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Research Article

Stock Market Autoregressive Dynamics: A Multinational Comparative Study with Quantile Regression

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We study the nonlinear autoregressive dynamics of stock index returns in seven major advanced economies (G7) and China. The quantile autoregression model (QAR) enables us to investigate the autocorrelation across the whole spectrum of return distribution, which provides more insightful conditional information on multinational stock market dynamics than conventional time series models. The relation between index return and contemporaneous trading volume is also investigated. While prior studies have mixed results on stock market autocorrelations, we find that the dynamics is usually state dependent. The results for G7 stock markets exhibit conspicuous similarities, but they are in manifest contrast to the findings on Chinese stock markets.

1. Introduction

The time series property of dynamic stock prices and indexes is of great importance and has drawn plenty of attention from researchers during the past few decades. Stock market autocorrelation has significant practical value since it has direct implication on predictability and thus trading opportunities in stock markets. Based on the sample composition, sample period, and data frequency, a wide range of results have been reported from negative to positive autocorrelation (Campbell et al. [1], Campbell et al. [2], Lewellen [3], and Lo and MacKinlay [4]). The statistical methods employed in these studies all focus on the conditional mean of return distributions. In this paper we adopt a novel statistical method proposed by Koenker and Xiao [5], the quantile autoregression (QAR) model, to examine the influence of lagged returns on the current return over the whole spectrum of return distribution. The QAR model enables us to investigate the state-dependent dynamics of stock markets and it is better equipped to capture the nonlinear features of the data.

This paper makes contributions to the literature threefold. First, it studies the stock markets in seven major developed countries and China, the largest emerging economy in the world. Three recently published papers share some common objectives and methodology with our paper. Baur [6] studied 600 European stocks and Dow Jones Stoxx 600 index (representing companies of various sizes across 18 European countries) with first-order QAR model. Their detailed analysis shows that negative and large returns are the driving force behind the general pattern of autoregressive parameter estimates. Gebka and Wohar [7] investigate the causal effect of past trading volume on return with stock market data from nine Asian Pacific countries with quantile regressions. Their sample includes stock markets in Australia, Indonesia, Japan, Korea, Malaysia, Singapore, Taiwan, Thailand, and USA. Similar patterns are found in terms of the relation between lagged returns and the current return as identified in the literature. Zhu et al. [8] study Shenzhen Component index of China, S&P 500, and Stoxx Europe 600 indexes with QAR models. But their focus is on the mutual spillover effects among the three indexes and asymmetric dependence in different range of returns (low, medium, and high quantiles, and positive versus negative returns). They do not even report autoregression results, which we believe deserve direct attention.

Second, Chinese stock markets (Shanghai and Shenzhen) show quite different characteristics from those in developed countries. The coefficients of QAR display irregular shapes with a significant fraction of quantiles within the confidence intervals of ordinary least squares (OLS) estimates. The return autocorrelation is relatively stable (homogeneous) across quantiles for Shanghai and Shenzhen. This pattern is in sharp contrast to the findings for other countries where the effect of lagged return(s) on current return is generally a clearly decreasing function across quantiles. The recent global stock market turbulence has shown the increasing influence of Chinese stock market, but direct evidence of its state-dependent autocorrelation is lacking. To the best of our knowledge this is the first study that reveals such characteristics of Chinese stock market.

Third, the contemporaneous relation between stock index return and trading volume is investigated within the QAR model, and pronounced difference is identified between Chinese stock market and G7 stock markets. For all the markets in developed economies the index return is related to volume in an almost monotonic increasing fashion. The correlation is negative at lower quantiles and turns positive at upper quantiles. For both Chinese stock exchanges, the majority (especially middle) part of the volume coefficient is relatively flat but has explosive upward tail (positive) in lower quantiles and downward tail (negative) in upper quantiles. Such marked contrast has not been reported in literature. We argue that these tails are caused by the daily price fluctuation limits at Chinese stock exchanges.

The remainder of this paper proceeds as follows. Section 2 reviews related literature. Section 3 briefly introduces the quantile regression model and its advantages over conventional regression models. Section 4 outlines the QAR models employed in this study, collects the results on all nine stock exchanges, and discusses similarities and differences of the findings. Section 5 concludes.

