FINANCIAL CRISES AND STRUCTURAL BREAKS IN AUTOCORRELATION ON THE BRICS' STOCK MARKETS

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—Abstract—

The phenomenon of positive autocorrelation in daily stock index returns is often viewed as a consequence of stable behavioral patterns of certain investor groups (see e.g. Sentana and Wadhwani, 1992, Koutmos, 1997). However, such patterns may change due to extreme events, i.e. financial crises, and affect the autocorrelation of returns. Emerging markets have experienced severe crises in a recent decade and are therefore a suitable object to study.

Thus the focus of the current paper is on identifying substantial changes in autocorrelation of emerging markets index returns after experiencing these failures of financial system. For this purpose we look for structural breaks in parameters of an ARMA-GARCH-model with the standard procedure of endogenous search. The other innovation of the current paper is checking robustness of the results received on the first step with dummies that control switches in regimes.

Our approach did not detect that financial crises lead to structural breaks in the autocorrelation of the stock market returns in BRIC countries and thus influence the information efficiency. Identified structural breaks were due to removing of price limits for China in 1992 and taking away the leading player for India in 1992.

Key Words: *autocorrelation of stock returns, structural breaks, feedback trading, price limits*
JEL Classification: G14, C22

1. INTRODUCITON

There is a plethora of papers devoted to autocorrelation in stock returns. The earliest literature found little evidence in favor of any autocorrelation concluding that the random walk models are good approximations to the stock price data and hence supporting the efficient market hypothesis *(Fama, 1970)*. Later there was appearance of ample group of papers that revealed presence of autocorrelation in stock returns that needed to be explained. Given previous findings many theoretical models of stock prices focus on explaining stock returns with both a positive short-term correlation and a negative long-term correlation *(e.g., Delong et al, 1990, Daniel, Hirshleifer and Subrahmanyam, 1998; and Barberis, Shleifer, and Vishny, 1998)*. Time series for various mature/developed and emerging/developing stock

markets have been already modeled as well as explored for the presence of instability of autocorrelation during the time.

This paper explores autocorrelation patterns in the time series of stock markets for four emerging countries (Brazilia, Russia, India and China). These countries are of research interest since BRIC stock markets can be different from the others due to historical and institutional factors. The aim of this article is to detect structural breaks in autocorrelation of stock returns on BRIC markets and to find out whether these breaks were associated with financial crises or not. We consider the Asian crisis of 1997-98, the crises in Russia and in Brazil in 1998-99 as potential dates of structural changes. Contribution of this paper to the existing literature is rather evident since, to the best of our knowledge, there is no other research studying stock market crises in BRICs and Thailand. The methodological innovation consists in applying a Bai-Perron procedure for endogenous search of break dates and justification of results by utilizing dummies that control switches in regimes.

The structure of the paper is organized as follows: Section 2 discusses theory and methodological issues. Section 3 presents the data used. Section 4 describes results for modeling time series of the stock returns of BRIC's countries and contains empirical results of test on structural breaks existence. The final section contains concluding remarks.

2. THEORY AND ECONOMETRICS

2.1. Autocorrelation

The fundamental theory of the finance in the face of efficient market hypothesis (EMH) argues that stock prices quickly reflect all available information. Particularly, a weak form of EMH which claims that the current price of a stock reflects its own past prices so that for participants of the financial markets this means absence of the opportunity to find misevaluated stocks. But at the same time there are a lot of investors on the financial markets who make their decisions on the ground of past stock return.

The phenomenon of the stock autocorrelation was thoroughly analyzed by the previous researches. *Boudoukh, et al* (1994) gives an overview of the three schools that provide different explanations of autocorrelation of short-horizon shock, namely: school of loyalists, revisionist and heretics. According to the insights of the first scholars both the pattern and the magnitude of the correlations are consistent with measurement error in the data[1] (e.g., nonsynchronous trading[2], price discreteness, or bid-ask spreads[3]), institutional structures (e.g., trading mechanisms such as different market structures or trading/nontrading periods), or microstructure effects (e.g., systematic changes in either inventory holdings or the flow of information). They assume that market rationally process information so that market efficiency holds but significant autocorrelation arises from market frictionless. For example, *Mech (1993)* shows that transaction costs can cause positive autocorrelation in stock returns. Such costs prevent informed investors to go to the market and to react to news quickly so that delays in the delivery of information into stock price are caused and positive autocorrelation in stock price arises. Because of nonsynchronous trading related to some stocks the reported prices for these securities don't reflect the news that was released after the last trade in this stock occurs. The prices of such securities respond to the news when it trades following day. So that it can induce positive portfolio autocorrelation. However, posterior empirical paper written by *Boudoukh, Richardson, and Whitelaw (1994)* provides the evidence that the degree of daily aggregate return autocorrelation is too large to be completely explained by transaction costs and non-synchronous trading hypothesis. Thus, particular theory can be found for explanation of autocorrelation in individual stock prices. Beliefs of the revisionists[4] are similar to the

[1] See Keim (1989)
[2] See Atchison et al (1987), Perry (1985), Boudoukh (1994).
[3] See Conrad, Gultekin and. Kaul (1997).
[4] See Lo and MacKinlay (1992), Hameed (1992).

view of the first school of thoughts (markets are efficient) but even in the frictionless market short-term autocorrelation of the returns can arise. The reason for that is time- varying economic risk premium that can be explained by intertemporal asset-pricing models. Changes of past market returns, past size returns, interest rate spreads and another risk factors can cause variation in risk premium in short term. The view of the heretics is depart from the two previous schools in the sense that they believe that market are not rational so that profitable trading strategies do exist as well as psychological factors are important for pricing securities. Several papers examines trading rules both individual securities and portfolios that are employed in order to extract excess profit[5].

Many studies concluded that autocorrelation in stock returns is not fixed and varies in time. Changes in autocorrelation can be explained by changes in causes of autocorrelation. We will focus on regulation changes (taxation, changes in derivatives trading regulation, price limits regulation, etc.) and shifts in the structure of investors playing on the market as the reasons for breaks in return autocorrelation.

