Analyses of Extreme Events on Emerging Capital Markets

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This study deals with the statistical methods of contagion-effects on emerging capital markets. After fitting probability distribution on the empirical data, and cross-market correlation sensibility test were used on time series (2002-2009) of Hungarian, Polish Russian and US government bond, stock and currency markets to study their behavior under extreme and normal circumstances. The aim of this analysis is to identify the possible differences between emerging and developed capital markets to investigate the validity of economic axioms according to the relation of bond, stock and currency markets on the emerging markets.

Keywords: power-law test, cross-market correlation

1. Introduction

This study analizes global capital market as a network of national economies, which are networks of markets themselves. There are market actors such as investment banks, state treasuries, national banks, etc. The global network operates under the following rules: quasi free movement of production factors (labor, capital, goods, and intellectual properties), technical progress, international markets, deregulation, liberalization, lack of coordination of economic policies, and liberalized capital accounts. (Wang – Chen 2003) .

To examine singularity and historicity of market distortions, this study models economic networks as graphs, where nodes are individuals or organizations and the edges are the social interactions between them (Barabási – Albert 1999). It is necessary to examine the human factor in case of nodes on the market to understand the

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occurrence of bubbles[3] and decoupling effects[4] in a non-linear world. The conditions of the bounded rationality model, in which decisions are made under uncertainty resulting in current prices and expected future prices co-evolving over time with mutual feedback, are closer to reality by giving a deeper description of the mispricing problems than the rational homo oeconomicus model. During operations, market actors, who learn by using heuristics, are possibly biased[5], while their reactions are non linear[6]. (Barabási – Albert 1999, Hommes – Wagenne 2008, di Mauro et al. 2008)

Many real-life complex networks are neither completely regular[7] nor completely random. There are complex systems, in which conditions are constantly changing giving a rise to endogenously engendered novelty. Simple complexity models are characterized by fat tails in returns distribution, long memory and interacting agents (Hommes – Wagenne 2008). The extended characteristics are the followings: (1) particular states of the system are singular, (2) processes are non-linear and frequency-dependent, (3) strength and direction of causal relations are highly divergent in terms of magnitude and power, (4) exogenous events are influencing the system but events in the system are not completely dependent on the environment, (5) there is a hierarchical order between elements and particular emergent properties (Herrmann-Pillath 2000).

Scale-free[8] networks are special cases of complex networks. They are inhomogeneous in nature, which means that nodes have very few link connections and yet a few nodes have many connections. In comparison with a random network, complex networks have the same size and an average degree, but the average path length is somewhat smaller. The clustering coefficient is much higher as well, while

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[3] Occurrence of bubbles were simulated in a rational and well informed market environment too when markets deviate from full rationality in asset pricing. Therefore they do not request uncertain circumstances (Hommes – Wagenne 2008).

[4] A divergence between development in a financial market benchmark and its effect on real economy (di Mauro et al. 2008).

[5] Their sentiment varies over time, according to prevailing market mood (Hommes – Wagenne 2008).

[6] Economic agents do not respond strongly to relatively small changes in prices, but larger price movements may trigger a disproportionately larger response with a strong effect on other economic variables (di Mauro et al. 2008).

[7] There are two generic aspects to understand real networks: the nearest-neighbor coupled network (a lattice) and the randomly connected network (Erdősi-Rényi model). In a lattice, every node is joined only by a few of its neighbors creating a homogenous network with low level of dynamism, which is clustered, without small-world effect. Random networks can appear quite suddenly. They are homogenous without showing clustering in general, but have small-world effect. The connectivity approximately follows a Poisson distribution. (Wang – Chen 2003)

[8] scale-free: "The shape of the degree distribution does not change over time, namely, does not change due to further increase of the network scale." (Wang – Chen 2003)

there are a few "big" nodes (hubs) with very large degrees (very large number of connections to bring the other nodes of the network close to each other). A quantity x obeys a power law if it is drawn from a probability distribution, $P(x) \sim x^{-\alpha}$, where α is a constant parameter of the distribution known as the exponent or scaling parameter[9]. The probability P(x) that a vertex in the scale-free network interacts with x other vertices decays as a power law, following therefore majority of cases has very low probability presenting a dissonance between expected value and mode which is the opposite to harmony at random networks. (Wang – Chen 2003, Csermely 2008)