2. Literature Review

This study is primarily related to two groups of research, one on dynamic autocorrelation of stock returns and the other one on the relation between stock return and trading volume. The findings of both groups have direct implications on stock price predictability and thus market efficiency.

Decades of empirical research have provided a wide range of results on autocorrelation of stock returns. For example, Campbell et al. [2] report significant positive autocorrelation for daily, weekly, and monthly stock index returns calculated from the CRSP database, with the autocorrelation slightly stronger for daily data. Lo and MacKinlay [4] attribute the positive autocorrelation in daily stock returns to nonsynchronous trading. Lewellen [3] studies momentum and autocorrelation of stock returns with monthly data from CRSP and reports negative autocorrelation, although the correlation is generally weak.

A classic research of relationship between volume and price is Osborne [9]. Crouch [10] and Westerfield [11] find that trading volume and stock price change have positive correlation. Morgan [12] shows that the variance of stock price changes and trading volume are positively related. Blume et al. [13] investigate whether trading volume can indicate the quality of information revealed by prices and provide a theoretical explanation for a wide use of volume in forecasting the stock price. McQueen et al. [14] mainly research the delayed reaction of small stocks to good news. Llorente et al. [15] focus on the relationship between volume and return of individual stocks. Their theoretical and empirical results reveal that informed trading has influence on the relation between volume and return autocorrelation. In his study of contemporaneous correlation, Chen [16] finds that returns and volume are negatively correlated in the bear market, whereas in the bull market the correlation is positive. As for the dynamic relation, the stock return is capable of predicting trading volume in both bull and bear markets, but the evidence for volume predicting returns is weaker. Chen works with monthly data of S&P 500 index and does not apply quantile regressions. Nevertheless, his finding on the contemporaneous relation is in line with ours if we can think of low quantiles as bear market and high quantiles as bull market.

Among the studies on the international stock markets, Lee and Rui [17] research shows that volume cannot predict the next day's index returns in Shanghai and Shenzhen stock markets in China. Säfvenblad [18] reveals that the Sweden stock index return and stock return have high autocorrelations. Bissoondoyal-Bheenick and Brooks [19] analyze the predicting power of trading volume on stock return in the Australian stock market and find some predictive power for high-volume firms and little predictive power for small firms.

A strand of research explores the causal relationship between returns and trading volumes. In a study of nine national markets Chen et al. [20] find a causal link between volume and stock indexes in some countries. Chuang et al. [21] and Gebka and Wohar [7] analyze the causality between stock return and trading volume relation based on quantile regressions. Working on data from NYSE, S&P 500, and FTSE, Chuang et al. [21] show that the influences of volume on return are usually heterogeneous across different quantiles and those of return on volume are more stable. The quantile causal effects of volume on return exhibit a spectrum of symmetric V-shape relations. This pattern is consistent with the finding in Karpoff [22] although Karpoff's discussion is on the contemporaneous relation rather than causal relation. Gebka and Wohar [7] investigate the causal effect of trading volume on return with stock market data from nine Asian Pacific countries and have similar findings to those in Chuang et al. [21] including the V-shape causal relation. Chuang et al. [23] research the contemporaneous and causal relationship between the trading volume and the stock return (volatility) with a bivariate GJR-GARCH model, and their empirical analysis shows that the contemporaneous relation and causal relation between stock return and trading volume are significant and robust across all sample stock markets.

At the cross of the two groups of research above are Campbell et al. [1] who investigate the relationship between the autocorrelations of daily stock index returns and stock market trading volume. The results show that the first-order daily return autocorrelation tends to decline with volume for stock indexes and individual large stocks. Their finding indicates that a stock price decline on a high-volume day is more likely than a stock price decline on a low-volume day to be associated with an increase in the expected stock return.

3. Quantile Regression

Most studies surveyed above employ traditional regression models that essentially investigate relations between the expectations of dependent and explanatory variables, and such models often come with assumptions that variables are normally distributed. A relatively new family of statistical models, quantile regressions (QR), in contrast, can explore such relation within the full range of quantiles of the conditional distribution of the dependent variable.

