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# Volatility Estimators in Econometric Analysis of Risk Transfer on Capital Markets**

A b s t r a c t. The purpose of the research is to compare the performance of different volatility measures while used in testing for causality in risk between several emerging and mature capital markets. The following volatility estimators are considered: Parkinson, Garman-Klass, Rogers-Satchell, Garman-Klass-Yang-Zhang and Yang-Zhang and the AR-GARCH(1,1)-t model. Additionally, the extreme value theory is also applied. Several emerging capital markets are checked for being the source of the risk for both emerging and developed markets. The group of emerging markets includes the most intensively growing economies in the world. The final results are such as the number of relationships between the markets is considerably lower when the methods taken from the extreme value theory are used.

K e y w o r d s: causality in risk, extreme value theory, growing emerging economies, risk transfer, volatility

J E L Classification: G15; Q47.

## Introduction

The purpose of the research is to compare the performance of different volatility measures while used in testing for causality in risk between several emerging and mature capital markets. The problem considered in the report

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is rather complex from methodological perspective because it includes: a comparison of several estimators of volatility such as Parkinson (1980), Garman and Klass (1980), Rogers and Satchell (1991), Garman, Klass, Yang and Zhang (1991) and Yang and Zhang (2000) while Value at Risk is calculated, a comparison of the mentioned estimators when extreme value theory (McNeil and Frey, 2000; Fałdziński, 2014) was added and testing for causality in risk using Hong et al. (2009) procedure as well as Candelon, Joëts and Tokpavi (2013) procedure. The GARCH(1,1) model with t-Student error distribution is considered as the benchmark for all the comparisons. The wide empirical analysis is also provided in the paper. The two groups of markets represented by main indices are considered, i.e. emerging ones, such as: Brazil (BOVESPA), Russia (RTS, MICEX), China (SSE), India (BSE), Turkey (XU 100), Indonesia (JCI) and Mexico (IPC) and mature ones, such as: USA (S&P 500, Great Britain (FTSE 100), Germany (DAX), France (CAC 40), Japan (NIKKEI 225), Switzerland (SSMI), Hong Kong (HSI), South Korea (KOSPI) and Australia (AOR). The group of emerging markets includes the most likely intense growth economies that determine the state of the market, capital flows and global relationships. We try to establish the source and the effect of risk in most important capital markets in the era of globalization as well as to determine the most likely time periods for risk transferring. This paper develops and continues the research reported in our previous publications (Fałdziński et al., 2012, Osińska et al., 2012), in which GARCH-POT methodology has been applied. In this paper we not only compare different volatility measures but also use them for causality in risk testing and find them useful in certain cases. These findings are of methodological and practical nature. The paper can be included into spillover analysis, which can be examined in many ways. One of the results of spillover effect can be contagion. Contagion is defined as a significant increase in market co-movement after a shock to one country. The paper by Forbes and Rigobon (2002) defines and illustrates this problem while a wide survey of methods of its analysis can be found in Burzała (2014). In our publication we demonstrate that thanks to the extreme value theory only big shocks on financial markets, that may or may not cause contagion, are considered. Risk transfer from one market to another, examined in this report, can be considered as an incentive for contagion but it is not a sufficient condition.

## 1. The Methodology

In our previous research (Fałdziński et al., 2012, Osińska et al. 2012) we applied Granger causality in risk definition that was formulated by Hong

(2001) and testing idea that was derived by Hong (2001) and further modified by Hong et al. (2009). It was based on spectral representation of time series. In this paper Candelon et al. (2013) test is applied. It differs from Hong's test in two ways. Firstly, a multivariate linear regression is used to calculate the LR-type test and secondly, the breaks in Value at Risk (VaR) at different probability levels are considered. According to the definition of Granger causality in risk $\{Y_{1t}, Y_{2t}\}$ is a bivariate not necessarily stationary stochastic time series and $A_{lt} = A_{lt}\left(I_{l(t-1)}\right)$ $l = 1,2$ is the VaR at level $\alpha \in (0,1)$ for $Y_{lt}$ predicted using the information set $I_{l(t-1)} = \left\{Y_{l(t-1)}, Y_{l(t-2)} \ldots, Y_{l1}\right\}$ available at time $t-1$. $A_{lt}$ satisfies $P\left(Y_{lt} < A_{lt} \mid I_{l,(t-1)}\right) = \alpha$. We define $V_{lt} = I\left(Y_{lt} > A_{lt}\right)$ $l = 1,2$ which denotes the VaR break indicator. The break indicator takes on the value of 1 when VaR is exceeded by loss and takes on the value of 0 otherwise. Let assume that $A = \{\alpha_1, ..., \alpha_m\}$ is the set of $m$ different probability levels. Next, we consider a vector $Z_{i,t}(A) = [V_{i,t}(\alpha_1), ..., V_{i,t}(\alpha_m)]$ $i = 1,2$ comprising of $m$ different variables at time $t$ respective to the assumed set of probability levels.

