to returns comovement differs dependent on

the pair of countries chosen. These are all reasons why identifying country specific determinants for asset market comovement is very difficult. In fact, mostly they are probably at best secondary effects.

In general our results show that for a dynamic macroprudential monitoring we will need new methodologies. Such methodologies need to be able to quantify the interconnectedness amongst a large number of assets across many markets. To this end, this paper presents such a methodology: we quantify within and between market interconnectedness, and use network theory to present, quantify and monitor these relationships and how they change in time. Thus, future extensions of our work can be the development of hierarchical stress test models, where one can describe the interconnections of single stocks based on the sector and country based influences and macroeconomic shocks. Further it should be possible to use a model with data in higher frequency for the monitoring of financial stress and changes in spillover behavior.

Acknowledgements

The authors are grateful for discussions in the Kiel Institute staff seminar, the staff seminar at Kiel University, with participants at the Center for Polymer Research at Boston University, and with participants of the NBER summer institute and the conferences WEHIA and CEF. MR is grateful for partial funding of this research from the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement no. 619255. The article is also part of a research initiative launched by the Leibniz Community.

Appendix A. Statistical properties of the data

	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 A.1: Number of stocks by sector and country.

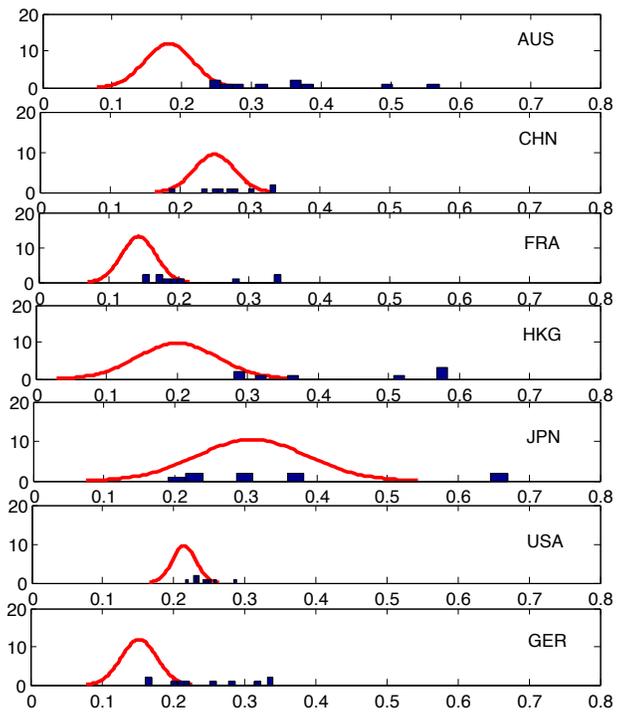


Figure A.1: Distribution of between-sector correlations of stocks (red curve) versus average correlations within the same sector (bars) for 7 countries. The correlation of stocks within sectors is mostly significantly higher than the average correlation and show higher dispersion. The remaining 8 markets behave similarly. Only for China and most of the Japanese market we observe a different behavior.