To understand the singularities of financial crises, we have to study how scale-free complex networks can describe synchronization, transition processes and failures. Singularities are the results of non-linear dynamics in the economy, when small changes in systemic characteristics cause large-scale implications at the macro level (Herrmann-Pillath 2000). Synchronizability of a scale-free network is about the same as a star-shaped coupled network driven by tiny fraction of distant links (small world effect); so hubs are playing a similar role as single star-center. In these networks, that is the explanation for the error tolerance and the attack vulnerability phenomenon. The network is robust during the random removal of a fraction of nodes; but after the preferential removal of key nodes, the system performance decreased. Phase transition was described between scale-free and random networks. The connectivity number is emerging after the collapse of the "stable" scale-free state. The system is random in its "chaotic" phase with high evolutionary performance until a new "stable", scale-free combination is established (Grubestic et al. 2008, Wang – Chen 2003, Yuan – Wang 2007).

By using the complex scale-free network model, a lot of unusual events on the financial market could be described. The "singularities", which are resulted by the scale-freeness of real networks, are summarized in three levels of complexity. The first level of time series means, that the autocorrelation function of returns is a monotonically decreasing function holding at least for approximately 20 trading days. Price returns and volatility are locally nonstationary, but asymptotically stationary. The second level, the so called event-based trade allows synchronous interaction in the same economic sector of each time series with all the others. The third level of complexity means a collective behavior during extreme market events. (Bonano et al. 2001)

2. The aim of this paper

This assumption about a hierarchical market structure could be obvious, if we are thinking on the US capital market's 45% share from global capitalization. Therefore

[9] The scaling parameter typically lies in the range $2 < \alpha < 3$, but there could be occasional exceptions. (Clauset et al. 2009)

it is crucial to take a closer look on emerging market's deviations from the probable, "normal" stage. This study presents several theoretical concepts of identifying extreme market movements and spillover of correlation.

"Perfect storms" of capital markets are characterized by big falls in one equity price, which is accompanied by simultaneous big falls in other equity prices – multivariate normal distributions are unfeasible tools to describe heavy tail's "garden of improbable events".

This paper structured as follows to study the properties of contagion: after the overview of the mythological issues from the theoretical literature, the existences of fat tailness on the sample markets are presented by tail distribution tests. The systemic cause of these extreme events is explained in the third part of this work – dealing with a static and semi-dynamic modeling of return-correlation-time triangle.

3. Methodology

The introduction of methodology was divided on two parts: after tests of fat tailness of each participant market and instrument come the tests of network behavior.

3.1. Tail distribution tests of each market or instrument

The proof of the existence of heavy tailness (the "garden") structured as follows:

- Possible asymmetries and tailness were tested at first with the indispensable skewness and kurtosis tests. If the positive and negative sides behave different according these tests, it is necessary to analyze only the separated tails of the empirical distributions – after the rejection of normal distribution hypothesis with the usage of Kolmogorov-Smirmov test of normality[10].

- The rejection of normality suggests that tails could be bigger or smaller than the case of normal distribution. Therefore it is necessary to run basic R^2 based fitting-test[11] with general models of exponential and power-law distributions to separate the tailed and quasi non tailed cases from each other.

- Than estimated power-law properties were studied deeper by Clauset, Shalizi and Newman's (2007) improved quantile-based maximum likelihood estimation (MLE) method[12,] to estimate the scale parameter α. Size of the tails is determined by the scale parameter α – as smaller the α, as fatter is the tail. P-values are given by Monte Carlo procedures: the power-law model is fitted for generated syn-

[10] Jacque-Bera test of normality is also a common procedure.

[11] R-square – measures how successful the fit is in explaining of the variation of the data. A value closer to 1 indicates a better fit. General model for exponential: f(x) = a*exp(b*x) and for power-law: f(x) = a*x^b+c.

[12] Scripted in MATLAB, see http://www.santafe.edu/~aaronc/powerlaws/.

thetic data sets, and the number of times is counted when the Kolmogorov-Smirnov is larger than observed goodness-of-fit (maximum distance between the tail probability or cumulative distribution function of the empirical data and the fitted power-law model). (Clauset et al. 2009, Quismorio 2009)

3.2. Test of common developments under normal and extraordinary events

Power law properties on one or both sides of the empirical distributions signs the existence of the "garden of improbable events", but it is necessary to model the interconnections between the main markets and the emerging markets under these circumstances. Several issues have to be considered during the modeling process:

- Constantly high level of correlation could be interpreted as a sign of financial convergence (Stavárek 2009). But some strange developments could be find, when we investigate dynamics of the correlation over time. There are several ways to model cross correlations on network of markets. Each market or instrument has the same role in equal models, but this holistic view has some disadvantages: definition of correlation period, weekend distortions and too much smoothing or black out effect during aggregation (Kiss 2009). If there is one "stable points" of exchange for the selected instruments as main or leader markets with dominant level of liquidity and capitalization, hierarchic, or top-bottom structures are able to build. Copula-based approach is the most progressive idea, which deals with each market or instrument as an univariate margin of a "global" multivariate distribution – where the multivariate dependence structure is represented by a copula as Sklar's theorem suggests (Embrechts et al. 2001).
- There are several approaches to identify market interdependencies, we can employ both static and moving window approaches or we can calculate time-varying correlation from conditional covariances and variances given by BEKK-GARCH methods (Babatskaja et al. 2008).
- Linear correlation is a natural scalar measure of dependence in elliptical distributions (as multivariate normal and t-distribution), but it can be misleading under heavy-tailed distributions as power-law or t_2-distributions. Using of Kendall't tau[13] or Spearman's rho[14] could be better alternative to calculate dependence (concordance[15]) for nonelliptical distributions as Embrechts et al. (2001) suggest[16].

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[13] Kendall's tau for the random vector (X;Y)T is defined as
$\tau(X;Y) = P\{(X - X')(Y - Y') > 0\} - P\{(X - \sim X)(Y - \sim Y) < 0\}$;where $(X'; Y')^T$ is an independent copy of $(X;Y)^T$. Hence Kendall's tau for (X;Y)T is simply the probability of concordance minus the probability of discordance (Embrechts et al. 2001).

[14] Spearman's rho for the random vector (X;Y)T is defined as $\rho_S(X;Y) = 3(P\{(X - X')(Y - Y'') > 0\} - P\{(X - X')(Y - Y'') < 0\})$; where $(X;Y)^T$,$(X';Y')^T$ and $(X'';Y'')^T$ are independent copies (Embrechts et al. 2001).

[15] Let $(x; y)^T$ and $(x'; y')^T$ be two observations from a vector $(X;Y)^T$ of continuous random variables. Then $(x; y)^T$ and (x'; y')T are said to be concordant if $(x - x')(y - y') > 0$, and discordant if $(x - x')(y - y') < 0$ (Embrechts et al. 2001).

- To compare more than two correlation coefficients, a χ^2 test is required. After the Z score standardization of the empirical correlation coefficients (r_1, r_2, … r_k) which were calculated from a sample with n_1, n_2, … n_k components, theoretical correlation coefficients (R_1, R_2, … R_k) have to be tested with a H_0, that they are equal (H_0: $R_1=R_2=\ldots=R_k$) (Lukács 1999).

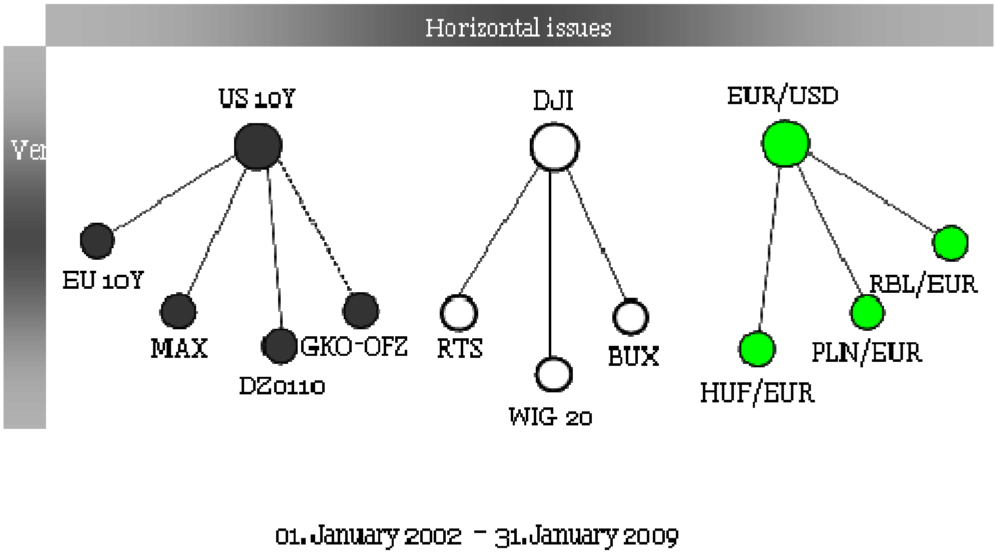
Due to the central role of US capital markets, usage of hierarchical models is more discursiveness. In this case we have to assume that the contagion developments are top-bottom processes. To measure correlations, moving window approach is the most feasible for our research, because the common developments were analyzed as the follows:

