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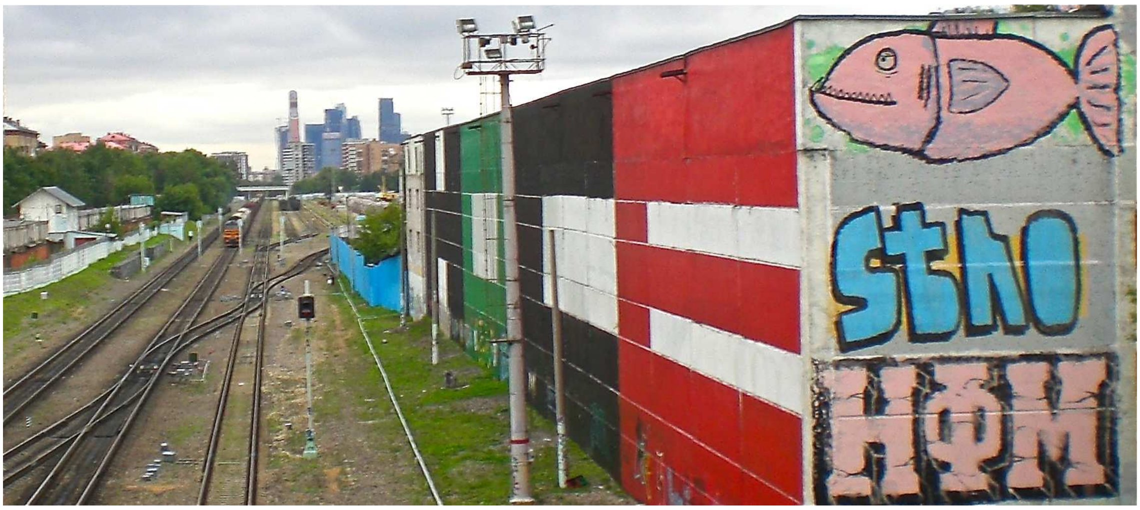

Market Correlations

FORTS Derivative Market Diagnostics

Issue 39 April 2016

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MARAGING PARTNERS

Maraging Partners LLC is a Moscow-based FX management advisory firm.

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Maraging Partners is a team with a unique composition of skills and professional backgrounds. Looking at the global markets through the optics of expert analysis and the scientific method, we are able to find and implement novel solutions to the problem of currency risk management and "alpha" utilization.

Independence of our employee-owned company from the influence of financial intermediaries aligns our interests with those of our clients.

Our seasoned Capital Management team with demonstrated public track record are open to exclusive cooperation with Family Offices, Funds of Funds and are ready to consider capital introduction offers.

Cover art: Large scale irrationality of market actors drives speculative profits.

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FORTS Derivative Market Diagnostics

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Contents

1 About this document

This is the 39 -th issue of the FORTS Market Correlations Review.

1.1 Purpose and the target audience of this document

Regularly updated data on the strength of correlation among various financial time series, observed on various time scales, including the information about lagged correlations of the leader-follower type, is of considerable value to portfolio managers, analysts, corporate treasurers, and some portfolio investors. The correlation strength data should be used in risk/reward portfolio optimization. The lagged correlation data open up new possibilities of market analysis and forecasting.

These reports are issued monthly.

To customize this report for a geographical region or a set of markets of interest to you, please contact us directly.

1.2 How the document is organized

We stive to make every issue as self-sufficient as possible, therefore each issue contains, along with the new information, a large fraction of introductory materials, which may be already familiar to the readers of the previous issues, but which is necessary to understand the approach. Some formulations can be repeated literally if that provides for the best clarity and completeness of the exposition: our style is considerably different from that of investment journalism.

Technical definitions are given in the Appendices.

2 Executive Summary

Table 1: Index values for March 2016 .

month	year	volatility	CSI_{FORTS}	$CBPI_{\mathrm{FORTS}}$	$CBPI_{\mathrm{FORTS},0}$	$R_{2\mathrm{FORTS}}$
March	2016	0.00393	0.475	0.0510	0.0591	0.0276

Values of the correlation indices for the past month are given in Table 1.

Fig. 1 allows one to compare the history of CSI, CBPI and R_2 with the history of volatility, and comprises data from February of 2009 through March of 2016 .

From the point of view of the correlation approach, the following features of this month's data are noteworthy.

- As figure 1 indicates, QE1 and QE2 ended with CSI_{FORTS} (see Section 4) above 0.40. The continuation of QE in 2014 coincided with presistently low levels of CSI, but in October 2014, a rise in volatility conicided with a significant rise in CSI_{FORTS}. All three QEs were followed by an increase in CSI.
- The "European QE", officially known as EAPP, was initially accompanied by a new reduction in the level of CSI.
- After the Fed rate hike in December 2015, EUR/USD became the "risk-off" currency pair, correlated negatively with Brent and RTS and positively – to USD/RUB.
- The correlation phenomenon we refer to as the "solo party" of the RUB has continued in March,and due to the "sticky" nature of this phenomenon, we expect it to continue in April.

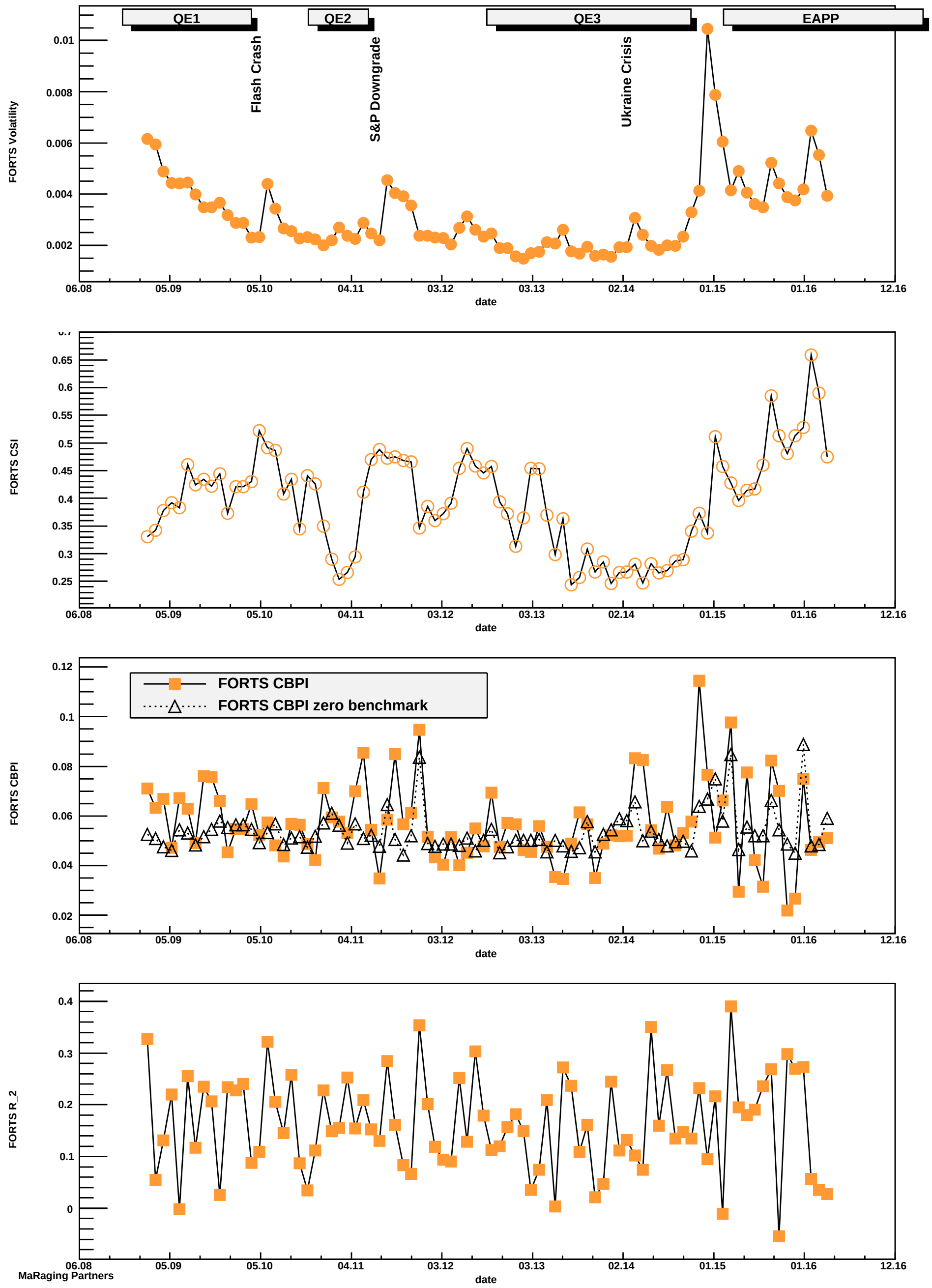

Figure 1: Time evolution of volatility, correlation strength index (FORTS CSI), correlation predictability index (FORTS CBPI) and R_2. Time axis is labeled in the **MM.YY** format.

