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Keywords: financial markets, comovement, financial crisis, stock correlations, networks

JEL classification: G15, G01, F36

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Abstract

In the current era of strong worldwide market couplings the global financial village became highly prone to systemic collapses, events that can rapidly sweep through out the entire village. Here we present a new methodology to assess and quantify inter-market relations. The approach is based on the correlations between the market index, the index volatility, the market Index Cohesive Force and the meta-correlations (correlations between the intra-correlations.) We investigated the relations between six important world markets - U.S., U.K., Germany, Japan, China and India from January 2000 until December 2010. We found that while the developed "western" markets (U.S., U.K., Germany), are highly correlated, the interdependencies between these markets and the developing "eastern" markets (India and China) are very volatile and with noticeable maxima at times of global world events (2001: 9/11-attacks, 2003: Iraq war, SARS, etc). The Japanese market switches "identity" - it switches between periods of high meta-correlations with the "western" markets and periods that it behaves more similar to the "eastern" markets. These and additional reported findings illustrate that the methodological framework provides a way to quantify the evolvement of interdependencies in the global market, to 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. Hence, the new approach can help to develop a sensitive "financial seismograph" to detect early signs of global financial crises so they can be treated before developed into world wide events.

1 Introduction

Has the world become one small financial global village? Coupling between the world's different markets has become stronger and stronger over the past years, as is evidenced by the financial difficulties, which are affecting many markets around the globe, especially since late 2008. The growing financial integration allows capital to flow rather freely between countries and markets. Investments in stocks can be diversified into global portfolios, consisting of multiple assets from a large number of markets. As a result, stock markets have turned into an extended and strongly coupled complex system, in which large movements in price and volatility are likely to be transferred from one market to the other due to portfolio readjustments. Engle et al. [1] have shown that volatility clusters are likely to occur jointly in different markets. This fact and other evidence of the interdependencies between the world's economies emphasize the need to understand the coupling and integration of stock markets around the world. As the financial crisis of 2008 was not even considered a possibility by the leading economic theories [2], it is necessary to rethink and reformulate the understanding and quantification of the coupling between different markets.

When it comes to the analysis of individual markets, a wealth of different measures have been devised and used to analyze similarity between financial time series. These include Pearson's correlations [3, 4, 5, 6], co-movement measures [7], recurrence patterns [8], and regime switching approaches [9, 10]. There are also studies of the co-movement of different stock markets. Forbes and Rigobon [11] have shown that a high level of dependence is visible between most markets and that changes in correlation are coupled to volatility changes. However, there are mixed results about the driving forces of the amount of co-movement and of financial integration. While King et al. [12] did not clearly identify the reasons for changes in the correlation, Beile and Candelon [13] found evidence that increased trade and financial liberalization go hand in hand with a synchronization of stock markets. Furthermore, Ahlgren and Antell [14] found that markets are linked closer in times of crisis which significantly hampers the possibility to diversify investments and thus risks. Additional studies looked at correlation structures in particular markets, like Tumminello et al. [15], or at the correlation between the indices of different markets, see e.g. Song et al. [18].

Recently, Kenett et al. investigated the dynamics of correlations between stocks belonging to the S&P 500 index, and the residual (partial) correlations after removing the influence of the index [3]. To this end, the Index Cohesive Force (ICF), which is the ratio between the average stock correlation, and average stock partial correlation, was introduced. Studying the dynamics of these quantitative measures, a transition in the dynamics of the U.S. market at the end of 2001 was observed. Here we expand these previous analyses to the investigation of other markets. We further extend the scope of the analysis by studying the markets intra and inter correlations. First, we study correlation

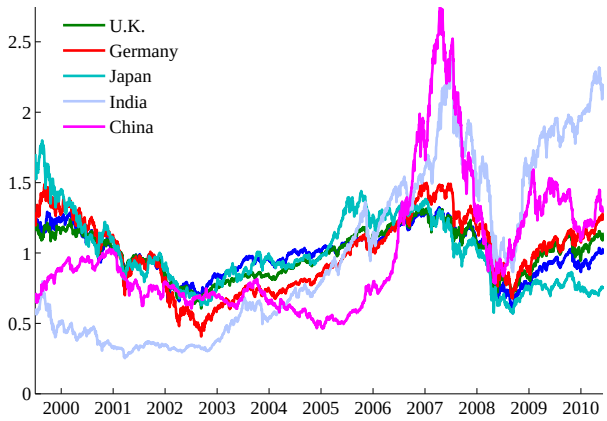

Fig. 1: Normalized stock price indices; S&P 500 (U.S.), FTSE 350 (U.K.), DAX 30 Performance (Germany), NIKKEI 500 (Japan), BSE 100 (India), and SSE Composite (China). All indices have been normalized by their mean. The indices of the U.S., U.K. and Germany (blue, green and red line) appear almost as if they are shifted parallel, which is a sign of their high correlation. Note that all price indices are based on stock prices in local currency.

structures on the level of single markets, the market intra-correlation. Next, we study the correlation between different market pairs, according to three measures - the market index correlation, market meta-correlation, and market ICF correlation.

2 Methods

The similarity between stock price changes is commonly calculated via the Pearson's correlation coefficient. The raw stock correlations [5] are calculated for time series of the log of the daily return, given by:

$$r_i(t) = log[P_i(t)] - log[P_i(t-1)] \tag{1}$$

Where $P_i(t)$ is the daily adjusted closing price of stock i at day t. The raw stock correlations are calculated using Pearson's correlation coefficient between every pair of stocks i and j, where

$$C(i,j) = \frac{\langle (r_i - \langle r_i \rangle)(r_j - \langle r_j \rangle) \rangle}{\sigma_i \sigma_j} \tag{2}$$

$\langle\rangle$ denotes average, and σ_i are the standard deviations (STD).

Partial correlation is a powerful tool to investigate how the correlation between two stocks depends on the correlation of each of the stocks with a third

mediating stock or with the index as is considered here. The residual, or partial, correlation between stocks i and j, using the Index (m) as the mediating variable is defined by [6, 16, 21].

$$\rho(i,j|m) = \frac{C(i,j) - C(i,m)C(j,m)}{\sqrt{(1-C^2(i,m))(1-C^2(j,m))}} \tag{3}$$

Note that according to this definition, $\rho(i,j|m)$ can be viewed as the residual correlation between stocks i and j, after subtraction of the contribution of the correlation between each of the stocks with the index.

To investigate the dynamics of correlations in capital markets, we make use of a running window analysis. We use a short time window, of 22-trading days, which is equivalent to one work month, with a full overlap. Thus, for example the first window will be days 1-22, the second window day 2-23, etc. At each window we calculate stock correlation and partial correlation matrices, and average them. This results in a value of correlation (partial correlation) for each stock, representing its average correlation (partial correlation) to all other stocks. This is defined as

$$\overline{C(i)} = \frac{1}{N-1}\sum_{j\neq i}^{N} C(i,j) \tag{4}$$

$$\overline{PC(i)} = \frac{1}{N-1}\sum_{j\neq i}^{N} \rho(i,j|m) \tag{5}$$

Finally, we calculate the average of average correlations (partial correlations), which represents the total average correlation (partial correlation) in the market,

$$C^{intra} = \frac{1}{N}\sum_{i=1}^{N} \overline{C(i)} \tag{6}$$

$$PC^{intra} = \frac{1}{N}\sum_{i=1}^{N} \overline{PC(i)} \tag{7}$$

We denote this variable as the intra-correlation (intra partial correlation), as it represents the average correlation of stocks belonging to one given market.

Next, we investigate the synchronization of two given markets. To this end, we calculate correlation and lagged cross correlation between the intra correlations of each market. The correlation of market correlations is denoted as market meta-correlation (MC), given by

$$MC(d) = \frac{\sum_{t=1}^{N-d}\left(\overline{C^i(t)} - \left\langle \overline{C^i} \right\rangle\right)\left(\overline{C^j(t)} - \left\langle \overline{C^j} \right\rangle\right)}{\sqrt{\sum_{t=1}^{N-d}\left(\overline{C^i(t)} - \left\langle \overline{C^i} \right\rangle\right)^2}\sqrt{\sum_{t=1}^{N-d}\left(\overline{C^j(t)} - \left\langle \overline{C^j} \right\rangle\right)^2}} \tag{8}$$

$$d = 0, \pm 1, \pm 2, \ldots, \pm N - 1 \tag{9}$$

Market	Stocks used	Index used	# before	# filtered
U.S.	S&P 500	S&P 500	500	403
U.K.	FTSE 350	FTSE 350	356	116
Germany	DAX Composite	DAX 30 Performance	605	89
Japan	Nikkei 500	Nikkei 500	500	315
India	BSE 200	BSE 100	193	126
China	SSE Composite	SSE Composite	1204	69

Tab. 1: Summary of data used

Where d is the lag.

Recently, it was shown that the market index has a cohesive effect on the dynamics of the stock correlations [3, 6]. This refers to the observed effect the index has on stock correlations, where we have found that larger changes of the index result in higher stock correlations, and as such more cohesive force. The Index Cohesive Force is defined as $ICF(\tau)$ – the index cohesive force calculated over a time window τ, as a measure of the balance between the raw and residual correlations given by,

$$ICF(\tau) = \frac{\overline{\langle C(i,j)\rangle_\tau}}{\overline{\langle \rho(i,j|m)\rangle_\tau}} = \frac{C_\tau^{intra}}{PC_\tau^{intra}} \tag{10}$$

where τ is the time window, during which the average correlation and average residual correlation are calculated. $\overline{\langle C(i,j)\rangle_\tau}$ and $(\overline{\langle \rho(i,j|m)\rangle_\tau})$ are the mean of average correlation and average partial correlation.

