Interconnectedness in the Global Financial Market

Matthias Raddant[a,b] Dror Y. Kenett[c]

(a) Kiel Institute for the World Economy, Kiel, Germany
(b) Kiel University, Department of Economics
(c) Office of Financial Research, U.S. Department of the Treasury, Washington DC

Agenda

Motivation

Financial integration has let to global financial markets, markets are linked to each other
Economic issues:

- Is this actually true?
- Are these relationships stable?
- Are all markets synchronized at the same level?

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Technical issue:

- Describe a system with $N > T$?
- Statistical significance in a network?
- Keep computational effort reasonable
- Work with non-synchronous data

Literature

Four strands of related literature

- Implications of market openness on **business cycles**: Brooks and Del Negro (JEF 2004), Beine and Candelon (QF 2011), Imbs (RES 2004). Business cycles can become more synchronized. Depends also on similarities in industry structure, often overshadowed by country-specific effects
- Pure **financial contagion**: Rigibon (JIE 2003), Dutt and Mihov (JMCB 2013), Bekaert et al. (JoF 2009), Forbes and Chinn (RES 2004): cross-country vs. sectoral factors
- Asset pricing and **comovement** within markets: Barberis et al. (JFE 2005), Green and Hwang (JFE 2009) and between markets: Fry et al. (JBES 2010), Forbes and Rigobon (JF 2002)
- **Network** science approaches to **contagion**: Mantegna and Stanley (1999), Summer (ARFE 2013), Glasserman and Young (JBF 2015)

Data

- Data from Compustat and Datastream for **15 countries**
- Australia, Brazil, China, Spain, France, UK, Hongkong, India, Japan, South Korea, the Netherlands, Singapore, USA, Canada and Germany.
- **1 July 2006 – 30 June 2013** (8 years) $T = 1329$ trading days and $N = 3828$ stocks
- Aggregation to weekly returns $T' = 365$
- Top-level **sector information** GICS/TRBC

Sector-wise analysis

- To reduce the dimensionality some clustering of the stocks is helpful, here we use existing sector information, however, also an endogenous determination is possible
- We should however check if the sector information is a useful grouping
- Is the correlation of stocks within a sector higher than the average correlation?
- **Yes**, for all except China and Japan

Within-sector correlations vs average correlation

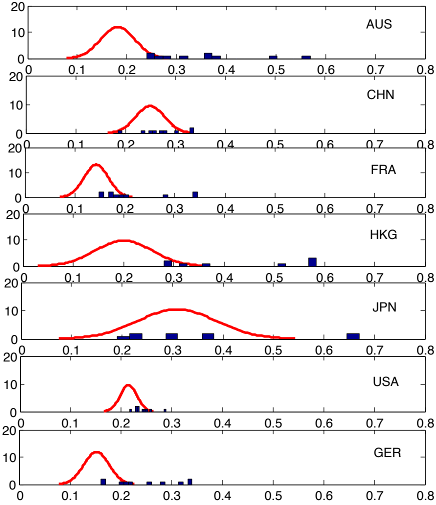


Figure : Histograms of between-sector correlations (red curve) vs. average correlations within the same sector (bars) for 7 countries.

De-Garching

Volatility clustering and fat tails make it difficult to measure comovement. Way out: assume stock returns can be described by the GARCH model. 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 us of the conditional variance h_t to calculate **filtered returns** 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.

Estimation

1. Estimate GARCH(1,1) and calculate filtered returns
2. Estimate pairwise dependencies for all pairs of stocks ij (robust regression, t-distributed errors)

$$r_i^f = \beta_{0,ij} + \beta_{1,ij} r_j^f \tag{3}$$

3. and obtain a matrix of p-values p_{ij}
4. Average over all stocks in one sector in one country and all stocks in one sector in another country

Non-synchronous trading

The stocks are traded on markets all around the globe: what to do?

- turn to weekly returns (bad time resultion)
- or: apply some correction on daily data
- Recent literature: Hayashi and Yoshida (AISM 2008), Christensen, Kinnebrock, Podolskij (JoE 2010)

Assume that in a large time window the correlations of the weekly and the daily returns should be very similar if they were synchronous. 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. We can calculate the element-wise (notation: ./) ratio of the p-values of the weekly and daily estimates.