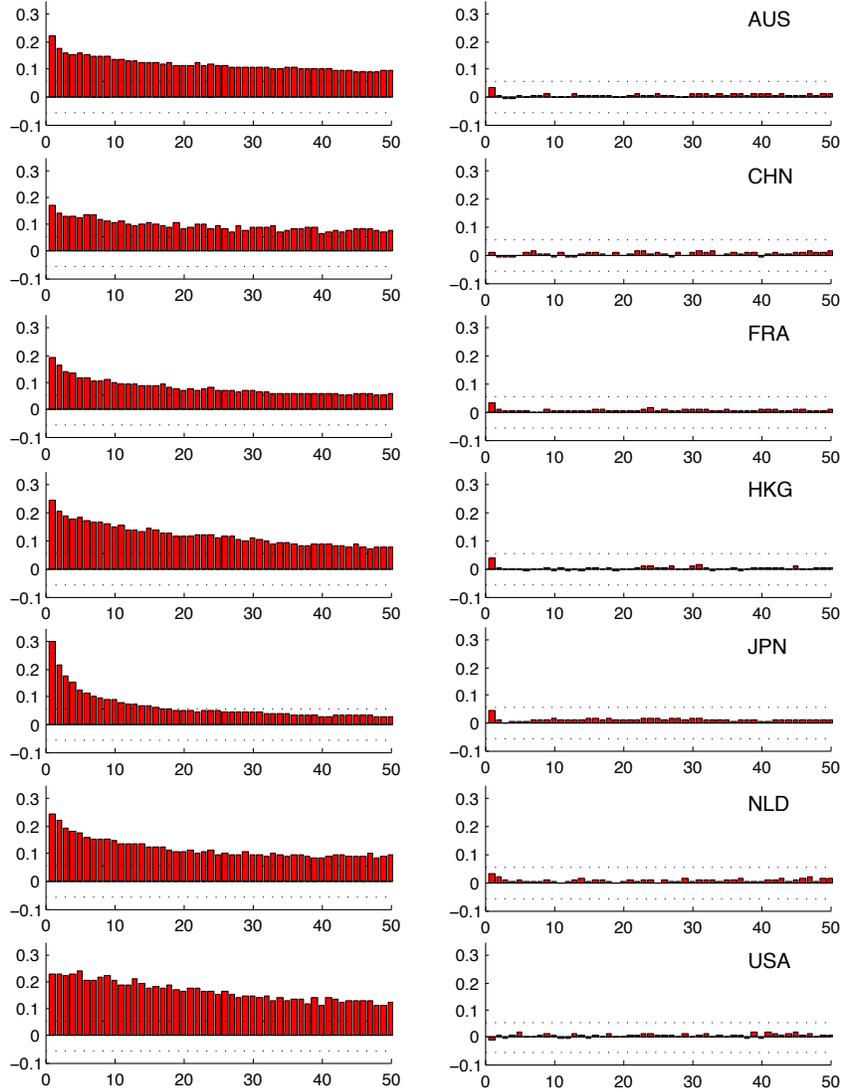


Figure A.2: Average auto-correlation functions for the absolute raw (left) and filtered returns (right) up to lag 50 for 7 countries. Although the markets show different levels of autocorrelation and different speed of decay, the GARCH(1,1) is able to produce de-garched time series which sufficient (insignificant) levels of autocorrelation. The results of the other 8 markets are very similar.

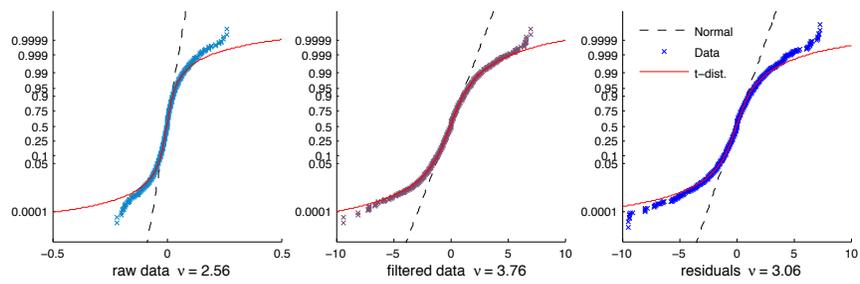


Figure A.3: Distributions of the raw returns (left panel), filtered returns (middle panel) and residuals (right panel) and fitted t-distributions. Sub-sample of roughly 20,000 observations. The degrees of freedom for the fitted t-distribution are given below each plot.

Appendix B. Robustness Analysis

A test for our results is to check whether the estimated dependencies differ from the results of the standard multivariate GARCH models. Prominent versions are the Constant Conditional Correlation model Bollerslev (1990) 1990), the Dynamic Conditional Correlation model Engle (2002), or the Model by Baba, Engle, Kraft and Kroner (BEKK). One limitation of these models is that it is not possible to estimate these models with the entirety of our data jointly, but it is possible to check if the obtained correlations from a pairwise estimation are similar to the correlations obtained from the filtered data (where the volatility is removed for each time series independently).