3 Data

For the analysis reported in this paper we use data of the daily adjusted closing price from stocks in six different markets, all downloaded from Thomson Reuters Datastream. The markets investigated are the U.S., U.K., Germany, Japan, India and China. These include the four main stock markets as well as two less developed markets for comparison of the results. For each market we aimed for a sample as broad as possible, without any ex ante selection of branches. See Table 1 for details on the used stocks.

The number of stocks finally used in our analysis shrinks down significantly, because we only consider stocks that are active from January 2000 until December 2010. We used volume data to identify and eliminate illiquid stocks from our sample. In our case this corresponded to filtering for stocks which had no movement in the price for more than 6 percent of the 2700 trading days (a list of the stocks used can be found in the supplementary information). In total the analysis is based on round about 3 million daily price observations.

It should be noted that the correlations we measured have some explanatory limitations, which are mainly due to structural differences of the markets and to selection issues of the stocks. First of all, the dataset is by construction

biased towards long-lived stocks. Secondly, the intra-market correlations have been calculated on the basis of a market index, which composition is undergoing changes over time. However, we are pretty certain that the exact composition of the index used for the normalization does not have significant influence on the results.

When we compare time series from different markets we have to perform some adjustments, mostly due to differences in trading days. We either only used data from days in which trading was done in both markets or we replaced missing data with the observation of the last trading day. These two methods yield almost exactly the same results for the correlation analysis. When comparing all markets together we used the joint trading days of the London and Frankfurt stock exchange (which is the bilateral pair which has the most overlap with all other markets) and again replaced missing observations for all other markets with last days observation.

For comparisons of the U.S. and Japan one should be aware that it makes sense to consider observations of day t for the U.S. and $t + 1$ for Japan (the date barrier is in the Pacific), since these observations are closer to each other in terms of trading hours. Similar considerations can be taken for China and India, although the effect here is much weaker.

In general the correlations that we calculate might also be influenced by the amount of overlap in daily trading hours, the amount of overlap in trading days, and general economic differences (as mentioned in the discussion). Also, the results depend on the time scale. Here we are interested in the medium run (a few weeks). A different kind of analysis of short-run effects, including a more detailed look on volatility, could be done with high-frequency (tick) data.

4 Results

4.1 Dynamics of the individual markets

A first proxy to the dynamics of the different world's economies is the dynamics of their leading market indices. Here we focus on six of the world's largest economies, representing western markets – U.S., U.K., and Germany – and eastern markets - Japan, India and China. The stock price indices of these countries are presented in Figure 1, showing mostly very similar dynamics.

Investigating the index volatility, rather than the index price reveals meaningful hidden information. Studying Figure 2, a similarity is observed between the three "western" markets, while the volatility peaks of the "eastern" markets only coincide for some time periods. Thus, it is reasonable to ask whether such uniformity between some markets, and multiformity between others, can be quantified.

4.2 Dynamics of market intra-correlations

To understand the dynamics of capital markets, much research has focused on the analysis of correlations [5, 17, 19, 20]. It is standard practice to calculate

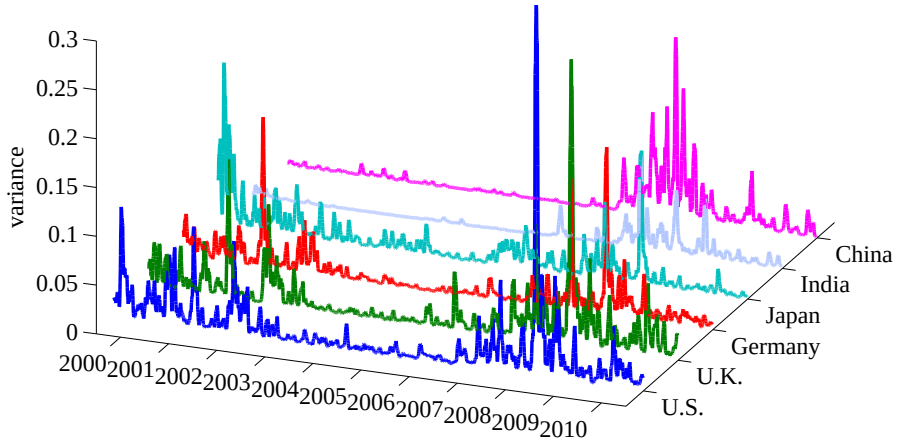

Fig. 2: Relative volatility in the markets within a 22-day window. The price indices data was standardized for the 10-year interval (the mean is zero and the variance is 1 for each complete time series). The volatility peaks for the U.S, U.K. and Germany mostly coincide while there is less similarity with Japan. India and China show a very different behavior of volatility, especially until 2007.

the correlations between stocks in a given market, and we correspondingly calculate the correlations between the time series of the stock daily returns, for each market separately. To obtain a better understanding of the dynamics of correlations in each market, a sliding window approach is used to calculate the market intra-correlations, using a 22-day window. In Figure 3 we present the dynamics of the intra-correlations for each of the six markets.

For each market, a bursting behavior for the intra-correlations is observed. This is consistent with previous findings [6]. Furthermore, a similarity in the appearance of intra-correlation bursts is noted for some of the markets as is elaborated in the next section.

Next, we calculate for each of the markets the Index Cohesive Force (ICF, Figure 4). High values of the ICF correspond to a state in which the market index dominates the behavior of the market, thus making it stiff and more prone to systematic failures. By studying Figure 4, it is possible to observe that some markets are similar in their dynamics of the ICF. Some similarities can be observed for the U.S., U.K., Germany, and Japan, whereas China shows a significantly different behavior. The ICF of the U.S. and Japan displays similarity in trend and magnitude, whereas U.K., India and Germany have a similar trend but much lower magnitude. Finally, China shows very different behavior than all other markets.

Markets featuring similar values of the ICF will have a similar dependency on the market index. Thus, if the indices of these markets are highly correlated, these markets should be strongly coupled. As such, the ICF provides new

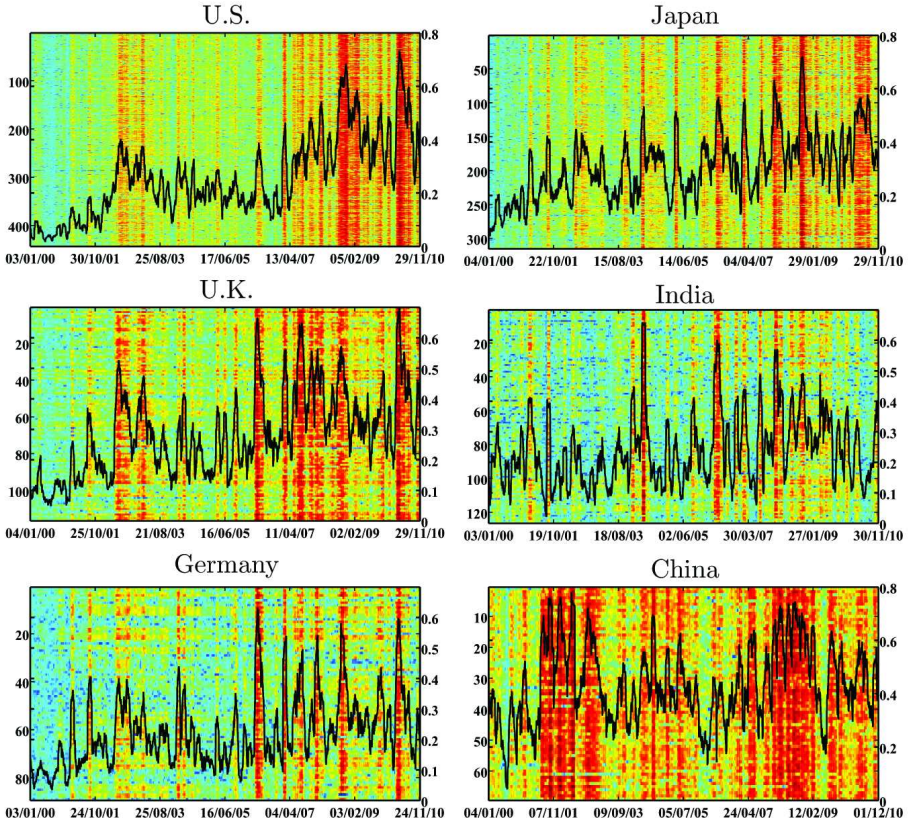

Fig. 3: Dynamics of the intra correlation. For each market, we use a 22-day window, and in each window calculate the intra correlation. This results in the dynamics of the intra correlation for the period of 2000–2010, for each market separately. Each horizontal line represents the average correlation of one stock (the left ordinate displays the number of the stock). The western markets and Japan show a similar behavior, visualized through vertical stripes at the same time, showing syncronized waves of strong correlations. The black line shows the average of all correlations at a given 22-day window. The right ordinate shows the correlation value. The trend is increasing for all countries exept China.