3 Data analysis and interpretation

3.1 Our approach. Correlation diagnostics.

Our approach prioritizes quantitative measurement over modeling, although models may emerge on the stage of data interpretation. The data processing is transparent and reproducible. In these reports, we limit ourselves with statistics of the second degree: variance (or volatility) and correlation function understood as a time lag dependency.

When forced behavior of any kind dominates the markets, correlations among market instruments grow in the absolute value, becoming exteremely positive or negative. In the process, a peculiar degeneration in the diversity of financial instruments takes place, so that to understand the dynamics, it becomes sufficient to classify them simplistically as riks-on instruments and safe havens. This degeneration in the diversity of instruments accompanies the degeneration in the diversity of participant's behavioral patterns.

We use correlation math to build indicators which are, in essence, behavioral, and apply them to diagnose the markets. This allows us to draw independent conclusions not based on the mainstream techniques of either fundamental or "technical" (according to the common usage) analysis. So far we have introduced and been using the Correlation Strength Index, Correlation Predictability Index, and the Two-Point Correlation Regime Index.

The Correlation Strength Index CSI_{FORTS} is a measure of the intermarket correlations in the chosen set of instruments, averaged over the instruments. The "correlation strength" is the absolute value of the Pearson correlation coefficient. The formal definition of CSI_{FORTS} is given in A.4.

The Correlation Predictability Index $CBPI_{\mathrm{FORTS}}$ is an extension of the CSI technique to the non-zero lags. CBPI is constructed out of auto-correlation coefficients with 1 hour lag, taken by absolute value. The formal definition of $CBPI_{\mathrm{FORTS}}$ is given in A.5.

The two-point correlation regime index R_2 is defined in A.6. R_2 allows us to distinguish among a trending regime, an oscillatory one and the one of the "efficient market".

The further exposition is based on these techniques. The technical definitions are given in Appendices A.

3.2 Data and Notation

We analyze data on five most liquid FORTS futures markets, representing factors of market dynamics important for Russia. In the charts and in the equations, the following notation is used:

1. RI: the closest futures contract on Russia's RTS stock market index, having at least three momths till expiration

2. BR: the closest futures contract on Brent oil, having at least one month till expiration. BR is a proxy for one of Russia's leader export commodities, crude oil.

3. ED: the closest futures contract on EUR/USD, having at least one month till expiration.

4. EU: the nearest three-month contract on EUR/RUB, an important hedging instrument for Russia's importers

5. SI: the nearest three-month contract on USD/RUB, an important hedging instrument for Russia's commodity exporters

3.3 Time Frames

To conduct correlation analysis, two time frame are essential: the time scale of the time series and the periodicity of the data aggregation into correlation measures.

First, one should define the time duration sufficiently long so that one can talk about existence of a market price on this time frame. The larger is liquidity, the shorter is this time duration. In the case of FORTS, we analyze price data on hourly time periods, with the exception of R_2, which is a daily measure with the day beginning and end set at 1900 Moscow time.

Second, correlations are statistics of data arrays of certain length. In these reports, this length is one month.

In the below sections brief conclusions are summarized, based on the detailed analysis of CSI, CBPI and R_2.

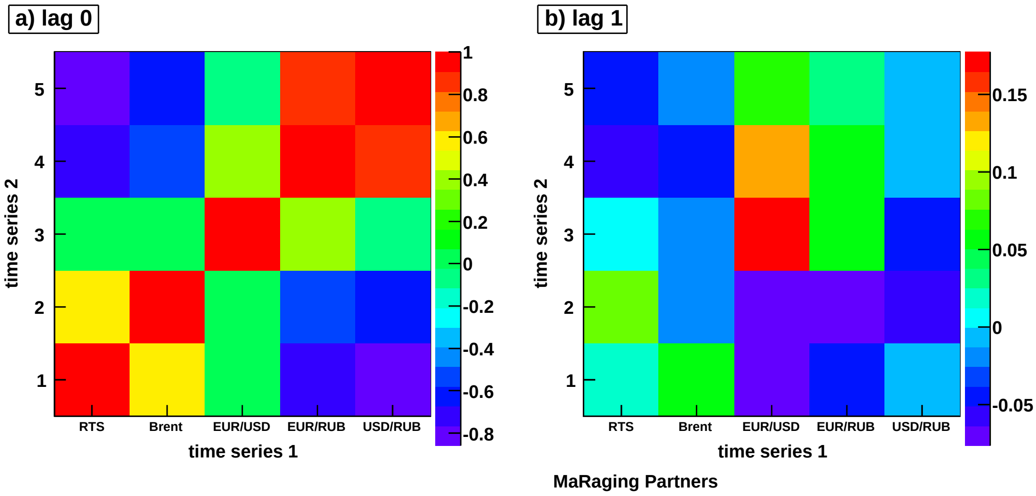

Figure 2: Correlation strength map for March 2016 . The color-coded quantity is the Pearson correlation coefficient. The cell at the crossing of the i-th column and the j-th row contains the correlation coefficient between instruments i and j, corresponding to a) zero lag b) i lagging with respect to j by one hour ($t_d = t_i - t_j = 1$, with time unit being one hour.) The indices from 1 to 5, are assigned in the following order: 1 – RTS, 2 – Brent, 3 – EUR/USD, 4 – EUR/RUB, 5 – USD/RUB.

4 Correlation Strength Index Analysis

The top panel 1 reflects the overall trend to the lowering of volatility. Splashes of volatility stand out against this backdrop. The first of them is the Flash Crash of May 2010. The second visble one is September 2011 when S&P have lowered the sovereign credit rating of the US. In both cases, the local CSI maximum falls on the month preceding the volatility splash and the splash itself occurs at a high CSI level. The all-time CSI maximum falls on April 2010.

These extreme events allow us to hypothesize that high levels of CSI after a lengthy period of rising prices of risky assets diagnose the markets as being “overbought”. The necessary caveat is that the CSI (just like CBPI, and volatility) are devoid of any information on the absolute price level of any assets: the indexes are formed on the basis of time series of *logarithmic returns*. Therefore, it is more correct to say that markets get "tired", which means that the behavioural patterns of the participants are degenerating. Such a degeneration is revealed in the correlation analysis as a degeneration of the multitude of instruments: it is either "buy everything" or "sell everything", and the first transforms into the second and vice versa.

The components of the FORTS CSI are shown in Fig. 2. Fig. 2 allows one to analyze index components visually, using instrument pairs that give the highest contribution. The time series of values for each of the non-diagonal cells in the left panel can be found in 3 and 4, for the right panel – in figures 5, 6, and also 7 and 8.

