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Detecting Risk Transfer in Financial Markets using Different Risk Measures

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Abstract

High movements of asset prices constitute intrinsic elements of financial crises. There is a common agreement that extreme events are responsible for that. Making inference about the risk spillover and its effect on markets one should use such methods and tools that can fit properly for catastrophic events. In the paper Extreme Value Theory (EVT) invented particularly for modelling extreme events was used. The purpose of the paper is to model risky assets using EVT and to analyse the transfer of risk across the financial markets all over the world using the Granger causality in risk test. The concept of testing in causality in risk was extended to Spectral Risk Measure i.e., respective hypotheses were constructed and checked by simulation. The attention is concentrated on the Chinese financial processes and their relations with those in the rest of the globe. The original idea of the Granger causality in risk assumes usage of Value at Risk as a risk measure. We extended the scope of application of the test to Expected Shortfall and Spectral Risk Measure. The empirical results exhibit very interesting dependencies.

Keywords: extreme value theory, risk measures, Granger causality in risk, Chinese financial processes

JEL Classification: C58, G15

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1 Introduction

High movements of asset prices constitute intrinsic elements of financial crises. These large market movements have never been regarded as something positive, but always brought confusion and even erratic behaviour of investors. Such movements are particularly significant and harmful if they lead to the risk transmission between the financial markets. That risk spillover is vital not only for investors, but also for institutions supervising financial markets. It is crucial for the risk management and for the market participants to understand how the risk spillover mechanism is transmitted between markets. The risk spillover effect may lead to large losses and from that point of view the accurate risk management can incorporate such losses is priceless. To include efficient risk management in financial institutions we should have identified events that cause the risk spillover effect. There is a common agreement that extreme events are responsible for that, but there is a wide discussion on how to properly model and quantify them for risk management purposes (Embrechts, Klüppelberg, Mikosh 2003, Szegö 2004). It is a well-known fact that standard methods or models such as portfolio analyses and volatility models (for instance GARCH(1,1) with normal distribution) are not suitable because they pay little attention to extreme events. If one wants to infer about the risk spillover and its effect on markets one should use such methods and tools that can fit properly for catastrophic events. In order to ensure that we used Extreme Value Theory (EVT), which was invented particularly for modelling extreme events. The existing literature (Kuester, Mittnik, Paolella 2006; Harmantzis, Miao, Chien, 2006; Fałdziński 2011) shows that EVT is more appropriate than other methods for estimating risk measures.

The purpose of the paper is to analyse transfer of risk across the financial markets all over the world with the use of the Granger causality in risk test developed by Hong (2001) and Hong, Liu, Wang (2009). In contrast to Lee and Lee (2009) we focus our attention on the Chinese financial processes and their relations with those in the rest of the globe. Following the results obtained by Lim et al. (2009) we assumed the informational market efficiency in the long run. In the original idea of the Granger causality in risk the Value at risk was employed as a risk measure. In this paper we propose to extend the scope of application of the test to Expected Shortfall and Spectral Risk Measure.

The rationale for using different risk measures is that they exhibit different risk transmission patterns. Financial markets are affected significantly by the events which occur with various probabilities (smaller and higher) and various frequencies (various time intervals). The three risk measures mentioned above provide a wide range of the risk spillover mechanism. In this paper we concentrate our attention on detection whether financial risk observed in one region can be thought as a reason of similar reactions in other regions in the sense of Granger causality.

2 Measuring risk at capital market using extreme value theory

The Value at risk (VaR) has become a standard risk measure for financial risk management due to its conceptual simplicity, ease of computation and ready applicability. To remind the concept, the Value at risk at the confidence level α is:

$$VaR_\alpha = q_\alpha, \tag{1}$$

where q_α is the relevant quantile of the loss distribution (which gives losses a positive sign and profits a negative one) over a daily horizon period on a futures contract position. Commonly used levels are 90%, 95% and 99%. However, VaR has been charged as having several conceptual problems. Artzner, Delbaen, Eber, Heath (1997) and (1999), among others, have cited the following shortcomings. Firstly, VaR measures only percentiles of profit-loss distributions and disregards any loss beyond its level. Secondly, VaR is not a coherent risk measure since it does not satisfy the subadditivity condition. To remedy the problems inherent in VaR, Artzner, Delbaen, Eber, Heath (1997) proposed the concept of expected shortfall (ES):

$$ES_\alpha = \frac{1}{1-\alpha}\int_\alpha^1 q_p\, dp. \tag{2}$$

The term expected shortfall comes from Acerbi, Nordio, Sirtori (2001) where proof of the coherence of ES was given, among others. ES measure takes an average of quantiles in which tail quantiles have equal weights and non-tail quantiles have a zero weight. ES is the average of the worst $(1-\alpha)100\%$ of losses. Both VaR and ES cover statistical aspects of risk but not include investor's individual attitude towards the risk. A user who is risk-averse might prefer to work with a risk measure that takes into account his/her risk aversion. Such a perspective takes us to the class of spectral risk measures (SRM). In the terms of loose an SRM is a quantile-based risk measure that takes the form of:

$$M_\phi = \int_0^1 \phi(p) q_p\, dp. \tag{3}$$

where $\phi(p)$ is some weighting function that reflects the user's risk aversion. A spectral risk measure was proposed by Acerbi (2002). To obtain a spectral risk measure, the user must specify a particular form for his/her risk-aversion function. The most natural way is to choose a utility function. One of the possible candidates is an exponential utility function defined as: $U(x) = -e^{-Rx}$, where $R > 0$ is the Arrow-Pratt coefficient of absolute risk aversion. The final exponential weighting function is given as:

$$\phi(p) = \frac{Re^{-R(1-p)}}{1-e^{-R}}. \tag{4}$$

This function is attractive because it depends only on a single parameter, namely, the coefficient of the absolute risk aversion. One could apply a power utility function, but a user must be careful to ensure the choice of a proper function for the particular problem (for more details see Dowd *at al.* 2008). The weighting function rises exponentially with p, that is with higher p the weights are higher associated with higher losses. The risk aversion parameter R plays a role in the spectral risk measure similar to the confidence level α in the VaR and ES. In the case of analysis of events with huge size that break the limits determined by the mentioned risk measures, the Extreme Value Theory (EVT) is applicable. For further analysis the Peaks over Threshold (POT) method (Embrechts, Klüppelberg, Mikosch 2003) is applied in this paper. Briefly, the Peaks over Threshold method assumes that a given sequence of i.i.d. observations $X_1, \ldots, X_n$ comes from an unknown distribution function F, but our interest concentrates on excesses over a high threshold value u. It was showed in Leadbetter, Lindgren, Rootzen (1983) that the POT applies also to stationary sequences under some realistic conditions. Conditional excess distribution function (cedf) F_u could be found in accordance with the theorem of Pickands (1975), Balkema and de Haan (1974). It says that for a large class of underlying distributions F, the conditional excess distribution function $F_u(y)$, for u large, is well approximated by $F_u(y) \approx G_{\gamma,\sigma}(y)$, $u \to \infty$, where

$$G_{\gamma,\sigma}(y) = \begin{cases} 1 - \left(1 + \frac{\gamma}{\sigma} y\right)^{-\frac{1}{\gamma}}, & \gamma \neq 0; \\ 1 - e^{-\frac{y}{\sigma}}, & \gamma = 0 \end{cases} \tag{5}$$