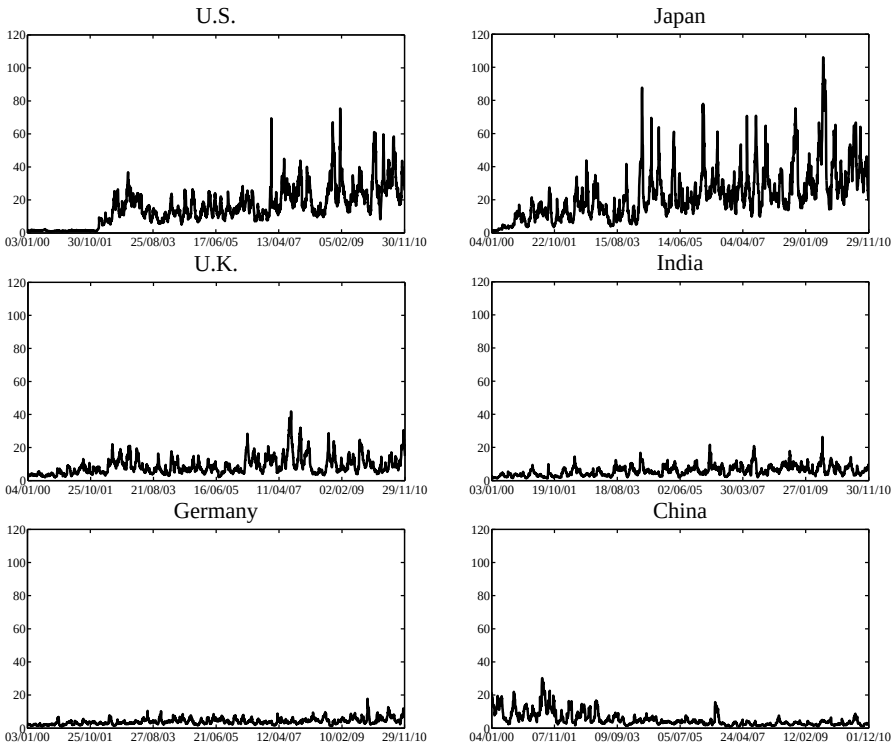

Fig. 4: Dynamics of the ICF. Dynamics of the Index Cohesive Force (ICF), for the period of 2000 - 2010. The dynamics of the ICF is plotted for each market separately, using the same scale. Some similarities can be observed for the U.S., U.K., Germany, and Japan, whereas China shows a significantly different behavior. The ICF of the U.S. and Japan displays similarity in trend and magnitude, whereas U.K., India and Germany have a similar trend but much lower magnitude. Finally, China shows very different behavior than all other markets.

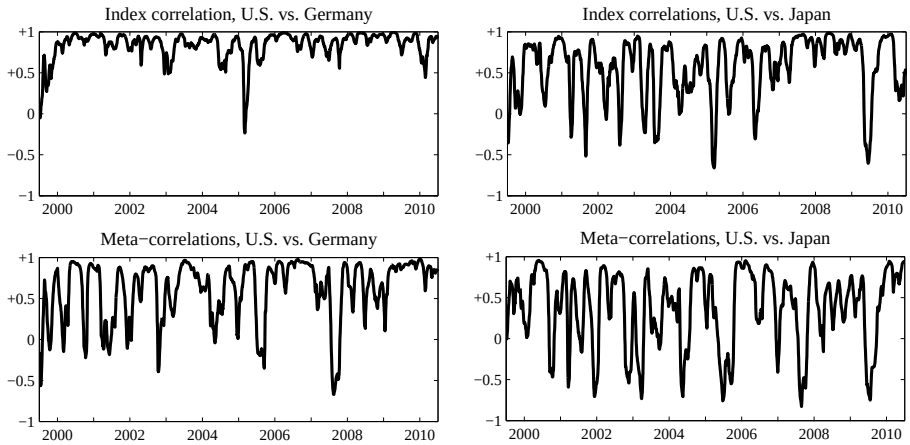

Fig. 5: Index correlations (top) and Meta-correlations (bottom) for the U.S vs. Germany (left) and Japan (right). Both calculated using a 66-day window. The U.S. and Germany show a higher similarity for both measures than the U.S. and Japan. While both measures fluctuate over time, we observe that high correlations do not necessarily show jointly in the top and the bottom figure. We can thus differentiate between times of identical price movements (high index correlation) and global stress (high index correlation and high meta-correlation).

important information on these couplings.

4.3 Inter-market correlations in the global financial market

The observed similarities of indices and correlation patters leads to the question of how synchronized stock markets are with respect to changes in these measures. Thus, we computed the meta-correlations – the correlations between the intra-correlations, using a 66-day window. The index correlations, the index volatility correlations and the ICF correlations were calculated using the same window size.

According to the index correlations the three "western" markets - U.S., U.K. and Germany - are highly correlated. The index correlations between Japan and India and all other markets are significantly weaker (the difference between these two groups is even more visible for the index volatility). China finally seems rather uncorrelated with the rest of the world, although some upward trend is visible (see Figures 9 and 12 in the Supplementary Information). However, index correlations capture only partially the inter relations between different markets.

While the ICF provides a valuable measure to assess the state of each individual market, it is highly fluctuating. Thus, the ICF correlations between markets do not provide a reliable measure of the inter relations.

Much better results are obtained using the meta-correlations. Using this measure, we found that the three "western" markets have a high level of uniformity. The Japanese market appears to be significantly more influenced by the "west" than the Indian market, the Chinese has the lowest correlations. The latter is in line with what was expected for example given the capital controls and regulations in China and limitations for foreign investors (see e.g. [22, 23]). Using a cross-correlation analysis, it is possible to further investigate the level of synchronization between the different markets. Typically, the lag (the time delay for maximum cross correlation) is 0 for high correlations and it fluctuates for low correlations. Generally speaking, we observe that the magnitude of inter market correlations fluctuates similarly like the magnitude of the intra-market correlations of the different market pairs (see Figure 5 for the correlations of the U.S., Germany and Japan and the Supplementary Information for the meta and index correlations for all markets).

4.4 Dynamics of the global financial village

The coupling of markets, as quantified by the meta-correlation, changes over time. The Japanese market switches between following the "western" and following the "eastern" worlds: for some time intervals it behaves very similar to the U.S. market (which is also similar to the U.K. and Germany markets), and at other times, the intra-correlations of Japan behave more similar to that of the Asian countries. Similar observations can be made for U.K. and Germany and their similarity to the U.S. vs. Asia. The interdependencies between India and China and the more developed markets are very volatile over time and show maxima in years with important global events (2001: 9/11-attacks, 2003: Iraq war, SARS, etc.). To illustrate the general development, we show the differences in coupling between markets during 2001 and 2010 (see Figure 6). The line strength is proportional to the level of the meta-correlations. The world's financial markets show a higher uniformity in the later years of our analysis.[1]

5 Discussion

This paper presents a new framework for quantitative assessments of the coupling and interdependences between different markets in the global financial village. The new approach also provides the means to study feedback between the micro (intra market) and the macro (inter markets) levels. More specifically, the stock-stock correlations in the individual markets represent local market dynamics, whereas the meta-correlations represent global market dynamics. Thus, the methodology presented here of intra and meta correlation analysis provides the means to study the bottom-top and top-down feedback mechanisms which take place in the world's economies.

[1] A video visualizing the development of market interdependencies is available as part of the Supplementary Information: http://dl.dropbox.com/u/16978699/globalmarket.mp4

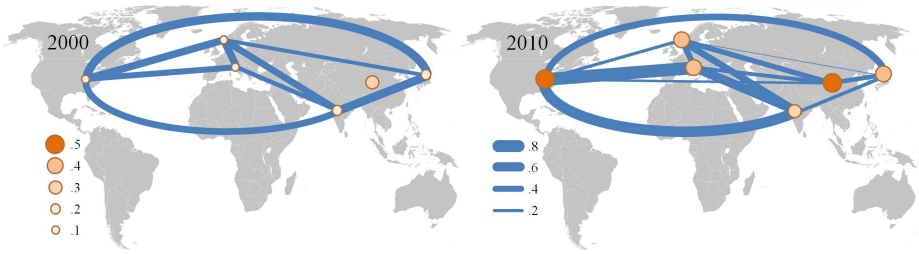

Fig. 6: The global financial village for the years 2000 (left) and 2010 (right). The node size is proportional to the inter-correlations (left legend). The width of the edges of the graph is proportional to the meta-correlation between the markets it connects (right legend). For 2000 we observe markets with low intra-correlations and inter-correlations of similar magnitude, excluding China. For 2010 we observe much higher intra-correlations in all markets and a denser network of interdependencies. (The nodes for the U.K. and Germany are further away from each other than their geographical position.)

Our results provide new information about the uniformity preset in the world's economies. We find significant uniformity for the three western markets, whereas Japan and India, display a greater extent of multiformity; however, this multiformity is time dependent, and periods of significant uniformity with the western markets are observed. Unlike these, the case of China is significantly different, and all analyses show that it is significantly different than the other markets.

Finally, some interesting observations can be made about the general development of financial markets. It has been much debated that markets have become more coupled over the last years, and that we are observing the downside of this development right now during the debt crisis within the Eurozone and the U.S., expressed in pronounced synchronized movements of stock markets. From our analysis it becomes evident that this uniformity does not only stem from an increase of correlation between markets, but that there has also been an ongoing simultaneous shift towards uniformity in each single market.

In conclusion, using new specially devised analysis methods, we provide the means to investigate and quantify uniformity and multiformity in the global market, and changes in these measures. In the current era, when the global financial village is highly prone to systemic collapses which can sweep the entire village, our approach can provide a sensitive "financial seismograph" to detect early signs of global crises.