In the case of the Granger non-causality the null hypothesis is:

$$H_0 : E\left[Z_{1,t}(A) \mid I_{t-1}\right] = E\left[Z_{1,t}(A) \mid I_{1,t-1}\right], \tag{1}$$

where $I_{1,t} = \{Z_{1,s}(A), s \le t\}$ and $I_t = \{Z_{1,s}(A), Z_{2,s}(A), s \le t\}$ with the alternative

$$H_1 : E\left[Z_{1,t}(A) \mid I_{t-1}\right] \ne E\left[Z_{1,t}(A) \mid I_{1,t-1}\right]. \tag{2}$$

The null hypothesis says that the process $\{Y_{2t}\}$ does not Granger-cause the process $\{Y_{1t}\}$ in risk at the set of different levels $\alpha$ with respect to $I_{t-1}$. Candelon et al. (2013) have shown that the test statistic can be formulated using multivariate linear regression of the form

$$Z_{1,t}(A) = \psi_0 + \psi_1 Z_{2,t-1}(A) + ... + \psi_L Z_{2,t-L}(A) + \varepsilon_{1t} \tag{3}$$

where $\psi_0$ is the (m,1) dimensions vector of constants, $\psi_s, s = 1, ..., L$ are the $(m,m)$ dimensions matrices of parameters and $\varepsilon_{1t}$ is $(m,1)$ dimensions residual process.

The null hypothesis corresponds to the situation when $H_0 : \psi_1 = ... = \psi_L = 0$ which is fulfilled for $Z_{1,t}(A) = \psi_0 + \varepsilon_{2t}$. The multivariate test statistic is defined as follows:

$$LR = \left[T - (mL+1)\right]\left[\log\left(\left|\varepsilon_2^{'}\varepsilon_2\right|\right)\right] - \left[\log\left(\left|\varepsilon_1^{'}\varepsilon_1\right|\right)\right] \tag{4}$$

where $T$ is the number of observations of time series $m$ is the number of different probability levels assumed, $L$ is the number of lags in the regression. It informs about the time delay since the beginning till the end of the risk transfer.

The test statistic follows $\chi^2$ distribution with $Lm^2$ degrees of freedom. Due to the parameter uncertainty Dufour (2006) proposes a Monte Carlo method to obtain p-values. In order to check the hypothesis of spillovers in financial markets different volatility measures have been used. These measures determine the empirical results and therefore are worth comparing. They do not affect the characteristics of the Candelon et al. test because it operates on breaks of VaR which can be defined at different levels. To estimate Value at Risk the following methods have been applied:

1. Volatility estimators such as:

a) Parkinson (1980) (P)

$$\sigma_P = \sqrt{\frac{1}{4\ln(2)}\sum_{i=1}^{N}\left(\ln\left(\frac{h_i}{l_i}\right)\right)^2},$$

b) Garman and Klass (1980) (GK)

$$\sigma_{GK} = \sqrt{\sum_{i=1}^{N}\frac{1}{2}\left(\ln\left(\frac{h_i}{l_i}\right)\right)^2 - (2\ln(2)-1)\left(\ln\left(\frac{c_i}{o_i}\right)\right)^2},$$

c) Rogers and Satchell (1991) (RS)

$$\sigma_{RS} = \sqrt{\sum_{i=1}^{N}\ln\left(\frac{h_i}{c_i}\right)\ln\left(\frac{h_i}{o_i}\right) + \ln\left(\frac{l_i}{c_i}\right)\ln\left(\frac{l_i}{o_i}\right)},$$

d) Garman, Klass, Yang and Zhang (1991) (GKYZ)