Of course, being the cause of the changes in market frictions instability of the last can lead to shifts in the size of autocorrelation. As for the transaction costs, regulatory restrictions on price movements and etc, the informational efficiency of the stock market can deteriorate because of increase in transaction costs or narrowing in the corridor of permissible price movements. Following the mechanism presented by *Mech (1993)* it can be logically assumed that increase in transaction costs can prevent higher number of investors from going to the market until the increased transaction costs will be lower benefits from utilizing new information. Thus investors react to the coming information with delay and it results in the deterioration of the information inefficiency of the stock market. *Baltagi et al (2006)* investigated the effect of a transaction tax increase on the Chinese stock markets happened on May 10, 1997. On the base of the fact that after the event the volatility shocks are less quickly absorbed by the stock market they came to conclusion that the increase in the stamp tax rate led to deterioration of the market efficiency. *Gelman and Burhop (2007)* utilizing similar methodologies as ours investigate the influence of changing transaction costs (taxes) but no impact of these events on structural changes on German stock market was found (the structural break was found on the date of Leipzig Bank collapse). Due to the long observation period for each target time series and abundance of the events happened to the explored stock markets we don't reject opportunity to find structural breaks in the autocorrelation in line with arguments mentioned above.

More exotic hypothesis that was poorly analyzed by the previous authors is structural breaks in autocorrelation due to the financial crisis. To the best of our knowledge there is no other research studying stock market crises in BRICs as a possible reason of structural breaks in the stock markets. The viability of this hypothesis can be supported by the feedback traders' theory. These traders base their strategy on the trends in past stock prices and stick to the technical rules causing a correlation in stock returns. Feedback traders fall into two groups: "positive" ("negative") feedback traders systematically follow the strategy of buying (selling) after price rises and selling (buying) after price falls. So that strategy of "positive" feedback traders only reinforce price movements that create trends on the market when prices will continually overshoot the levels suggested by current publicly available information. As the market corrects for this over-reaction in the following trading period, prices tend to move in the opposite direction and so negative autocorrelation is induced. The opposite situation is true for negative feedback traders who tend to induce positive autocorrelation in stock returns. Hence we receive that different sign and strength of autocorrelation can be assigned to the dominance of particular group of the investor on the market, either positive feedback traders, or negative ones. Negative (positive) stock return autocorrelation would suggest dominance on the market of positive (negative) feedback traders for a particular asset. Such trading strategies are thought to deteriorate trends causing overshooting, excess volatility and increased market vulnerability (see *Dornbusch and Park, 1995; Choe, Kho & Stulz, 1999;*

[5] Jegadeesh and Titman (1992), Brock, Lakonishok, and LeBaron (1992)

Kim and Wei, 2002). Following *Sentana and Wadhwani (1992)* negative feedback traders dominate at low levels of volatility and positive feedback traders dominate at high levels of volatility. Such theoretical implication makes it reasonable to expect the dominant influence of the positive feedback traders during the financial crises when volatility of markets is rather high that result in the decrease level of positive autocorrelation or even change of its sign. Also there are papers where authors blame the international investors for a number of financial market disasters, such as the 1997 Asian currency crises *(Radelet and Sachs, 1998)*. Also there is some empirical evidence that during the Asian and the Russian financial crises in 1997 and 1998 respectively emerging as well as mature stock markets investors show a pronounced positive feedback trading pattern *(Bohl et al, 2007)*. Therefore for the purposes of our analysis we propose three potential dates: July, 2, 1997 - devaluation of the Thailand Baht that is responsible for the start of the Asian crisis; August, 17, 1998 - devaluation of the Russian ruble; January, 13, 1999 - devaluation of the Brazilian real.

2.2. Methodology.

The focus of our paper is search of structural changes in autoregressive moving-average processes of BRIC's stock indices returns. Under our definitions the structural break takes place if only part of parameters changes. So, change in model's parameters means change in autocorrelation of stock index returns.

First, the daily index returns are presented as autoregressive moving average ARMA(p,q) models (we have four different models for four indices):

$$r_t = \alpha_0 + \alpha_1 \cdot r_{t-1} + \cdots + \alpha_p \cdot r_{t-p} + e_t + \beta_1 \cdot e_{t-1} + \cdots \beta_q \cdot e_{t-q} \quad (1)$$

The increase in autocorrelation and deterioration of market efficiency would lead to larger absolute values of alpha-coefficients (other than α_0) and beta coefficients and to greater fit of the regression model as a whole and vice versa. Moreover we deal with violation of classical assumptions concerning error terms. Error terms are fat-tailed usually following t-distribution rather than normal distribution. Additionally, they usually display conditional heteroscedasticity, so we expect our error terms to be dependent. To account for these features, we estimate equation (1) using the GARCH-Maximum Likelihood algorithm with t-distribution[6].

In a next step we concentrate on the search of structural breaks the best fitted model parameters. For this purpose, the existence of structural breaks with the sequential sup-LR algorithm suggested by Bai and Perron (2003) is investigated. Since we do not explicitly know the dates of possible disturbances the endogenous algorithm is used. Thus on the first step of this procedure we test the null hypothesis H0: 'no breaks at all' against the alternative H1:'one structural break at some date'. The test used is the following:

$$\sup_{\lambda_i \in \Lambda_\varepsilon^i} LR_T(\lambda_i)$$

$$LR = 2[(l_1 + l_2) - l_r], \quad (2)$$

where l_1, l_2 and l_r are the maximized values of the log-likelihood function in the subsamples before, and after a possible break date Ti = T*λi and for the whole sample respectively. λi = Ti/T is a segment of the subsample before the break from the whole sample. This break should have a minimum distance e to the adjacent breaks: λi-1+e < λi < λi+1-e. Thereby we ensure that all periods between two adjacent breaks are at least (T*e) days long. Since we have a rather large sample for all BRIC stock index returns, we use e = 5%. Thus λ1 in our case belongs to [0.05, 0.95]. In this way we treat each possible date and calculate the Likelihood ratio statistics in order to find the most significant one. Hence this

[6] Details concerning modeling are presented in Section "Results".

algorithm allows us to find the break date at which the highest shift in one of the ARMA-GARCH parameters occurred. Testing for the statistical significance of the selected date was hold by using the critical values provided by Bai and Perron (2003). If this break is significant, we repeat the procedure for the two subsamples and so on, until no significant breaks can be found in any subsample.