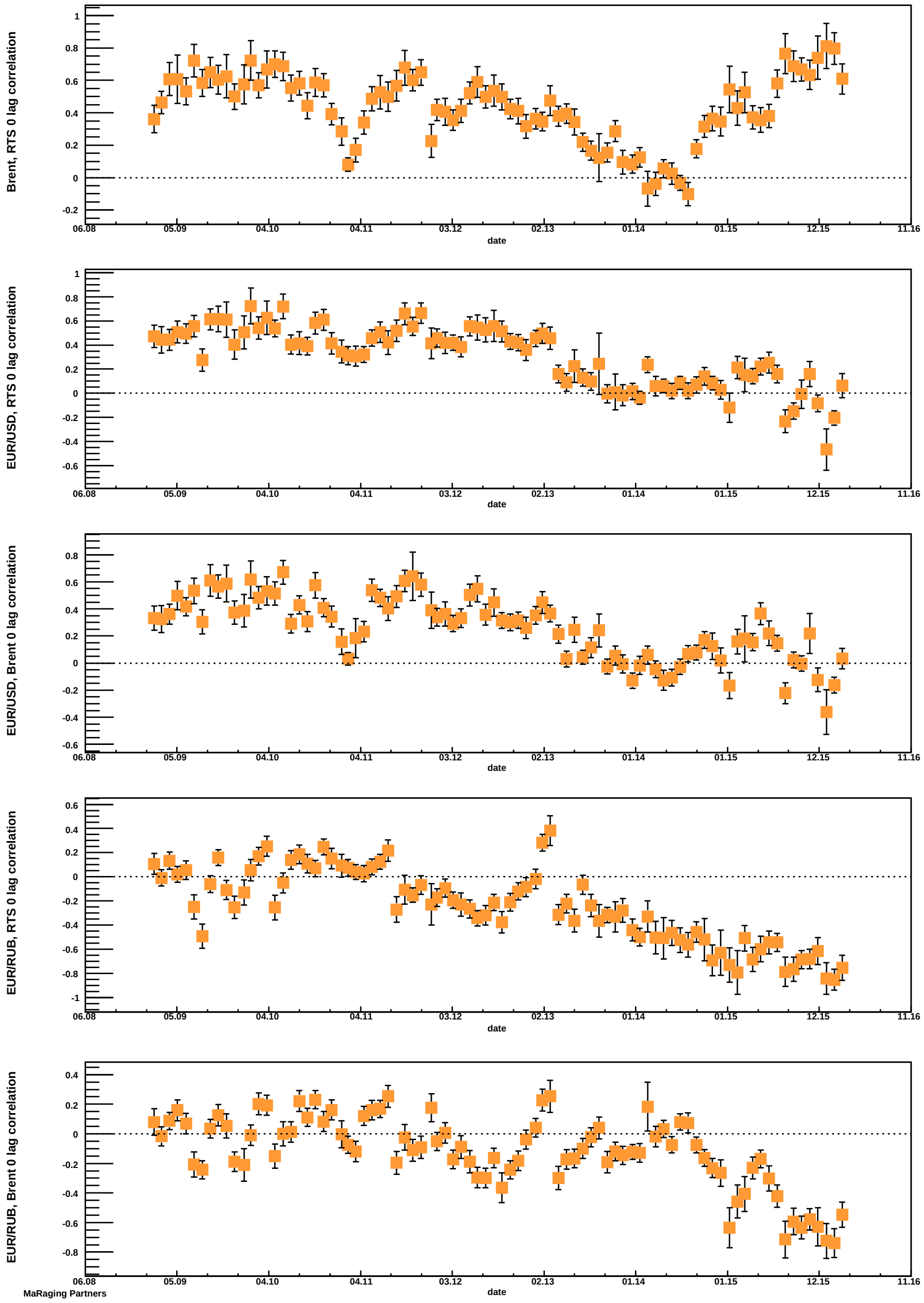

Figure 3: Correlation of logarithmic returns. Zero lag. BR and RI, ED and RI, ED and BR, EU and RI, EU and BR. The coefficients are normalized according to the Pearson coefficient formula (Section A.3).

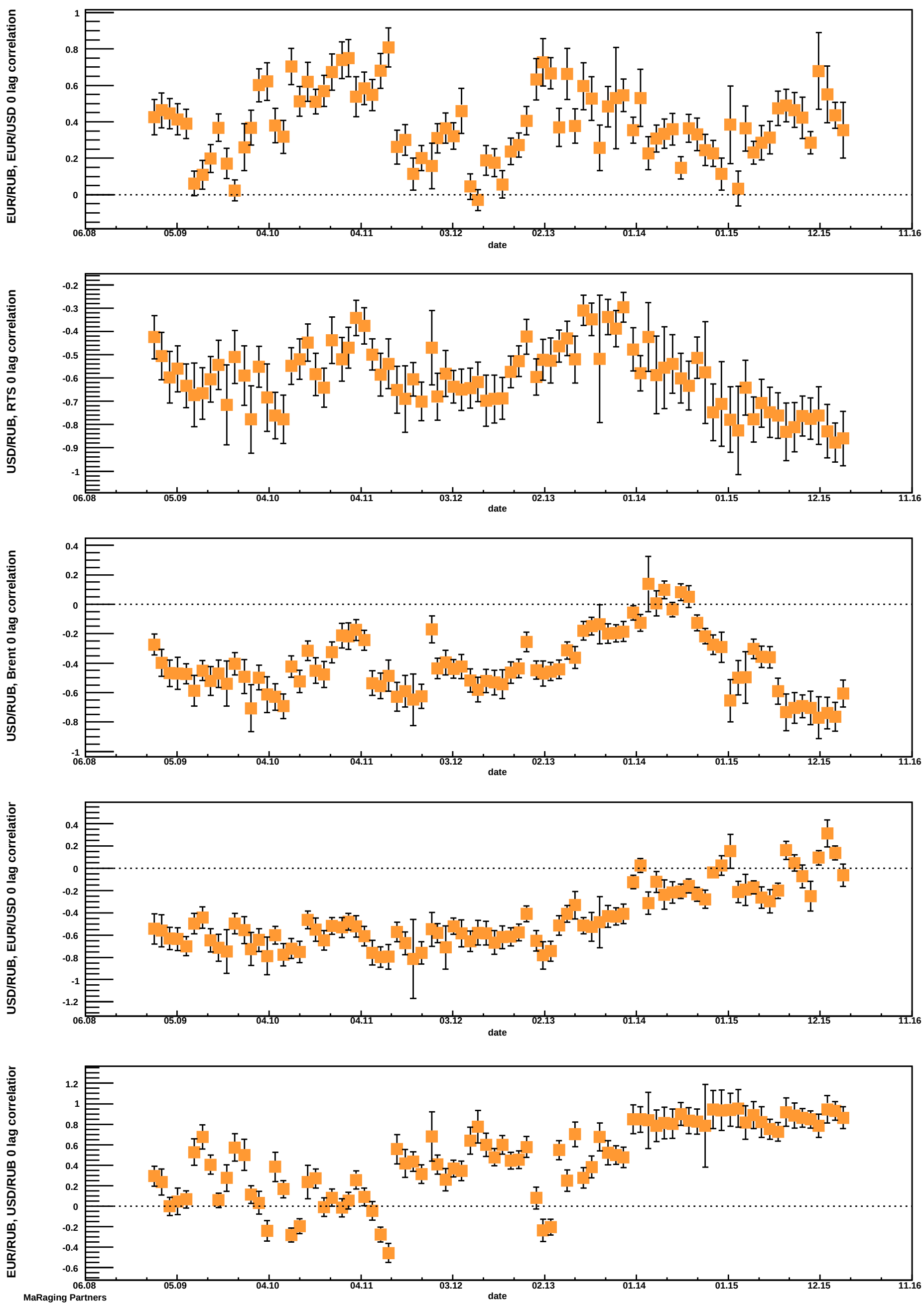

Figure 4: Correlation of logarithmic returns. Zero lag. EU and ED, SI and RI, SI and BR, SI and ED, EU and SI. The coefficients are normalized according to the Pearson coefficient formula (Section A.3).

5 Analysis of the Correlation Predictability Index

The efficient market hypothesis, which postulates equal informedness of all market participants, by its very nature, is an overstatement serving to simplify abstract theoretization, even though the degree of practically valuable informedness about the future among the modern market participants is very low. Quantitative monitoring of the degree to which the real markets deviate from the null hypothesis of efficient markets, and characterization of specific manifestation of these deviations – market instruments, seasons, time frames – are valuable to all market participants who have a resource of time and money management in order to exploit such deviations.

We have developed the FORTS CBP Index to monitor the strength of the correlation effects such as the leader-follower effects, as well as autocorrelation effects in the FORTS markets. The strategies to exploit such effects can be classed under the umbrella term "correlation arbitrage". The index is designed to monitor potential efficiency of such strategies.

While the CSI components reflect the degree to which fundamentally connected assets, such as USD/RUB, crude oil price and the Russian equities, move in a lockstep, the CBPI components reflect the degree to which the "knee jerk reactions" among the assets, in response to changes in other assets, are not instantaneous. The hypothetical efficient market is supposed to demonstrate an agreement, modulo uncertainties of the measurement, between $CBPI_{\mathrm{FORTS}}$ and $CBPI_{\mathrm{FORTS},0}$ (see definitions in Section A.5), and a consistency with zero, again modulo uncertainties of the measurement, of each correlation function at non-zero lags. In reality, as the market efficiency grows, the autocorrelation and lagging effects we are after can migrate towards shorter time scales.

Figures 9,10,11,12,13,14 show the correlation functions for the past month.