for $y \in [0, (x_F - u)]$ if $\gamma \geq 0$ and $y \in \left[0, -\frac{\sigma}{\gamma}\right]$ if $\gamma < 0$, where $G_{\gamma,\sigma}$ is the generalized Pareto distribution and x_F is right endpoint of F. According to the Pickands-Balkema-de Haan theorem, for $x \geq u$, we can use the tail estimate $\widehat{F}(x) = (1 - F(u))\, G_{\gamma,\mu,\sigma}(x) + F(u)$ to approximate the distribution function $F(x)$ where μ is a location parameter. It can be shown that $\widehat{F}(x)$ is also generalized Pareto distribution, with the same shape parameter γ. An important problem is the choice of the threshold u, because it reflects the values of estimated parameters. It is suggested in the theory, that the choice should be based on the compromise between bias and variance. In the case of higher level of threshold, we should expect to get less bias. On the other hand we get less excesses that result a higher variance. Taking high quantiles representing high losses, the p^{th} quantile of the loss distribution at the confidence level $p > F(u)$ is given by inverting the formula for $\widehat{F}(x)$, then substituting unknown parameters of the GPD by estimates $(\widehat{\gamma}, \widehat{\sigma})$, we get estimate:

$$VaR_p = u + \frac{\widehat{\sigma}}{\widehat{\gamma}} \left(\left(\frac{n}{N_u} p \right)^{-\widehat{\gamma}} - 1 \right) \tag{6}$$

and the ES is estimated by:

$$ES_p = \frac{\widehat{q}_p}{1-\widehat{\gamma}} + \frac{\widehat{\sigma} - \widehat{\gamma}u}{1-\widehat{\gamma}} \tag{7}$$

where N_u denotes the number of exceeding observations.
To estimate the spectral risk measure with exponential risk-aversion function (4) we substitute (6) into:

$$M_\phi = \int_0^1 \frac{Re^{-R(1-p)}}{1-e^{-R}} \left[u + \frac{\widehat{\sigma}}{\widehat{\gamma}} \left(\left(\frac{n}{N_u} p \right)^{-\widehat{\gamma}} - 1 \right) \right] dp. \tag{8}$$

It is now clear that given the unconditional fat-tailed characteristic of futures price changes, the assumption of modelling market risk with the thin-tailed Gaussian distribution is inappropriate. The existing approaches for estimating the profit/loss distribution of a portfolio of financial instruments can be generally divided into three groups: non-parametric historical simulation methods, parametric methods based on volatility models and methods based on the Extreme Value Theory. McNeil and Frey (2000) joint all these three approaches to remove their drawbacks and get out their best features. We assume that X_t is a time series that represents daily observations of log return on a financial asset price, which are given by $X_t = \mu_t + \sigma_t Z_t$, where Z_t is a white noise process with zero mean, unit variance and the marginal distribution function $F_Z(z)$. We assume that μ_t is the expected return and σ_t is the volatility of the return. To implement an estimation procedure for the process X_t, we need to choose a dynamic conditional mean as well as a conditional variance model. McNeil and Frey defined the conditional risk measure for one day horizon with relation to process X_t as follows:

$$VaR_q^t = \mu_{t+1} + \sigma_{t+1} VaR(Z)_q, \tag{9}$$

$$ES_q^t = \mu_{t+1} + \sigma_{t+1} ES(Z)_q. \tag{10}$$

where $VaR(Z)_q$ is the q^{th} quantile of a noise variable Z_t and $ES(Z)_q$ is the corresponding expected shortfall.
Furthermore in this paper we implement analogical formula for the conditional spectral risk measure in the form:

$$SRM_q^t = \mu_{t+1} + \sigma_{t+1} SRM(Z)_q, \tag{11}$$

where $SRM(Z)_q$ is the SRM estimate for a noise variable Z_t.
Such an approach requires a volatility model estimated for returns. Thus, firstly, we estimate μ_{t+1} and σ_{t+1}, and calculate model's standardized residuals. Secondly, we apply the Extreme Value Theory to calculate the $VaR(Z)_q$, $ES(Z)_q$ and $SRM(Z)_q$ with the use of the POT method based on the standardized residuals. We would like to stress that in the paper $VaR(Z)_q$, $ES(Z)_q$ and $SRM(Z)_q$ are estimated with the use of the standardized residuals obtained from the GARCH(1,1) model. The details are given in section 3.1.

3 Testing for the Granger causality in risk

The concept of the Granger causality was the subject of substantial critics in the philosophical context but it is widely known and very practical. In fact Granger's definition is related to predictability of one variable using previous values of another one. Originally (Granger 1969) it was formulated for two stationary time series X_t and Y_t that constituted the whole information set available at time t. As the concept has become more and more popular it was extended to nonstationary time series (Toda and Yamammoto 1995), and what was very important in financial econometrics, implemented for conditional variance and for risk measures (Cheung and Ng 1996). Advantages and disadvantages of different definitions of causality in Granger's sense and their applications were widely discussed in Osińska (2011). In the presented paper we would like to turn one's attention on the causality in risk concept. In short, we can say that using past information the Granger causality in risk concept allows testing whether the history of the occurrence of significant risk in one market has predictive power for the occurrences of large risk in other markets. In the sense of predictability it corresponds to the original idea of the Granger causality. It should be understood in terms of co-dependence between different financial instruments, portfolios or markets that occurred if the risk limits are broken. This means that breaking the VaR (or ES or SRM) in one market results in exceeding maximum risk levels in other markets. Such a situation may correspond with the contagion phenomenon in a negative sense or with positive impulses spreading all over the financial markets.

Formally, the Granger causality in risk is defined as follows (Hong, 2001). Let $\{Y_{1t}, Y_{2t}\}$ is a bivariate not necessarily stationary stochastic time series. Let $A_{lt} = A_{lt}\left(I_{l(t-1)}\right)$ be the VaR at level $\alpha \in (0,1)$ for Y_{lt} predicted using the information set $I_{l(t-1)} = \{Y_{l(t-1)}, Y_{l(t-2)}, \ldots, Y_{l1}\}$ available at time $t-1$ ($l = 1, 2$). A_{lt} satisfies $P\left(Y_{lt} < A_{lt}|I_{l(t-1)}\right) = \alpha$. In the case of the Granger non-causality the null hypothesis is:

$$H_0: \qquad P\left(Y_{1t} < A_{1t}|I_{1(t-1)}\right) = P\left(Y_{1t} < A_{1t}|I_{t-1}\right) \quad \text{almost surely,} \tag{12}$$

where $I_{t-1} \equiv \left(I_{1(t-1)}, I_{2(t-1)}\right)$ with the alternative

$$H_1: \qquad P\left(Y_{1t} < A_{1t}|I_{1(t-1)}\right) \neq P\left(Y_{1t} < A_{1t}|I_{t-1}\right). \tag{13}$$

The null hypothesis says that the process $\{Y_{2t}\}$ does not Granger-cause the process $\{Y_{1t}\}$ in risk at level α with respect to I_{t-1}. The alternative hypothesis says that the process $\{Y_{2t}\}$ Granger-causes the process $\{Y_{1t}\}$ in risk at level α with respect to I_{t-1}. Comparing the above definition with the original one we may state that it concentrates only on the violations of VaR's computed for a given portfolio represented by Y_{1t}. So we interpret it as if information about the second portfolio represented by Y_{2t} could help change the probability of breaking the VaR of the first portfolio Y_{1t}. The definition captures the general characteristics of the Granger causality concept above a certain risk level.