$$\sigma_{GKYZ} = \sqrt{\sum_{i=1}^{N}\left(\ln\left(\frac{o_i}{c_{i-1}}\right)\right)^2 + \frac{1}{2}\left(\ln\left(\frac{h_i}{l_i}\right)\right)^2 - (2\ln(2))\left(\ln\left(\frac{c_i}{o_i}\right)\right)^2}$$

e) Yang and Zhang (2000) (YZ)

$$\sigma_{YZ} = \sqrt{\sigma^2_{overnight\ volatility} + k\sigma^2_{open\ to\ close} + (1-k)\sigma^2_{RS}}$$

$$k = \frac{0,34}{1,34 + \dfrac{N+1}{N-1}}, \qquad \sigma^2_{opent\ to\ close\ volatility} = \frac{1}{N-1}\sum_{i=1}^{N}\left[\ln\left(\frac{c_i}{o_i}\right) - \overline{\ln\left(\frac{c_i}{o_i}\right)}\right]^2,$$

$$\sigma^2_{overnight\ volatility} = \frac{1}{N-1}\sum_{i=1}^{N}\left[\ln\left(\frac{o_i}{c_{i-1}}\right) - \overline{\ln\left(\frac{o_i}{c_{i-1}}\right)}\right]^2,$$

where $N$ is the number of days taken into estimation, $h_i$ is the highest price, $l_i$ is the lowest price, $o_i$ is the open price and $c_i$ is the close price at day $i$.

2. Conditional volatility models (AR(p)-GARCH(1,1) and AR(p)-TARCH(1,1) both with Student error distribution (Zakoian, 1994)
3. Conditional volatility models with the extreme value theory (AR(p)-GARCH(1,1) with Student error distribution and Peaks over Threshold (POT) approach (McNeil and Frey, 2000; Fałdziński, 2014).
4. Volatility estimators described in 1 with Peaks over Threshold (POT) approach.

It is worth mentioning that using the extreme value theory represented by Peaks over Threshold (POT) enables identifying shocks (extreme changes) in some financial markets that affect other markets. Thus finding the break in VaR when POT approach is applied is a strong argument for the spillover effect.

The Peaks over Threshold method was described in Fałdziński (2014). To explain it briefly let us assume that a given sequence of i.i.d. observations $X_1,\dots,X_n$ comes from unknown distribution function $F$, where we are interested in excesses over a high threshold value $u$. Conditional excess distribution function (cedf) $F_u$ is defined as $F_u(y) = P(X - u \le y \mid X > u)$, $0 \le y \le x_F - u$, where $X$ is a random variable, $u$ is a given threshold, and $y = x - u$ is the excess (McNeil and Frey, 2000). The distribution $F_u$ can be written as:

$$F_u(y) = \frac{F(u+y) - F(u)}{1 - F(u)} = \frac{F(x) - F(u)}{1 - F(u)} \tag{5}$$

The realizations of the random variable $X$ lie between 0 and $u$, therefore the estimation of $F$ in this interval generally poses no problems. According to the Pickands-Balkema-de Haan (Pickands (1975), Balkema, de Haan (1974)) theorem, for $x \ge u$, we can use the tail estimate

$\hat{F}(x) = (1 - F_n(u))G_{\gamma,\mu,\sigma}(x) + F_n(u)$, where $G_{\gamma,\mu,\sigma}(x)$ is the generalized Pareto distribution (GDP), to approximate the distribution function $F(x)$. It can be shown that $\hat{F}(x)$ is also generalized Pareto distribution, with the same shape parameter $\gamma$, but with scale and location parameters, correspondingly equal: $\tilde{\sigma} = \sigma(1 - F_n(u))^{\gamma}$ and $\tilde{\mu} = \mu - \tilde{\sigma}\left((1 - F_n(u))^{-\gamma} - 1\right)/\gamma$. Thus, the POT estimator of $x_p$ is obtained by inverting the formula for $\hat{F}(x)$ Then substituting unknown parameters of the GPD by estimates $(\hat{\gamma}, \hat{\sigma})$, we get:

$$\hat{x}_p = \hat{F}^{\leftarrow}(p) = G^{-1}_{\hat{\gamma},u,\hat{\sigma}}\left(\frac{p - F_n(u)}{1 - F_n(u)}\right) = u + \frac{\hat{\sigma}}{\hat{\gamma}}\left(\left(\frac{1-p}{1 - F_n(u)}\right)^{-\hat{\gamma}} - 1\right). \quad (6)$$