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

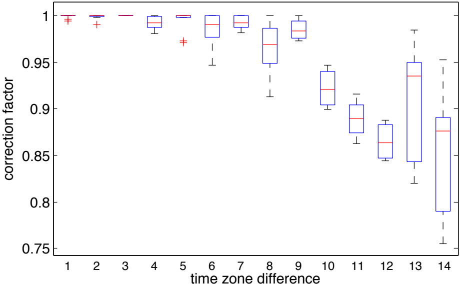
Non-synchronous trading

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. For numerical reasons we remove few entries outside $[0, 1]$. The corrected p-values can then be obtained as

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



From estimation results to networks

For all stocks

- Define **threshold** γ for p
- Remove entries/links with a value below this threshold
- Define $adj_{ij} \propto (\gamma - p_{ij})$

For sectors

- **Average** p for pairs of country/sector–country/sector
- Remove entries/links below threshold
- Discard dependencies from sectors smaller 2×3
- Define $adj_{ss} \propto (\gamma - p_{ij \in s})$

For countries ...

Visualize network with Gephi using the Yifan Hu algorithm

Estimation results

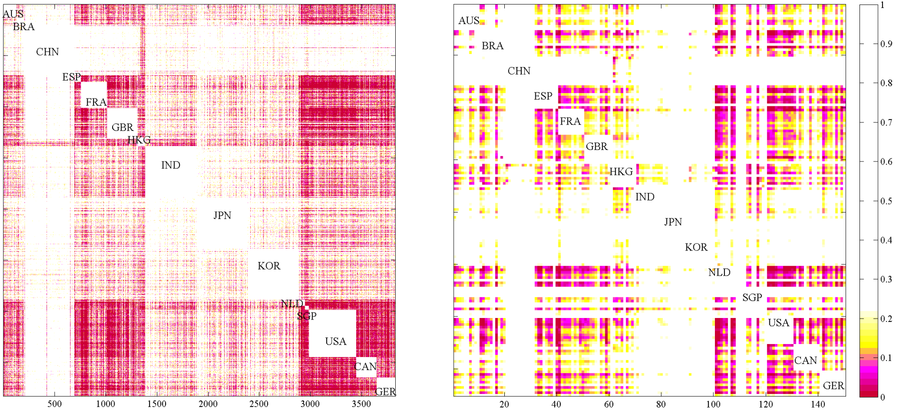
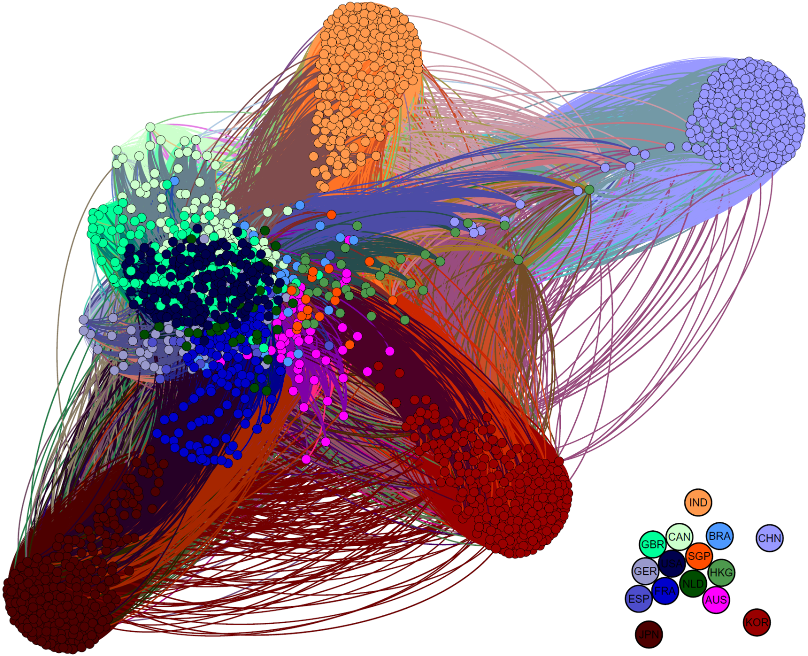
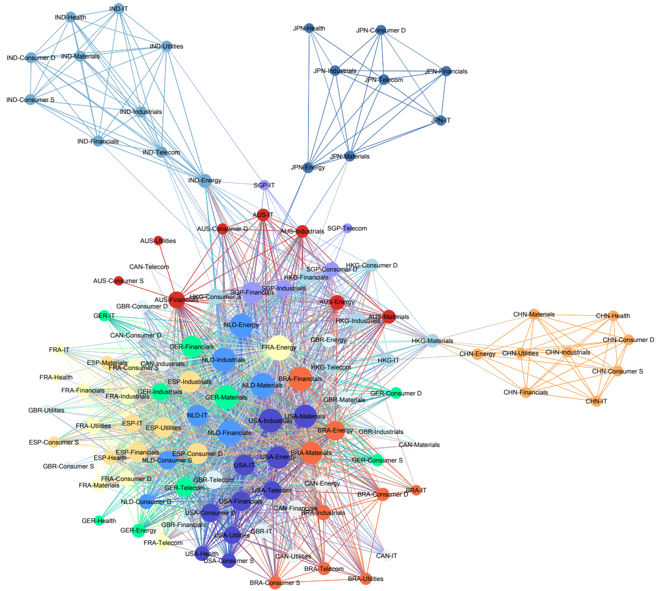