The procedure suggested by Bai and Perron (2003) allowed to identify structural breaks if one or several parameters of either the mean equation or the conditional variance one significantly change. Because the focus of our paper is to verify changes in the autocorrelation terms or moving averages parameters due to financial crises, on the second step of our testing procedure we perform a Wald test for individual coefficients. It was conducted to verify if the autoregressive parameters (or moving average parameters) are different in the equations for any two adjacent subsamples:

$$W = \frac{(\alpha_{1,1} - \alpha_{1,2})^2}{\sigma^2_{\hat{\alpha}_{1,1}} + \sigma^2_{\hat{\alpha}_{1,2}}}, \tag{3}$$

where $\sigma^2_{\hat{\beta}_{1,1}}$ and $\sigma^2_{\hat{\beta}_{1,2}}$ are asymptotic variances of the autoregressive parameter estimates for each of the subsamples. However, due to the presence of a nuisance parameter, the test-statistics is not necessarily $\chi^2(1)$-distributed as in the standard case and it is reasonable to use Bai and Perron (2003) critical values again.

If the Wald test reveals the significant break in at least in one of the parameters, procedure with dummy is run on the third step to justify robustness of the break points found on the first two steps. Under this procedure we assume stability in the parameters of the conditional variance equation except for the constant term but allow a break to occur either in ARMA-part or in the GARCH-constant term Now the following equation is estimated (particularly for the AR-process):

$$r_t = \alpha_0 + \sum_{i=1}^{n} \gamma_{0i} \cdot d_i + \alpha_1 \cdot r_{t-1} + \cdots + \alpha_p \cdot r_{t-p} + \sum_{i=1}^{n} \gamma_{1i} \cdot d_i \cdot r_{t-i-p} + e_t,$$

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{n} \gamma_{3i} \cdot d_i + \alpha_1 \cdot e_{t-1}{}^2 + b_1 \cdot \sigma^2{}_{t-1}. \tag{4}$$

Here dummies are responsible for switching in regimes suggesting a change in the parameters of the mean equation. Except for the initial assumption the procedure with dummies is similar to the procedure applied on the first step of the search. Under this procedure we again treat each date not forgetting about the minimum distance of two adjacent possible breaks. For each date equation (4) is estimated on all sample in order to detect the most significant break point. On the first step n=1 and dummy d1=0 for t< tj and =1 for t$\geq$tj. tj$\in [0.05T, 0.95T]$. The point with the highest value of the likelihood function is chosen to run an endogenous test on structural breaks similar to that described above. Because the main logic of the procedure presented by Bai and Perron (2003) we use their critical values to verify the statistical significance. After finding the first significant break point, we repeat the procedure for the two subsamples and so on, until no significant breaks can be found in any subsample. Supposing the first highest break found is T^1_{br} on the second step n=2 for the subsample before the first break and for the subsample after the first break. d1 is fixed and d2=0 for t< T^1_{br}.and d2=1 for t$\geq T^1_{br}$. For the sample before the first break d2=0 for t< tj and d2=1 for t$\geq$tj, tj$\in [0.05T, T^1_{br}]$. For the sample after the first break d2=0 for t< t j and d2=1 for t$\geq$tj. tj$\in [T^1_{br}, 0.95T]$. On the third step d1 is fixed and d1=0 for t< T^1_{br} and d2=1 for t$\geq T^1_{br}$, d2 is fixed and d2=0 for t< T^2_{br}.and d2=1 for t$\geq T^2_{br}$, d3 is varying, and so on. Having finished the search of structural changes with dummies, the Wald test is applied to test the significance in change of each concrete parameter including the autoregressive one which is of our interest. And again we use critical values of Bai and Perron (2003) for the case of difference in one parameter to verify the statistical significance of the breaks identified with dummies.

Having implemented the above described procedure we make a conclusion about the significance of change in the autocorrelation. Finally we check whether the endogenously estimated break points lie close to the dates related to the start of target financial crises. For such purposes we approximately asses the confidence intervals for each break point following the logic of Gelman and Burhop (2008). Thus we worked with the confident intervals of the length +/-2 months. Thus we consider all dates up to two months before and after and tried to identify as more events as possible as potential cause of the found structural break. If the date of Financial crises fell into the confident interval then we treated the hypothesis "financial crises influence the changes in the predictability of the stock market" as confirmed, otherwise we reject it and tried to find another explanation.

3. DATA DESCRIPTION

For the search of the structural breaks on the stock markets on BRIC we collect domestic BRIC stock market indexes in local currency. The BRIC stock indexes are the BOVESPA for Brazil (4207 observations), the index of the Russian trading system for Russia (3250 observations), the India BSE (100) National index for India (5220 observations) and the Shanghai Se Composite index for China (4467 observations).

Returns are proxied by the log difference change in the price index:

$$R_t = \log P_t - \log P_{t-1},$$

where R_t –return at time t,

P_t, P_{t-1} - value of the stock price index at time t, t-1.

The data were sourced from DataStream. The sample data for each country cover different periods, as whole our sample covers the period from March 1989 through February 2008. News on the explored stock markets sourced from Reuters and Bloomberg was utilized for the identification of the event caused the found structural break. We routinely checked each point that fall into the confident interval and on the base of the existed theory we made conclusion.

For a preliminary analysis of the data, Table 2 (see Appendix 3) provides summary statistics of stock indices returns. As can be seen, the index returns for all countries apart from Russia are positively skewed. High excess kurtosis detects thickness in the tails. The Jarque-Bera test for joint normal kurtosis and skewness rejects the normality hypothesis, this is a common feature of all financial data. The magnitude of average returns and standard deviation are quite similar and don't differ substantially. The first order autocorrelation ρ is not high for the stock indexes of all countries, Russia ($\rho=0.081$) and India ($\rho=0.104$) have higher value of autocorrelation then Brazil ($\rho=0.062$) and China ($\rho=0.044$).