On the top of the vertical (stock, bond and currency markets) dimensions there are indicators form US, due to the central role of their capital markets. Hungarian, Polish and Russian markets[17] are containing the "emerging" part of the sample. Inflation targeting monetary policy of the European Union underlined the necessity of a long term bond market benchmark from the continent (as EU 10Y bond).

[16] If X and Y are continuous random variables whose copula is C, then Kendall's tau and Spearman's rho satisfy the following properties for a measure of concordance:
1. κ is defined for every pair X;Y of continuous random variables.
2. $-1 \leq \kappa_{X;Y} \leq 1$, $\kappa_{X;X} = 1$and $\kappa_{X;-X} = -1$.
3. $\kappa_{X;Y} = \kappa_{Y;X}$.
4. If X and Y are independent, then $\kappa_{X;Y} = \kappa_{\Pi} = 0$.
5. $\kappa_{-X;Y} = \kappa_{X;-Y} = -\kappa_{X;Y}$.
6. If C and C' are copulas such that C < C',then $\kappa_C \leq$¶ $\kappa_{C'}$.
7. If $\{(X_n;Y_n)\}$ is a sequence of continuous random variables with copulas C_n,and if $\{C_n\}$ converges pointwise to C, then $\lim_{n\to\infty} \kappa_{C_n} = \kappa_C$. (Embrechts et al. 2001)

[17] There are some distortions of validity in the case of bond markets due to the data collection, because in the case of Russia, there is only data available for federal bond market (GKO-OFZ) after 9. 1. 2006.; while there are only single bond prices in Poland (so DZ0110 was taken into consideration thanks to it's fitting to the examined interval), which is opposite of Hungarian bond market index (MAX).

Figure 1 Observed markets



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Logarithmic return series were used (1) with daily frequencies and are constructed from the price series (S_t) between 2. 1. 2002 and 31. 1. 2009 to study an entire conjuncture cycle in the world economy.

$$Y_t=[\log(S_t)-\log(S_{t-1})]*100 \qquad (1)$$

At hierarchical view we have to study the return fluctuations on the main market (Ym_t). Therefore it is necessary to split its development (2) on monotonic stages.

$$D_{Ym} = D_{Ym}(t_n) = (Y_m(t_n) - Y_m(t_{n-1})) \qquad (2)$$

Turning points were set by $D_{Ym}(t_n) \times D_{Ym}(t_{n+1}) < 0$ cases, therefore monotone emerging and declining periods { $l_1, l_2, \dots, l_k.$ } could be defined. Than we have to study, how the return developments on the *n* emerging markets (Yen_t) were determined in these intervals { $l_1, l_2, \dots, l_k.$ }.

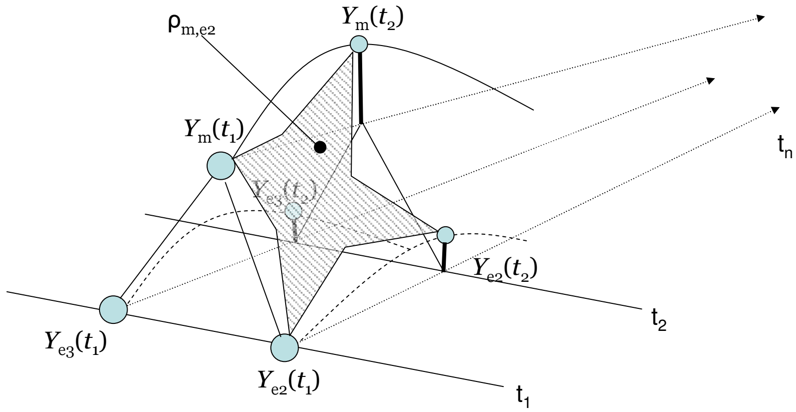
$$D_{Yen} = D_{Yen}(t_n) = (Y_{en}(t_n) - Y_{en}(t_{n-1})) \qquad (3)$$