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Supplementary Information

A Meta and index correlations as a function of time

The following plots are pairwise comparisons of all six markets. We show the correlation at lag 0 and the lag with the maximum correlation (which can also be interpreted as a kind of significance indicator, strong fluctuations far from lag 0 would then indicate no significant correlation exists for a this time window).

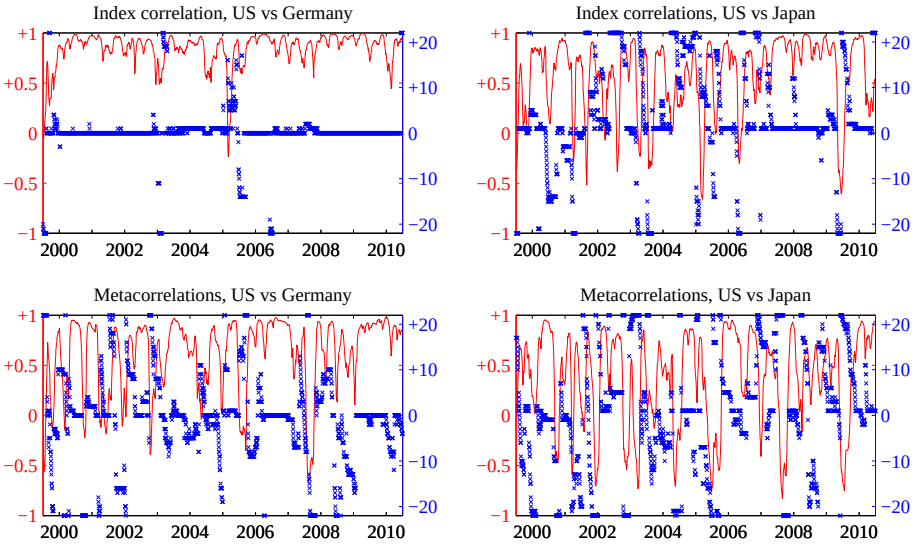

Fig. 7: Index correlations (top) and Meta-correlations (bottom), Lag with maximum correlation (blue cross) and correlation at lag 0 for the cross-correlation of the indices. Both performed for a 66-day window.

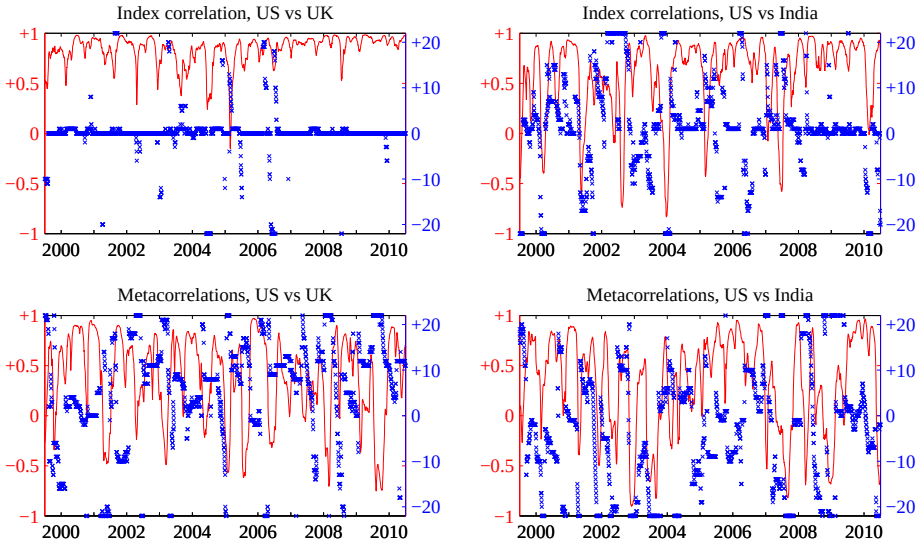

Fig. 8: Index correlations (top) and Meta-correlations (bottom), Lag with maximum correlation (blue cross) and correlation at lag 0 for the cross-correlation of the indices. Both performed for a 66-day window.

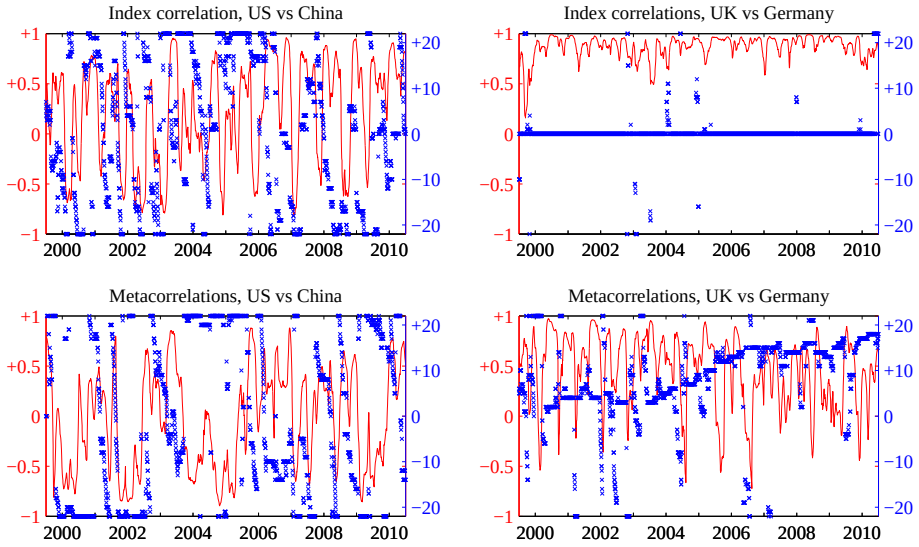

Fig. 9: Index correlations (top) and Meta-correlations (bottom), Lag with maximum correlation (blue cross) and correlation at lag 0 for the cross-correlation of the indices. Both performed for a 66-day window.

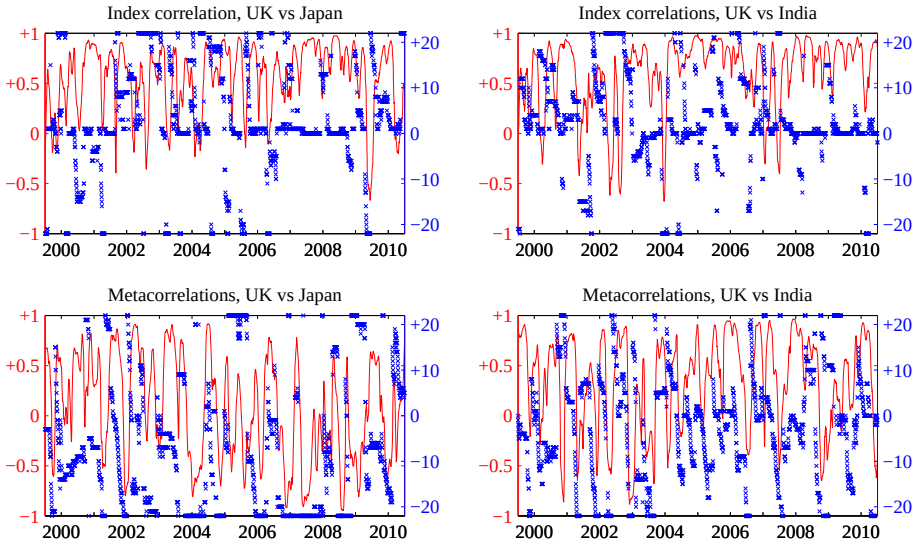

Fig. 10: Index correlations (top) and Meta-correlations (bottom), Lag with maximum correlation (blue cross) and correlation at lag 0 for the cross-correlation of the indices. Both performed for a 66-day window.

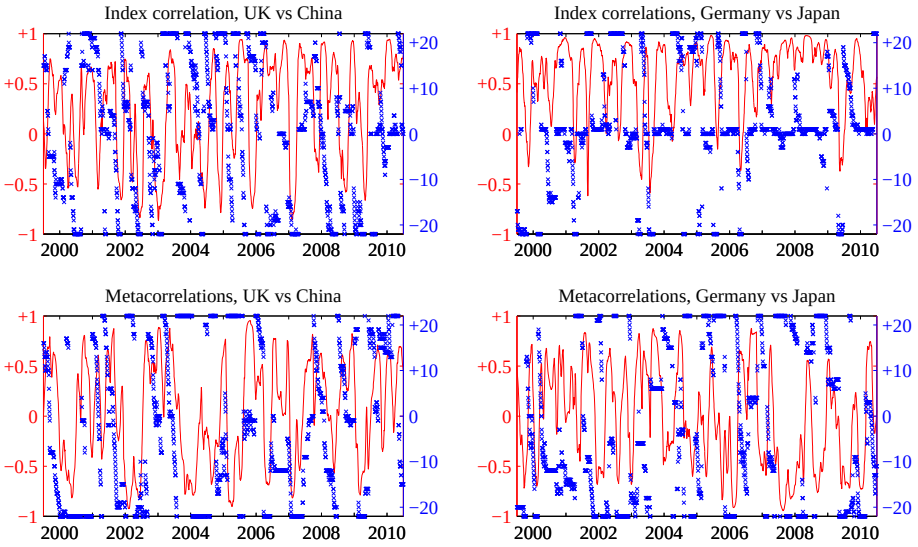

Fig. 11: Index correlations (top) and Meta-correlations (bottom), Lag with maximum correlation (blue cross) and correlation at lag 0 for the cross-correlation of the indices. Both performed for a 66-day window.