It is evident from Figures 1-4 (see Appendix 3) all the markets had up trend over the observation period, very intensive growth can be denoted from 2003-2004 for different markets that is primarily caused by the economic growth of these countries.

4. RESULTS

In this section we are going to find out break dates of structural changes in autocorrelation. For this purpose we define the model best fitted to the data – ARMA-model of type (p, q), where as usual p corresponds to the number of lags that homogeneous part of the difference contains and q is number of lags in moving-average part. For break dates identification and check of significance in the models' parameters the tests and procedure described in Section 3 are utilized.

4.1. ARMA-models

In order to define a possibly adequate ARMA-model of daily returns of the BRIC countries we apply the Box-Jenkins procedure. Simultaneously using several criteria (Schwartz information criteria, Q-statistics, R^2 and adjusted R^2) we find the same optimal models for daily returns of Brazil, India and China for the whole sample (from 1 January 1992 for Brazil, from 17 March 1989 for India and from 2 January 1992 for China to 14 February 2008 for all countries).These models contain one autoregressive component of lag one (see Table 2, Appendix). The better fitted models for Russia (estimation period is from 9 January 1995 to 14 February 2008) includes one moving average component of lag one (see Table 2, Appendix). For modeling variance we employ the most widely used GARCH model is GARCH(1,1). The (1,1) in parentheses is a standard notation in which the first number shows how many moving average lags, or GARCH terms, are specified in the variance equation while the second number shows how many autoregressive lags, or ARCH terms, appear in the equation. Sometimes models with more than one lag are needed to find good variance forecasts. Nevertheless we used the model GARCH(1,1) thanks to its accuracy and simplicity.

From Table 2 (Appendix) one can see that all the models that fit our data best contain autocorrelation in residuals, and significant at one percent level. Q_{20}-statistics proves this fact. Such autocorrelation can serve as an evidence for a "long memory" in index return. Probably, it can say that better model can be found utilizing autoregressive fractionally integrated moving average models (*Bryzgalova, Gelman, 2008*) or by means of accounting for possible structural breaks. All coefficients in estimated models are positive and significant at one percent level except for Brazil that is meaningful at 3 percent level. Identification of autocorrelation of stock returns in the short period seems to be a norm rather than an exception.

In the theoretical part of this paper we provided a set of arguments that can account for the positive sign in autocorrelation, main of them is market frictions and negative feedback trading. Bohl and Siklos (2004), for example, argued that negative feedback trading is dominated on the emerging stock markets. Since there is no clear evidence of such behavior on the stock markets in BRIC provided in any study we suggest market frictions as more probable explanation for dependence on daily returns of BRIC stock markets. Like many emerging markets, the Brazilian, Russian, Indian and Chinese stock markets also suffer from unsatisfactory corporate governance, market manipulation, insider trading and numerous infrastructure problems. Moreover, optimal models found for the stock markets of BRIC countries raise problems of their ineffectiveness. Of course, further research and utilization of more advanced econometric methodologies are needed for more fundamental conclusions.

4.2. Identifying structural changes

In the process of endogenous search of structural breaks we checked each date except for the certain amount of the first and last trading days for the each time series and calculated the LR statistics for each tested point. Statistical significance of the identified date with the maximum LR statistics was defined on the base of the critical values suggested by Bai and Perron (2003). This procedure was routinely repeated until no more structural breaks were found. This procedure allowed us to identify a structural change when even only one of the parameters in the model varied. Following the purpose of our work on the second step we continued to test significance of the structural break just in the mean equation with the Wald test. Finally, for the time series where the Wald test proved structural breaks we conducted the search of structural breaks via dummies in order to check the robustness of our outcomes. Values of the parameters in the mean equation derived on the first step are very close to the same ones received on the final step for the significant structural breaks. Such consistency of the results only strengthens the robustness of the outcomes.

Results are different for each time series: not all stock markets in the BRIC group underwent structural breaks in autocorrelation during the explored time periods. Therefore for Brazil we identified 2 structural breaks on the first step (see Table 3, Appendix). As the Wald test indicated the first break identified on 1 September 1994 happened due to the decrease in the constant term in the mean equation from 0.013 to 0.002. All other parameters remained relatively unchanged. The second break indicated on 18 January 1999 was primarily due to changes in the parameter a_1, which reflects the sensitivity of conditional variance to the prior day shock, as the Wald test showed at 2.5 percent significance level: it dropped from 0,196 to 0,058. The procedure with dummies proved only the first break point as it was expected due to the fact that dummies were responsible for changes only in the parameters of the mean equation and the constant term of the variance one; the other parameters in the variance equation were assumed to be constant (for results of procedure with dummy refer to Table 7, Appendix).

As for Russia on the first step we also identified two structural break points (see Table 4, Appendix). These dates were 17 June 1996 and 22 July 2002. For both break points we can conclude that the parameters of both the mean equation and the conditional variance one do not differ by more than two standard errors from subsample to subsample with the exception of the parameter b_1 in the conditional variance equation for the first break point. Since the Wald tests did not prove structural changes in the target parameters we did not continue the search of the break with dummies.

In general we can conclude for the Brazilian stock market as well as for the Russian one that there were no structural breaks in the autocorrelation term and hence in the predictability of returns.

The search of structural breaks in the Indian stock markets identified 5 points (see Table 6, Appendix). As a result of the first break point on 11 June 1992 the Wald test identified significant increase in the autocorrelation term from 0.132 to 0.31 on the 1 percent level. It means increase in the predictability of the stock market returns by 7.6 times from the first 3.2 years of our observation period to the next 3.8 years. The procedure with dummies proved the robustness of this result on 1 percent significance level. The second and third structural breaks were identified on 10 April 1996 and 26 February 1996 respectively. On the base of the Wald test at 10 percent level we can infer that these structural breaks were due to changes in the parameters of the variance equation. The fourth break was identified on 8 November 1998 and the fifth one was revealed on 28 April 2003. For both breaks parameters of the mean equation did not differ by more than 2 standard errors from subsample to subsample. The Wald test proved this result and indicated no significant change in the autocorrelation and thus in the predictability at 10 percent level. Also for these break points the Wald test indicated that the variance equation parameters exhibit no significant changes. The checking procedure with dummies confirmed all results received before (Table 8, Appendix).