Originally proposed by Koenker and Bassett Jr. [24], quantile regression allows for recognizing relationships between variables outside of the mean of the data, making it useful in understanding outcomes that are nonnormally distributed and that have nonlinear relationships with predictor variables. Therefore, it can expose a variety of heterogeneity in response dynamics. In other words, conventional regression models such as OLS can provide information most relevant for “average” observations, yet quantile regression provides greater flexibility to identify differing relationships at different parts of the distribution of the dependent variable. Another advantage of quantile regression over OLS regression is that the quantile regression estimates are more robust against outliers in the response measurements, which gives it an edge when handling heteroskedasticity, skewness, and leptokurtosis in financial data.

In the spirit of QR models, Koenker and Xiao [5] propose QAR models to study time series characteristics in which autoregressive coefficients may take distinct values over different quantiles of the innovation process. A standard QAR(p) model is as follows:

$$\begin{aligned} Q_{y_t}\left(\tau \mid y_{t-1}, \ldots, y_{t-p}\right) \\ = \theta_0(\tau) + \theta_1(\tau) y_{t-1} + \cdots + \theta_p(\tau) y_{t-p} + \varepsilon_t, \end{aligned} \tag{1}$$

where τ is within the range between 0 and 1. The autoregressive coefficients may be τ-dependent and thus can vary across the quantiles.

Quantile regression models have gained increasing interest in economic and financial studies in recent years since they are capable of capturing some information in the data that conventional regression models often miss. For example, when studying herding behaviors in Chinese stock markets Chiang et al. [25] are able to spot herding behavior with QR that are undetectable with regular regression models. Baur [6] argues that QR can provide further insight by going beyond the degree of dependence among global stock markets to study the structure of dependence. A shift in dependence structure is identified after the recent global financial crisis. Using data of more than 400 individual UK stocks Gebka and Wohar [26] explore how the variation of autocorrelation coefficients in different quantiles can be explained by factors such as size, volume, volatility, and liquidity. They argue that these variables are related theoretically to the potential causes of autocorrelations in returns, such as nontrading, bid-ask spread, and partial price adjustment effects.

4. Empirical Analysis

Our empirical analysis studies major composite stock indexes from eight countries: China, US, Germany, France, Canada, Japan, Italy, and United Kingdom. For China both the Shanghai and the Shenzhen composite indexes are covered. The starting date of the sample period is somewhat different for the stock markets under study to maximize the amount of data that is available, but the ending date is common for all markets as October 10, 2014. The starting date for Shanghai and Shenzhen Composite Index is April 8, 1991. For stock indexes in most developed countries the starting date of the sample period is January 13, 1993. For the Italian FTMIB index the starting date is May 27, 2009. Daily index data (level and trading volume) is collected for each index, namely, Shanghai and Shenzhen Composite Indexes, German DAX, French CAC 40, Canadian S&P-TSX, US S&P 500, Japanese Nikkei 225, Italian FTMIB, and British FTSE 100.

4.1. Quantile Autoregressive Model. Returns used in this study are calculated as logarithmic stock index differences. The trading volume is calculated as logarithmic trading volume.

The basic model in this study is a standard QAR(p) model as in (1). In Baur et al. [27] only QAR(1) model is considered without specification tests. To choose the order in QAR(p) model, we employ the Bayesian information criterion (BIC) for model selection. As a result, the number of lagged returns in the selected models varies for each index as follows: 3 for Shanghai Composite, 7 for Shenzhen Composite, 6 for German DAX, 5 for French CAC 40, 5 for Canadian S&P TSX, 5 for US S&P 500, 1 for Japanese Nikkei 225, 1 for Italian FTMIB, and 6 for British FTSE 100.

To investigate the relation between return and trading volume we include trading volume as an additional explanatory variable:

$$\begin{aligned} Q_{r_t}\left(\tau \mid r_{t-1}, \ldots, r_{t-p}, \mathrm{vol}_t\right) \\ = \theta_0(\tau) + \theta_1(\tau) r_{t-1} + \cdots + \theta_p(\tau) r_{t-p} + \alpha \cdot \mathrm{vol}_t \\ + \varepsilon_t. \end{aligned} \tag{2}$$

Equation (2) can be estimated with standard software package such as R. The interval of τ is $[0.05, 0.95]$ with the step of 0.05. Despite the contemporaneous nature of the trading volume in (2), it can also be understood in the spirit of a dynamic trading process. With the advancement of information technology most investors have access to stock market data (including stock prices and volumes at minimum) in almost real time. Thus intraday contemporaneous volume is one of the factors that can drive price movement. For example, after observing an abnormally high volume in early trading hours, investors would take it into account when designing and executing trading strategies later in the day.