The resulted row vectors have to divide on emerging and declining group (determined by $D_{Ym}(t_n)$), than the extraordinary and normal stages were separated – according to their outlying properties in the tail distributions. Synchronizations between $D_{Ym}(t_n)$ and $D_{Ye1}(t_n)$, $D_{Ye2}(t_n)$, …, $D_{Yen}(t_n)$ raw vectors were signed by Spearman's rho correlation coefficients (4).

$$\rho_{DYm(li),\, DYek(li)} = \mathrm{cov}(D_{Ym}(l_i), D_{Yek}(l_i)) \,/\, \sigma_{DYm(li)}\, \sigma_{DYek(li)} \qquad (4)$$

To separate normal and extreme log return developments on the main market, normal distribution was fitted on its empirical distribution. Heavy tails were identified, where the theoretical and empirical distribution diverged. Than the significance of difference between normal and extreme average returns, standard deviations and correlation coefficients were compared with the usage of chi-square test.

Figure 2 Semi-dynamic hierarchical windowed correlation



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4. Results

4.1. Descriptive statistics

Standard picture of efficient markets are showed by the higher level of standard deviation at higher mean level of logarithmic means. But there is a lack of normal distribution as Kolmogorov-Smirnov test for normality suggest. Negative skewness means fatter left (dropping) side, against a robust right (emerging) side. Therefore extreme events had higher occurrence during negative developments, while positive movements were similar mostly in the case of all emerging stock markets opposing to Dow Jones Industrial. Bond markets behave quietly similar – except GKO-OFZ, which is the most fragile instrument in the sample. We can find the opposite in the case of currency markets due to the opposite logic of exchange rates. While the main currencies are determined by the devaluation trend of USD against EUR with rare test backs, emerging actors behave extremely during their devaluation. Kurtosis is the indicator of the representation of mode inside the distribution. High kurtosis means a robust mode with dangerous backyard filled with extreme events – so the market usually operates normally, but it collapses when something weird happen.

Table 1 Data overview and descriptive statistics for the return series

						Kolmogorov-Smirnov	
	N	Skewness	Kurtosis	Mean	SD	Z	Asymp. Sig. (2-tailed)
DJI	1817	0.1241	10.2356	-0.0001	0.0128	4.1869	0.0000
RTS	1817	-0.6625	14.1959	0.0004	0.0225	4.8399	0.0000
BUX	1817	-0.3164	9.2518	0.0002	0.0159	2.6750	0.0000
WIG 20	1817	-0.2585	2.4823	0.0001	0.0161	2.0375	0.0005
US 10Y	1817	-0.1076	2.0352	0.0000	0.0007	1.8553	0.0020
EU 10Y	1817	-0.1124	1.3083	0.0000	0.0004	1.7123	0.0057
MAX	1817	-0.1237	18.6461	0.0002	0.0044	7.0802	0.0000
DZ0110	1537	-0.1507	5.6904	0.0000	0.0022	5.9033	0.0000
GKO-OFZ	780	-3.6813	42.6656	0.0000	0.0014	9.0965	0.0000
USD/EUR	1817	-0.2348	3.7052	0.0002	0.0063	2.0230	0.0006
HUF/EUR	1817	1.3987	12.8395	0.0001	0.0057	4.2770	0.0000
RBL/EUR	1817	0.7882	8.5373	0.0003	0.0053	3.5858	0.0000
PLN/EUR	1790	0.6517	5.2166	0.0001	0.0064	3.1172	0.0000

Source: own calculations

4.2. *Test for power-law and exponential logarithmic yield distributions*

According to literature suggestions, tail asymptotic distribution was examined on two ways. At first exponential and power-law tail distributions had to be separated by a simple R^2 based fitting-test[18]. Than estimated power-law properties were studied by Clauset, Shalizi and Newman's (2007) improved quantile-based maximum likelihood estimation (MLE) method[19], to estimate the scale parameter α. Size of the tails is determined by the scale parameter α – as smaller the α, as fatter is the tail. P-values are given by Monte Carlo procedures: the power-law model is fitted for generated synthetic data sets, and the number of times is counted when the Kolmogorov-Smirnov is larger than observed goodness-of-fit (maximum distance between the tail probability or cumulative distribution function of the empirical data and the fitted power-law model). (Clauset et al. 2009, Quismorio 2009)

[18] R-square – measures how successful the fit is in explaining of the variation of the data. A value closer to 1 indicates a better fit. General model for exponential: f(x) = a*exp(b*x) and for power-law: f(x) = a*x^b+c.
[19] Scripted in MATLAB, see http://www.santafe.edu/~aaronc/powerlaws/.