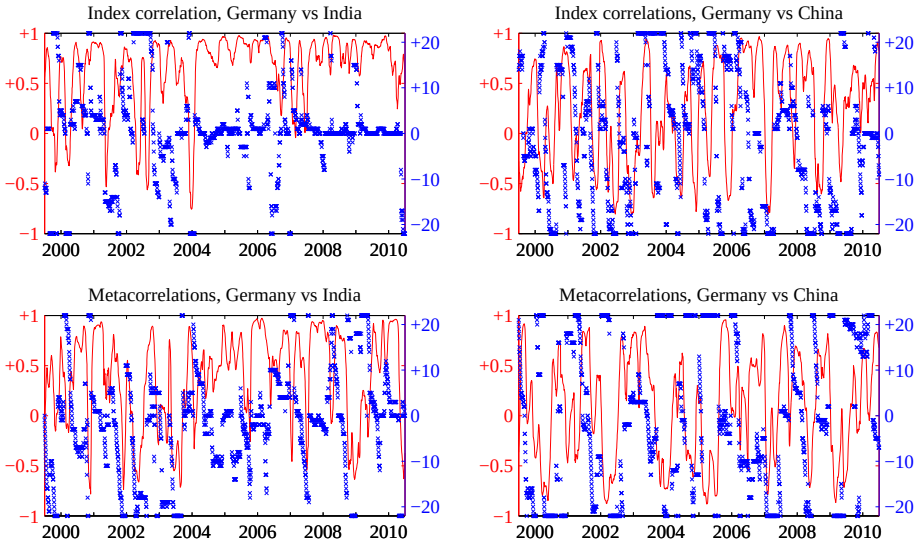

Fig. 12: Index correlations (top) and Meta-correlations (bottom), Lag with maximum correlation (blue cross) and correlation at lag 0 for the cross-correlation of the indices. Both performed for a 66-day window.

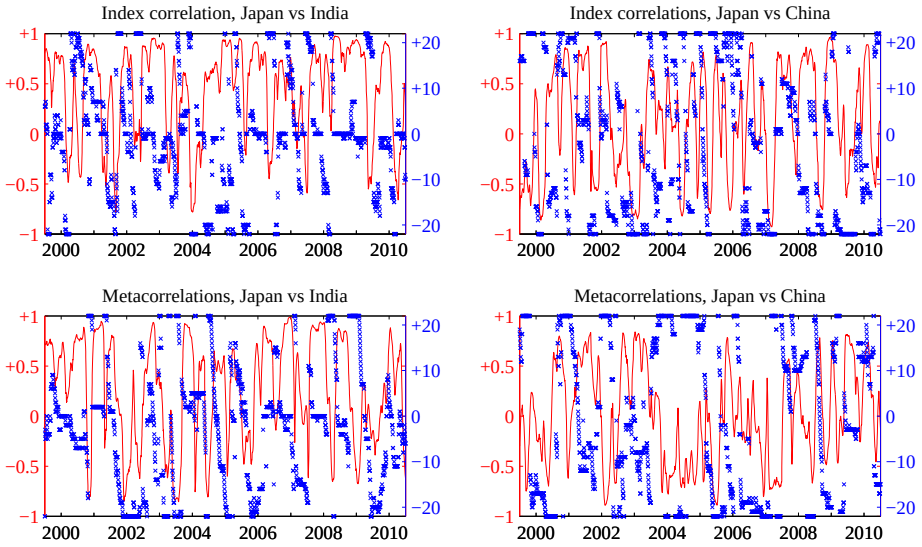

Fig. 13: Index correlations (top) and Meta-correlations (bottom), Lag with maximum correlation (blue cross) and correlation at lag 0 for the cross-correlation of the indices. Both performed for a 66-day window.

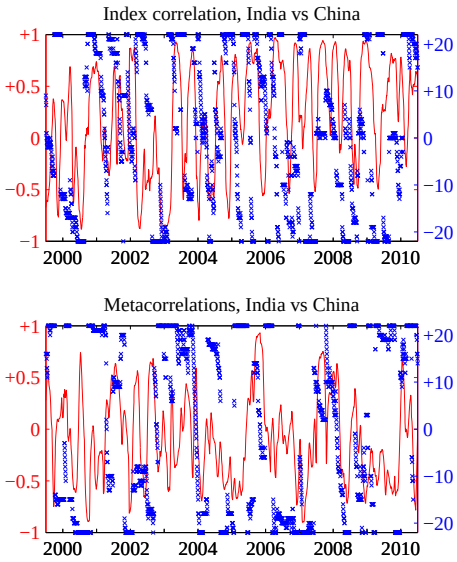

Fig. 14: Index correlations (top) and Meta-correlations (bottom), Lag with maximum correlation (blue cross) and correlation at lag 0 for the cross-correlation of the indices. Both performed for a 66-day window.

B Correlations year-by-year

The year-by-year correlations were calculated as the average over all 66-day windows of each year. The pairs are sorted in decending order by total average correlation. Averaging by years allows us to judge on the general – medium to long run – interdependence between markets.

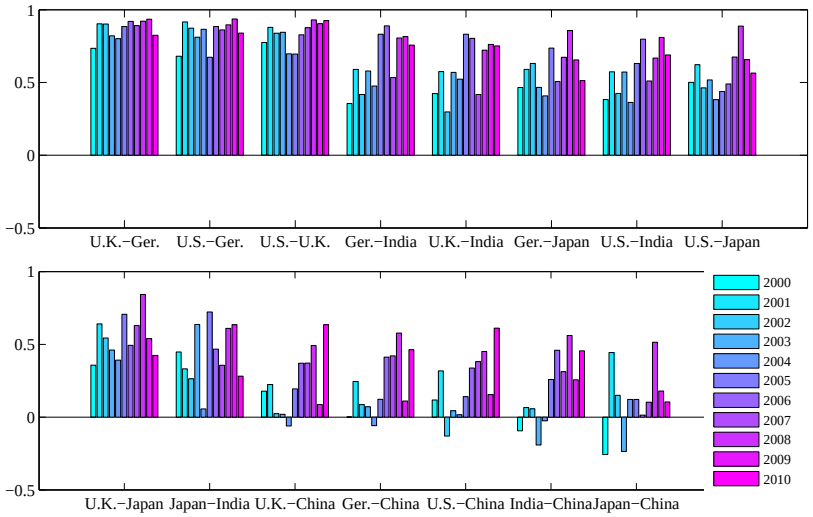

Fig. 15: Average correlation of price indices year-by-year. For each year we calculate the average of all 66-day windows.

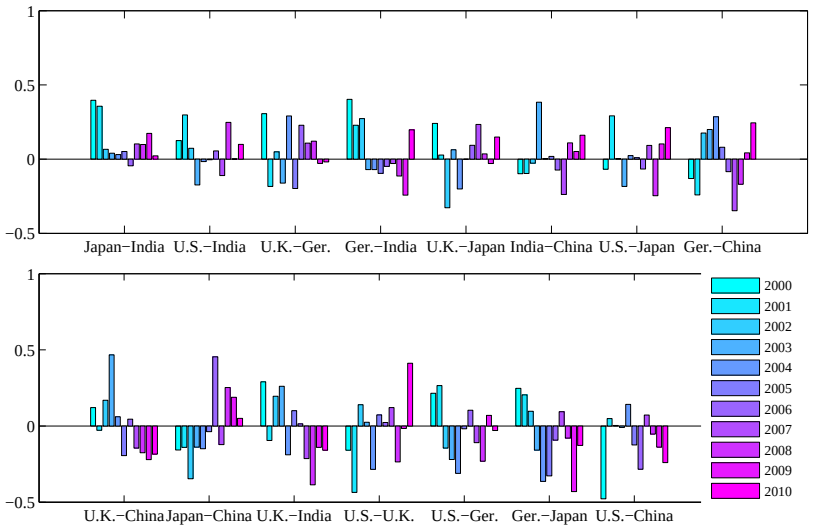

Fig. 16: Average correlation of ICF, year-by-year. For each year we calculate the average of all 66-day windows.

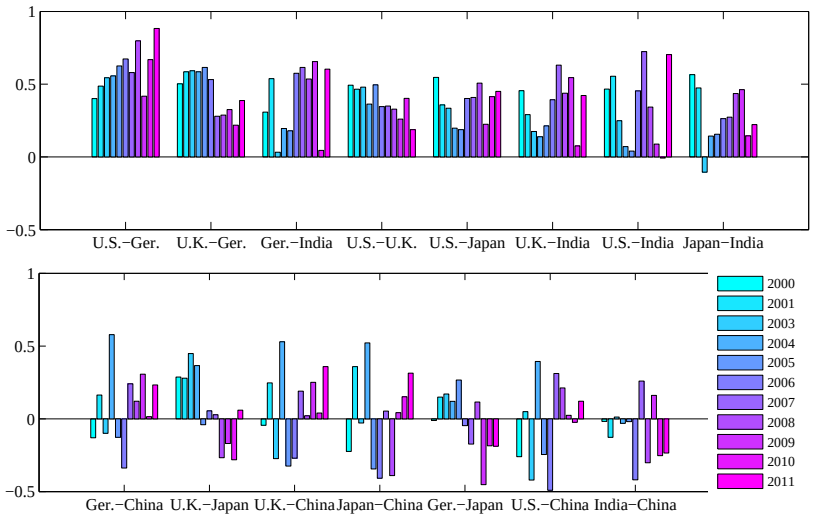

Fig. 17: Average Meta-correlations, year-by-year. For each year we calculate the average of all 66-day windows.