The estimation results are reported in Tables 1–9 and Figures 1–9. In each figure the estimate of coefficients is

Table 1: Shanghai Composite Index Quantile Regression Result.

τ	$\theta_1(\tau)$	$\theta_2(\tau)$	$\theta_3(\tau)$	α
0.05	0.0388	0.0358	−0.0473	0.1651^{***}
0.15	0.0119	0.0459^{***}	0.0651^{***}	0.0091
0.25	0.0052	0.0426^{***}	0.0695^{***}	−0.0178
0.35	−0.0064	0.0330^{***}	0.0801^{***}	−0.0033
0.45	−0.0009	0.0299^{***}	0.0748^{***}	−0.0089
0.55	0.0125	0.0213^{***}	0.0784^{***}	−0.0055
0.65	0.0217^{**}	0.0208^{**}	0.0877^{***}	-0.0181^{*}
0.75	0.0193^{**}	0.0202^{***}	0.0867^{***}	0.0040
0.85	0.0397^{**}	0.0199^{**}	0.0800^{***}	0.0585^{***}
0.95	0.0244	0.0215	0.0718^{*}	-0.0902^{*}

Note: ***significance at 1% level, **significance at 5%, and *significance at 10%.

Table 2: Shenzhen Composite Index Quantile Regression Result.

τ	$\theta_1(\tau)$	$\theta_2(\tau)$	$\theta_3(\tau)$	$\theta_4(\tau)$	$\theta_5(\tau)$	$\theta_6(\tau)$	$\theta_7(\tau)$	α
0.05	0.0575^{*}	−0.0497	−0.0048	0.0495	−0.0160	-0.1028^{***}	0.0009	0.0738^{**}
0.15	0.0302^{***}	0.0032	0.0532^{***}	0.0496^{***}	−0.0184	-0.0642^{***}	−0.0026	0.0439^{**}
0.25	0.0254^{*}	0.0122	0.0782^{***}	0.0314^{**}	−0.0124	-0.0463^{***}	0.0066	0.0368^{***}
0.35	0.0377^{***}	0.0143	0.0756^{***}	0.0326^{***}	−0.0156	-0.0441^{***}	−0.0025	0.0476^{***}
0.45	0.0372^{***}	0.0204^{**}	0.0759^{***}	0.0260^{***}	−0.0085	-0.0344^{***}	0.0023	0.0481^{***}
0.55	0.0140^{***}	0.0098	0.0743^{***}	0.0402^{***}	0.0108	-0.0268^{***}	0.0090	0.0636^{***}
0.65	0.0210^{**}	0.0065	0.0721^{***}	0.0488^{***}	0.0282^{**}	-0.0285^{***}	0.0132	0.0791^{***}
0.75	0.0166	0.0045	0.0584^{***}	0.0539^{***}	0.0271^{**}	-0.0336^{***}	0.0174	0.0792^{***}
0.85	0.0343^{**}	0.0171	0.0392^{***}	0.0508^{***}	0.0303	-0.0485^{***}	0.0461^{**}	0.0521^{**}
0.95	0.0501	0.0081	0.0117	0.0517	0.0566	−0.0465	0.0662^{***}	-0.1385^{***}

Note: ***significance at 1% level, **significance at 5%, and *significance at 10%.

Table 3: Germany DAX Index Quantile Regression Result.