To compare the correlations for the entire time series as well as for a rolling window, we will estimate the DCC model, which will deliver a time dependent correlation matrix. To limit the computation time we choose a sub-sample of 77 randomly selected stocks and estimate the DDC pairwise (the BEKK model delivers almost identical results). For a detailed discussion of the model the reader is referred to Bauwens et al. (2006) and Engle (2002). In brief, within a multivariate GARCH model one tries to find a matrix of conditional variances denoted H_t . In the specification of the DDC model by Engle and Sheppard it is assumed that the correlations between the assets are time varying, such that (in the $p = q = 1$ case)

$$H_t = D_t R_t D_t \quad (\text{B.1})$$

where

$$D_t = \text{diag}(h_{11,t}^{1/2}, \dots, h_{NN,t}^{1/2}) \quad (\text{B.2})$$

with the h_t s as defined before and

$$R_t = \text{diag}(q_{11,t}^{1/2}, \dots, q_{NN,t}^{1/2}) Q_t \text{diag}(q_{11,t}^{1/2}, \dots, q_{NN,t}^{1/2}) \quad (\text{B.3})$$

where

$$Q_t = (1 - \alpha - \beta) \bar{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1} \quad (\text{B.4})$$

where α and β are parameters, \bar{Q} is the unconditional variance of u , and $u_{it} = \varepsilon_{it} / \sqrt{h_{it}}$.

The resulting h_t s from the different models are extremely similar and hence also the correlation coefficients are almost identical, at least when one averages over the entire time period. The left and middle panel in figure B.1 both show a scatter plot of the correlation coefficients of the time series of raw returns versus the time series normalized by the estimated volatility. Both correct the calculated correlation coefficient downwards by the same amount. The right panel shows a scatter plot of the correlation coefficients of the DCC model versus those of our uni-variate filtering.

These results also hold on average when looking at the averaged dynamic correlation coefficient for the 13 time windows we used for our analysis. Figure B.2 shows scatter plots of correlation coefficients for filtered returns time series (uni-variate vs. DCC model) for 4 of the 13 time windows. The plots show slightly greater variation than the plots for the entire time period.

The results also hint that it is possible to look a correlation networks one much smaller time scale then in the remainder of the paper, if one used the dynamic correlation coefficients from the DCC model. This would however necessitate to employ the estimation on a massive computer cluster using parallel computation.

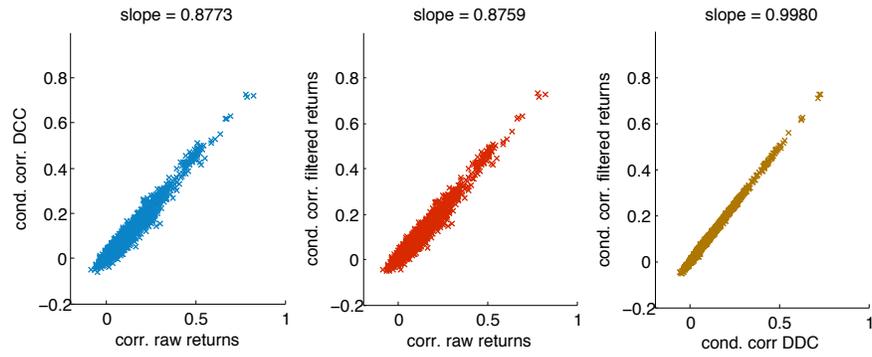


Figure B.1: The left panel shows the correlation of raw returns vs. the correlation conditional on the volatility estimated by the DCC model. The middle panel shows the same for the correlation vs. the correlation of the GARCH filtered returns. The right panel compares the correlation coefficients from the simple GARCH and DCC model. Both models correct the correlation to about 87% of the one that one would get from the raw returns.