The testing idea derived by Hong (2001) and modified by Hong et al. (2009) is

based on the cross-spectral density of a bivariate covariance stationary process V_{1t} and V_{2t}, where $V_{lt} = I(Y_{lt} > A_{lt})$ $l = 1, 2$ 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.
The hypotheses corresponding to (12) and (13) can be transformed into the expected value level:

$$H_0: \qquad E\left(V_{1t}|I_{1(t-1)}\right) = E\left(V_{1t}|I_{t-1}\right) \quad \text{almost surely,} \tag{14}$$

$$H_1: \qquad E\left(V_{1t}|I_{1(t-1)}\right) \neq E\left(V_{1t}|I_{t-1}\right). \tag{15}$$

For unidirectional causality the test statistic takes the form:

$$Q_1(M) = \frac{1}{D_{1T}(M)^{\frac{1}{2}}}\left[T\sum_{j=1}^{T-1} k^2\left(\frac{j}{M}\right)\widehat{\rho}(j)^2 - C_{1T}(M)\right], \tag{16}$$

$C_{1T}(M)$, $D_{1T}(M)$ are the mean and the variance, $k\left(\frac{j}{M}\right)$ is the kernel function, $\widehat{\rho}(j)$ is the sample cross-correlation function between V_{1t} and V_{2t}, M is lag order between Y_{1t} and Y_{2t}. As it was emphasized by Hong, Liu, Wang (2009) the test statistic does not check exactly the null but it is a necessary condition that allows capturing the most important information on the average. There exists an analogue of (16) for bidirectional causality concept denoted $Q_2(M)$ (see for more details Hong, Liu, Wang 2009). It should be stressed that in Hong (2001) the Granger causality in risk has been considered only in the case on simple model GARCH(1,1) with normal conditional distribution. It is also important to emphasize that in Hong, Liu, Wang (2009) formal results have been provided only under $V_{lt}(\theta_l) = V_l(I_{l(t-1),\theta_l})$ $(l = 1, 2)$ where θ_l is an unknown finite-dimensional parameter.
To verify the pair of hypotheses (14)-(15), we propose to use the expected shortfall and the spectral risk measures. It is indicated in Hong, Liu and Wang (2009) that Granger causality in risk focuses on the comovements between the left tails of two distribution. In that regard we believe that it is better to use ES or SRM (instead of VaR) as risk measures to ensure better fit to tails. We applied these three risk measures to take into account broad spectrum of possible risk spillover patterns which we believe are hard (or even impossible) to find only by using VaR due to its shortcomings. It is expected that the results obtained for the ES should be stronger than those computed for the VaR because the ES denoted the situation when VaR was already exceeded. The same relation is valid for ES and SRM. It is based on ability to satisfy the coherence axioms (Artzner, Delbaen, Eber, Heath 1997) and taking into account risk-aversion parameter. Of course one can use $VaR(\alpha')$ and $VaR(\alpha)$ for $\alpha' > \alpha$, but then we are expose to VaR shortcomings. Then hypotheses are modified as follows.
Let $B_{lt} = B_{lt}(I_{l(t-1)})$ for $l = 1, 2$ be the Expected Shortfall at confidence level $\alpha \in (0, 1)$ for Y_{lt} predicted using the information set $I_{l(t-1)} = \{Y_{l(t-1)}, Y_{l(t-2)}, \ldots, Y_{l1}\}$ available at time $t-1$. Then $ES_{lt} = I(Y_{lt} > B_{lt})$ $l = 1, 2$ is the ES break indicator

(constructed similarly to the VaR break indicator). The break indicator takes on the value of 1 when ES is exceeded by loss and takes on the value of 0 otherwise. In the case of ES hypotheses to be tested are

$$H_0: \quad E\left(ES_{1t}|I_{1(t-1)}\right) = E\left(ES_{1t}|I_{t-1}\right) \quad \text{almost surely,} \tag{17}$$

$$H_1: \quad E\left(ES_{1t}|I_{1(t-1)}\right) \neq E\left(ES_{1t}|I_{t-1}\right). \tag{18}$$

Let $C_{lt} = C_{lt}(I_{l(t-1)})$ for $l = 1, 2$ be the Spectral Risk Measure with parameter R for Y_{lt} predicted using the information set $I_{l(t-1)} = \{Y_{l(t-1)}, Y_{l(t-2)}, \ldots, Y_{l1}\}$ available at time $t-1$. Let $SRM_{lt} = I(Y_{lt} > C_{lt})$ $l = 1, 2$ be the SRM break indicator (constructed similarly to the VaR and ES break indicator). Hypotheses corresponding to the Granger causality in risk in the case of SRM are considered to take the forms

$$H_0: \quad E\left(SRM_{1t}|I_{1(t-1)}\right) = E\left(SRM_{1t}|I_{t-1}\right) \quad \text{almost surely,} \tag{19}$$

$$H_1: \quad E\left(SRM_{1t}|I_{1(t-1)}\right) \neq E\left(SRM_{1t}|I_{t-1}\right). \tag{20}$$

Adequacy of the results of the Hong, Liu, Wang (2009) test for the corresponding pairs of hypotheses (17)-(18) and (19)-(20) was confirmed by similar Monte Carlo simulation. The results are available from the authors upon request. It should be stressed that hypotheses (14)-(15) are not equivalent to hypotheses (17)-(18) and (19)-(20).

3.1 Steps of the research

We take into account the number of violations of the respective risk measure when testing for causality in risk. It does not occur very often, however its consequences are very strong. We tested for the Granger causality in risk for the three risk measures: VaR, ES and SRM, respectively. In the first step of the research we estimated GARCH(1,1) with t-Student error distribution.
The conditional mean was defined by the autoregressive model with GARCH type error:

$$Y_t = \psi_0 + \psi_1(L)Y_t + \sqrt{h_{Y_t}}\zeta_t, \tag{21}$$

where: ζ_t, is error terms with conditional t-distribution with ν degrees of freedom, $\psi(L) = \sum_{i=1}^{q} \psi_i L^i$, are polynomial autoregressive operators, h_{Y_t}, denote conditional variance of the corresponding time series.
The conditional variance is modelled using GARCH(1,1) representation with t-Student error distribution:

$$h_{Y_t} = \gamma_0 + \gamma_1 \xi_{t-1}^2 + \delta_1 h_{Y_{t-1}}, \tag{22}$$

where: $\xi_t = \sqrt{h_{Y_t}}\zeta_t$. According to the aforementioned Peaks over Threshold method we used standardised residuals from GARCH(1,1) model with t-disturbances to estimate parameters of Generalized Pareto Distribution with assumed threshold u. The choice of threshold is the weak spot of POT theory: it is arbitrary and therefore judgmental (Dowd (2005)). We set u as a value corresponding to a 10% level for all observations in time series which is the standard level. It is often seen that 10% level is a proper compromise between bias and variance. In the next step all the three risk measures were estimated in accordance with formulas (9), (10) and (11). They were compared with original series to obtain a sequence of violations. In the last step we tested for the Granger causality in risk for VaR, ES and SRM, respectively.
In the last step the following pair of mutually excluding hypotheses was used:
H_0: Chinese financial processes do not Granger-cause in risk financial processes in other countries
H_1:Chinese financial processes do Granger-cause in risk financial processes in other countries
The opposite direction of causality was checked as well. In the case of the GARCH model and generalized Pareto distribution parameters were estimated with the maximum likelihood method. We calculated the integral (8) using numerical integration, and in this case we applied one-third Simpson's method (see, for details Miranda and Fackler 2002).