Figure : p-values for the stock-stock dependencies (left) and its sector averages (right). The stocks are arranged by countries and the abbreviated country names are plotted along the main diagonal. Entries for dependencies within countries have been removed.

Stocks



Sectors


IND-IT
IND-Health
IND-Utilities
IND-Consumer D
IND-Materials
IND-Consumer S
IND-Industrials
IND-Financials
IND-Telecom
IND-Energy
JPN-Health
JPN-Consumer D
JPN-Industrials
JPN-Telecom
JPN-Financials
JPN-IT
JPN-Materials
JPN-Energy
SGP-IT
AUS-IT
AUS-Consumer D
AUS-Industrials
SGP-Telecom
AUS-Utilities
CAN-Telecom
AUS-Consumer S
HKG-Consumer D
SGP-Consumer D
HKG-Financials
SGP-Industrials
SGP-Financials
HKG-Consumer S
AUS-Financials
AUS-Energy
GBR-Consumer D
AUS-Materials
HKG-Industrials
GER-IT
NLD-Energy
CAN-Consumer D
GBR-Energy
HKG-Materials
GER-Financials
FRA-Energy
FRA-IT
NLD-Industrials
HKG-IT
ESP-Materials
CAN-Industrials
FRA-Consumer S
HKG-Telecom
FRA-Health
ESP-Industrials
BRA-Financials
NLD-Materials
FRA-Financials
GER-Industrials
FRA-Industrials
GER-Materials
GER-Consumer D
GBR-Materials
GBR-Utilities
NLD-IT
USA-Materials
USA-Industrials
FRA-Utilities
ESP-IT
ESP-Utilities
BRA-Energy
GBR-Industrials
NLD-Financials
ESP-Consumer S
CAN-Materials
ESP-Financials
ESP-Consumer D
BRA-Materials
ESP-Health
NLD-Consumer S
USA-Energy
GER-Consumer S
GBR-Consumer S
USA-IT
FRA-Consumer D
FRA-Materials
GBR-Telecom
CAN-Energy
GER-Telecom
USA-Telecom
BRA-IT
BRA-Consumer D
NLD-Consumer D
USA-Financials
CAN-Financials
BRA-Industrials
USA-Consumer D
GER-Health
GBR-Financials
GER-Energy
GBR-IT
USA-Utilities
FRA-Telecom
USA-Health
USA-Consumer S
CAN-Utilities
CAN-IT
BRA-Telecom
BRA-Consumer S
BRA-Utilities
CHN-Materials
CHN-Health
CHN-Consumer D
CHN-Energy
CHN-Utilities
CHN-Industrials
CHN-Consumer S
CHN-Financials
CHN-IT