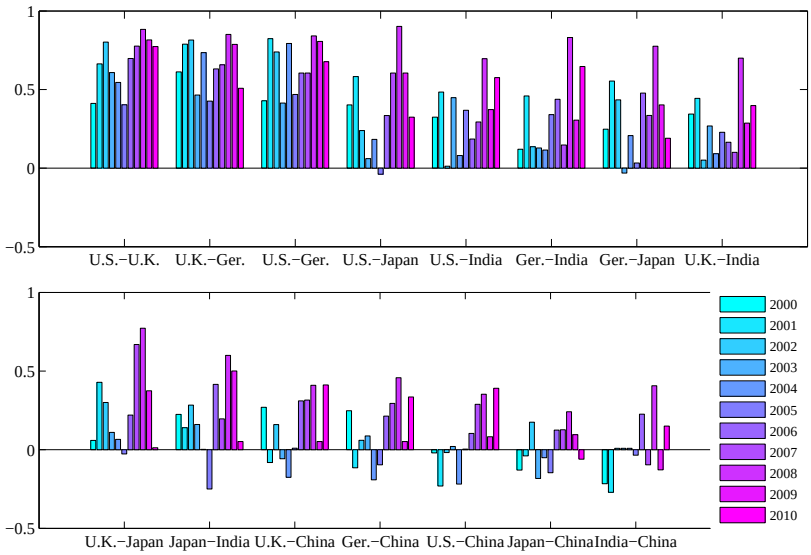

Fig. 18: Average index volatility correlation, year-by-year. For each year we calculate the average of all 66-day windows.

C Partial correlations

To complement the average correlations presented in the main text we present here the partial correlations, visualizing the effect of the index (resp. the removal of it).

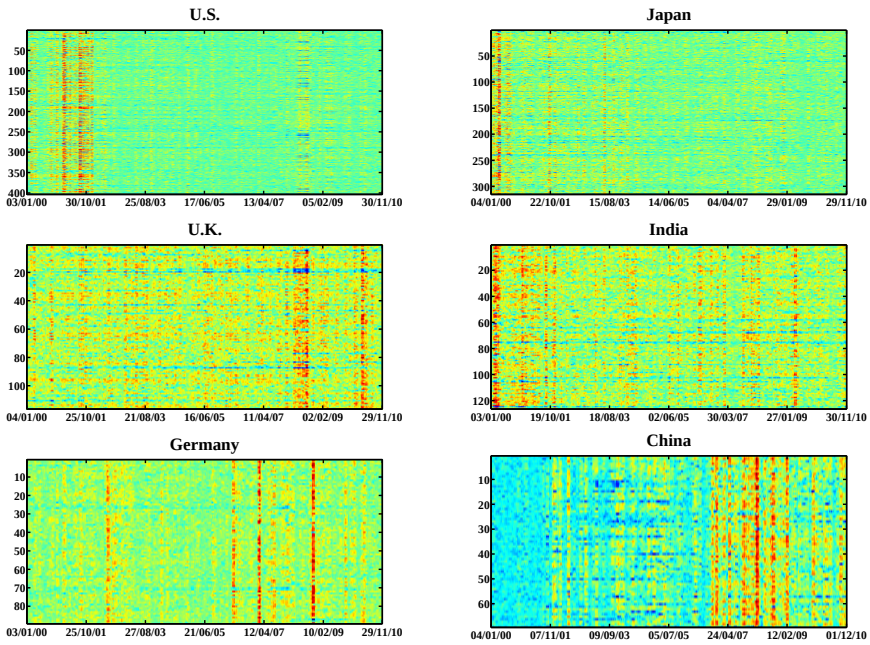

Fig. 19: Dynamics of the intra partial correlation. For each market, we use a 22-day window, and in each window calculate the intra partial correlation, removing the effect of the index. Each horizontal line represents the average correlation of one stock (the left ordinate displays the number of the stock).

D List of stocks used

Germany

ADIDAS, ADVA OPTICAL NETWG., AIXTRON, ALLIANZ, ARCANDOR, AUGUSTA TCHG., AURUBIS, BALDA, BASF, BMW PREF., BMW,BAYER, BEIERSDORF, BIJOU BRIGITTE MODISCHE ACCESSOIRES, BILFINGER BERGER, CELESIO, CENTROTEC SUSTAINABLE, COMMERZBANK, CONTINENTAL, DAB BANK, DAIMLER, DEUTSCHE BANK, DOUGLAS HOLDING, DRAEGERWERK PREF., DRILLISCH, DEUTSCHE TELEKOM, E ON, ELMOS SEMICONDUCTOR, FIELMANN, FREENET, FRESENIUS MED. CARE, FRESENIUS MED. CARE PREF., FRESENIUS, FRESENIUS PREF., GEA GROUP, GENERALI DTL. HLDG., GFK, HANNOVER RUCK., HEIDELB. DRUCKMASCHINEN, HEIDELBERGCEMENT, HENKEL, HENKEL PREF., HOCHTIEF, BOSS (HUGO), BOSS (HUGO) PREF., INDUS HOLDING, IVG IMMOBILIEN, JENOPTIK, JUNGHEINRICH, K + S, KUKA, LEONI, LINDE, LOEWE, DEUTSCHE LUFTHANSA, MAN, MAN PREF., MEDION, MERCK KGAA, METRO, MLP, MORPHOSYS, MUEHLBAUER HOLDING, MUENCHENER RUCK., PFEIFFER VACUUM TECH., PORSCHE AML. HLDG. PREF., PROSIEBEN SAT 1 MEDIA, PSI, PUMA RUDOLF DASSLER SOT., RWE, RWE PREF., SALZGITTER, SAP, SGL CARBON, SIEMENS, SINGULUS TECHNOLOGIES, SIXT, SIXT PREF., SOFTWARE, SOLARWORLD, STADA ARZNEIMITTEL, SUEDZUCKER, SUESS MICROTEC, THYSSENKRUPP, TUI, UNITED INTERNET, VOLKSWAGEN, VOLKSWAGEN PREF., VOSSLOH

UK

AEGIS GROUP, AGGREKO, ALLIANCE TRUST, AMEC, ANGLO AMERICAN, ARM HOLDINGS, ASSOCIATED BRIT. FOODS, ASTRAZENECA, AVIVA, BAE SYSTEMS, BALFOUR BEATTY, BANKERS INV.TRUST, BARCLAYS, BARRATT DEVELOPMENTS, BBA AVIATION, BELLWAY, BERKELEY GROUP HDG., BG GROUP, BHP BILLITON, BP, BRITISH AIRWAYS, BRITISH AMERICAN TOBACCO, BRITISH LAND, BRITISH SKY BCAST. GROUP, BT GROUP, BUNZL, CABLE & WIRELESS COMMS., CAPITA GROUP, CAPITAL SHOPCTS. GROUP, CENTRICA, COLT GROUP, DAILY MAIL A, DIAGEO, DIXONS RETAIL EDINBURGH INV. TRUST, ELECTROCOMP., FIDELITY, EUR. VALUES, FIRST GROUP, FOREIGN & COLONIAL, G4S, GENESIS EMRG. MARKET, GKN, GLAXOSMITHKLINE, HAMMERSON, HAYS, HOME RETAIL GROUP, HSBC HDG., IMI, IMPERIAL TOBACCO GP., INTERNATIONAL POWER, ITV, JOHNSON MATTHEY, JPMORGAN AMERICAN IT., KINGFISHER, LADBROKES, LAND SECURITIES GROUP, LEGAL & GENERAL, LLOYDS BANKING GROUP, LOGICA, LONMIN, MAN GROUP, MARKS & SPENCER GROUP, MERCANTILE IT., MISYS, MONKS INV. TRUST, MORRISON (WM) SPMKTS., MURRAY INTL., NATIONAL EXPRESS, NATIONAL GRID, NEXT OLD MUTUAL, PEARSON, PENNON GROUP, PERSIMMON, PROVIDENT FINANCIAL, PRUDENTIAL, RANDGOLD RESOURCES, RANK GROUP, RECKITT BENCKISER GROUP, REED ELSEVIER, RENTOKIL INITIAL, REXAM, RIO TINTO, RIT CAPITAL PARTNERS, ROLLS-ROYCE GROUP, ROYAL BANK OF SCTL. GP., ROYAL DUTCH SHELL B, RSA INSURANCE GROUP, SABMILLER, SAGE GROUP, SAINSBURY (J), SCHRODERS, SCHRODERS NV, SCOT. & SOUTHERN ENERGY, SCOTTISH INV. TST., SCOTTISH MORTGAGE, SEGRO, SERCO GROUP, SEVERN TRENT, SHIRE, SMITH & NEPHEW, SMITHS GROUP, STANDARD CHARTERED, TATE & LYLE, TAYLOR WIMPEY, TESCO, UNILEVER (UK), UNITED BUSINESS MEDIA, UNITED UTILITIES GROUP, VODAFONE GROUP, WH SMITH WHITBREAD, WITAN INV. TRUST, WOLSELEY, WPP, x3I GROUP

US (Ticker symbols)