4 Empirical analysis

The subject of the research concentrated on dependencies between time series of 36 stock exchange indices from all over the world and 19 currencies exchange rates quoted against the U.S. dollar (Table 1).
Special attention was paid to the Chinese financial markets, represented by the Shanghai Stock Exchange Composite Index (SSE) as well as its subindices SSE A and SSE B. The first subindex represents A shares i.e. the common shares issued by companies registered in Mainland China and denominated in Chinese currency. On the other hand, B shares are denominated in Chinese Yuan but offered and traded in foreign currencies. Since 1992 B shares have been traded on both stock exchanges located in China, in Shanghai they have been offered in U.S. dollars and in Shenzhen – in H.K. dollars. Furthermore, we considered the Chinese Yuan against US dollar exchange rate. Daily observations from Feb. 1, 2006 till Feb. 18, 2011 were taken into account (sample: 2–1326, i.e. 1325 observations). They were divided into two groups: before the financial crisis from Feb. 1, 2006 till Jul. 31, 2008 (sample: 2-658) and during and after the crisis from Aug. 1, 2008 till Feb. 18, 2011 (sample: 659–1326). All the data were transformed into logarithmic rates of return according to the formula: $r_t = -100 \cdot (\ln P_t - \ln P_{t-1})$. In the case of short position the data were transformed according to $r_t = 100 \cdot (\ln P_t - \ln P_{t-1})$. It should be mentioned

that in the empirical analysis logarithmic rates of return r_t are used as Y_{lt} in Granger-causality test.

4.1 The results of testing for causality in risk

The most important part of the research was to examine the way the risk is transmitted from one stock market to another. On the basis of the GARCH models with t-Student error distribution we estimated Value at Risk as well as Expected Shortfall at 95 per cent confidence level. To apply the spectral risk measure we need to choose a suitable value for the coefficient of the absolute risk aversion R. The higher R is, the more we care about the higher losses relative to the others. It therefore makes sense to apply an EVT approach in the first place if we care a great deal about the very high losses (i.e. extremes) related to the non-extreme observations, and this requires that R takes a high value. In principle, this can be any positive value, so we decided to follow Cotter and Dowd (2006) and set $R = 100$. We decided to focus on China as

Table 1: Indices and stock exchange used in empirical analysis

Index	Country	Index / Exchange rate	Country	Exchange rate	Country
AEX	Holland	KOSPI	South Korea	USDCHF	Switzerland
AMEX	USA	MERVAL	Argentina	USDCNY	China
ATG	Greece	NIKK225	Japan	USDEGP	Egypt
ATX	Austria	NSDQCOMP	USA	USDEUR	European Union
BEL20	Belgium	NZ50	New Zealand	USDGBP	United Kingdom
BOVESPA	Brazil	OMXSPI	Sweden	USDHKD	Hong Kong
BSESN	India	PX50	Czech Republic	USDIDR	Indonesia
BUX	Hungary	RTS	Russia	USDILS	Israel
CAC40	France	S&P500	USA	USDINR	India
DAX	Germany	SMSI	Spain	USDJPY	Japan
DJCA	USA	SSE	China	USDKRW	South Korea
DJIA	USA	SSE A	China	USDMYR	Malaysia
FTSE100	United Kingdom	SSE B	China	USDNOK	Norway
HEX	Finland	SSMI	Switzerland	USDNZD	New Zealand
HIS	China	STI	Singapore	USDSEK	Sweden
IPCMEX	Mexico	TA100	Israel	USDSGD	Singapore
ISE100	Turkey	TWAII	Taiwan	USDTWD	Taiwan
JKSE	Indonesia	USDARS	Argentina		
KLSE	Malaysia	USDBRL	Brazil		

one of the fastest growing economies in the last decade. The Chinese stock market as a significant part of economy experienced huge gain and – to some extend – integrated with other financial markets. It was interesting to examine whether and how much Chinese stock market has become a part of the global financial system with its entire positive and negative effects such as the risk spillover or contagion. To obtain more detailed results and more convincing conclusions we decided to take into consideration three main Shanghai Stock Indices: SSE, SSE A and SSE B. For comparison the same analysis was made for HSI – representing Hong Kong market fully integrated with the global financial processes. Additionally DJIA was chosen to serve as a benchmark for drawing conclusions. Some of the results for SSE, DJIA, HSI are shown in Figures 1, 2 and 3. The dynamics of the risk was similar across the markets although some specific characteristics can be noticed. The range of price changes in the international markets like the New York and Hong Kong Stock Exchanges was bigger than in the officially regulated market in China.

Figure 1: The estimated risk measures for SSE in Feb. 1, 2006 till Feb. 18, 2011

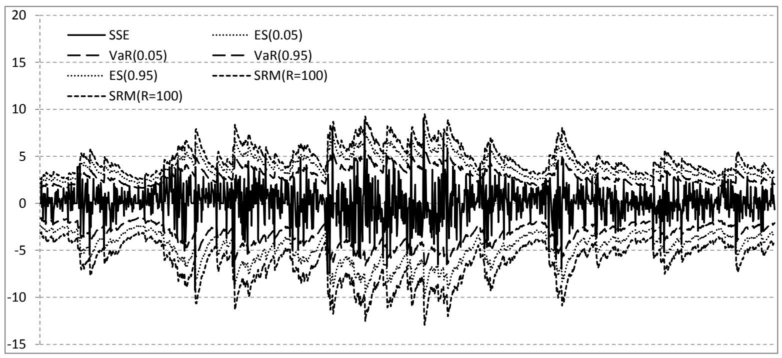
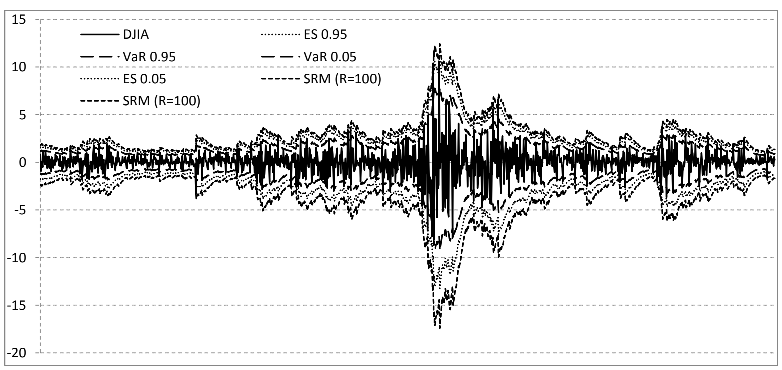
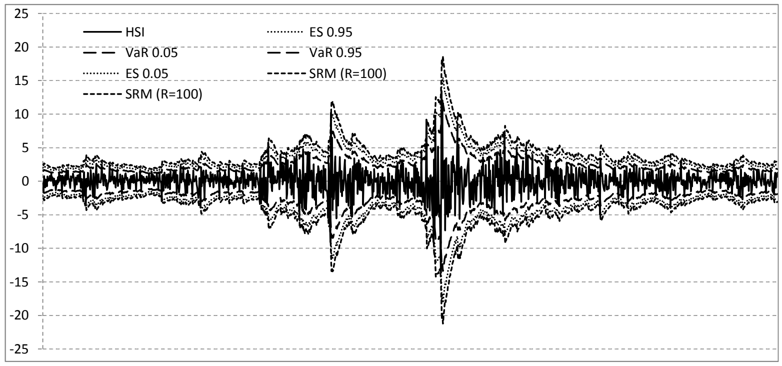