If $N_u$ is the number of exceedances of the threshold $u$ and $n$ is the total number of realizations that we have from the distribution $F$, Value-at-Risk in the Peaks over Threshold method equals:

$$VaR(\alpha) = u + \frac{\hat{\sigma}}{\hat{\gamma}}\left(\left(\frac{n}{N_u}\alpha\right)^{-\hat{\gamma}} - 1\right), \quad (7)$$

where $\alpha$ is a tolerance level.

## 2. Characteristics of the Data

According to World Economic Outlook released in 20161 the potential for economic growth in China is projected to decrease from 7.3 in 2014 to 6.0 in 2017 although it will still remain a very important country. The most prospective growth is projected in India: from 7.3 in 2014 to 7.5 in 2017 and in Mexico: from 2.3 in 2014 to 2.9 in 2017. Other countries like Russia and Brazil are expected to lose their growth rate and reach negative values. As concerns Turkey, its growth rate in 2015 was quite high. It amounted to 4% with decreasing perspective. There are also other very fast developing emerging economies like Kenya or Nigeria but we excluded them from the study because of relative smaller liquidity in financial markets. Another very fast developing economy is Indonesia, which yearly growth rate in 2015 was 5.5%. Among these countries there is a competition to be not only the best

[1] http://www.imf.org/external/pubs/ft/weo/2016/update/01/pdf/0116.pdf

emerging economy in the world but also a very important investment market. In sequent years one may observe and predict development of new important economic areas. In Fig. 1 the annual growth rate of mentioned economies in 2006–2015 has been shown.

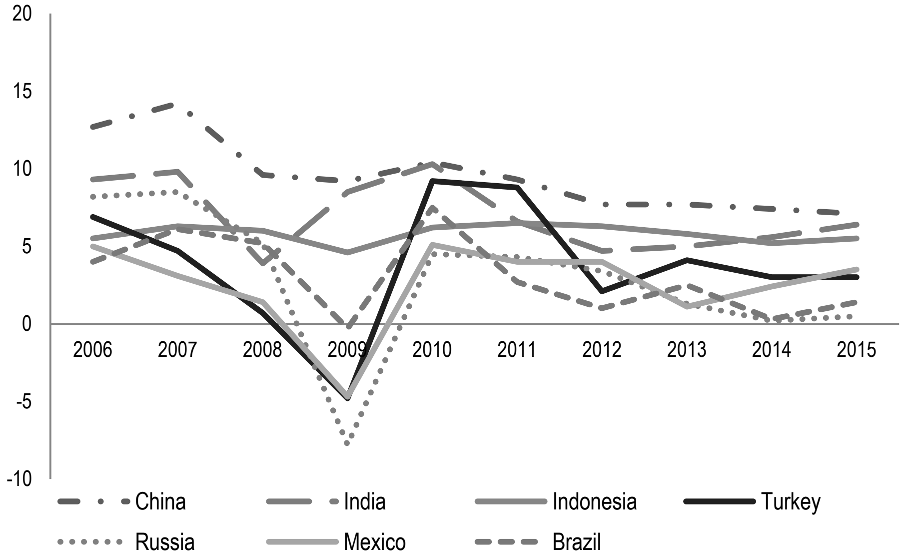


Figure 1. Annual growth rate in emerging economies over 2006–2015 [in %][2]

The dynamics of Chinese economy is still dominating although it started to decline after 2012. The opposite tendency can be noticed for India. Indonesia's growth seems to be stable over the decade. Mexico, Turkey, Brazil and Russia suffered hard from the recession in 2009, but Mexico seems to be the most promising for the future. The data suggest that so called "BRIC group" that was considered a new economic body at the beginning of XXI century is no longer the case and other developing countries try to move from peripheries to the center.