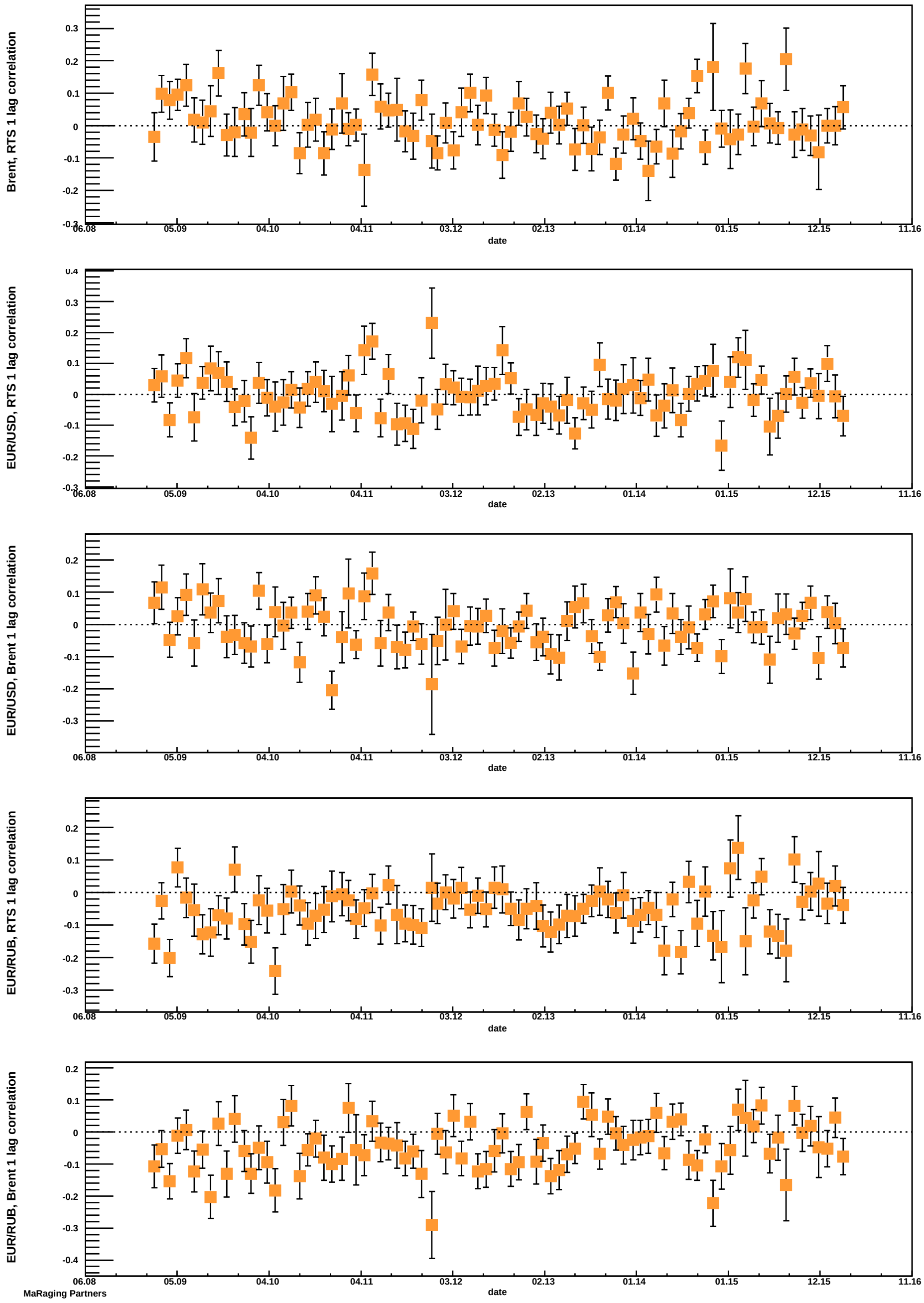

Figure 5: Correlation of logarithmic returns in the futures. 1 hour lag. BR and RI, ED and RI, ED and BR, EU and RI, EU and BR. Out of two time series, the first one (see the order of reference in the vertical axis title) is one hour late with respect to the second one. The coefficients are normalized according to Pearson coefficient formula (section A.3).

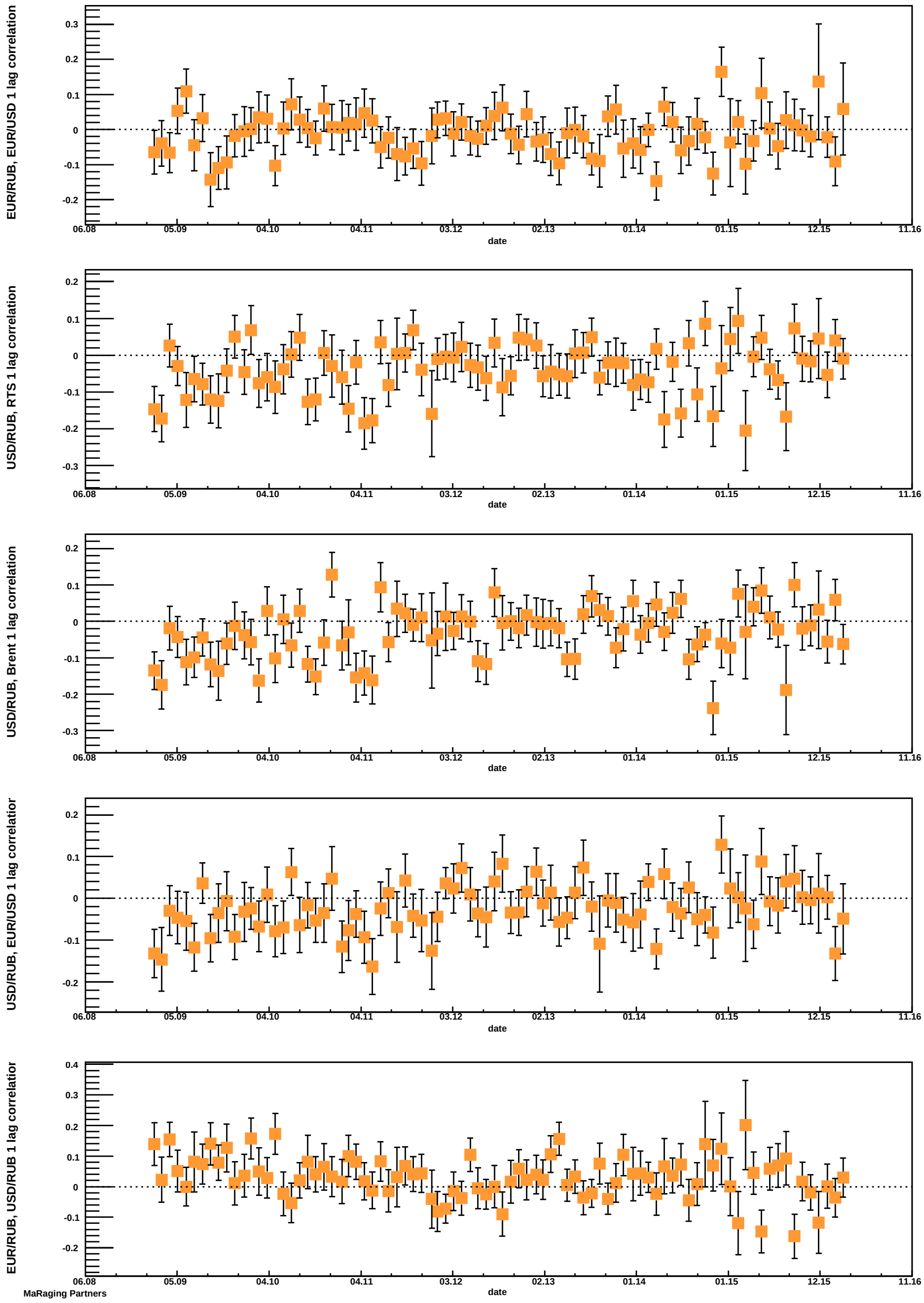

Figure 6: Correlation of logarithmic returns in the futures. 1 hour lag. EU and ED, SI and RI, SI and BR, SI and ED, EU and SI. Out of two time series, the first one (see the order of reference in the vertical axis title) is one hour late with respect to the second one. The coefficients are normalized according to Pearson coefficient formula (section A.3).