Figure 2: The estimated risk measures for DJIA in Feb. 1, 2006 till Feb. 18, 2011



In the period of the crisis the changes were bigger than in the other time periods. It is worth noting that violations (breaks) of the spectral risk measure (cases when SRM is exceeded by loss) are less frequent than the expected shortfall as well as the VaR breaks. So the results obtained for the SRM are significantly more important for forecasting the risk transfers than the results obtained for the ES and/or VaR. It is connected with the idea behind these three risk measures. The SRM breaks down only in cases when really extreme events (catastrophic) occur. When they occur it is

Figure 3: The estimated risk measures for HSI in Feb. 1, 2006 till Feb. 18, 2011



more probable that these events will bring spillover effect because of its magnitude and rarity. Table 2 reports representative test statistics for the Granger causality in risk at α=95% confidence level (with p-values) when SRM is applied for some selected indices. We found extremely significant evidence on one-way Granger causality in risk between SSE (as a cause) and BOVESPA, DJIA, MERVAL, NIKK225, S&P500 (as the results). On the other hand we observed strong evidence on one-way the Granger causality in risk between DAX, FTSE100, KOSPI (as causes) and SSE (as the result). Total results obtained in this research were generalized with respect to the Chinese stock and currency market and presented in tables 3-7 (all of the specific results are available upon request). The results were put into three panels, with respect to the sample size: the whole sample, the period before the crisis and the period during and after the crisis. In Table 2 the results for testing the Granger causality in risk for SSE are shown. One of the important parameters is the lag number M. It informs about the time delay since the beginning till the end of the risk transfer. The following rule has been observed. The longer delay the more often the null hypothesis of the Granger non-causality in risk is rejected. It may result from the fact that the financial capital moves from one market to another not necessarily in a direct way, so the results of testing for the causality in risk can show both: direct and indirect relations. The greater number of intermediaries the longer delay can be observed. One of the most basic facts is that the Granger causality in risk appears significantly more often for long position (losses) than for short position (profits), i.e. large losses are transmitted faster and with greater magnitude around the globe. Long (short) position means the holder of the position owns the financial instrument and will profit if the price of the security goes up (down). This specific result confirms the theory that negative news has more significant effect than positive information. It is important that before, during and after the financial crisis of 2007–2009, the Granger causality in risk could be observed at 95 per cent confidence level for $M = 20$ and $M = 40$. It is also important that the most negative impulses obtained for the ES long (ES for long position hereafter as ES long and respectively for ES short) and SRM long (SRM for long position hereafter as SRM long and respectively for SRM short) are observed only after 20 days, thus a certain time period is necessary for transferring the most risky capital in both directions from Hong Kong to the USA and opposite. Before the crisis the number of markets infected with the risk coming from and to the SSE was approximately equal to these infected after Aug. 1, 2008. This only confirms that Extreme Value Theory is considerably useful to estimate the risk, particularly during some major disturbances in the markets. It means that large losses and large gains during the crisis were modelled effectively and a market participant could take into consideration extreme events with high efficiency. From this perspective EVT is suitable for practical applications. In case of risk measures'

Table 2: The results of testing for Granger-causality in risk at 95% confidence level from Feb. 1, 2006 till Feb. 18, 2011 when Spectral Risk Measure is applied in case of long position

M (lag order)	5	10	20	40	M	5	10	20	40
SSE →	12, 644	10, 177	9, 194	6, 497	BOVESPA	−1, 081	−1, 560	−2, 229	−3, 151
BOVESPA	(0,000)	(0,000)	(0,000)	(0,000)	→ SSE	(0,86)	(0,941)	(0,987)	(0,999)
SSE →	−1, 104	−2, 277	−2, 278	−3, 236	DAX →	27, 499	20, 422	13, 939	8, 492
DAX	(0,865)	(0,944)	(0,989)	(0,999)	SSE	(0,000)	(0,000)	(0,000)	(0,000)
SSE →	20, 068	16, 517	15, 354	11, 667	DJIA →	−1, 097	−1, 582	−2, 262	−3, 188
DJIA	(0,000)	(0,000)	(0,000)	(0,000)	SSE	(0,864)	(0,943)	(0,988)	(0,999)
SSE →	4, 561	4, 546	2, 893	0, 775	FTSE100	8, 939	8, 539	7, 009	4, 283
FTSE100	(0,000)	(0,000)	(0,002)	(0,219)	→ SSE	(0,000)	(0,000)	(0,000)	(0,000)
SSE →	−1, 073	1, 206	1, 884	0, 683	KOSPI →	−0, 348	2, 418	2, 449	1, 018
KOSPI	(0,858)	(0,114)	(0,03)	(0,247)	SSE	(0,636)	(0,008)	(0,007)	(0,154)
SSE →	−1, 073	−1, 548	−2, 213	−3, 143	MERVAL	10, 526	7, 379	5, 528	4, 057
MERVAL	(0,858)	(0,939)	(0,987)	(0,999)	→ SSE	(0,000)	(0,000)	(0,000)	(0,000)
SSE →	12, 644	9, 004	5, 552	2, 457	NIKK225	−1, 081	−1, 560	−2, 229	−3, 151
NIKK225	(0,000)	(0,000)	(0,000)	(0,007)	→ SSE	(0,86)	(0,941)	(0,987)	(0,999)
SSE →	12, 644	12, 264	10, 401	6, 986	NZ50 →	−1, 081	−1, 560	−2, 229	−3, 019
NZ50	(0,000)	(0,000)	(0,000)	(0,000)	SSE	(0,86)	(0,941)	(0,987)	(0,999)
SSE →	−1, 081	−1, 560	−0, 851	−0, 269	S&P500	−1, 081	−1, 560	−2, 229	−3, 166
S&P500	(0,86)	(0,941)	(0,803)	(0,606)	→ SSE	(0,86)	(0,941)	(0,987)	(0,999)

→ represents the direction in test for Granger causality in risk. The numbers in parentheses are the *p*-values.

breaks the following inequality holds: $SRM < ES < VaR$. This implies an increasing number of violations of the sequent risk limits. On the one hand that means that SRM fails only when extreme events occurs but on the other, VaR fails even in cases of regular losses or gains (ES is between SRM and VaR). In case of VaR causality in risk may not be present and more importantly the question arise whether there is spillover effect or just normal capital movement. Of course someone could use VaR at higher level of confidence (e.g. 0.99 or more), but then we are exposed to VaR drawbacks (i.e. incoherence). It means that risk could be underestimated and there will be more breaks which could bring about causality in risk. The spillover effect then could be confused with improper risk estimation. In case of ES it is less plausible to happen, but still we are bounded by its averaging.

This boils down to two conclusions. Firstly, that Spectral Risk Measure fulfils its purpose and is more useful and safe to use than other risk measures (ES and VaR) particularly during the crises. We should remember that SRM depends on utility function and R and the user must be cautious when using them. Secondly, the events which break down SRM are so significant (i.e. huge magnitude) that they easily bring about causality in risk. The direction of the risk spillover was mainly observed from the stock markets to the SSE and obviously bi-directional for all risk measures. In the case of the SRM long for small M ($M = 5$ and $M = 10$) the stock exchange in Shanghai was the source of the risk few times more often than the other stock markets.