τ	$\theta_1(\tau)$	$\theta_2(\tau)$	$\theta_3(\tau)$	$\theta_4(\tau)$	$\theta_5(\tau)$	$\theta_6(\tau)$	α
0.05	0.1126^{***}	0.0798^{**}	0.0738^{**}	0.1294^{***}	0.0482	0.0349	-0.2647^{***}
0.15	0.0586^{**}	0.1010^{***}	0.0349	0.0614^{***}	−0.0133	−0.0187	-0.1504^{***}
0.25	0.0404^{**}	0.0581^{***}	0.0155	0.0460^{***}	−0.0035	−0.0182	-0.0797^{***}
0.35	0.0259^{*}	0.0229^{*}	0.0122	0.0331^{***}	−0.0045	−0.0201	-0.0381^{***}
0.45	0.0014	−0.0082	−0.0074	0.0146^{*}	-0.0297^{***}	-0.0265^{***}	-0.0211^{**}
0.55	-0.0268^{***}	-0.0330^{***}	−0.0096	−0.0007	-0.0268^{**}	-0.0427^{***}	−0.0056
0.65	-0.0456^{***}	-0.0643^{***}	-0.0245^{**}	-0.0213^{**}	-0.0341^{***}	-0.0538^{***}	0.0202^{*}
0.75	-0.0703^{***}	-0.0827^{***}	-0.0453^{***}	−0.0205	-0.0430^{***}	-0.0684^{***}	0.0456^{***}
0.85	-0.1101^{***}	-0.1011^{***}	-0.0659^{***}	-0.0317^{**}	-0.0674^{***}	-0.0716^{***}	0.1012^{***}
0.95	-0.1158^{***}	-0.0925^{***}	-0.1213^{***}	−0.0372	-0.1096^{***}	-0.0800^{***}	0.2242^{***}

Note: ***significance at 1% level, **significance at 5%, and *significance at 10%.

plotted with a dashed line, with the corresponding confidence interval shown as a shaded area. The corresponding OLS estimate is plotted with a solid red line and its confidence interval with dotted red lines.

4.2. Shanghai Composite Index and Shenzhen Composite Index. Chinese stock market is composed of Shanghai Stock Exchange and Shenzhen Stock Exchange, so we analyze the composite index of each market separately. (The QAR estimation results are available for quantiles between 0.05 and 0.95 at intervals of 0.05. To save space we only report results at intervals of 0.10 in tables.)

In Shanghai stock market, the influence of lagged returns on the current return shows variations. The influences are not monotonic, with frequent ups and downs across the quantiles. As we can see in Table 1 that for Shanghai market the coefficient of r_{t-1} is only significant between 0.65 and 0.85, but the effects of r_{t-2} and r_{t-3} are mostly significant. The volume has significant relation with the current return in lower quantiles and upper quantiles only. As shown in

Table 4: France CAC40 Index Quantile Regression Result.

τ	$\theta_1(\tau)$	$\theta_2(\tau)$	$\theta_3(\tau)$	$\theta_4(\tau)$	$\theta_5(\tau)$	α
0.05	0.1118***	0.0683*	0.0615*	0.1321***	0.0009	−0.2957***
0.15	0.0577***	0.0345*	0.0454**	0.0513***	−0.019	−0.1254***
0.25	0.0385**	0.0451***	0.0137	0.0285**	−0.0157	−0.0588***
0.35	0.0233**	0.0109	−0.0136	0.0132	−0.0206***	−0.0463***
0.45	−0.0080	−0.0229**	−0.0270**	0.0039	−0.0298***	−0.0160
0.55	−0.0333***	−0.0533***	−0.0561***	−0.0057	−0.0531***	0.0002
0.65	−0.0411***	−0.0745***	−0.0736***	−0.0371***	−0.0605***	0.0087
0.75	−0.0469***	−0.0867***	−0.0851***	−0.0251	−0.0656***	0.0311*
0.85	−0.0565***	−0.0991***	−0.0960***	−0.0461**	−0.0851***	0.0624***
0.95	−0.1161***	−0.1303***	−0.1524***	−0.0202	−0.1086***	0.1620***

Note: *** significance at 1% level, ** significance at 5%, and * significance at 10%.

Table 5: Canada S&P-TSX Index Quantile Regression Result.

τ	$\theta_1(\tau)$	$\theta_2(\tau)$	$\theta_3(\tau)$	$\theta_4(\tau)$	$\theta_5(\tau)$	α
0.05	0.1519***	0.0280	0.1294***	0.0756**	0.0121	−0.4963***
0.15	0.1383***	0.0215	0.0647***	0.0465	0.0126	−0.2572
0.25	0.0846***	0.0001	0.0227	0.0144	−0.0139	−0.1317***
0.35	0.0719***	−0.0036	0.0067	−0.0010	−0.0163	−0.0542***
0.45	0.0475***	−0.0370***	−0.0187	−0.0150	−0.0255**	−0.0253*
0.55	0.0342***	−0.0658***	−0.0153	−0.0256**	−0.0444***	0.0058
0.65	0.0161	−0.0902***	−0.0237**	−0.0299***	−0.0409***	0.0554***
0.75	−0.0102	−0.0931***	−0.0348***	−0.0378***	−0.0773***	0.1142***
0.85	−0.0066	−0.0872	−0.0547	−0.0467**	−0.0970	0.1646
0.95	−0.0473	−0.1088	−0.0871**	−0.0698**	−0.1500	0.3723

Note: *** significance at 1% level, ** significance at 5%, and * significance at 10%.