AA, AAPL, ABC, ABT, ACAS, ACE, ADBE, ADI, ADM, ADP, ADSK, AEE, AEP, AES, AET, AFL, AGN, AIG, AIV, ALL, ALTR, AMAT, AMD, AMGN, AMT, AMZN, AN, ANF, APA, PC, APD, POL, ASH, AVB, AVP, AVY, AXP, AYE, AZO, BA, BAC, BAX, BBBY, BBT, BBY, BC, BCR, BDX, BEN, BF-B, BHI, BIG, BIIB, BK, BLL, BMC, BMS, BMY,

BRCM, BSX, BXP, C, CA, CAG, CAH, CAM, CAT, CB, CBE, CCE, CCL, CCU, CEG, CELG, CHK, CHRW, CI, CIEN, CINF, CL, CLX, CMA, CMCSA, CMI, CMS, CNP, COF, COP, COST, CPB, CPWR, CSC, CSCO, CSX, CTAS, CTL, CTSH, CTXS, CVG, CVH, CVS, CVX, D, DD, DDR, DDS, DE, DELL, DGX, DHI, DHR, DIS, DOV, DOW, DRI, DTE, DUK, DVN, DYN, EBAY, ECL, ED, EFX, EIX, EK, EL, EMC, EMN, EMR, EOG, EP, EQR, ERTS, ESRX, ESV, ETFC, ETN, ETR, EXC,EXPD, F, FCX, FDO, FDX, FE, FHN, FII, FISV, FITB, FO, FRX, GAS, GCI, GD, GE, GENZ, GILD, GIS, GLW, GPC, GPS, GR, GT, GWW, HAL, HAR, HAS, HBAN, HD, HES, HIG, HNZ, HOG, HON, HOT, HPQ, HRB, HST, HSY, HUM, IACI, IBM, IFF, IGT, INTC, INTU, IP, IPG, IR, ITT, ITW, JBL, JCI, JCP, JDSU, JEC, JNJ, JNY, JPM, JWN, K, KBH, KEY, KG, KIM, KLAC, KMB, KO, KR, KSS, LEG, LEN, LH, LIZ, LLL, LLTC, LLY, LM, LMT, LNC, LOW, LSI, LTD, LUK, LUV, LXK, M, MAR, MAS, MAT, MBI, MCD, MCHP, MCK, MDP, MDT, MHP, MI, MKC, MMC, MMM, MO, MOLX, MOT, MRK, MRO, MS, MSFT, MTB, MTG, MTW, MU, MUR, MWV, MYL, NBL, NBR, NE, NEM, NI, NKE, NOC, NOV, NOVL, NSC, NSM, NTAP, NTRS, NUE, NVDA, NVLS, NWL, NWS-A, NYT, ODP, OMC, OMX, ORCL, OXY, PAYX, PBI, PCAR, PCG, PCL, PCP, PDCO, PEP, PFE, PG, PGN, PGR, PH, PHM, PKI, PLD, PLL, PNC, PNW, POM, PPG, PPL, PX, Q, QCOM, QLGC, R, RDC, RF, RHI, RIG, RL, ROK, RRC, RRD, RSH, RTN, S, SBUX, SCHW, SEE, SHW, SIAL, SLB, SLE, SLM, SNA, SNDK, SO, SPG, SPLS, SRE, SSP, STI, STJ, STR, STT, STZ, SUN, SVU, SWK, SWY, SYK, SYMC, SYY, T, TAP, TE, TEG, TER, TEX, TGT, THC, TIE, TIF, TJX, TLAB, TMK, TMO, TROW, TRV, TSN, TSO, TSS, TWX, TXN, TXT, TYC, UIS, UNH, UNM, UNP, USB, UTX, VAR, VFC, VLO, VMC, VNO, VRSN, VZ, WAG, WAT, WEN, WFC, WFMI, WFR, WFT, WHR, WM, WMB, WMT, WPI, WPO, WY, X, XEL, XL, XLNX, XOM, XRX, YHOO, YUM, ZION

Japan

ADEKA, ADVANTEST, AEON, AEON CREDIT SERVICE, AIFUL, AIR WATER, AISIN SEIKI, AJINOMOTO, ALPS ELECTRIC, AMADA, AMANO, AOC HOLDINGS, ASAHI BREWERIES, ASAHI GLASS, ASAHI KASEI, BANK OF KYOTO, BANK OF YOKOHAMA, BRIDGESTONE, BROTHER INDUSTRIES, CALSONIC KANSEI, CANON, CANON MARKETING JAPAN, CAPCOM, CASIO COMPUTER, CEDYNA FINANCIAL, CENTRAL GLASS, CHIBA BANK, CHIYODA, CHUGAI PHARM., CHUGOKU BANK, CHUO MITSUI TST. HDG., CITIZEN HDG., COMSYS HOLDINGS, CREDIT SAISON, CSK, DAI NIPPON PRINTING, DAICEL CHM. INDS., DAIDO STEEL, DAIFUKU, DAIHATSU MOTOR, DAIICHI SANKYO, DAIKIN INDUSTRIES, DAINIPPON SCREEN MNFG., DAINIPPON UMIT. PHARMA, DAITO TST. CONSTRUCTION, DAIWA HOUSE INDUSTRY, DAIWA SECURITIES GROUP, DCM HOLDINGS, DENKI KAGAKU KOGYO KK, DENSO, DISCO, ,DON QUIJOTE, DOWA HDG., EAST JAPAN RAILWAY, EBARA ,EDION, EISAI, FAMILYMART, FANUC, FAST RETAILING, FUJI HEAVY INDS., FUJIFILM HDG., FUJIKURA, FUJITSU, FUKUOKA FINANCIAL GP., FUKUYAMA TRANSP., FURUKAWA ELECTRIC, GMO INTERNET, GUNMA BANK, HACHIJUNI BANK, HAMAMATSU PHOTONICS, HIKARI TSUSHIN, HINO MOTORS, HIROSE ELECTRIC, HITACHI, HITACHI CABLE, HITACHI CAPITAL, HITACHI CHEMICAL, HITACHI CON. MCH., HITACHI HIGH-TECHS., HITACHI KOKI, HITACHI KOKUSAI ELECTRIC, HITACHI METALS, HOKUETSU KISHU PAPER, HOKURIKU ELEC. POWER, HOKUTO, HONDA MOTOR, HOUSE FOODS, HOYA, H2O RETAILING, IBIDEN, ISETAN MITSUKOSHI HDG., IT HOLDINGS, ITOCHU, TOCHU TECHNO-SOLUTIONS, IYO BANK, IZUMI, J S R, JAFCO, APAN AVNS. ELTN. IND., JAPAN SECS. FINANCE, APAN TOBACCO, GC, JS GROUP, JTEKT, K'S HOLDINGS, KAJIMA, KAKEN PHARMACEUTICAL, KAMIGUMI, KANDENKO, KANEKA, KANSAI ELECTRIC PWR., KANSAI PAINT, KDDI, KEIHIN, KEWPIE, KEYENCE, KIKKOMAN, KIRIN HOLDINGS, KOITO MANUFACTURING, KOKUYO, KOMATSU, KOMORI, KONAMI, KONICA MINOLTA HDG., KUBOTA, KURARAY, KUREHA, KURITA WATER IND., KYOCERA, KYOWA EXEO, KYOWA HAKKO KIRIN, LEOPALACE21, LINTEC, MABUCHI MOTOR, MAKINO MILL. MACHINE, MAKITA, MARUBENI, MARUI GROUP, MARUICHI STEEL TUBE, MAZDA MOTOR, MEDIPAL HOLDINGS, MINEBEA, MIRACA HDG., MISUMI GROUP, MITSUBISHI, MITSUBISHI ELECTRIC, MITSUBISHI STATE, MITSUBISHI GAS CHM., MITSUBISHI HEAVY INDS., MITSUBISHI LOGIS-