Significant links

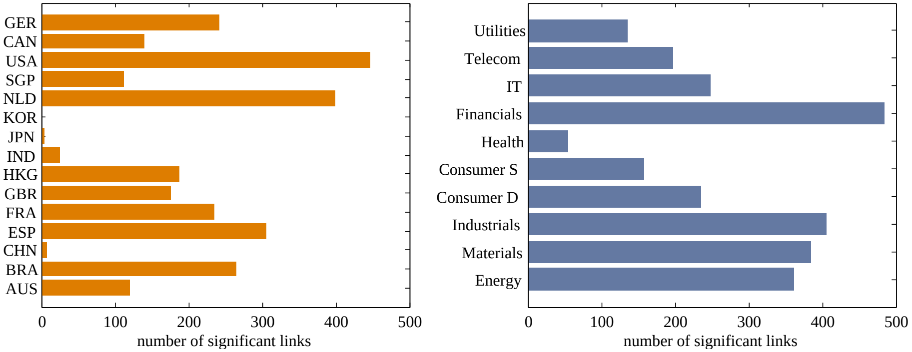
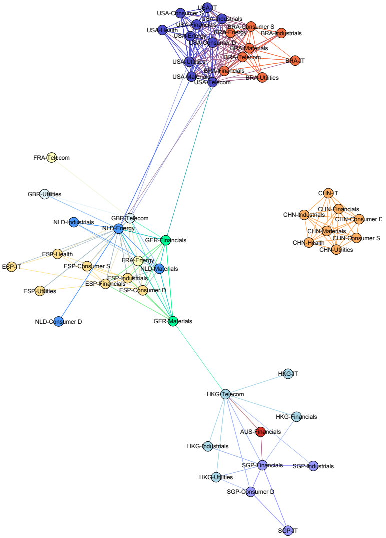
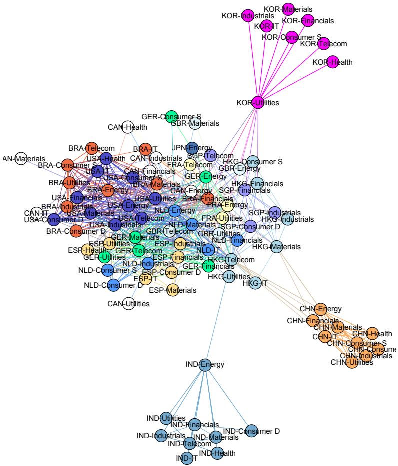


Figure : Number of significant links between sectors on the country (left) and sector level (right).

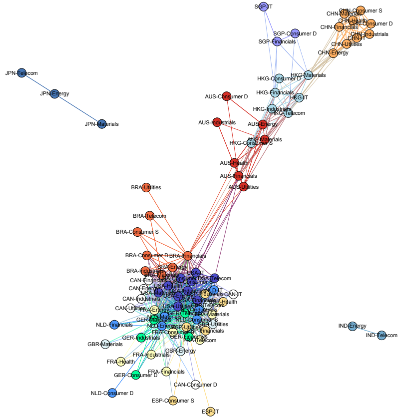
Jan 07 – Dec 07



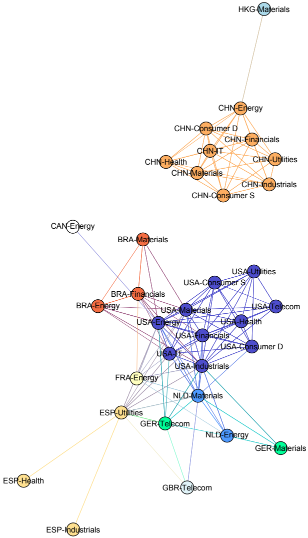
Jul 08 – Jun 09



Jan 11 – Dec 11



Jul 12 – Jun 13



Dynamics

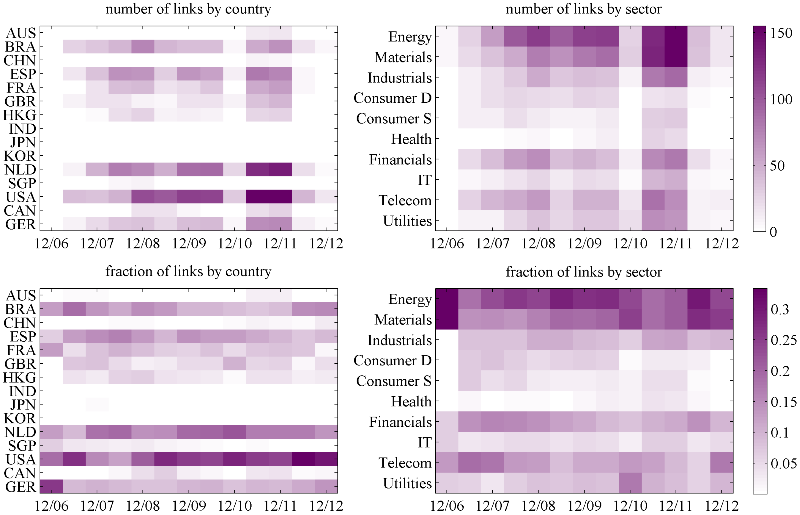


Figure : Number of significant links over time by country and by sector.