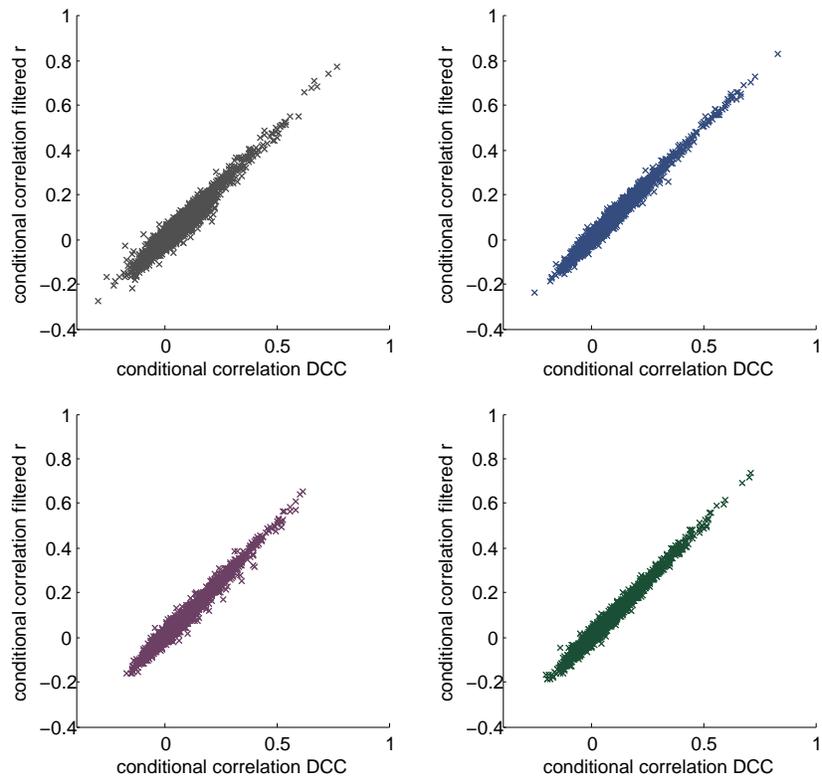


Figure B.2: Scatter plots of the correlations of the filtered returns versus the average of the correlation from the DCC model for 4 randomly chosen time windows.

Appendix C. Network visualizations

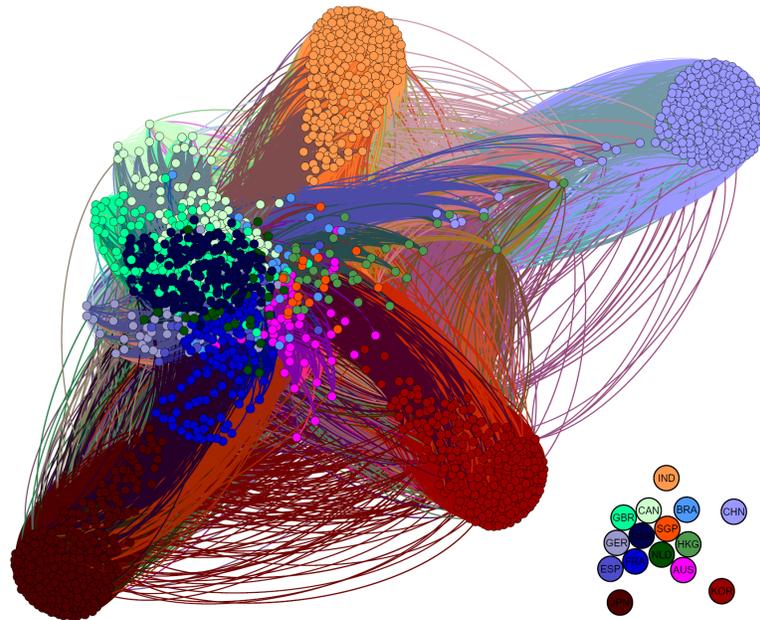


Figure C.1: Network representation based on the estimated dependencies from the weekly data. The figure shows a visualization of the network of stocks where the weighted links correspond to stock dependencies that at least satisfy the 90 percent confidence interval. Stocks from the same country have the same color, a legend of the color coding is shown at the bottom right. We observe that the stocks of most countries form a mixed cluster in the center of the figure. However, we still observe regional structures as well as parts of national stocks markets that are at the periphery of the mixed cluster. The stocks from the markets in India, China, Japan, and South Korea are not part of the central cluster. These countries show different levels of connectedness towards it. While parts of the Japanese market seem to form a bridge towards the different parts of the center, the connections of Chinese stocks are weaker and less diverse. The visualization was performed in Gephi using the Yifan Hu multilevel algorithm.