TICS, MITSUBISHI TANABE PHARMA, MITSUB.UFJ LSE.& FINANCE, MITSUI, MITSUI CHEMICALS, MITSUI FUDOSAN, MITSUI MNG. & SMELT., MITSUI OSK LINES, MITSUMI ELECTRIC, MIZUHO SECURITIES, MS & AD INSURANCE GP. HDG., MURATA MANUFACTURING, NABTESCO, NAMCO BANDAI HDG., NEC, NGK INSULATORS, NGK SPARK PLUG, NHK SPRING, NIDEC SANKYO, NIHON UNISYS, NIKON, NINTENDO, NIPPON CHEMI-CON, NIPPON ELEC. GLASS, NIPPON EXPRESS, NIPPON KAYAKU, NIPPON MEAT PACKERS, NIPPON SHEET GLASS, NIPPON SHOKUBAI, NIPPON TELG. & TEL., NIPPON TV. NETWORK, NIPPON YUSEN KK, NISSAN CHEMICAL INDS., NISSAN MOTOR, NISSAN SHATAI, NISSHA PRINTING, NISSHIN SEIFUN, NISSHINBO HOLDINGS, NITTO DENKO, NOF, NOK, NOMURA HDG., NSK, NTN, NTT DATA, OBAYASHI, OJI PAPER, OKASAN SECURITIES GROUP, OKUMA, OKUMURA, OLYMPUS, ONWARD HOLDINGS, ORACLE JAPAN, ORIX, OSG, PACIFIC METALS, PANASONIC, PANASONIC ELECTRIC WORKS, PARK24, PIONEER, PROMISE, RENGO, RICOH, ROHM, RYOHIN KEIKAKU, SANKEN ELECTRIC, SANKYO, SAPPORO HOLDINGS, SECOM, SEGA SAMMY HDG., SEINO HDG., SEKISUI CHEMICAL, SEKISUI HOUSE, SEVEN & I HDG., SHARP, SHIKOKU ELECTRIC POWER, SHIMACHU, SHIMADZU, SHIMAMURA, SHIMIZU, SHIN-ETSU CHEMICAL, SHINKO ELEC.INDS., SHIONOGI, SHISEIDO, SHIZUOKA BANK, SHOWA SHELL SEKIYU, SMC, SOFTBANK, SONY, STANLEY ELECTRIC, STAR MICRONICS, SUMITOMO, SUMITOMO BAKELITE, SUMITOMO CHEMICAL, SUMITOMO ELECTRIC IND., SUMITOMO HEAVY INDS., SUMITOMO METAL MINING, SUMITOMO REAL. & DEV., SUMITOMO RUBBER INDS., SUMITOMO TRUST & BANKING, SURUGA BANK, SUZUKEN, SUZUKI MOTOR, SYSMEX, TAISHO PHARM., TAIYO NIPPON SANSO, TAIYO YUDEN, TAKARA HDG., TAKASHIMAYA, TDK, TERUMO, THK, TODA, TOHO, TOHO TITANIUM, TOHOKU ELECTRIC PWR., TOKAI CARBON, TOKAI RIKA, TOKUYAMA, TOKYO BCAST. SY. HDG., TOKYO DOME, TOKYO ELECTRON, TOKYO STEEL MNFG., TOKYO TATEMONO, TOKYO TOMIN BANK, TOKYU, TOKYU LAND, TONENGENERAL SEKIYU KK, TOPPAN PRINTING, TORAY INDS., TOSHIBA, TOSHIBA MACHINE, TOSHIBA PLANT SYS. & SVS., TOSHIBA TEC, TOSOH, TOTO, TOYO SEIKAN, TOYO SUISAN KAISHA, TOYODA GOSEI, TOYOTA BOSHOKU, TOYOTA INDS., TOYOTA MOTOR, TOYOTA TSUSHO, TREND MICRO, TSUBAKIMOTO CHAIN, TSUMURA, UNI CHARM, UNY, USHIO, WACOAL HDG., YAHOO JAPAN, YAKULT HONSHA, YAMADA DENKI, YAMAGUCHI FINL. GP., YAMAHA, YAMAHA MOTOR, YAMATAKE, YAMATO HDG., YAMATO KOGYO, YAMAZAKI BAKING, YASKAWA ELECTRIC, YOKOGAWA ELECTRIC, ZEON, 77 BANK

China

SHN. ACCORD PHARM., SHENZHEN SED IND., SHENZHEN TEX. (HDG.), CHINA FANGDA GP., SHENZHEN SEG, SHN.HUAQIANG IND., NORINCO INTL. COOPN., HEFEI MEILING, GUANGZHOU BAIYUNSHAN PHARM., GUANGZHOU DONGFONG HOTEL, GUANGXI LIUGONG MCH., GUANGZHOU HENGYUN ENTS. HLDG., AN HUI WENERGY, HUNAN INVESTMENT GP., JIANGLING MOTORS, CREATE TECH. & SCI., CHONGQING SANXIA PS., HAINAN HAIDE IND., WEIFU HIGH TECH. GP., GUI ZHOU TYRE, XIBEI BRG., NORTHEAST PHARM., BEIJING MAINSTREETS INV. GP., JIAOZUO WANGFANG ALUM., WUHU CONCH PROFL. & SCI., LIAN YUN GANG IDEAL GP., TONGLING NONFR. MTLS. GP., FUJIAN SANMU GP., NINGXIA YOUNGLIGHT CHEMS., GUANGDONG FENGHUA ADVD. TECH. (HLDG.), CHANGCHUN HIGH NEW TECH., FUJIAN YONGAN FOREST., HENAN STAR HI-TECH, JIANGNAN MOULD & PLASTIC TECH., XIAMEN XINDE, HUNAN ZHENGHONG SCTC. DEV., HUBEI SHUANGHUAN SCTC., HJG. TIANLUN RLST. DEV., HEFEI FENGLE SEED, BEIJING YANJING BREW., CHINA ZHENHUA (GP.) SCTC., APELOA, SHANXI SANWEI GP., SUFA TECH. IND. CNNC, LANZHOU SANMAO INDL., BEIJING NEW BLDG. MATS. PUBLIC, JIANGXI WANNIANQING CMT., CHENGDU HUASUN GROUP, NW. YONGXIN CHM. IND., FAW CAR, SICHUAN JIUZHOU ELEC., YANTAI MOON, GUANGDONG GOWORLD, SHAANXI QINCHUAN MCH. DEV., CITIC GUOAN INFO. IND., BEIJING SHUNXIN AGRIC., YUNNAN COPPER, CHINA DALIAN INTL. COOPN. (GROUP) HOLDINGS, JIANGSU FASTEN, XIANDAI INVESTMENT, AEROSPACE HI-

TECH HLDG. GP., SOYEA TECHNOLOGY, NANNING SUG. IND., JINLING PHARM., XUANHUA CON. MCH., TIANJIN FAW XIALI AUTMB., UNISPLENDOUR, YUNNAN NANTIAN ELT., SHN. CHIWAN PETROLEUM SUPP. BASE

India

ABAN OFFSHORE, ABB, ACC, ADITYA BIRLA NUVO, ALOK INDUSTRIES, AMBUJA CEMENTS, AMTEK AUTO, APOLLO HOSPS.ENTERPRISE, AREVA T & D INDIA, ARVIND, ASHOK LEYLAND, ASIAN PAINTS, AUROBINDO PHARMA, AVENTIS PHARMA, AXIS BANK, BAJAJ HOLDINGS & INVS., BALLARPUR INDUSTRIES, BALRAMPUR CHINI MILLS, BANK OF BARODA, BANK OF INDIA, BATA INDIA, BEML, BHARAT ELECTRONICS, BHARAT FORGE, BHARAT HEAVY ELS., BHARAT PETROLEUM, BIRLA CORPORATION, BOMBAY DYEING & MNFG., BOSCH, BRITANNIA INDS., CASTROL INDIA, CENTURY TEXTILES & INDS., CESC, CHENNAI PETROLEUM, CIPLA, COLGATE-PALMOLIVE INDIA, CONTAINER CORP. OF INDIA, CORPORATION BANK, CROMPTON GREAVES, CUMMINS INDIA, DABUR INDIA, DR REDDYS LABORATORIES, EID PARRY (INDIA), EIH, ENGINEERS INDIA, ESSAR SHIPPING PORTS & LOGIST., FEDERAL BANK, GAIL (INDIA), GILLETTE INDIA, GLXSK. CSM. HLTHCR., GLAXOSMITHKLINE PHARMS., GRASIM INDUSTRIES, GTL, GUJ. ALKALIES & CHEMS., GUJ. NARMADA VLY. FRTZ., GUJ. STE. FERT. & CHEMS., H C L INFOSYSTEMS, HDFC BANK, HERO HONDA MOTORS, HINDALCO INDUSTRIES, HINDUJA VENTURES, HINDUSTAN CONSTRUCTION, HINDUSTAN PETROLEUM, HINDUSTAN UNILEVER, HINDUSTAN ZINC, HOTEL LEELA VENTURE, HOUSING DEVELOPMENT FIN., ICICI BANK, IDBI BANK, IFCI, INDIA CEMENTS, INDIAN HOTELS, INDIAN OIL, INDUSIND BANK, INFOSYS TECHNOLOGIES, ITC, JINDAL SAW, JUBILANT LIFE SCIS., KOTAK MAHINDRA BANK, LIC HOUSING FINANCE, MADRAS CEMENT, MAHANAGAR TEL. NIGAM, MAHINDRA & MAHINDRA, MANGALORE REFINERY & PETROCHEMICALS, MAX INDIA, MOSER BAER INDIA, MPHASIS, NATIONAL ALUMINIUM, NESTLE INDIA, NIRMA, NOVARTIS INDIA, OIL & NATURAL GAS, ORCHID CHEMS. & PHARMS., ORIENTAL BK.OF COMMERCE, PFIZER, PIRAMAL HEALTHCARE, P& G. HYGIENE & HLTH. CARE, RANBAXY LABS., RASHTRIYA CHEMS. & FERT., RAYMOND, RELIANCE CAPITAL, RELIANCE INDUSTRIES, RELIANCE INFRASTRUCTURE, ROLTA INDIA, SATYAM COMPUTER SERVICES, SESA GOA, SHIPPING CORP.OF INDIA, SIEMENS, SRF, STATE BANK OF INDIA, STEEL AUTHORITY OF INDIA, STERLING BIOTECH, SUN PHARMACEUTICALS, TATA CHEMICALS, TATA COMMUNICATIONS, TATA GLOBAL BEVERAGES, TATA MOTORS, TATA POWER, TATA STEEL, THERMAX, TITAN INDUSTRIES, TUBE INVESTMENTS OF IDA., VOLTAS, WIPRO, WYETH, ZEE ENTERTAINMENT ENTS.

E Video

The video at *http://dl.dropbox.com/u/16978699/globalmarket.mp4* shows the development of inter-market relations. In the left graph the node size is proportional to the average-correlations and the width of the edges is proportional to the meta-correlations. The right graph has nodes proportional to relative price index volatility and edges strength proportional to price index correlation.