Table 3: The results of testing for Granger-causality in risk for SSE (percentage of rejecting the null at 95% level is shown)

		SSE → Indices				Indices → SSE				SSE ↔ Indices			
	Risk measure lag (M)	5	10	20	40	5	10	20	40	5	10	20	40
Sample: 2–1326	VaR long	34,0%	32,1%	24,5%	18,9%	15,1%	17,0%	18,9%	11,3%	49,1%	49,1%	60,4%	52,8%
	VaR short	3,8%	9,4%	7,5%	1,9%	3,8%	3,8%	3,8%	1,9%	17,0%	26,4%	24,5%	26,4%
	ES long	34,0%	35,8%	28,3%	20,8%	9,4%	17,0%	20,8%	18,9%	45,3%	50,9%	52,8%	52,8%
	ES short	9,4%	9,4%	13,2%	18,9%	9,4%	9,4%	11,3%	13,2%	18,9%	22,6%	43,4%	43,4%
	SRM long	28,3%	34,0%	67,9%	58,5%	32,1%	39,6%	88,7%	71,7%	79,2%	81,1%	79,2%	62,3%
	SRM short	9,4%	13,2%	60,4%	39,6%	3,8%	5,7%	39,6%	47,2%	69,8%	79,2%	50,9%	50,9%
Sample: 2–658	VaR long	9,4%	9,4%	7,5%	1,9%	9,4%	22,6%	22,6%	22,6%	30,2%	35,8%	35,8%	37,7%
	VaR short	1,9%	0,0%	0,0%	0,0%	5,7%	3,8%	0,0%	3,8%	18,9%	32,1%	32,1%	41,5%
	ES long	41,5%	34,0%	28,3%	28,3%	13,2%	13,2%	17,0%	18,9%	34,0%	41,5%	43,4%	45,3%
	ES short	9,4%	11,3%	18,9%	26,4%	0,0%	1,9%	7,5%	20,8%	7,5%	32,1%	50,9%	54,7%
	SRM long	22,6%	30,2%	98,1%	90,6%	3,8%	3,8%	96,2%	98,1%	96,2%	90,6%	88,7%	90,6%
	SRM short	11,3%	18,9%	92,5%	84,9%	0,0%	11,3%	88,7%	79,2%	92,5%	84,9%	83,0%	75,5%
Sample: 659–1326	VaR long	34,0%	34,0%	28,3%	18,9%	9,4%	5,7%	3,8%	0,0%	39,6%	39,6%	34,0%	35,8%
	VaR short	7,5%	13,2%	15,1%	15,1%	3,8%	5,7%	5,7%	11,3%	20,8%	37,7%	30,2%	35,8%
	ES long	24,5%	24,5%	26,4%	24,5%	3,8%	1,9%	13,2%	17,0%	28,3%	34,0%	39,6%	49,1%
	ES short	11,3%	11,3%	28,3%	49,1%	56,6%	43,4%	45,3%	49,1%	32,1%	37,7%	43,4%	67,9%
	SRM long	24,5%	28,3%	71,7%	60,4%	3,8%	7,5%	84,9%	79,2%	84,9%	77,4%	77,4%	88,7%
	SRM short	7,5%	5,7%	45,3%	45,3%	0,0%	3,8%	28,3%	32,1%	69,8%	81,1%	79,2%	69,8%

The relations between Chinese currency and the international stock markets have changed in time. Before the financial crisis of 2007-2009 they were rather incidental and concentrated on a small number of markets. During the crisis and later the scale of transferring the risk became greater. The source of the risk was most frequently external. The general view is that relations in the whole sample were weaker than the same relations in the period starting with the approximate date of the crisis symptoms. Greater uncertainty at the global market implies more frequent movements at the market and more volatility. That is why the Granger causality in risk is more frequent for SRM than for ES and far more frequent than for VaR, i.e. larger losses (gains) on one market generate higher probability that such losses (gains) will be transmitted to other markets. The obtained results are fairly important because the empirical

Table 4: The results of testing for Granger-causality in risk for HSI (percentage of rejecting the null at 95% level is shown)

		SSE → Indices				Indices → SSE				SSE ↔ Indices			
	Risk measure lag (M)	5	10	20	40	5	10	20	40	5	10	20	40
Sample: 2–1326	VaR long	17,0%	15,1%	13,2%	9,4%	37,7%	50,9%	50,9%	49,1%	66,0%	71,7%	71,7%	67,9%
	VaR short	9,4%	9,4%	17,0%	18,9%	5,7%	5,7%	5,7%	3,8%	32,1%	30,2%	37,7%	47,2%
	ES long	22,6%	35,8%	34,0%	20,8%	45,3%	47,2%	52,8%	52,8%	67,9%	75,5%	77,4%	75,5%
	ES short	18,9%	20,8%	17,0%	13,2%	15,1%	17,0%	17,0%	20,8%	30,2%	35,8%	49,1%	50,9%
	SRM long	32,1%	56,6%	88,7%	69,8%	37,7%	58,5%	90,6%	86,8%	75,5%	81,1%	83,0%	75,5%
	SRM short	15,1%	22,6%	69,8%	47,2%	7,5%	7,5%	60,4%	60,4%	84,9%	88,7%	64,2%	56,6%
Sample: 2–658	VaR long	15,1%	20,8%	20,8%	15,1%	45,3%	50,9%	50,9%	49,1%	67,9%	73,6%	75,5%	69,8%
	VaR short	1,9%	3,8%	1,9%	3,8%	3,8%	3,8%	3,8%	1,9%	18,9%	26,4%	22,6%	18,9%
	ES long	18,9%	28,3%	49,1%	34,0%	50,9%	58,5%	56,6%	49,1%	50,9%	66,0%	67,9%	73,6%
	ES short	5,7%	1,9%	7,5%	11,3%	22,6%	18,9%	20,8%	20,8%	22,6%	34,0%	41,5%	62,3%
	SRM long	26,4%	49,1%	86,8%	83,0%	35,8%	66,0%	96,2%	92,5%	75,5%	84,9%	88,7%	83,0%
	SRM short	17,0%	18,9%	94,3%	66,0%	11,3%	13,2%	83,0%	83,0%	96,2%	96,2%	92,5%	79,2%
Sample: 659–1326	VaR long	20,8%	20,8%	13,2%	11,3%	30,2%	32,1%	30,2%	35,8%	50,9%	49,1%	54,7%	52,8%
	VaR short	17,0%	15,1%	13,2%	11,3%	1,9%	5,7%	7,5%	9,4%	30,2%	37,7%	43,4%	47,2%
	ES long	17,0%	22,6%	35,8%	28,3%	43,4%	41,5%	50,9%	64,2%	58,5%	56,6%	54,7%	64,2%
	ES short	20,8%	20,8%	24,5%	30,2%	7,5%	9,4%	13,2%	18,9%	13,2%	28,3%	30,2%	45,3%
	SRM long	9,4%	28,3%	58,5%	39,6%	37,7%	49,1%	69,8%	62,3%	56,6%	58,5%	66,0%	62,3%
	SRM short	9,4%	3,8%	28,3%	35,8%	11,3%	1,9%	35,8%	56,6%	50,9%	66,0%	66,0%	71,7%

Table 5: The results of testing for Granger-causality in risk for CNY against USD (percentage of rejecting the null at 95% level is shown)