On the opposite side – developed financial markets are represented by traditional markets such as the USA, the Great Britain, Germany, France, Switzerland and Australia that was completed by relatively new but mature markets from Far East Asia such as Hong Kong and South Korea. In the paper we took into account the linkages between stock markets from different continents so North and Latin Americas, Asia, Australia and Europe are

[2] Source: based on International Monetary Fund data.

represented. Such a selection does not cover all possible linkages but allows answering the question of direction of capital transfers in both periods: the bullish and the bearish markets. Big (and often negative) shocks in the financial market are usually perceived negatively by all groups of investors, market makers and supervisors. They may be due to: huge market uncertainty, policy changes, unpredicted information, speculative attacks, and transfers from other markets. Sometime many causes may act simultaneously. Some of them may cause extreme changes in values of losses (and/or profits). In general the process of globalization caused that the financial markets seem to act in the same way; they are linked. It is interesting that little attention is paid to the big and positive changes in financial markets.

However in the literature one can find several individual cases of little linkages between different markets. For example China during Asian crisis 1997–1998 was an example of completely separated market that was analyzed by Lardy (1998). On the other hand, when markets are related it can be expected to transfer from one market to another like in the period 2007–2009 between USA and Europe. Risk can be generated locally or take the specific form like it was in 1997 between Japan and USA (see: Peek and Rosengren, 1997).

To answer the question of risk transfer between emerging and mature markets we used daily data from the period 03.01.2010–02.01.2015 (T=1260 observations). The log returns has been used for calculations in the form: $r_t = 100\left(\ln(P_t) - \ln(P_{t-1})\right)$, while testing for Granger causality in risk we have used different lags $L = 5,10,15,25$ and we obtained p-values using Monte Carlo simulations (Dufour, 2006), having assuming 1000 repetitions. In figure 2 the comparison of VaR breaks' computed with different volatility estimators basing on DAX returns is shown. One can notice that the highest values are indicated by Garman, Klass, Yang and Zhang estimator. In figure 3 the results of the latter are compared with the AR(1)-GARCH(1,1) with POT model. In the cases of shocks the AR(1)-GARCH(1,1) with POT seem to perform better.

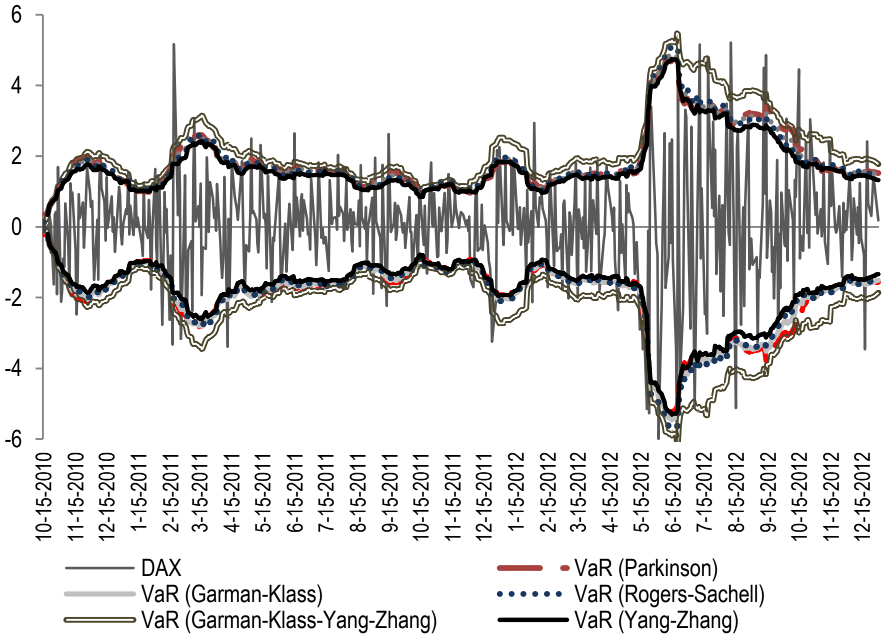


Figure 2. VaRs computed with different volatility estimators basing on DAX returns