Identification of structural breaks on the Chinese stock market provided 4 break points, namely: 11 June 1992, 23 January 1996, 29 October 1997 and 12 December 2005. As for the first identified break there is an obvious sharp decrease in the autocorrelation term from 0.972 to -0.041. In the absolute value autocorrelation decreased nearly 24 times. Besides the autocorrelation term the Wald test showed that the first structural change was also due to significant change in the variance equation parameters. As for the rest indicated break points there were no any significant changes in the autocorrelation terms but the constant in the mean equation tended to vary significantly over all subsamples. As for the results for other countries in the BRIC group the procedure with dummies only proved the results received on the first two steps of our analysis (Table 9, Appendix).

The high value of the likelihood ratios for all detected structural breaks derived on the first step of the search corresponds to significance of all results on 1 percent level except for the last break in China that is significant at 5 percent.

As it was treated for the Brazilian stock market the only break date with a significant change in the constant term of the mean equation is 2 September 1994. For Brazil it can be simply explained by sharp decrease of the inflation form 50% a month in June of 1994 to less than 3% by September of the

same year due to imposition of the new national currency into circulation since 1 July 1994 under the government anti-inflation plan.

In the case of *India* the significant break in autocorrelation was revealed on 11 June 1992 as mentioned above. We suppose that this change in autocorrelation of stock returns could be caused by taking away the leading player from the Indian stock exchange as a result of the $1 billion scandal. In May 1992 it was revealed that a broker Harshad Mehta had been funneling the state bank's and corresponding banks' money illegally into the Bombay Stock Exchange. Money raised in the inter-bank obligation market was then used by Mehta for speculation in the stock market[7]. With huge amounts of money not known to have been supplied by banks, Mehta drove the exchange on a long boom (that took off in July 1991).

How could the behavior of one person change the autocorrelation in stock returns? The following explanation seems reasonable to us. Being the leader on the market Mehta was able to keep liquidity and high volume of trades. High liquidity and large volumes of trade led to lower autocorrelation themselves (*Shen and Wang, 1998*) and allowed for low bid-ask spreads. These low spreads meant low transaction costs that led to less price adjustment delays and to lower autocorrelation in returns (*Mech, 2003*). When the player left the market liquidity lowered, volume of trades diminished, spreads become high. These high transaction costs caused mispricing by making it unprofitable for investors to trade on minor information. Greater price adjustment delays strengthened autocorrelation in returns and increased their predictability making the market less efficient.

The only break date with a significant change in the predictability for the *Chinese* stock market over the observation period is the 11 May 1992. This date is 5 days after the event when the maximum 1 percent limit on daily price fluctuation on 9 out of 15 shares listed on the Shanghai securities exchange was loosened to 5 percent and 11 day before the analogous event when the same exchange abolished restrictions on the fluctuation of share prices at all and allowed to float freely on the market. As a result of the last event Shanghai SE Composite gained 105.5% from the previous close and turnover nearly doubled. All these dates fall into the confidence interval of the found break point and very probably could result in the structural instability on the stock market. In the literature this effect gained the name of "the positive price-limit effect". If a market is subject to a price-limit regulation, the shock will not be completely realized in a trading day and will be partly realized during the subsequent trading days (see *Chiang and Wei, 1995, Chou, 1997)*. It means that the information shocks are acquired less quickly and therefore positive autocorrelation may appear meaning that market becomes less efficient. Both the explicit and implicit price limits are common in the world of capital markets. For example, for the derivative markets price limits are rather usual. As it could be observed from the financial crisis started from the second half of 2007 limits on stock price movements were the norms. For the Taiwan stock market *Shen and Wang (1998)* found that the correlation of the returns is positively affected by price limits. Following the same logic it is more than evident that the extreme positive autocorrelation in the returns of the Chinese stock market was mainly caused by the existence of price limits but abolishment of these limitations led to sharp decrease in the predictability of stock returns, moreover, there was a change in the sign of autocorrelation from positive to negative.

As for the rest identified break points only significant changes in the constant terms of the mean equation were revealed. As it can be seen from Figures 1-4 (Appendix) this variability grasp changes in trends of the Chinese stock market over the defined subsamples. As it was expected identified variability in constants didn't coincide with movements in the inflation rate over the period because for the long period the Chinese stock market didn't reflect economic processes.

It is very interesting that we didn't reveal the break points caused by the changes in the transaction tax. For example, for the Shanghai stock market on May 10, 1997 the Chinese government

[7] Dubey, S. Grindlays, India in Talks Over Scandal. The Asian Wall Street Journal. 11 June 1992. P. 14.

increased the stamp tax on stock trading from 0.3 to 0.5%. The rate of this tax was being changed several times from 1997 to 2008 but our procedure of the endogenous search of structural breaks identified no points for which the significant interval would cover dates of changes in the stamp tax rates. Therefore we cannot support the hypothesis about the significant influence of the stock market turnover tax on information efficiency. Our results suggest that there were no significant changes either in the mean equation or in the constant term of variance equation. This finding is in some sense contrary to the results published for the Chinese stock market by *Baltagi et al (2006)* who found regime switching in the conditional variance equation as a result of the stamp tax rate increase on 10 May 1997. At the same time their results are not so robust because of the absence of the control for other possible structural breaks that could lead to spurious results.