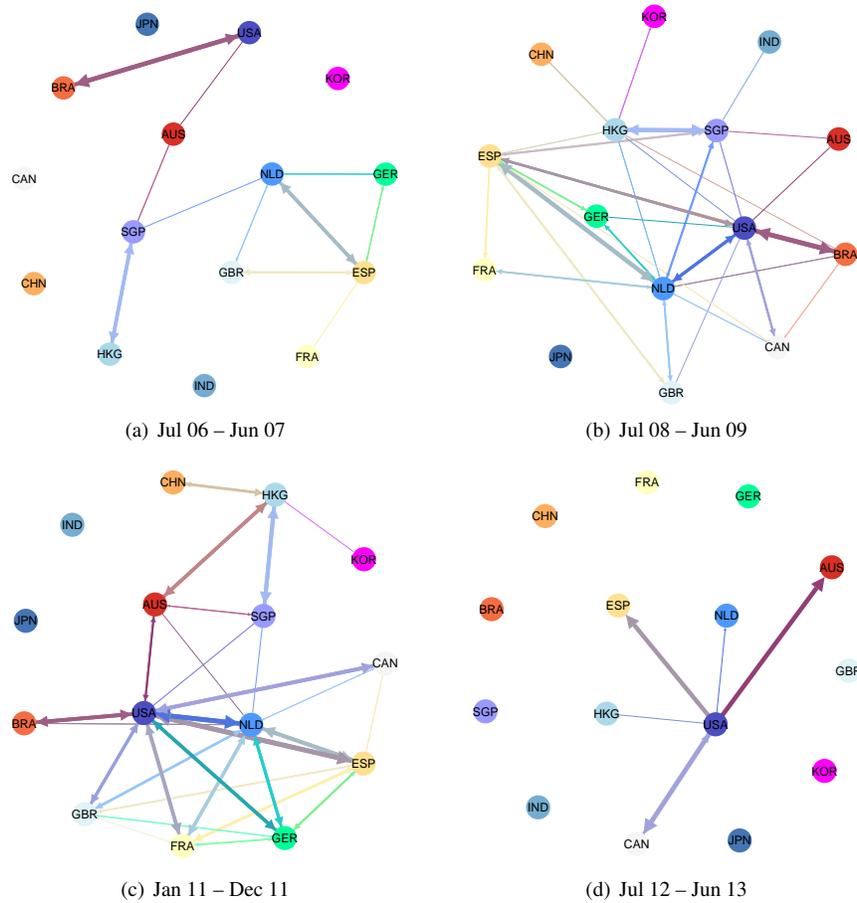


Figure C.2: Dynamics of country dependency networks. We show 4 networks that are representative for the dynamics within the total of 13 time windows. The weighted links represent an average p-value of 0.25 or better. This low threshold is necessary since the heterogeneity on the stock-stock interdependency level is rather large. This also indicates that there is 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.

References

- Ahlgren, N., Antell, J., 2010. Stock market linkages and financial contagion: A co-breaking analysis. *The Quarterly Review of Economics and Finance* 50 (2), 157–166.
- Barberis, N., Shleifer, A., Wurgler, J., 2005. Comovement. *Journal of Financial Economics* 75 (2), 283–317.
- Baur, D., Jung, R. C., 2006. Return and volatility linkages between the US and the German stock market. *Journal of International Money and Finance* 25, 598–613.
- Bauwens, L., Laurent, S., Rombouts, J. V., 2006. Multivariate garch models: a survey. *Journal of Applied Econometrics* 21 (1), 79–109.
- Beine, M., Candelon, B., 2011. Liberalisation and stock market co-movement between emerging economies. *Quantitative Finance* 11 (2), 299–312.
- Bekaert, G., Hodrick, R. J., Zhang, X., 2009. International stock return comovement. *Journal of Finance* 64 (6), 2591–2626.
- Billio, M., Getmansky, M., Lo, A. W., Pelizzon, L., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics* 104 (3), 535–559.
- Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: a multivariate generalized arch model. *The Review of Economics and Statistics*, 498–505.
- Brooks, R., Del Negro, M., 2004. The rise in comovement across national stock markets: Market integration or IT bubble? *Journal of Empirical Finance* 11 (5), 659–680.
- Christensen, K., Kinnebrock, S., Podolskij, M., 2010. Pre-averaging estimators of the ex-post covariance matrix in noisy diffusion models with non-synchronous data. *Journal of Econometrics* 159 (1), 116–133.
- Curme, C., Tumminello, M., Mantegna, R. N., Stanley, H. E., Kenett, D. Y., 2015. Emergence of statistically validated financial intraday lead-lag relationships. *Quantitative Finance* 15 (8), 1375–1386.
- Diebold, F. X., Yılmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics* 182 (1), 119–134.
- Dutt, P., Mihov, I., 2013. Stock market comovement and industrial structure. *Journal of Money, Credit and Banking* 45 (5), 891–911.
- Engle, R., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics* 20 (3), 339–350.