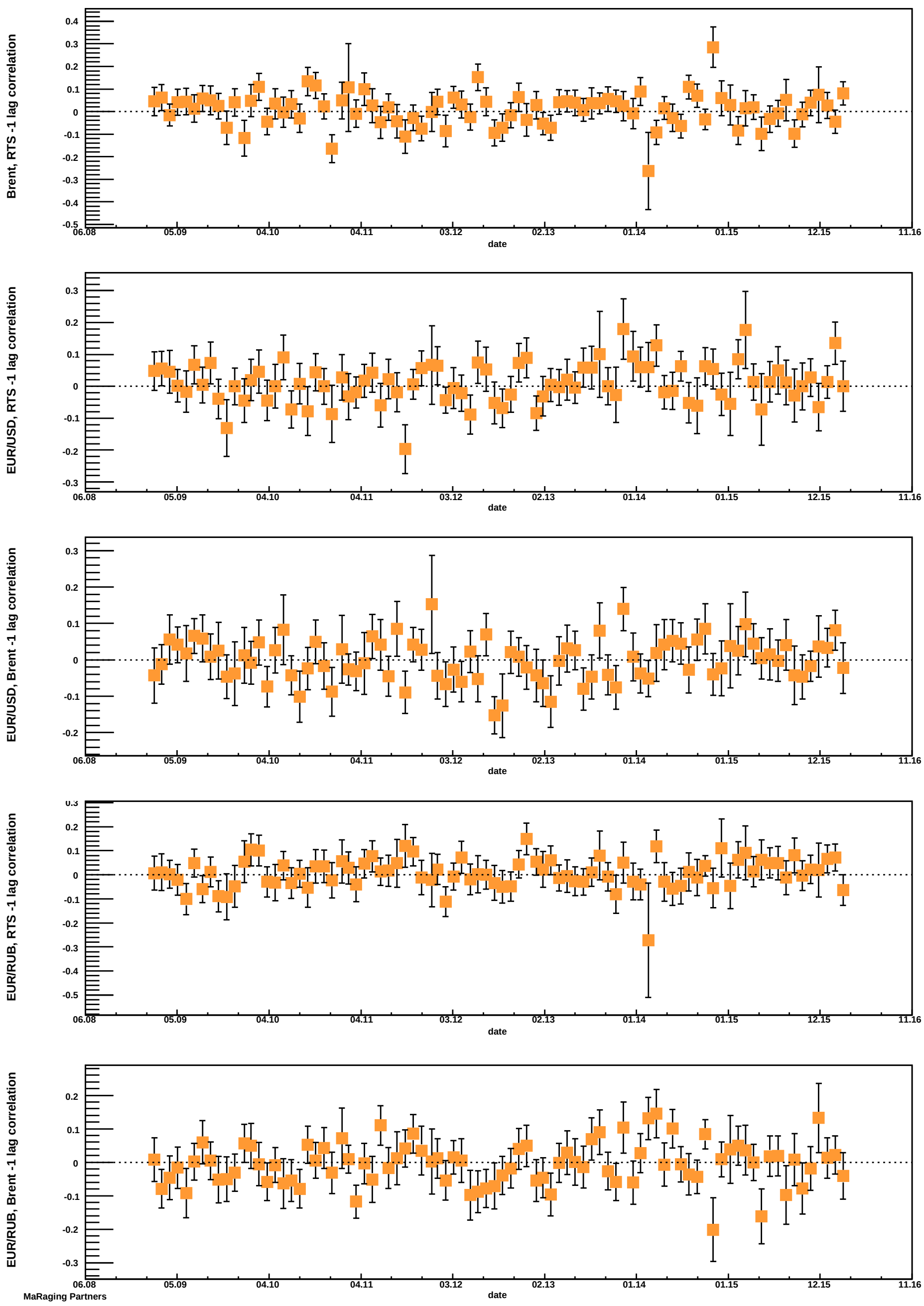

Figure 7: Correlation of logarithmic returns in the futures. 1 hour lag. BR and RI, ED and RI, ED and BR, EU and RI, EU and BR. Out of two time series, the first one (see the order of reference in the vertical axis title) is one hour ahead with respect to the second one. The coefficients are normalized according to Pearson coefficient formula (section A.3).

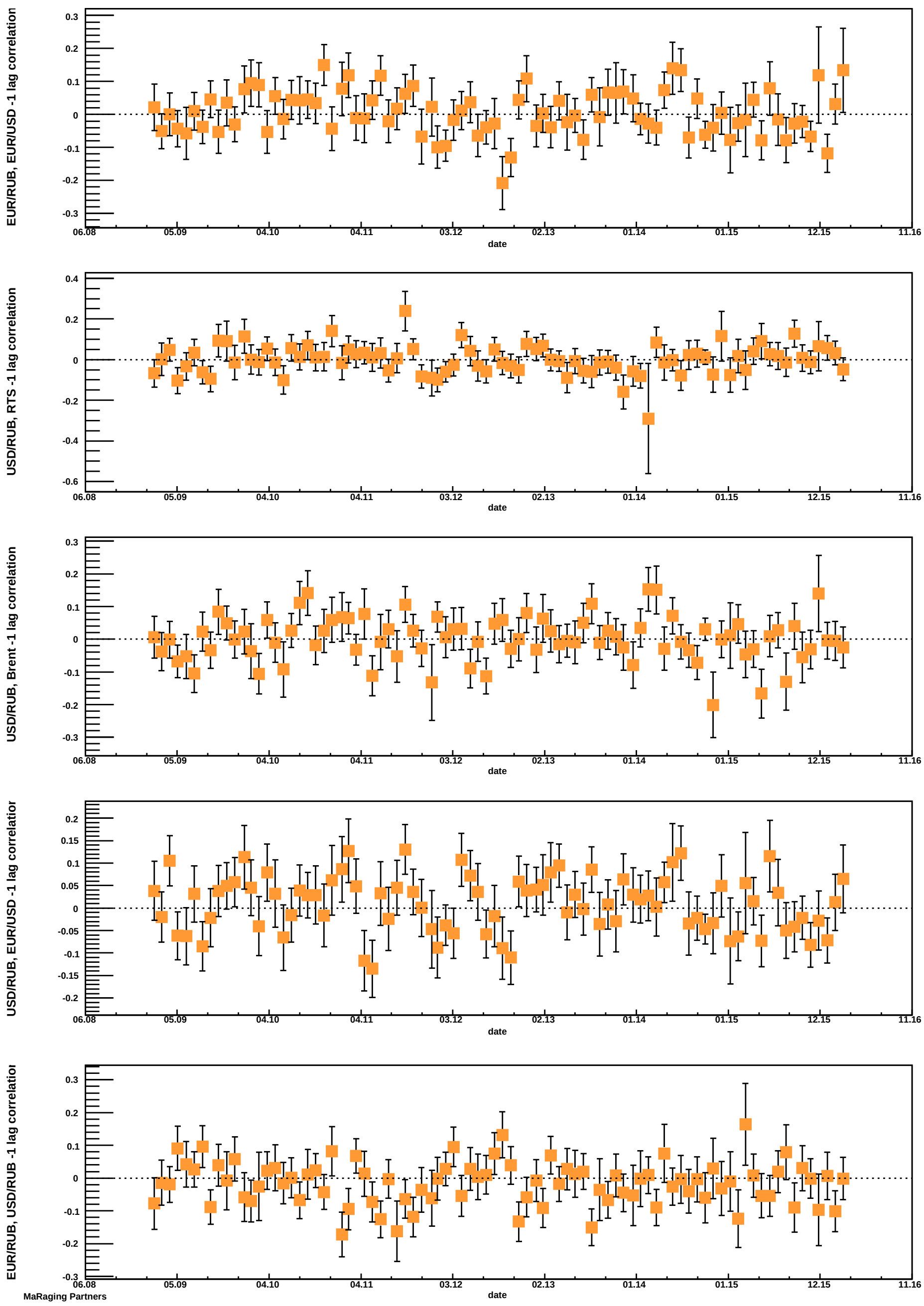

Figure 8: Correlation of logarithmic returns in the futures. 1 hour lag. EU and ED, SI and RI, SI and BR, SI and ED, EU and SI. Out of two time series, the first one (see the order of reference in the vertical axis title) is one hour ahead with respect to the second one. The coefficients are normalized according to Pearson coefficient formula (section A.3).

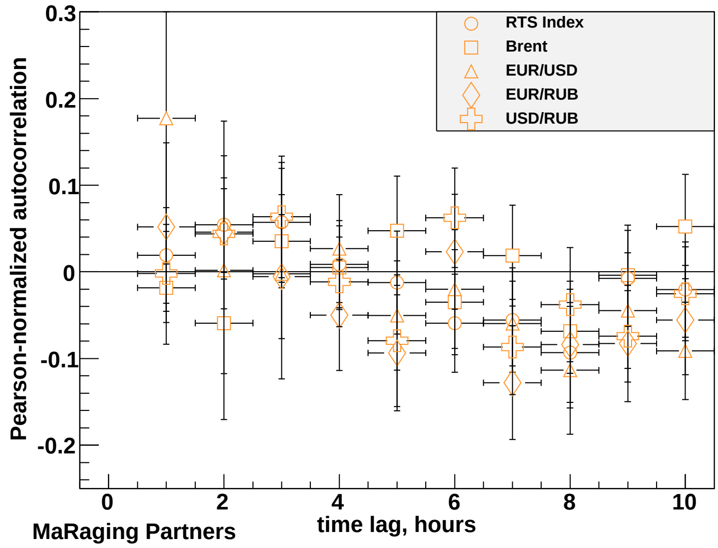

Figure 9: Autocorrelations of the logarithmic return time series, normalized according to Pearson coefficient formula (section A.3). In this normalization, the autocorrelation function at the zero lag equals 1 and is not shown.

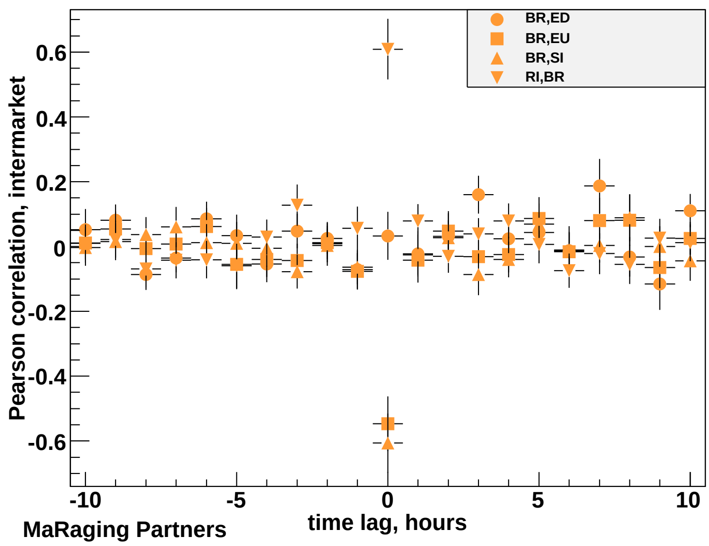

Figure 10: Intermarket correlations of BR with other futures, normalized according to Pearson coefficient formula (section A.3). ED: EUR/USD, EU: EUR/RUB, SI: USD/RUB, RI: RTS Index.