Table 2 Tail distributions

	Power-law distribution				Exponential distribution	
	Negative tail		Positive tail		Negative tail	Positive tail
	α	p	α	p	R^2	R^2
WIG 20	**1.9738**	**18.80%**	**2.1418**	**75.20%**	91.08%	94.30%
DJI	**1.8995**	**80.00%**	**1.8557**	**80.80%**	86.59%	81.05%
BUX	**1.7643**	**90.40%**	**2.0204**	**7.00%**	79.25%	80.93%
RTS	**1.8351**	**7.70%**	**1.9407**	**7.80%**	84.86%	72.34%
US 10Y	**2.0591**	**98.80%**	**2.1089**	**80.80%**	93.94%	91.90%
DZ0110	**2.2477**	**96.40%**	1.5072	0.00%	90.46%	92.95%
MAX	**1.7265**	**21.90%**	1.7709	***6.80%***	88.72%	77.89%
EU 10Y	2.5059	***5.90%***	1.7372	0.00%	**95.78%**	92.87%
GKO OFZ	1.2255	0.00%	1.2343	0.00%	**95.79%**	**97.25%**
USD/EUR	**2.0549**	**70.70%**	**2.0764**	**18.60%**	**98.00%**	91.58%
RBL/EUR	**1.9410**	**53.10%**	**1.8987**	**60.80%**	91.04%	82.85%
PLN/EUR	**1.9573**	**36.30%**	**1.8881**	**83.10%**	88.97%	87.27%
HUF/EUR	**1.9826**	**46.30%**	**1.8470**	**20.60%**	**98.66%**	78.38%

Source: own calculations

As literature said, there are significant differences in the thickness, which means that emerging markets have fatter negative tails than developed markets. During periods of boom longer and thicker tails were detected with a power-law exponent α close to 3, while periods of stagnation characterized by shorter and thinner tails with an exponential decay close to 1. (Quismorio 2009)

Such asymmetries are identified at the negative tails of the sample. Stock and currency markets are behaving as power-law in both cases of market developments, and their α exponent remains under the literally presented 2.5 to 3.5 interval – which signs a lot of opportunities for unpredictable events in each conjuncture phase. Bond markets have only negative power-law tails, but the fitting process could be too difficult due to the observed enormous kurtosis. EU 10Y indicator is smoother than US 10Y, which could be the result of strict inflation targeting monetary policy of the ECB.

According to the forms of distribution, there are no strict differences between developed and emerging markets, the difference in α is marginal.

4.3. Test of common developments under normal and extraordinary events

4.3.1. Static correlation on the entire observed period

In the case of stock markets on the entire period between 2002 and 2009, weak but significant (Sig.≈0) connection were signed by Spearmen's 2 tailed correlation between DJI and the emerging capital markets ($\rho_{RTS,\ DJI}$= 0.236; $\rho_{WIG\ 20,\ DJI}$= 0.239), while significant relation was only flagged between WIG20 and RTS ($\rho_{WIG\ 20,\ RTS}$= 0.046). Hungarian stock market had no significant correlation.