We found out that crises did not cause significant changes in autocorrelation particularly on the Brazilian (18 January 1999), Indian (26 February 1998, 8 November 1998) and Chinese (29 October 1997) stock markets. The structural break of the Brazilian stock market was due to the devaluation of the Brazilian real occurred on 13 January 1999. The structural break on the Indian market in November, 1998 also was due the financial crisis that could contagion between the emerging markets. The change in the autocorrelation for India is consistent with the feedback traders' behavior during the crisis but it is not the case for Brazil. As it was figured out above the Wald test didn't justify significance of this change in autocorrelation. Other breaks for India and China could be explained by the Asian crisis that began in July 1997 in Thailand and hurt many Asian countries. After the crisis volatility of the market increased. The decline in autocorrelation happened in the subperiod after the breaks points is in consistence with negative feedback traders' theory whose behavior intensified during the crisis period on the emerging markets (*Bohl and Siklos, 2004*). But the Wald test rejects the significance in the parameters' instability. The same is true for Russia where none of the identified break points can be explained by some of above mentioned crises.

Also we can note that such events as changes in regulation (e.g., establishment of the derivative markets, introduction of electronic trading system, and permission of short sales), rules of trading, etc., did not cause breaks in autocorrelation in stock indices returns, at least the algorithm applied did not reveal such break dates. Therefore from the search of structural breaks on the financial markets in BRIC we cannot reject the hypothesis of constant information efficiency before and after of enactment of some stock exchange laws. The event that attracts attention in the case of India is introduction, abandonment, and reintroduction with new rules of the carry-forward system[8] (the so called "badla") invented in the Bombay Stock Exchange. This system allowed players to roll over payments on transaction for some fixed period of time for some fee and was aimed to solve the problem of lack of liquidity on the market. In March 1994 badla was banned, amid complaints from foreign investors, with the expectation that it would be replaced by a futures-and-options exchange. Such an exchange was not established and badla was legalized again in January 1996 (with carry-forward limits) and banned again in July 2001. These changes seem to be significant, influence investors' incentives to trade, change volumes of trade and liquidity in the market. Thus, following a ban on forward trade, activity dropped as much as 90 percent in March 1994. All these factors might lead to changes in autocorrelation in returns. However the testing procedure did not reveal any date associated with major events around the badla.

5. CONCLUSION

The purpose of this paper was to test our hypothesis whether financial crises could lead to structural breaks in autocorrelation of stock index returns in emerging BRIC markets on the example of the 1990s' financial crises (the 1997 Asian, 1998 Russian, and 1999 Brazilian crises).

[8] For detailed description of the badla carry-forward trading system visit http://www.geocities.com/kstability/content/derivatives/badla.html .

Using Bai-Perron algorithm of endogenous search of breaks and applying procedure with dummies we get results that are surprising in some sense. Break points associated with crises identified from the Bai-Perron procedure led to no significant change in autocorrelation of stock indices returns on each the BRICs' stock markets. Outcomes are robust in the sense that endogenous search with dummies that allowed us to test changes in the mean equation and the constant term in the variance equation while keeping ARCH and GARCH terms constant provided the same conclusion. Thus the initial hypothesis of financial crises being possible causes of changes in autocorrelation is not supported.

However, the break dates that were identified on the Indian and Chinese markets and only one led to significant changes in autocorrelation were associated with regulatory measures. In the case of India it was removal of the leading player who had driven the market for one year using illegal money in June 1992. His removal led to increase in autocorrelation of stock returns. In the case of China it was abandonment of price limit that increased autocorrelation in May 1992. As we revealed regulatory changes particularly in price limits regulation can cause significant changes in stock returns autocorrelation and consequently their predictability leading to changes in market efficiency. The impact of price limits regulation on stock returns autocorrelation could be elaborated further and this will be the focus of our further research.

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APPENDIX

Table-1: Descriptive statistics of daily stock market indices

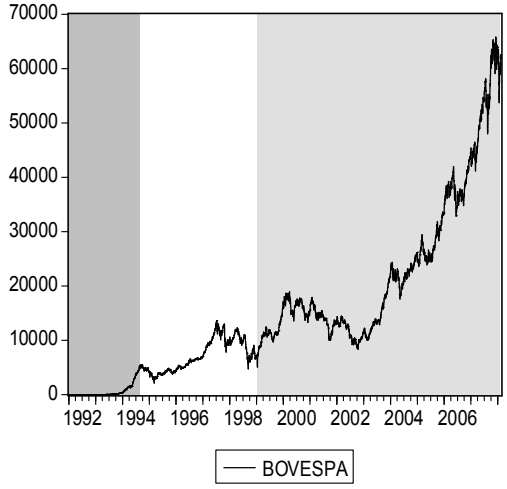
Country	Index	Period start	Period end	Number of observations	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Brazil	BOVESPA	1/1/1992	14/2/2008	4207	0.002740	0.001236	0.288176	-0.172292	0.026973	0.453002	10.55232
Russia	RTS	1/09/1995	14/2/2008	3250	0.001452	0.000727	0.294559	-0.373832	0.030743	-0.051363	24.25489
India	India BSE (100) National	3/17/1989	14/2/2008	5220	0.00049	0.000000	0.166409	-0.119364	0.016956	-0.117521	9.647457
China	Shanghai Se Composite	2/1/1991	14/2/2008	4467	0.000798	0.000000	0.719152	-0.179051	0.025493	5.992561	158.0126

Table-2: Estimates of ARMA-models

	Brazil	Russia	India	China
	ARMA(1,0)	ARMA(0,1)	ARMA(1,0)	ARMA(1,0)
α_0	0.002052*** (0.000285)	0.002006*** (0.000313)	0.000899*** (0.000190)	0.000766*** (0.000182)
α_1	0.035390** (0.015740)		0.150521*** (0.013733)	0.063129*** (0.01573)
β_1		0.079282*** (0.017979)		
a_0	6.56E-06*** (1.75E-06)	9.84E-06*** (1.98E-06)	6.38E-06*** (1.03E-06)	8.3E-06*** (1.096E-06)
a_1	0.097710*** (0.011378)	0.148207*** (0.014515)	0.127766*** (0.011143)	0.217559*** (0.015542)
b_1	0.904073*** (0.010258)	0.849787*** (0.012345)	0.856405*** (0.010764)	0.774548*** (0.011902)
SBC-value	-4.806734	-4.837755	-5.700250	-5.478706
Q20	60.726***	45.785***	52.401***	86.844***
R-squared	0.002559	0.005990	0.008291	0.001557
Adj. R^2	0.001609	0.004765	0.007530	0.000661