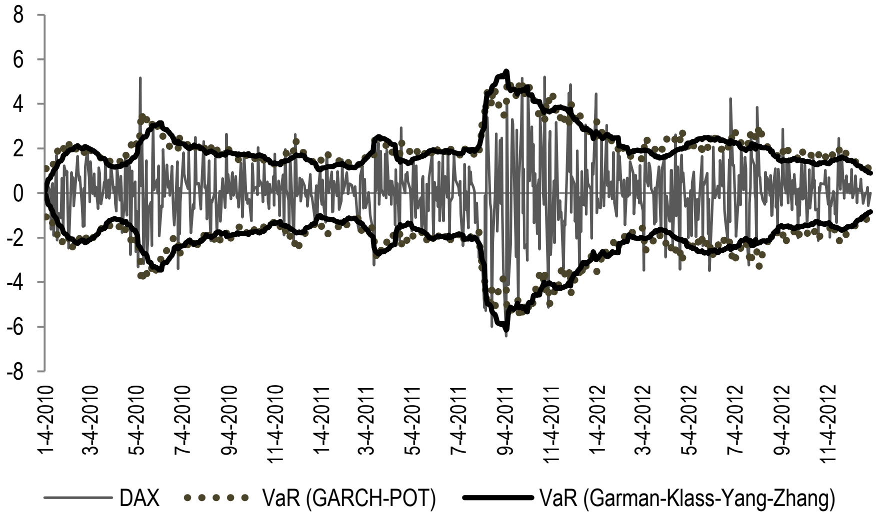


Figure 3. VaRs computed with GARCH-POT method and Garman-Klass-Yang-Zhang volatility estimator basing on DAX returns

A precise comparison of different estimators of volatility was presented in table 1. We compared the analyzed volatility estimators with AR-GARCH, AR-GARCH-POT and Garman-Klass-Yang-Zhang with POT using seven different loss functions (described below the table). The preferred model is AR-GARCH-POT which was indicated in 4 cases on 7. Twice the Garman-Klass-Yang-Zhang with POT was indicated and once the Rogers-Satchell estimator.

Table 1. Mean value of the loss functions for VaR(0.95)

| Method | QPS I | QPS II | QPS III | RLF | FLF | LF | OLF |
|---|---|---|---|---|---|---|---|
| AR-GARCH | 0.0988 | 5.0516 | 0.0360 | 0.0778 | 0.1669 | 0.1168 | 7.4261 |
| AR-GARCH-POT | **0.0940** | 4.8277 | **0.0337** | **0.0730** | 0.1647 | **0.1094** | 7.7466 |
| Parkinson | 0.1619 | 4.6296 | 0.0698 | 0.1028 | 0.1719 | 0.1642 | 5.7280 |
| Rogers-Satchell | 0.1770 | 6.0812 | 0.1020 | 0.1218 | 0.1877 | 0.1916 | **5.4615** |
| Garman-Klass | 0.1738 | 5.5389 | 0.0893 | 0.1159 | 0.1822 | 0.1834 | 5.4851 |
| Garman-Klass Yang-Zhang | 0.1323 | 4.5242 | 0.0499 | 0.0852 | 0.1638 | 0.1341 | 6.5845 |
| Yang-Zhang | 0.1979 | 6.7888 | 0.1331 | 0.1386 | 0.1991 | 0.2180 | 5.0100 |
| Garman-Klass-Yang-Zhang POT | 0.1303 | **4.3008** | 0.0500 | 0.0812 | **0.1615** | 0.1283 | 6.8112 |

*Note:* QPS I means Quadratic Probability Score function with binary loss function (Lopez, 1998), QPS II means Quadratic Probability Score function with size-adjusted loss function (Lopez, 1998), QPS III means Quadratic Probability Score function with size loss function (Blanco and Ihle, 1998), RLF means Regulatory Loss Function (Sarma et al., 2003), FLF means Firm's Loss Function (Sarma et al., 2003) with opportunity cost of capital equals 0.05, LF means Loss Function (Angelidis and Degiannakis, 2006) and OLF means Overestimation Loss Function (Fałdziński, 2011). The lowest (best) values of measures are in bold.

## 3. Causality in Risk between Emerging and Developed Markets

In this section we show the results of Hong et al. (2009) and Candelon et al. (2013) tests for Granger causality in risk when emerging markets are indicated to be a source of risk transfer. Having in mind the results shown in table 1 the following methods of volatility analysis were used: AR(p)-GARCH(1,1)-POT with t-distribution and Garman-Klass-Yang-Zhang volatility estimator. The results are presented in tables 2–5.