		USDCNY → Indices				Indices → USDCNY				USDCNY ↔ Indices			
	Risk measure lag (M)	5	10	20	40	5	10	20	40	5	10	20	40
Sample: 2–1326	VaR long	7,5%	7,5%	9,4%	7,5%	17,0%	11,3%	7,5%	7,5%	32,1%	28,3%	20,8%	26,4%
	VaR short	3,8%	1,9%	1,9%	1,9%	9,4%	15,1%	22,6%	22,6%	22,6%	49,1%	52,8%	54,7%
	ES long	5,7%	3,8%	3,8%	3,8%	9,4%	9,4%	5,7%	3,8%	22,6%	24,5%	28,3%	32,1%
	ES short	1,9%	9,4%	11,3%	13,2%	1,9%	11,3%	15,1%	15,1%	7,5%	22,6%	49,1%	39,6%
	SRM long	0,0%	0,0%	94,3%	81,1%	11,3%	11,3%	100,0%	86,8%	98,1%	90,6%	86,8%	88,7%
	SRM short	0,0%	9,4%	94,3%	77,4%	5,7%	26,4%	96,2%	73,6%	86,8%	92,5%	94,3%	88,7%
Sample: 2–658	VaR long	15,1%	15,1%	15,1%	11,3%	15,1%	11,3%	11,3%	7,5%	30,2%	35,8%	37,7%	32,1%
	VaR short	5,7%	7,5%	3,8%	3,8%	9,4%	15,1%	11,3%	11,3%	26,4%	41,5%	47,2%	47,2%
	ES long	7,5%	5,7%	18,9%	45,3%	5,7%	5,7%	20,8%	28,3%	7,5%	30,2%	37,7%	45,3%
	ES short	7,5%	9,4%	17,0%	20,8%	11,3%	15,1%	22,6%	28,3%	17,0%	28,3%	45,3%	52,8%
	SRM long	9,4%	9,4%	66,0%	73,6%	3,8%	5,7%	81,1%	62,3%	98,1%	84,9%	86,8%	81,1%
	SRM short	1,9%	7,5%	98,1%	83,0%	9,4%	20,8%	100,0%	98,1%	90,6%	98,1%	98,1%	92,5%
Sample: 659–1326	VaR long	1,9%	3,8%	3,8%	5,7%	15,1%	9,4%	1,9%	3,8%	28,3%	22,6%	22,6%	34,0%
	VaR short	1,9%	3,8%	1,9%	1,9%	5,7%	9,4%	15,1%	13,2%	15,1%	28,3%	28,3%	30,2%
	ES long	5,7%	3,8%	3,8%	13,2%	26,4%	20,8%	30,2%	28,3%	18,9%	32,1%	37,7%	37,7%
	ES short	7,5%	13,2%	30,2%	35,8%	1,9%	5,7%	17,0%	35,8%	5,7%	52,8%	69,8%	58,5%
	SRM long	7,5%	3,8%	45,3%	52,8%	15,1%	11,3%	43,4%	52,8%	69,8%	69,8%	79,2%	86,8%
	SRM short	3,8%	7,5%	79,2%	67,9%	3,8%	17,0%	83,0%	62,3%	75,5%	73,6%	71,7%	79,2%

testing for the Granger-causality in risk allows finding out the directions of flow of 'quick', i.e. most risky capital. In the period of five days, speculative capital exhibits the strongest tendency to escape from risky markets that induces the contagion effect.

Table 6: The results of testing for Granger-causality in risk for SSE A (percentage of rejecting the null at 95% level is shown)

		SSE_A → Indices				Indices → SSE_A				SSE_A ↔ Indices			
	Risk measure lag (M)	5	10	20	40	5	10	20	40	5	10	20	40
Sample: 2–1326	VaR long	21,8%	18,2%	12,7%	9,1%	41,8%	41,8%	40,0%	40,0%	49,1%	49,1%	49,1%	52,7%
	VaR short	3,6%	3,6%	3,6%	3,6%	1,8%	0,0%	0,0%	3,6%	21,8%	29,1%	34,5%	34,5%
	ES long	30,9%	30,9%	23,6%	20,0%	30,9%	27,3%	21,8%	21,8%	47,3%	47,3%	54,5%	47,3%
	ES short	10,9%	18,2%	16,4%	14,5%	3,6%	3,6%	1,8%	1,8%	7,3%	18,2%	43,6%	49,1%
	SRM long	20,0%	21,8%	80,0%	67,3%	38,2%	45,5%	96,4%	87,3%	90,9%	89,1%	87,3%	76,4%
	SRM short	3,6%	9,1%	70,9%	67,3%	0,0%	1,8%	87,3%	83,6%	94,5%	81,8%	76,4%	63,6%
Sample: 2–658	VaR long	14,5%	10,9%	7,3%	7,3%	43,6%	45,5%	38,2%	32,7%	45,5%	47,3%	50,9%	54,5%
	VaR short	1,8%	3,6%	1,8%	3,6%	0,0%	0,0%	0,0%	0,0%	18,2%	21,8%	27,3%	38,2%
	ES long	36,4%	25,5%	20,0%	25,5%	29,1%	36,4%	34,5%	38,2%	52,7%	60,0%	56,4%	50,9%
	ES short	10,9%	10,9%	14,5%	16,4%	3,6%	9,1%	10,9%	20,0%	9,1%	21,8%	45,5%	50,9%
	SRM long	20,0%	25,5%	83,6%	81,8%	18,2%	25,5%	96,4%	96,4%	96,4%	89,1%	90,9%	85,5%
	SRM short	1,8%	3,6%	87,3%	85,5%	1,8%	5,5%	96,4%	92,7%	96,4%	90,9%	96,4%	78,2%
Sample: 659–1326	VaR long	25,5%	34,5%	41,8%	38,2%	14,5%	9,1%	14,5%	14,5%	47,3%	56,4%	63,6%	58,2%
	VaR short	3,6%	3,6%	3,6%	3,6%	1,8%	0,0%	0,0%	3,6%	21,8%	29,1%	34,5%	34,5%
	ES long	18,2%	18,2%	20,0%	23,6%	5,5%	5,5%	12,7%	12,7%	21,8%	30,9%	36,4%	41,8%
	ES short	10,9%	14,5%	41,8%	38,2%	1,8%	1,8%	38,2%	32,7%	7,3%	43,6%	43,6%	45,5%
	SRM long	21,0%	23,8%	82,0%	69,3%	35,2%	43,5%	92,4%	84,3%	92,9%	92,1%	89,3%	79,5%
	SRM short	3,6%	5,5%	61,8%	63,6%	0,0%	0,0%	85,5%	83,6%	87,3%	83,6%	85,5%	96,4%

Table 7: The results of testing for Granger-causality in risk for SSE B (percentage of rejecting the null at 95% level is shown)