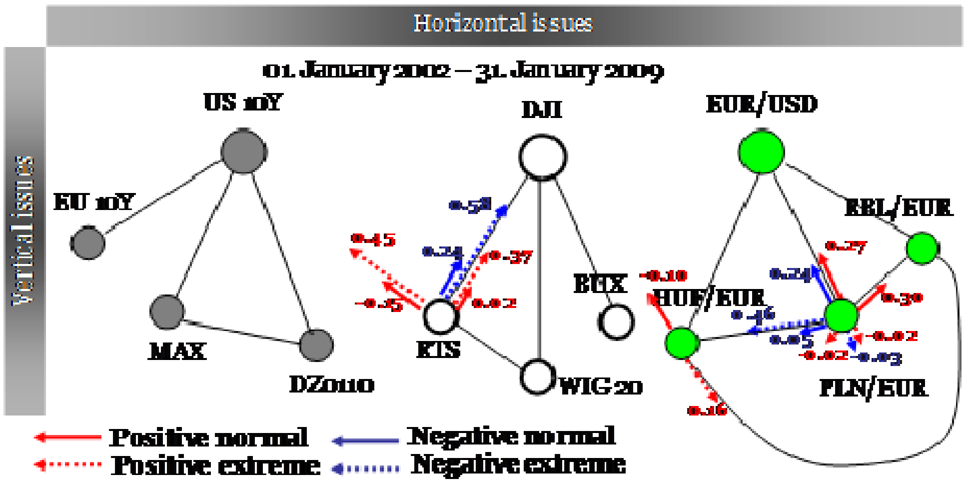
Developed bond markets had only significant but strong correlation ($\rho_{US\ 10Y,\ EU\ 10Y}$= 0.4726) during this period. Currency markets[20] had significant but varied correlations ($\rho_{EUR\ /USD,\ RBL/EUR}$= 0.915; $\rho_{EUR\ /USD,\ HUF/EUR}$= -0.064; $\rho_{EUR\ /USD,\ PLN/EUR}$= 0.11). PLN and HUF had also a strong significant connection ($\rho_{HUF\ /EUR,\ PLN/EUR}$= 0.44), while PLN and EUR relation remained weaker ($\rho_{HUF\ /EUR,\ PLN/EUR}$= 0.164). In Hungary, there was lack of significant correlation between bond, stock and currency markets, while WIG 20 was sensible on bond and currency market developments ($\rho_{WIG\ 20,\ US\ 10Y}$ = -0.111; $\rho_{WIG\ 20,\ EU\ 10Y}$= -0.106; $\rho_{WIG\ 20,\ MAX}$= 0.126; $\rho_{WIG\ 20,\ DZ0110}$= 0.06; $\rho_{EUR\ /USD,\ WIG\ 20}$= -0.055; $\rho_{WIG\ 20,\ HUF/EUR}$= -0.24; $\rho_{WIG\ 20,\ PLN/EUR}$= -0.21).Hungarian MAX index had converse relation with HUF and PLN exchange rates ($\rho_{MAX,\ HUF/EUR}$= -0.357; $\rho_{WIG\ 20,\ PLN/EUR}$= -0.249).

4.3.2. Dynamic correlation phenomena and tail distribution

The outputs of static spearmen's 2 tailed correlation signed poor inter connections on horizontal and vertical scale, but more detailed picture was provided after the establishment of quasi dynamic intervals ("windows"). Synchronisation of markets could depend on the probability of return developments.

[20] In the case of currency markets, it is necessary to study the exchange rate arrangements in analyzed countries as Stavárek (2009) suggest.

Figure 3 Calculated semi-dynamic hierarchical windowed correlation



Source: own calculations

The hypothesis, that the US (as “main”) markets playing a dominant role with on influence on the emerging markets, was mostly rejected. There were only several cases, when significant difference occurred between market common movements according to the main market’s normal or extreme stage. As Stavarek (2009) suggested, results were the inverse on currency market than on the others. USD-EUR relations had an indirect impact on Euro-zone candidate countries – PLN and HUF had a mediocre correlation under extreme strong periods of the euro, while PLN had a weak correlation with the EUR under normal circumstances. But this test was useful to sign the special role of Russian stock and currency markets – RTS moved only together with the main market (DJI) under extreme boosts and falls, and had a contrary connection to the WIG 20 under positive developments; while HUF, PLN and RBL tended to move together differently under stronger US dollar.

5. Discussion

Market risk management had to face with several problems in the last decade: market data returns are likely uncorrelated, but dependent, their probability distributions are heavy tailed, and extreme events appear in clusters while volatility is random (Embrechts et al. 2001). The conceptual model, which was presented in this study, had the same problems. More progressive solutions are given by the copulas as we mentioned in the methodological chapter, because probabilities and common developments are unified by them. But there are two causes to be careful during their usage: it is not clear from the basic models that the events on two or *n* margin's tails are happening in the same time, and correlation remained static in several applications.

To pay attention on the separation of monotonic or quasi monotonic developments of main market yields, ARIMA models could be more feasible – because short run fluctuations could be controlled better, than the presented multiplications of first derivates (or their rolling mean smoothed version). (Ramathan 2003)

6. Conclusion

Financial engineering facilitates the transformation and reshaping of risk, but some authors emphasize the disadvantage of network operations, in which the high efficiency on liquidity allocation capability and the ability of fast feedback through current account cause immanent instability of the current financial system with short-term orientation and unrelenting concentration of wealth (Brunnhuber et al. 2005, Magas 2005).