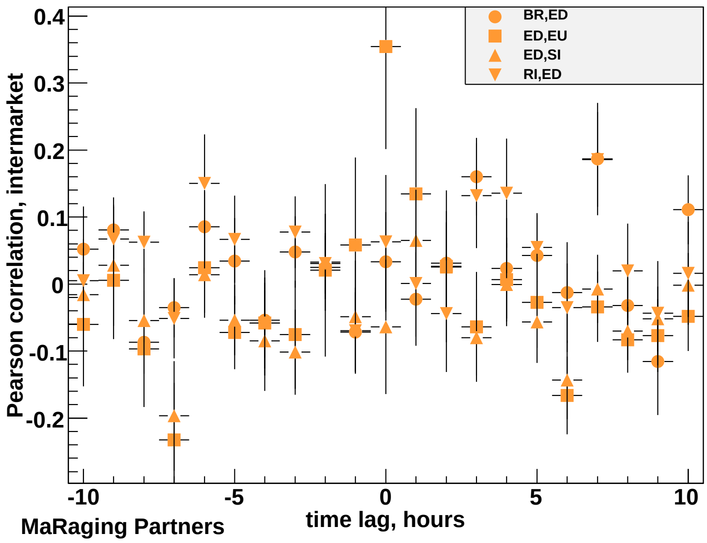

Figure 11: Intermarket correlations of ED with other futures, normalized according to Pearson coefficient formula (section A.3). BR: Brent, ED: EUR/USD, EU: EUR/RUB, SI: USD/RUB, RI: RTS Index.

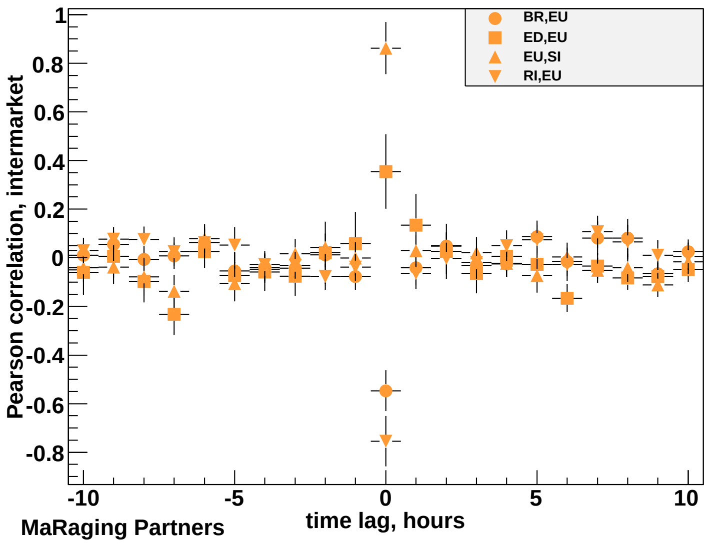

Figure 12: Intermarket correlations of EU with other futures, normalized according to Pearson coefficient formula (section A.3). BR: Brent, ED: EUR/USD, EU: EUR/RUB, SI: USD/RUB, RI: RTS Index.

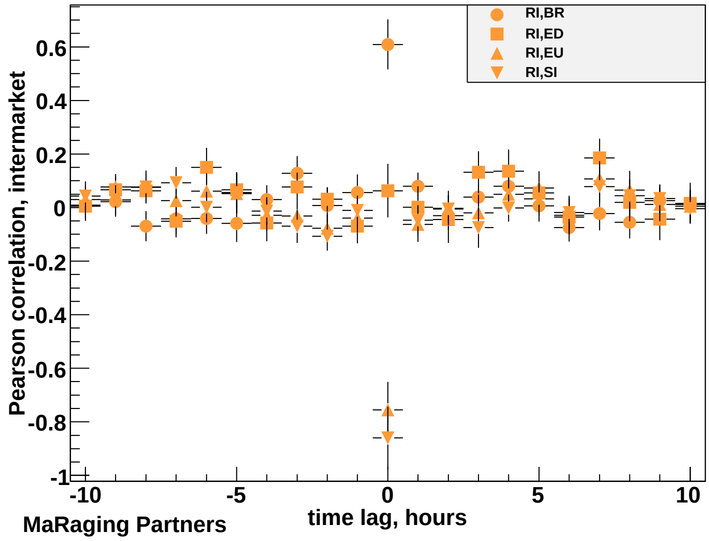

Figure 13: Intermarket correlations of RI with other futures, normalized according to Pearson coefficient formula (section A.3). BR: Brent, EU: EUR/RUB, ED: EUR/USD, SI: USD/RUB.

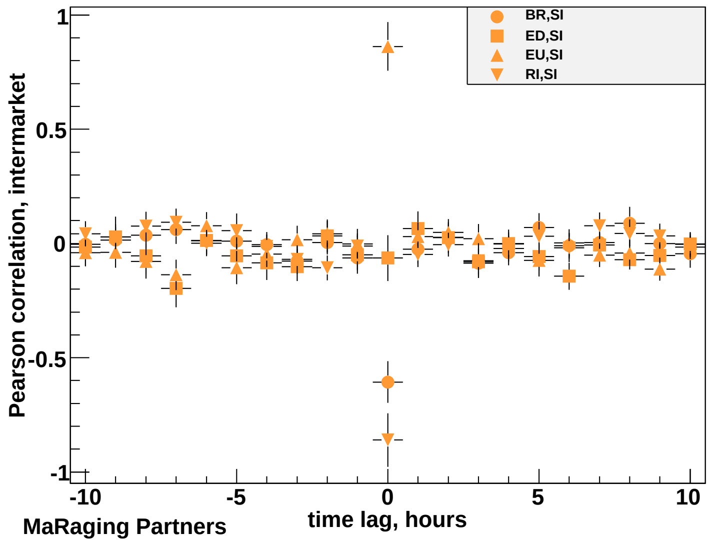

Figure 14: Intermarket correlations of SI with other futures, normalized according to Pearson coefficient formula (section A.3). BR: Brent, EU: EUR/RUB, ED: EUR/USD, RI (RTS Index).

Table 2: Benchmark values of R_2 for 20-day periods

model	value
geometric random walk with a trend	0.35
geometirc random walk, history-independent	0.079
geometirc random walk with an oscillation	-0.12

6 Analysis of the Correlation Regime Index R_2

Definition of R_2, the two-point correlation regime index, is given in A.6. Using a trending market model and an oscillating ("mean-reverting") model, as well as a random walk model with total history-independence, we have calculated the benchmark values of R_2 for these very different situations.

Trend and oscillation are the clean-cut opposite extreme cases. The efficient market hypothesis corresponds to the history-independent geometric random walk.

R_2 history is shown in Fig. 15. These charts illustrate the regime changes that took place. Even though on average, the values fluctuate around the efficient market level (dashed line), the seesaw pattern at some charts is noteworthy. The seesaw pattern may indicate a degree of predictability in the behaviour of R_2.

The auto-correlation of R_2 can be studied using two-dimensional charts where one month's R_2 is plotted as a function of R_2 for the previous month: 16,17,18, 19, 20. The non-zero auto-correlation causes the regression parameter p_1 to be non-zero. From the comparison of the charts, the difference between instruments, containing Russian components (RI, SI, EU) on the one hand, and ED, BR – on the other, is seen. In the case of the latter ones, the future R_2 is practically independent of the present, and forecasting is hard.

A Technical Definitions

A.1 Volatility

We work with logarithmic volatility. When working with a time series of logarithmic returns x(t), it is natural to define volatility as

$$V[x] = \sqrt{E[x^2(t)]|_t}, \tag{1}$$

where $E[\ ]|_t$ is the time averaging operator. According to the definition of a correlation function, volatility on a given time scale is the square root of the zero-lag value of the correlation function on that time scale.

A.2 Correlation

Correlation characterizes the degree of statistical dependendce between two or among seleveral random variables. The two-point correlation function of two time series $x_1(t)$ and $x_2(t)$ is defined by the formula:

$$C[t_d|x_1, x_2] = E[x_1(t + t_d)x_2(t)]|_t, \tag{2}$$

where t_d – is the time lag between the elements of the time series x_1 и x_2,

$$t_d = t_1 - t_2, \tag{3}$$

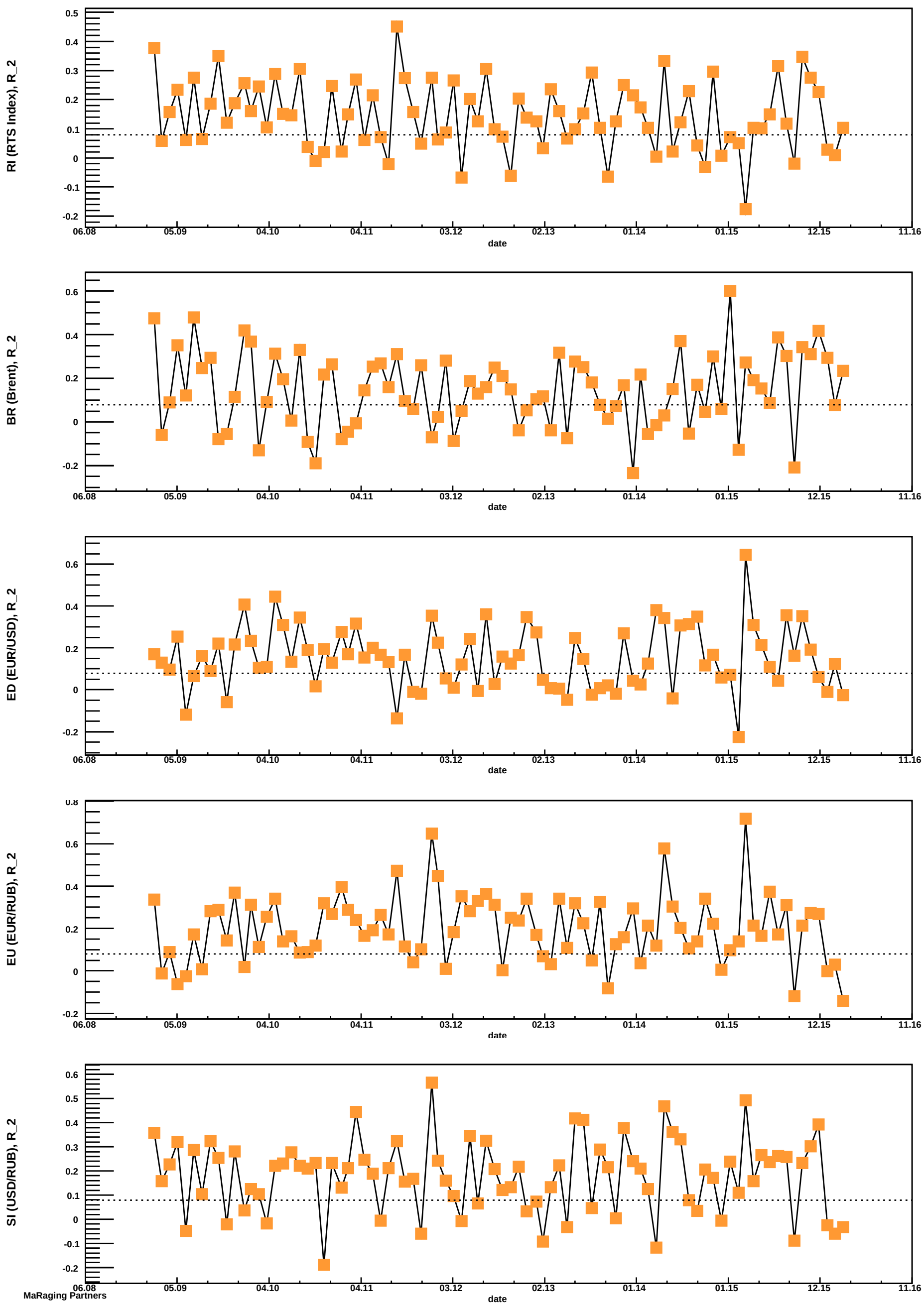

Figure 15: Correlation regime indices for the five instruments.

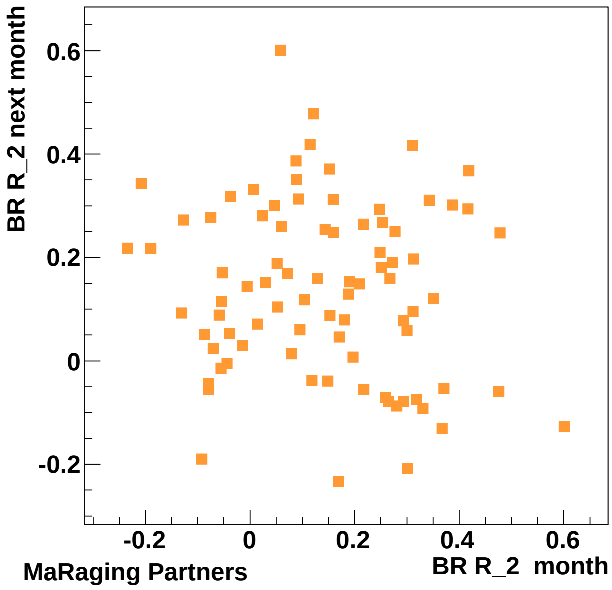

Figure 16: Next month's R_2 (vertical axis, y) as a function of the present R_2 (x) for BR. Least-squares regression: $y = p_0 + xp_1$.

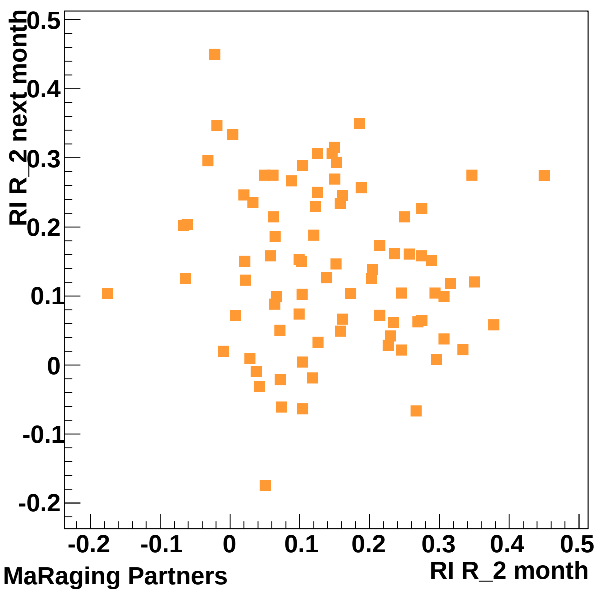

Figure 17: Same as Fig.16, for RI.

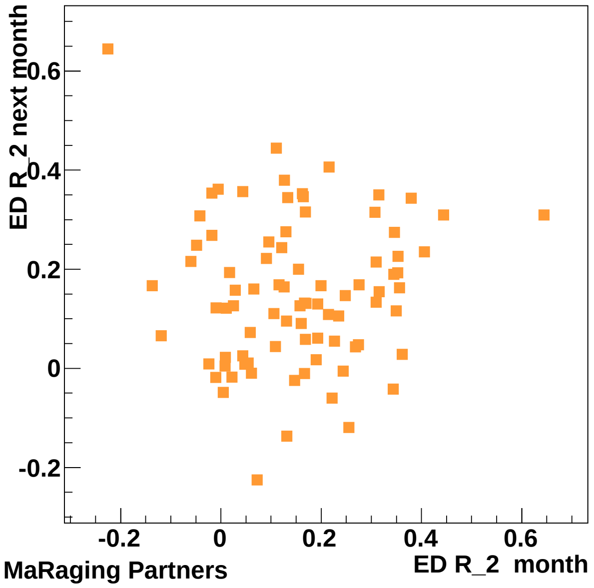

Figure 18: Same as Fig.16, for ED.

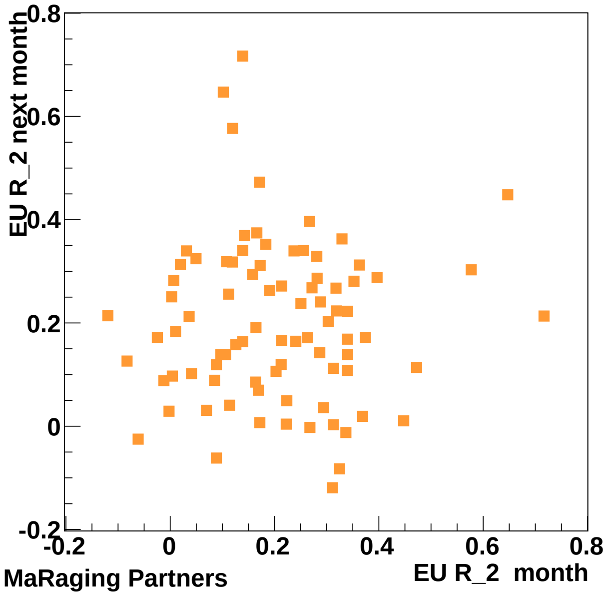

Figure 19: Same as Fig.16, for EU.

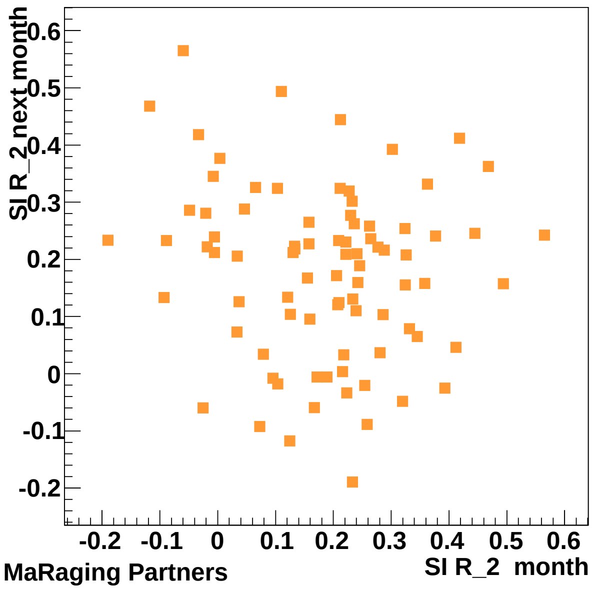

Figure 20: Same as Fig.16, for SI.

and $E[\ ]|_t$ is the time averaging operator.