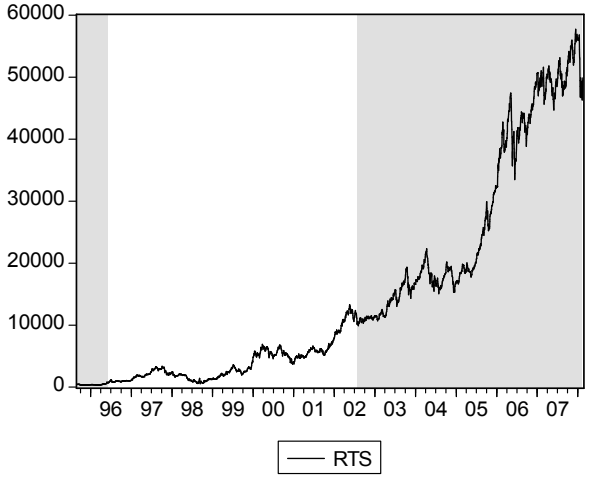
Estimates of ARMA-models for the **BOVESPA**, **RTS**, **India BSE (100) National, Shanghai SE Composite**. Asymptotic standard errors are in parenthesis. Each model presents an iteration of Box-Jenkins procedure. Q-statistics are reported for twenty lags. Values marked with ***, ** and * are significant at 1%, 5% and 10% level respectively. Source: Own calculations.

Figure-1*: Brazilian stock market index.



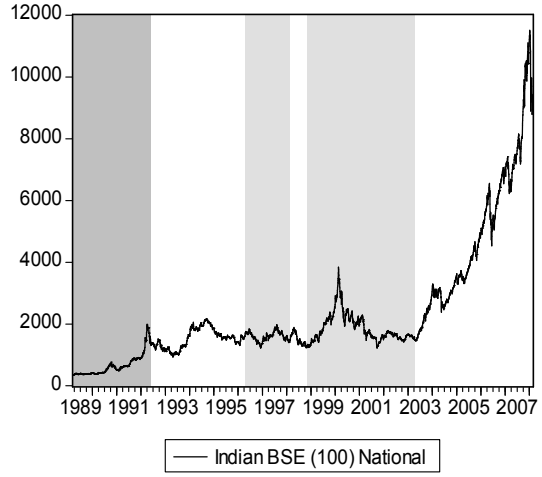
Source: Datastream

Figure-2*: Russian stock market index.



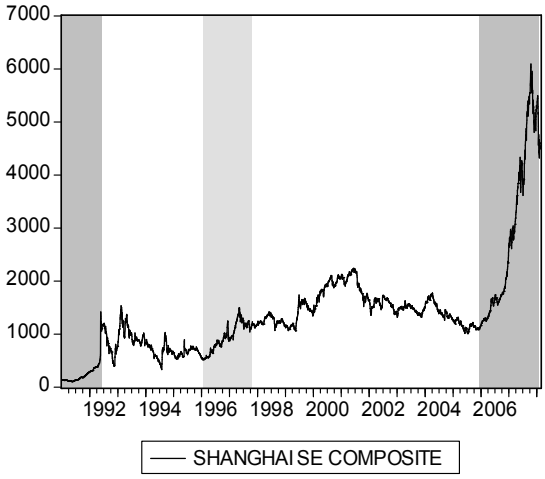
Source: Datastream

Figure-3*: India stock market index.



Source: Datastream

Figure-4*: Chinese stock market index.



Source: Datastream

*Switch in the color corresponds to the identified structural break points.

Table-3*: Brazil. ARMA(1.0)-GARCH(1.1)

	1/03/1992-9/01/1994	9/02/1994-1/17/1999	1/18/1999-2/14/2008
α_0	0.013567*** (0.001366)	0.002140*** (0.000547)	0.001426*** (0.000333)
α_1	0.022184 (0.038652)	0.054877* (0.030567)	0.007214 (0.020236)
a_0	4.93E-05 (4.00E-05)	1.19E-05** (4.92E-06)	8.32E-06** (3.35E-06)
a_1	0.085073*** (0.032842)	0.195772*** (0.033507)	0.057714*** (0.013197)
b_1	0.899877*** (0.040614)	0.822260*** (0.026589)	0.926430*** (0.017075)
R^2	0.000676	0.002942	0.000191
LL	1276.971	2685.525	6222.927

Table-4*: Russia. ARMA(0.1)-GARCH(1.1)

	9/01/1995-6/16/1996	6/17/1996-7/21/2002	7/22/2002-2/14/2008
α_0	0.001798 (0.001427)	0.001976*** (0.000673)	0.002148*** (0.000362)
β_1	0.116053*** (0.025165)	0.086308*** (0.025605)	0.059944** (0.027141)
a_0	0.000393*** (7.89E-05)	3.04E-05*** (8.10E-06)	1.47E-05*** (4.22E-06)
a_1	0.764339*** (0.217146)	0.144099*** (0.021722)	0.129506*** (0.025431)
b_1	-0.122329** (0.054279)	0.838466*** (0.019981)	0.820298*** (0.032541)
R^2	0.031858	0.004813	0.001999
LL	480.4735	3356.686	4073.196

Table-5*: India. ARMA(1.0)-GARCH(1.1)