- Engle, R. F., Shephard, N., Sheppard, K., 2008. Fitting vast dimensional time-varying covariance models. NYU Working Paper FIN-08-009, NYU.
- Forbes, K. J., Chinn, M. D., 2004. A decomposition of global linkages in financial markets over time. *The Review of Economics and Statistics* 86 (3), 705–722.
- Forbes, K. J., Rigobon, R., 2002. No contagion, only interdependence: measuring stock market comovements. *The Journal of Finance* 57 (5), 2223–2261.
- Fratzscher, M., 2012. Capital flows, push versus pull factors and the global financial crisis. *Journal of International Economics* 88, 341–356.
- Fry, R., Martin, V. L., Tang, C., 2010. A new class of tests of contagion with applications. *Journal of Business & Economic Statistics* 28 (3), 423–437.
- Gajurel, D. P., Dungey, M. H., 2015. Contagion and banking crisis—international evidence for 2007-2009. *Journal of Banking and Finance* 60, 271–283.
- Glasserman, P., Young, H. P., 2015a. Contagion in financial networks. OFR WP, 15–21.
- Glasserman, P., Young, H. P., 2015b. How likely is contagion in financial networks? *Journal of Banking & Finance* 50, 383–399.
- Gopikrishnan, P., Rosenow, B., Plerou, V., Stanley, H. E., 2001. Quantifying and interpreting collective behavior in financial markets. *Physical Review E* 64 (3), 035106.
- Green, T. C., Hwang, B.-H., 2009. Price-based return comovement. *Journal of Financial Economics* 93 (1), 37–50.
- Hayashi, T., Yoshida, N., 2008. Asymptotic normality of a covariance estimator for nonsynchronously observed diffusion processes. *Annals of the Institute of Statistical Mathematics* 60 (2), 367–406.
- Hu, Y., 2005. Efficient, high-quality force-directed graph drawing. *Mathematica Journal* 10 (1), 37–71.
- Imbs, J., 2004. Trade, finance, specialization, and synchronization. *The Review of Economics and Statistics* 86 (3), 723–734.
- Kaminsky, G., Reinhart, C., 2000. On crises, contagion, and confusion. *Journal of International Economics* 51 (1), 145–136.
- Kenett, D. Y., Raddant, M., Lux, T., Ben-Jacob, E., 2012. Evolvement of uniformity and volatility in the stressed global financial village. *PloS one* 7 (2), e31144.
- Lange, K. L., Little, R. J., Taylor, J. M., 1989. Robust statistical modeling using the t distribution. *Journal of the American Statistical Association* 84 (408), 881–896.
- Levy-Carciente, S., Kenett, D. Y., Avakian, A., Stanley, H. E., Havlin, S., 2015. Dynamical macroprudential stress testing using network theory. *Journal of Banking and Finance* 59, 164–181.

- Mantegna, R. N., Stanley, H. E., 1999. Introduction to econophysics: correlations and complexity in finance. Cambridge university press.
- Martens, M., Poon, S.-H., 2001. Returns synchronization and daily correlation dynamics between international stock markets. *Journal of Banking & Finance* 25 (10), 1805–1827.
- Newman, M., 2010. Networks: an introduction. Oxford University Press.
- Newman, M. E., 2006. Modularity and community structure in networks. *Proceedings of the National Academy of Sciences* 103 (23), 8577–8582.
- Raddant, M., Wagner, F., 2014. Transmissions in the stock markets of the US, UK, and Germany. Kiel working paper 1979.
- Rigobon, R., 2003. On the measurement of the international propagation of shocks: is the transmission stable? *Journal of International Economics* 61, 261–283.
- Song, D.-M., Tumminello, M., Zhou, W.-X., Mantegna, R. N., 2011. Evolution of worldwide stock markets, correlation structure, and correlation-based graphs. *Physical Review E* 84 (2), 026108.
- Summer, M., 2013. Financial contagion and network analysis. *Annu. Rev. Financ. Econ.* 5 (1), 277–297.
- Tumminello, M., Miccichè, S., Lillo, F., Piilo, J., Mantegna, R. N., 2011. Statistically validated networks in bipartite complex systems. *PloS ONE* 6 (3), e17994.