If x_1 and x_2 are one and the same time series, C becomes an auto-correlation function. Because to re-denote x_1 and x_2 and vice versa is equivalent to flipping the sign of t_d, the auto-correlation function is symmetric around 0 lag. An inter-market correlation function does not have to be symmetric.

Presence of statistically significant non-zero correlation coefficient between time series x_1 and x_2 at a certain positive lag L, when the lag is defined as above, allows one to conclude that a relationship of the "leader-follower" type holds between the two time series, with x_1 being the follower:

$$t_1 = t_2 + L. \tag{4}$$

If L is negative, then x_2 is the follower.

We observe the convention, according to which x_1 goes first and x_2 second in all figure notes, legends, axes labels and so on.

A.3 Pearson Correlation Coefficient

Pearson correlation coefficient C_P characterizes the degree of statistical dependendce between two random variables, and is the magnitude of correlation, normalized so that its absolute value does not execeed 1.

$$C_P \leq 1. \tag{5}$$

Because covariance of two variables can not exceed the geometric mean of their variances, the normalization requirement is satisfied by dividing the covariance by this geometric mean. In the notation introduced above,

$$C_P[t_d|x_1, x_2] = \frac{C[t_d|x_1, x_2]}{V[x_1]V[x_2]}. \tag{6}$$

A.4 The Correlation Strength Index CSI

CSI_{FORTS} is the measure of zero-lag correlation strength, averaged over the set of selected futures instruments. By the "correlation strength" we mean the absolute value of the Pearson correlation coefficient. With such a definition, because the coefficients are normalized, volatility does not enter the picture. It is obvious that with such a normalization, zero lag auto-correlations, being always 1, do not carry useful information. Therefore they are not included into the CSI. For the 5 instruments, we are left with 10 terms:

$$\begin{aligned}
&CSI_{\mathrm{FORTS}} = \frac{1}{10}(\\
&|C_P[0|\mathrm{RI,BR}]| + |C_P[0|\mathrm{RI,ED}]| + |C_P[0|\mathrm{RI,EU}]| + |C(0|\mathrm{RI,SI})| \\
&+|C[0|\mathrm{BR,ED}]| + |C[0|\mathrm{BR,EU}]| + |C[0|\mathrm{BR,SI}] \\
&+|C[0|\mathrm{ED,EU}]| + |C[0|\mathrm{ED,SI}]| \\
&+|C[0|\mathrm{SI,EU}]|)
\end{aligned} \tag{7}$$

In this notation, $C_P[t_d|A,B]$ is the correlation coefficient, normalized according to the Pearson formula, between time series A and B, with the time lag t_d (0 in the case of CSI). It follows from this definition, that CSI varies between 0 and 1.

$$CSI_{\mathrm{FORTS}} \leq 1 \tag{8}$$

Bouts of market panics, such as took place in Fall 2008, during the Flash Crash of 2010, as well as after the downgrade of the US sovereign credit rating in 2011, were characterized not only by high volatility, but also by high absolute value of the correlation (large positive and large negative values), which cause high values of the CSI.

A.5 The Correlation-Based Predictability Index CBPI

$CBPI_{\mathrm{FORTS}}$ is an extension of the CSI technique to the non-zero time lags. CBPI is constructed out of auto-correlation coefficients with 1 hour time lag and inter-market correlation coefficients with 1 and -1 hour lag. Similarly to the case of CSI, the absolute values of the Pearson correlation coefficients (without sign) are used. The 5 time series form 10 paris of non-identical time series. Each of these pairs can have two variants, differently ordered (which is the same as the time lag sign). Since the inter-market correlation is asymmetric, both signs of the time lag are equally informative and should be included. Therefore, we have 25 terms: 5 autocorrelation-based and 20 inter-market ones.

$$\begin{aligned}
&CBPI_{\mathrm{FORTS}} = \frac{1}{25}(\\
&|C_P[1|\mathrm{RI,RI}]| + |C_P[1|\mathrm{BR,BR}]| + |C_P[1|\mathrm{ED,ED}]| + |C_P[1|\mathrm{EU,EU}]| + |C_P[1|\mathrm{SI,SI}]| \\
&+|C_P[1|\mathrm{RI,BR}]| + |C_P[1|\mathrm{RI,ED}]| + |C_P[1|\mathrm{RI,EU}]| + |C_P[1|\mathrm{RI,SI}]| \\
&+|C_P[1|\mathrm{BR,ED}]| + |C_P[1|\mathrm{BR,EU}]| + |C_P[1|\mathrm{BR,SI}]| \\
&+|C_P[1|\mathrm{ED,EU}]| + |C_P[1|\mathrm{ED,SI}]| \\
&+|C_P[1|\mathrm{EU,SI}]| \\
&+|C_P[-1|\mathrm{RI,BR}]| + |C_P[-1|\mathrm{RI,ED}]| + |C_P[-1|\mathrm{RI,EU}]| + |C_P[-1|\mathrm{RI,SI}]| \\
&+|C_P[-1|\mathrm{BR,ED}]| + |C_P[-1|\mathrm{BR,EU}]| + |C_P[-1|\mathrm{BR,SI}]| \\
&+|C_P[-1|\mathrm{ED,EU}]| + |C_P[-1|\mathrm{ED,SI}]| \\
&+|C_P[-1|\mathrm{EU,SI}]|)
\end{aligned} \tag{9}$$

Like CSI, CBPI varies from 0 to 1.

$$CBPI_{\text{FORTS}} \leq 1 \tag{10}$$

To the extent that "efficient" markets are understood as memory-free, CBPI is a measure of market's deviation from the efficiency hypothesis, specific to a particular time scale (hour in the definition above).

An important caveat is that CBPI is subject to fluctuation, just like any random variable. Moreover, even though CBPI's deviation from zero measures the degree of predictability, a totally unpredictable market will, nevertheless, have a non-zero CBPI, whose value will, generally speaking, depend on how this inpredictable market functions or is modeled.

Therefore, even though CBPI itself is not difficult to measure, its interpretation is difficult because of an absense of a model-independent benchmark (reference). We use the following benchmark: take an estimate of the average standard deviation of the correlation coefficient (one hour in this case) over the component of the index. Estimate the mean of the distribution of the hypothetic quantity which is the modulus (absolute value) of the random variate (modeling the correlation coefficient), distributed according to the normal distribution with σ parameter equal to the standard deviation obtained, and zero mean. As one can calculate, that mean is

$$CBPI_{\text{FORTS},0} = \sigma\sqrt{2/\pi} \tag{11}$$

or approximately 0.8 σ, where σ is the width parameter of the normal distribution. This quantity models an expectation of $CBPI_{\text{FORTS}}$ for hypothetic efficient markets having the same uncertainty of the correlation coefficients as the real markets, but with any predictability effects (shifts in the mean of those coefficients).

A.6 Correlation Regime Index R_2. $R_{2\mathbf{FORTS}}$.

The two-point correlation regime index R_2 is based on daily data. It characterizes the degree and character of statistical relationship between yesterday's and today's price action. There are three basic regimes: the trend regime, the oscillatory regime ("mean reversion"), and the efficient market regime. In the latter case, two-point correlations can not help in forecasting.

The trend regime should not be confused with *trend continuity*. Over the course of a month, several visible trends ("waves") can pass, and the process whereby one waves gives way to another has no direct relation to the R_2 quantity. The waves can be observed in the trend regime, in the oscillatory regime, and in fully efficient markets.

$$\begin{aligned} R_2 = \frac{1}{7}(&C_P[1|C,C] + C_P[1|H,H] + C_P[1|L,L] \\ &+ C_P[1|C,H] + C_P[1|C,L] + C_P[1|H,L] + C_P[1|L,H]), \end{aligned} \tag{12}$$

where C_P has already been defined in Section A.3. The C, H, and L subscripts denote the time series of daily close, high and low, respectively.

In this formula, only 7 out of 9 possible terms are present. The absent terms are $C_P[1|H,C]$, the correlation between the change in the daily high and daily close with the day from which the high is taken lagging by one day behind the day for which the close is taken ($t_d = 1 = t_H - t_C$) and $C_P[1|L,C]$, the correlation between the change in the daily low and daily close with the day from which the low is taken lagging by one day behind the day for which the close is taken ($t_d = 1 = t_L - t_C$). These correlations did not enter 12 due to the triviality of these correlation effects and their weak sensitivity to the correlation regime.

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References

[1] Futures market efficiency diagnostics via temporal two-point correlations. Russian market case study. M. Kopytin and E. Kazantsev. (arXiv:1309.3844 [q-fin.TR])

[2] FX Forecast for Q4 2013: EUR/USD, USD/RUB, EUR/RUB