Imbalances of transitional countries were indicated by financial markets as models of bounded rationality and complex scale-free networks suggested. Developed countries have to face with extreme bullish and bearish circumstances, in which volatility of liquidity diffuse through the market. Emerging markets behave slightly altered, but it is not necessary to deeply revalidate the basic axioms on them as our results suggests. Differences could be found in their relationships to the occurrence of improbable events and their weak synchronisations under fat tailness. Capital flows are non-linear, therefore, the bottleneck-effects are caused by the withdrawal of the capital that is faster than its inflow. Occurrence of asymmetries means that negative shocks hit much harder these markets than positive news – so their collapse is much more sudden, while the recovery is slower. To handle emerging coutries as homogenous groups by foreign investors is the main reason of contagion effects – so if anything werid happens in these countries, funds are being extracted from other markets too (Égert – Koubaa 2004).

References

Babetskaia-Kukharchuk O., Babetskii I., Podpiera J. 2008: Convergence in exchange rates: market's view on CE-4 joining EMU. *Applied Economics Letters*, 15, pp. 385–390

Barabási, A-L., Albert, R. 1999: Emergence of Scaling in Random Networks. *Science.* 286, 509, Bonanno, G., Lillo, F., Mantegna, R. N. 2001: Levels of Complexity in Financial Markets. *Physica A.*, 299, pp. 16-27

Brunnhuber, S. - Finkc, A. - Kuhlec J. 2005: The financial system matters: future perspectives and scenarios for a sustainable future. *Futures*, 37, 4, pp 317-332

Clauset, A., Shalizi, C. R., Newman, M. E. J. 2009. Power-law distributions in empirical data. *SIAM Review, to appear.*

Csermely, P. 2008: Creative elements: network-based predictions of active centres in proteins and cellular and social networks. *Trends in Biochemical Sciences*, 33, 12, pp. 569-576.

di Mauro, F., Rüffer, R., Bunda, I. 2008: The Changing Role of The Exchange Rate in a Globalised Economy. *ECB Occasional Paper Series.* NO 94 / September 2008

Embrechts P., Lindskog f., McNeil A. 2001: *Modeling Dependence with Copulas and Applications to Risk Management*. Department of Mathematics ETHZ, Zürich

Grubesic, T. H., Matisziw, T. C., Murray, A. T., Snediker, D. 2008: Comparative Approaches for Assessing Network Vulnerability. *International Regional Science Review*, 31, 88

Herrmann-Pillath, C. 2000: How to Research Complex Systems: A Methodological Comparison of "ORDO-Liberalism" and "Regulation Theory". In: Labrousse, A., Weisz, J.-D., (eds.), *Institutional Economics in France and Germany*, Reihe Economics and Philosophy, Heidelberg: Springer, pp. 272-301.

Hommes, C., Wagene, F. 2008: Complex Evolutionary Systems in Behavioral Finance. In Hens, T., Schenk-Hoppé, K.R. (eds.) *Handbook of Financial Markets: Dynamics and Evolution*, Tinbergen Institute TI 2008-054/1 Tinbergen Institute Discussion Paper, ACADEMIC PRESS CeNDEF, School of Economics, University of Amsterdam

Kiss, G. D. 2009: Analysis of Diversification Problems in the Case of Hungarian and Russian Pension Investments. In Mgr. Cervinek, P. (ed.) New Economic Challenges - 1st International PhD Students Conference, Masaryk University - Faculty of Economics and Administration, Brno, pp. 25-30.

Lukács, O. 1999: *Matematikai Statisztika*. Műszaki Könyvkiadó, Budapest

Magas, I. 2005: A pénzügyi integráció hozadékai a világgazdaságban - empirikus tapasztalatok 1970-2002. In: Botos Katalin (szerk): *Pénzügyek és globalizáció*, SZTE GTK Közleményei, JATEPress, Szeged pp. 139-161

Quismorio, B. A. 2009: The Tail Distribution of the Philippine Stock Price Index. *Working Paper, University of Philippines-Diliman.*

Ramanthan R. 2003: *Bevezetés az ökonometriába*. Panem, Budapest

Stavárek, D. 2009: Assessment of the Exchange Rate Convergence in Euro-Candidate Countries. *Amfiteatru Economic Journal*, 11, 25, pp. 159-180.

Wang, X. F., Chen, G. 2003: Complex networks: small-world, scale-free and beyond. *Circuits and Systems Magazine, IEEE*, 3, 1, pp. 6-20.

Yuan, Baosheng – Wang, Bing-Hong – Li, Baowen 2007: Evolutionary Dynamics in Complex Networks of Adaptive and Competing Agents. *Working Paper, Great Eastern Life Assurance Co.*