	3/17/1989-6/10/1992	6/11/1992-4/09/1996	4/10/1996-2/25/1998	2/26/1998-11/07/1998	11/08/1998-4/27/2003	4/28/2003-2/14/2008
α_0	0.001177** (0.000464)	-0.000264 (0.000402)	6.64E-05 (0.000822)	0.000640 (0.000811)	0.000236 (0.000442)	0.002799 (0.000323)
α_1	0.131704*** (0.032504)	0.309846*** (0.027329)	0.194667*** (0.053172)	0.024567 (0.047918)	0.089322*** (0.033674)	0.071327** (0.029794)
a_0	5.54E-06*** (1.87E-06)	2.86E-06*** (8.86E-07)	0.000162*** (4.63E-05)	3.19E-05 (3.12E-05)	7.97E-06*** (3.08E-06)	8.33E-06 (2.58E-06)
a_1	0.070611*** (0.016745)	0.113994*** (0.021891)	0.247096** (0.109027)	0.059308 (0.037022)	0.162217*** (0.035010)	0.158894 (0.029005)
b_1	0.899096*** (0.020997)	0.875097 (0.019877)	-0.018354 (0.228783)	0.856503 (0.108622)	0.831162*** (0.031909)	0.818418 (0.029505)
R^2	0.018437	-0.001724	0.035019	-0.000913	0.009845	0.001852
LL	2407.034	3489.134	1050.407	1150.482	2535.145	3712.267

Table-6*: China. ARMA(1.0)-GARCH(1.1)

	1/02/1991-6/10/1992	6/11/1992-1/22/1996	1/23/1996-10/28/1997	10/29/1997-12/11/2005	12/12/2005-2/14/2008
α_0	0.004006 (0.004226)	-0.002788*** (0.000725)	0.003032*** (0.000793)	-0.000224 (0.000228)	0.003233*** (0.000517)
α_1	0.972427*** (0.021140)	-0.041015 (0.035191)	-0.051977 (0.054060)	0.005814 (0.022747)	-0.026005 (0.040445)
a_0	1.17E-06*** (1.83E-07)	5.51E-05*** (1.34E-05)	7.60E-05*** (2.36E-05)	1.97E-05*** (3.96E-06)	5.70E-06*** (2.52E-06)
a_1	0.692142*** (0.111256)	0.240618*** (0.040132)	0.284326*** (0.073503)	0.172461*** (0.027093)	0.087312 (0.021957)
b_1	0.341013*** (0.039804)	0.719594*** (0.033522)	0.579052*** (0.083547)	0.712614*** (0.039973)	0.896284** (0.023239)
R^2	-0.666839	-0.006393	-0.002173	-0.000079	-0.001281
LL	1485.422	2010.953	1126.136	6401.757	1560.234

*Source: Own calculations.

Procedure with dummies

Table-7*: Brazil.

	1/03/1992-9/01/1994	9/02/1994-2/14/2008
α_0	0,013468	0,001584
α_1	0,028435	0,018485
a_0	0,000054	0,000011
a_1	0,887727	0,887727
b_1	-4,28E-05	-4,28E-05

r_{br}= 0.013 - 0.012*d1 + 0.028* r_{br} (-1) - 0.010*d1* r_{br}(-1)
GARCH = 5.355e-005 + 0.100*RESID(-1)^2 + 0.888*GARCH(-1) - 4.280e-005*d1
d1=0 for t < 9/02/1994 and d1=1 otherwise.

Table-8*: India.

	3/17/1989-6/10/1992	6/11/1992-4/09/1996	4/10/1996-2/25/1998	2/26/1998-11/07/1998	11/08/1998-4/27/2003	4/28/2003-2/14/2008
α_0	0.000989	-0.000217	0.000192	0.000786	0.000199	0.002548
α_1	0.134559	0.313230	0.198045	0.028269	0.095080	0.073322
a_0	0.000009	0.000006	0.000013	0.000024	0.000010	0.000009
a_1	0.132496	0.132496	0.132496	0.132496	0.132496	0.132496
b_1	0.832798	0.832798	0.832798	0.832798	0.832798	0.832798

r_i = 0.001 - 0.001*d1 + 0.0004*d2 + 0.0006*d3 - 0.0006*d4 + 0.002*d5 + 0.135* r_i(-1) +
0.179*d1* r_i (-1) - 0.115*D2* r_i(-1) - 0.170*D3* r_i(-1) + 0.067*D4* r_i(-1) - 0.022*D5* r_i (-1)
GARCH = 8.705e-006 + 0.132*RESID(-1)^2 + 0.833*GARCH(-1) - 2.683e-006*d1 + 6.519e-006*d2 + 1.117e-005*d3 - 1.348e-005*d4 - 1.742e-006*d5
d1=0 for t < 6/11/1992 and d1=1 otherwise,
d2=0 for t < 4/10/1996 and d2=1 otherwise,
d3=0 for t < 2/26/1998 and d3=1 otherwise,
d4=0 for t < 11/08/1998 and d4=1 otherwise,
d5=0 for t < 4/28/2003 and d5=1 otherwise.

Table-9*: China

	1/02/1991-6/10/1992	6/11/1992-1/22/1996	1/23/1996-10/28/1997	10/29/1997-12/11/2005	12/12/2005-2/14/2008
α_0	0.000183	-0.002912	0.003124	-0.000225	0.003766
α_1	0.948243	-0.035836	-0.056213	0.014616	-0.017310
a_0	0.000001	0.000114	0.000070	0.000026	0.000042
a_1	0.132496	0.132496	0.132496	0.132496	0.132496
b_1	0.832798	0.832798	0.832798	0.832798	0.832798

r_{ch} = 0.0002 - 0.003*d1 + 0.006*D2 - 0.003*d3 + 0.004*d4 + 0.948* r_{ch}(-1) - 0.984*d1* r_{ch}(-1) - 0.020*d2* r_{ch}(-1) + 0.071*d3* r_{ch}(-1) - 0.032*d4* r_{ch}(-1)
GARCH = 9.131e-007 + 0.264*RESID(-1)^2 + 0.609*GARCH(-1) + 0.0001*d1 - 4.391e-005*d2 – 4.379e-005*D3 + 1.578e-005*d4
d1=0 for t < 6/11/1992 and d1=1 otherwise,
d2=0 for t < 1/23/1996 and d2=1 otherwise,
d3=0 for t < 10/29/1997 and d3=1 otherwise,
d4=0 for t < 12/12/2005 and d4=1 otherwise.

*Source: Own calculations.