Sectoral influences?

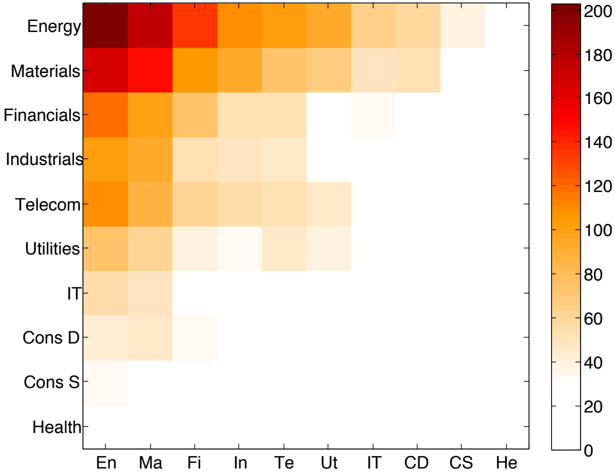


Figure : Number of significant links for all time windows, sector to sector, sorted.

Modularity

What is the most general structure that this network resembles? 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. Denote by c the groups...

$$\sum_{\text{edges}}(c_i, c_j) = \frac{1}{2}\sum_{ij} A_{ij}\delta(c_i, c_j) \tag{7}$$

The expected number of links: 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

$$\frac{1}{2}\sum_{ij} \frac{k_i k_j}{2m}\delta(c_i, c_j) \tag{8}$$

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

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

which describes in how far nodes of the same group are connected with each other. In order to compare calculate associativity coefficient $AC = Q/Q_{max}$.

Modularity

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
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 : Modularity of the network over time. 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

Conclusions

Some insights

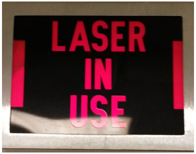
- Network analysis with meaningful statistics is possible and is useful for handling heterogeneity in stock characteristics
- Stock market dependencies show structures but are also very volatile
- **Financials, Materials, Energy** sector co-move heavily, depends on time-scale
- There is still segmentation between markets: Japan, Korea, China, India slightly de-coupled

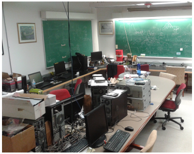
Possible extensions

- Endogenous sectors
- Portfolio application
- Correlation with macroeconomic quantities and other asset classes

Thank You

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. This paper benefited from helpful comments by Mark Flood, Shlomo Havlin, H. Eugene Stanley, Charles Taylor, Julie Vorman, and Peyton Young.





The data by sector

Sec	Energ	Mater	Indus	ConsD	ConsS	Health	Finan	IT	Telec	Utili
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 : Data by country and some statistics

Some statistics

	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 : Statistics for the returns time series. Variance, Kurtosis and the tail exponent have been calculated from all returns in each country.

Robustness

The robustness of these results (at least the pair-wise case) can be checked against slightly more elaborate models: Constant Conditional Correlation (Bollerslev 1990), Dynamic Conditional Correlation (Engle 2002), BEKK (Vector GARCH, Bauwens, 2006).

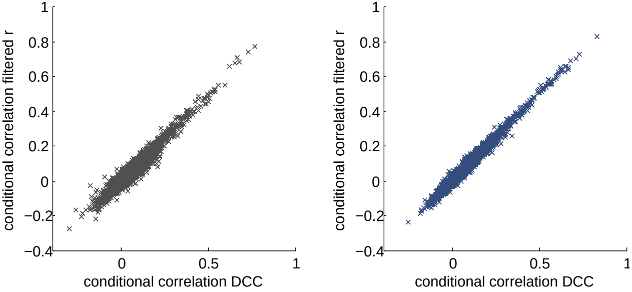


Figure : Scatter plots of the correlations of the filtered returns versus the average of the correlation from the DCC model for 2 randomly chosen time windows.

Volatility vs returns