		SSE_B → Indices				Indices → SSE_B				SSE_B ↔ Indices			
	Risk measure lag (M)	5	10	20	40	5	10	20	40	5	10	20	40
Sample: 2–1326	VaR long	34,5%	32,7%	25,5%	16,4%	40,0%	30,9%	23,6%	20,0%	60,0%	60,0%	63,6%	58,2%
	VaR short	9,1%	12,7%	18,2%	14,5%	7,3%	7,3%	5,5%	7,3%	14,5%	23,6%	30,9%	43,6%
	ES long	30,9%	29,1%	29,1%	23,6%	29,1%	21,8%	23,6%	20,0%	52,7%	58,2%	61,8%	50,9%
	ES short	12,7%	14,5%	12,7%	18,2%	10,9%	10,9%	7,3%	12,7%	21,8%	30,9%	40,0%	49,1%
	SRM long	25,5%	29,1%	63,6%	49,1%	38,2%	45,5%	80,0%	69,1%	78,2%	76,4%	74,5%	60,0%
	SRM short	3,6%	7,3%	65,5%	43,6%	7,3%	9,1%	58,2%	54,5%	78,2%	81,8%	60,0%	49,1%
Sample: 2–658	VaR long	18,2%	10,9%	9,1%	7,3%	23,6%	27,3%	29,1%	27,3%	41,8%	49,1%	47,3%	40,0%
	VaR short	3,6%	1,8%	1,8%	3,6%	9,1%	3,6%	5,5%	5,5%	25,5%	32,7%	34,5%	38,2%
	ES long	38,2%	34,5%	30,9%	38,2%	21,8%	29,1%	30,9%	34,5%	49,1%	63,6%	61,8%	52,7%
	ES short	1,8%	9,1%	12,7%	18,2%	1,8%	5,5%	9,1%	18,2%	9,1%	20,0%	45,5%	49,1%
	SRM long	23,6%	29,1%	89,1%	80,0%	10,9%	12,7%	96,4%	92,7%	98,2%	94,5%	90,9%	87,3%
	SRM short	1,8%	16,4%	94,5%	83,6%	0,0%	9,1%	90,9%	80,0%	90,9%	83,6%	94,5%	83,6%
Sample: 659–1326	VaR long	25,5%	25,5%	25,5%	20,0%	12,7%	12,7%	10,9%	9,1%	45,5%	47,3%	41,8%	47,3%
	VaR short	9,1%	12,7%	18,2%	14,5%	7,3%	7,3%	5,5%	7,3%	14,5%	23,6%	30,9%	43,6%
	ES long	21,8%	21,8%	27,3%	27,3%	12,7%	10,9%	16,4%	20,0%	32,7%	34,5%	45,5%	41,8%
	ES short	7,3%	9,1%	20,0%	36,4%	29,1%	29,1%	34,5%	20,0%	21,8%	30,9%	38,2%	41,8%
	SRM long	25,5%	29,1%	69,1%	52,7%	7,3%	10,9%	85,5%	80,0%	90,9%	83,6%	74,5%	85,5%
	SRM short	1,8%	5,5%	50,9%	50,9%	0,0%	5,5%	38,2%	43,6%	67,3%	76,4%	80,0%	81,8%

The results for SSE A (Table 6) and SSE B (Table 7) are similar in all three subsamples for all risk measures. These two markets have integrated and for that reason the results must be similar. We found significant Granger causality in risk between stock markets (AMEX, DAX, CAC40, DJCA, FTSE, KOSPI, NSDQCOMP, S&P500, RTS) and SSE A and SSE B in case of losses (ES long and SRM long) and less significant causality in case of gains. Both markets (SSE A and SSE B) are affected by other markets and the risk spillover effect is present. The risk transmission is particularly visible after 20 days and more, when almost in all cases the Granger causality in risk is significant.

In Table 8 we summarized the results with respect to interdependencies that resulted from the testing procedure. We can see that SSE, SSE A, SSE B do Granger-cause AMEX, BOVESPA, DJIA, MERVAL, NIKK225 in risk for long position in almost all of the cases. Appearance of BOVESPA and MERVAL should not be surprising because growing influence of China on Brazil and Argentina can be observed which obviously affects the stock markets. On the other hand ATG, HEX, FTSE100, BEL20, CAC40, SMSI do Granger-cause SSE, SSE A, SSE B in risk for long position in almost all of the cases. Influence of such indices like ATG, HEX and BEL20 is rather difficult to be explained relying only on the information coming from stock indices.

5 Final remarks

The results of the Granger-causality in risk can be considered in terms of contagion analysis. They answer the questions put at the beginning of the analysis about the source of risk and the speed of its diffusion. The results of testing the Granger-causality in risk show that in the whole sample period non-expected but positive signals (short position) were weaker than the corresponding negative signals (long position) for all risk measures VaR, ES and SRM considered in the paper. The strongest reaction was within 20 and 40 days periods. In the period of the last financial crisis, the impact of mutual reactions was more frequent than in the full sample. Positive signals were spread around slower than the negative ones taking into account the time lags. However the source of the risk in the global financial world is very difficult to situate. It is rather common that the capital is transferred from one market to another infecting them with panic, increasing volatility and finally causing violations in the VaR and/or ES and/or SRM. It depends on the magnitude of events. The period that contagion is spread is rather long (20 days). This evidence shows that the way of financial capital circulation in the global world is not necessarily simple and direct. On the other hand relatively long time delay between spreading the risk shows that the Chinese policy protecting financial markets helps to limit the risk coming from outside. It can be also confirmed by the fact that in the short-term distance of five days the inflow of speculative capital to China is limited only to some European and Asian markets. Stock and currency markets in China were rather the result than a source of the global risk.

Table 8: The direction of Granger causality in risk at 95% level (or less) for all lags (M) in case of long position with respect to Chinese stock market

SRM	ES	VaR		VaR	ES	SRM
AEX	BSESN	ATG		AMEX	AMEX	AMEX
ATG	DJCA	HEX		BSESN	BOVESPA	BOVESPA
BEL20	HEX			DAX	CAC40	DJCA
BUX				DJIA	DAX	DJIA
CAC40				KOSPI	DJCA	IPCMEX
DAX			→ SSE →	MERVAL	DJIA	MERVAL
FTSE100				NIKK225	FTSE100	NIKK225
HEX				NSDQCOMP	IPMCMEX	OMXSPI
KOSPI				S&P500	MERVAL	SMSI
RTS					NIKK225	S&P500
SMSI					NSDQCOMP	STI
STI					NZ50	
AEX	AEX	AEX		BOVESPA	AMEX	AMEX
AMEX	BSESN	ATG		BSESN	BOVESPA	BOVESPA
ATG	DAX	BEL20		MERVAL	DAX	DJCA
ATX	ISE100	CAC40			FTSE100	DJIA
BEL20	SSMI	DAX			IPMCMEX	FTSE100
BUX	TA100	FTSE100			MERVAL	IPCMEX
CAC40		JKSE			NSDQCOMP	MERVAL
DAX		KLSE	→ SSE_A →			NIKK225
DJCA		NZ50				S&P500
FTSE100		OMXSPI				STI
HEX		PX50				
ISE100		RTS				
KOSPI		SMSI				
RTS		S&P500				
SMSI		TA100				
SSMI						
STI						
TA100						
AEX	AEX	AEX		AMEX	AMEX	AMEX
ATG	ATX	ATG		BSESN	BOVESPA	BOVESPA
BEL20	BSESN	BEL20		DAX	DAX	DJCA
CAC40	CAC40	DAX		ISE100	DJCA	DJIA
DAX	DAX	HEX		KOSPI	DJIA	IPCMEX
DJICA	DJCA	JKSE		MERVAL	FTSE100	MERVAL
FTSE100	FTSE100	KLSE		NIKK225	IPCMEX	NIKK225
HEX	HEX	OMXSPI	→ SSE_B →	NSDQCOMP	MERVAL	OMXSPI
ISE100		PX50		S&P500	NIKK225	SMSI
KOSPI		SSMI			NSDQCOMP	S&P500
RTS		TA100			NZ50	STI
SMSI						
SSMI						
STI						
TA100						

"→" represents the direction in test for Granger causality in risk.

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