Table 2. Granger causality in risk for long position where AR-GARCH-POT with t-distribution was applied (5 up to 25 lags, Hong et al. test)

| | | |
|---|---|---|
| BOVESPA | → | AOR, BSE, CAC40, DAX, HSI, JCI, KOSPI, MICEX, NIKKEI225, RTS, SSE, SSMI, XU100 |
| BSE | → | AOR, JCI, KOSPI, MICEX, NASDAQ, SP500 |
| IPC | → | AOR, DAX, HSI, KOSPI, MICEX, NIKKEI225, RTS, S&P 500 |
| JCI | → | KOSPI |
| MICEX | → | AOR, BSE, HSI, KOSPI, NASDAQ, NIKKEI225, XU100 |
| RTS | → | AOR, BSE, HSI, KOSPI, NASDAQ, NIKKEI225 |
| SSE | → | FTSE100, KOSPI, NASDAQ |
| XU100 | → | HSI, KOSPI |

*Note:* "→" shows direction of causality.

Table 3. Granger causality in risk for long position where Garman-Klass-Yang-Zhang volatility estimator was applied (5 up to 25 lags, Hong et al. test)

| | | |
|---|---|---|
| BOVESPA | → | BSE, FTSE100, JCI, SSMI |
| BSE | → | AOR, BOVESPA, CAC40, DAX, FTSE100, HSI, IPC, KOSPI, NASDAQ, S&P 500, SSMI |
| IPC | → | AOR, BOVESPA, HSI |
| JCI | → | AOR, BOVESPA, BSE, CAC40, DAX, FTSE100, HSI, IPC, KOSPI, MICEX, NASDAQ, RTS, S&P 500, SSMI, XU100 |
| MICEX | → | AOR, BOVESPA, BSE, DAX, NASDAQ, S&P 500 |
| RTS | → | AOR, BOVESPA, BSE, DAX, FTSE100, NASDAQ, S&P 500 |
| SSE | → | BOVESPA, DAX, FTSE100, MICEX, NASDAQ, RTS, S&P 500 |
| XU100 | → | AOR, BOVESPA, BSE, CAC40, DAX, FTSE 100, JCI, KOSPI, NASDAQ, RTS, S&P 500, SSMI |

*Note:* "→" shows direction of causality.

Table 4. Granger causality in risk for long position where AR-GARCH-POT with t-distribution was applied (5 up to 25 lags, Candelon et al. test)

| | | |
|---|---|---|
| BOVESPA | → | AOR, BSE, DAX, HSI, IPC, KOSPI, NIKKEI 225 |
| BSE | → | IPC, KOSPI |
| IPC | → | BSE, CAC 40, FTSE 100, IPC, KOSPI, MICEX, NIKKEI 225, RTS, SSE |
| JCI | → | FTSE 100, KOSPI |
| MICEX | → | CAC40, FTSE 100, JCI, MICEX, SSE |
| RTS | → | BSE, CAC40, FTSE 100, IPC, JCI, MICEX, SSE |
| SSE | → | CAC40, JCI, MICEX |
| XU 100 | → | CAC40, FTSE 100, JCI, MICEX |

*Note:* "→" shows direction of causality.

Table 5. Granger causality in risk for long position where Garman-Klass-Yang-Zhang volatility estimator was applied (5 up to 25 lags, Candelon et al. test)

| | | |
|---|---|---|
| BOVESPA | → | AOR, BSE, CAC40, DAX, FTSE100, HSI, IPC, JCI, KOSPI, NASDAQ, NIKKEI225, SSE, SSMI |
| BSE | | AOR, CAC40, DAX, HSI, IPC, KOSPI NASDAQ, NIKKEI225, SSE |
| IPC | | AOR, BSE, CAC40, DAX, HSI, JCI, KOSPI, NASDAQ, NIKKEI225, SSE, S&P 500, SSMI |
| JCI | | BOVESPA, BSE, CAC40, DAX, IPC, KOSPI, NASDAQ, NIKKEI225, SSE |
| MICEX | | BSE, CAC40, DAX, HSI, IPC, KOSPI, NASDAQ, NIKKEI225, S&P 500, SSMI |
| RTS | | BOVESPA, AOR, BSE, CAC40, DAX, FTSE100, HSI, IPC, KOSPI, NASDAQ, NIKKEI225, S&P 500, SSMI |
| SSE | | BOVESPA, BSE, CAC40, DAX, HSI, IPC, KOSPI, NASDAQ, NIKKEI225 |
| XU100 | | BSE, CAC40, DAX, HSI, IPC, KOSPI, NASDAQ, NIKKEI225, S&P 500, SSMI |

*Note:* "→" shows direction of causality.

In the tables 2–5 the results of testing for Granger causality in risk for long positions (losses) are presented. Computing results for short positions (profits) we can observe lower number of relationships between the markets. It may suggest that taking into account profits the markets are more independent (they do not share profits) while in the case of losses otherwise situation takes place. The remained results are available on request. In general, we can say that the Garman-Klass-Yang-Zhang volatility estimator indicates the Granger causality in risk more frequently than the AR-GARCH-POT method. This was intuitively expected, because the latter method takes into account the extreme observations while the volatility estimators includes all observations corrected by the high, low minimum and maximum values. The results show that there is Granger causality in risk between emerging capital markets and highly developed ones. Some capital markets absorb risk more often than others. We can delineate the markets which absorb the risk (risk-takers) most frequently when the risk transfer is from emerging markets: AOR, CAC 40, FTSE 100, HSI, NIKKEI 225 and KOSPI in the case of the GARCH-POT method. In the case of the volatility estimators the group of the risk-takers is: AOR, BOVESPA, BSE, CAC 40, DAX, NIKKEI 225, S&P 500 and NASDAQ. The latter group is larger which is not surprising due the fact that volatility estimators fit better to the 'average values' of the time series. The overlapping of two methods of estimating Value-at-Risk and testing for Granger causality in risk is rather easily visible. The difference between Hong et all test and Candelon et al. test is such that in case of AR-GARCH-POT model the results are the same in 13 cases only. The causal impact of MICEX, RTS, SSE and XU 100 on other markets was found to be quite different while the impact of BOVESPA, BSE IPC and JPC can be considered as similar.

## Conclusions

In the paper we extended our previous investigations using quite sophisticated research methods and we concentrated on huge magnitude of changes (extreme values). Our findings should be considered when systemic risk in the global economy is analyzed. They are linked with the problem of spillover in the sense that risk transfer from one market to another can be considered as an incentive for extending negative trends (contagion) but it is not a sufficient condition.

In the paper we analyze the linkages between capital markets located in both emerging and developed economies. The difference between emerging and mature markets lays in different types of institutions like financial supervision, possibility of quoting the instruments from abroad, the number and type of listed instruments and, what is probably most important, in market liquidity. The question whether less liquid market can 'produce' more risk due to the lack of many alternatives within the market and more loosely rules is very important in the era of globalization. The answer can have many practical implications including financial regulations.

In our research it was indicated that basing on volatility estimators it is possible to find more "causal" relationships than basing on AR-GARCH-POT methods. It is due to the fact that volatility estimators are better fitted to the average volatility values than the methods based on the extreme value theory. We can observe risk transfer from emerging markets to the highly developed ones, so that the research helped to find the explanation of the problem put in the introduction. The markets which absorb risk transfers most frequently are: S&P500, CAC40, NIKKEI225, NASDAQ and FTSE100. The empirical results of Hong et al test and Candelon et al test are slightly different that results from different tolerance levels allowing in both testing procedures.

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## Estymatory zmienności w ekonometrycznej analizie transferu ryzyka na rynkach kapitałowych

Z a r y s t r e ś c i. Celem badania jest porównanie wykorzystania różnych estymatorów zmienności, zastosowanych do testowania przyczynowości w ryzyku, między kilkoma wybranymi rynkami wschodzącymi i rozwiniętymi. W pracy uwzględniono następujące estymatory zmienności: Parkinsona, Garmana i Klassa, Rogersa i Satchella, Garmana, Klassa, Yanga i Zhanga, Yanga i Zhanga oraz model GARCH(1,1)-t. Dodatkowo wykorzystano narzędzia teorii wartości ekstremalnych. Kilka wybranych rynków wschodzących zostało przebadanych, czy są źródłem ryzyka dla rynków rozwijających i rozwiniętych. Wyniki pokazują, że przyczynowość w ryzyku występuje rzadziej w przypadku modeli z wykorzystaniem teorii wartości ekstremalnych.

S ł o w a k l u c z o w e: przyczynowość w ryzyku, teoria wartości ekstremalnych, rozwój rynków wschodzących, transfer ryzyka, zmienność.