Figure 1, the autoregressive coefficients often fall outside the confidence interval of OLS estimation (especially for r_{t-1} and r_{t-3}), which suggests that a single estimate based on the expectation of variables often misses the state-dependent nature of the autoregressive relation.

As for the Shenzhen market, we can see in Table 2 that r_{t-1}, r_{t-3}, r_{t-4}, and r_{t-6} have consistently significant influence on current return except at a few quantiles. The other lagged returns have significant influence in various ranges of quantiles. In contrast to Shanghai market, the influence of r_{t-1} is significant at almost all quantiles. The relation between trading volume and the current return is consistently significant and mostly positive, gradually increasing in the middle quantile range of 0.25 to 0.75, but sharply decreasing above the 0.75 quantile.

4.3. Stock Indexes in G7 Countries. In this section we study the stock market indexes in G7 countries, including Germany DAX, France CAC 40, Canada S&P TSX, United States S&P 500, Japan Nikkei 225, Italy FTMIB Index, and United Kingdom FTSE 100 Index.

Although the QAR models come with different orders for the stock indexes in these developed economies, the results clearly share many common characteristics. For each lagged return, the influence on current return is decreasing with the quantile increasing. The influence is positive at lower quantiles and negative at upper quantiles, which means that the influence of lagged returns on the current return is decreasing with the quantile τ increasing. The confidence interval is bigger at tail quantiles than in the middle of quantiles due to larger variation in the extreme quantiles. Pattern of significance (as observed in tables) varies by country, but in general the autocorrelations are consistently significant in high quantiles, while significance at low quantiles is patchy.

To better understand the state-dependent nature of the autoregression results, let us take the return of the previous day as an example, which generally has the biggest effect on the current return. If r_{t-1} is positive, it has positive effect in low quantiles (alleviation/reversal) and negative effect in high quantiles (dampen extreme return/continuation), which shows an overall *alleviation* effect. Thus if the return in the previous day is positive the range of return is *narrower*, other things being equal. If r_{t-1} is negative, it has negative effect in low quantiles (aggravation/continuation) and positive effect in high quantiles (aggravation/reversal), which show an overall *aggravation* effect. Thus the range of observed returns *increases* for negative values of lagged returns. This is consistent with the common observation that market volatility tends to increase following trading days with negative returns. Keep in mind that this finding is not the same as most results reported in literature that stock index usually shows reversal after large price changes and continuation following

Table 6: United States S&P 500 Index Quantile Regression Result.

τ	$\theta_1(\tau)$	$\theta_2(\tau)$	$\theta_3(\tau)$	$\theta_4(\tau)$	$\theta_5(\tau)$	α
0.05	0.1150***	0.0247	0.0620	0.0426	−0.0401	−0.7977***
0.15	0.0569***	0.0574***	0.0391*	0.0290	0.0155	−0.4292***
0.25	0.0179	0.0224	−0.0017	0.0273*	−0.0065	−0.2527***
0.35	−0.0021	0.0058	−0.0058	0.0174	−0.0200	−0.1441***
0.45	−0.0341***	−0.023**	−0.0018	−0.0039	−0.0335***	−0.0492***
0.55	−0.0630***	−0.0472***	−0.0107	−0.0166*	−0.0460***	0.0095
0.65	−0.0726***	−0.0626***	−0.0231**	−0.0287**	−0.0591***	0.0747***
0.75	−0.1002***	−0.0861***	−0.0454***	−0.0443***	−0.0773***	0.1480***
0.85	−0.1079***	−0.1148***	−0.0760***	−0.0563***	−0.0984***	0.2989***
0.95	−0.1714***	−0.1353***	−0.1178***	−0.0828**	−0.1529***	0.6792***

Note: *** significance at 1% level, ** significance at 5%, and * significance at 10%.

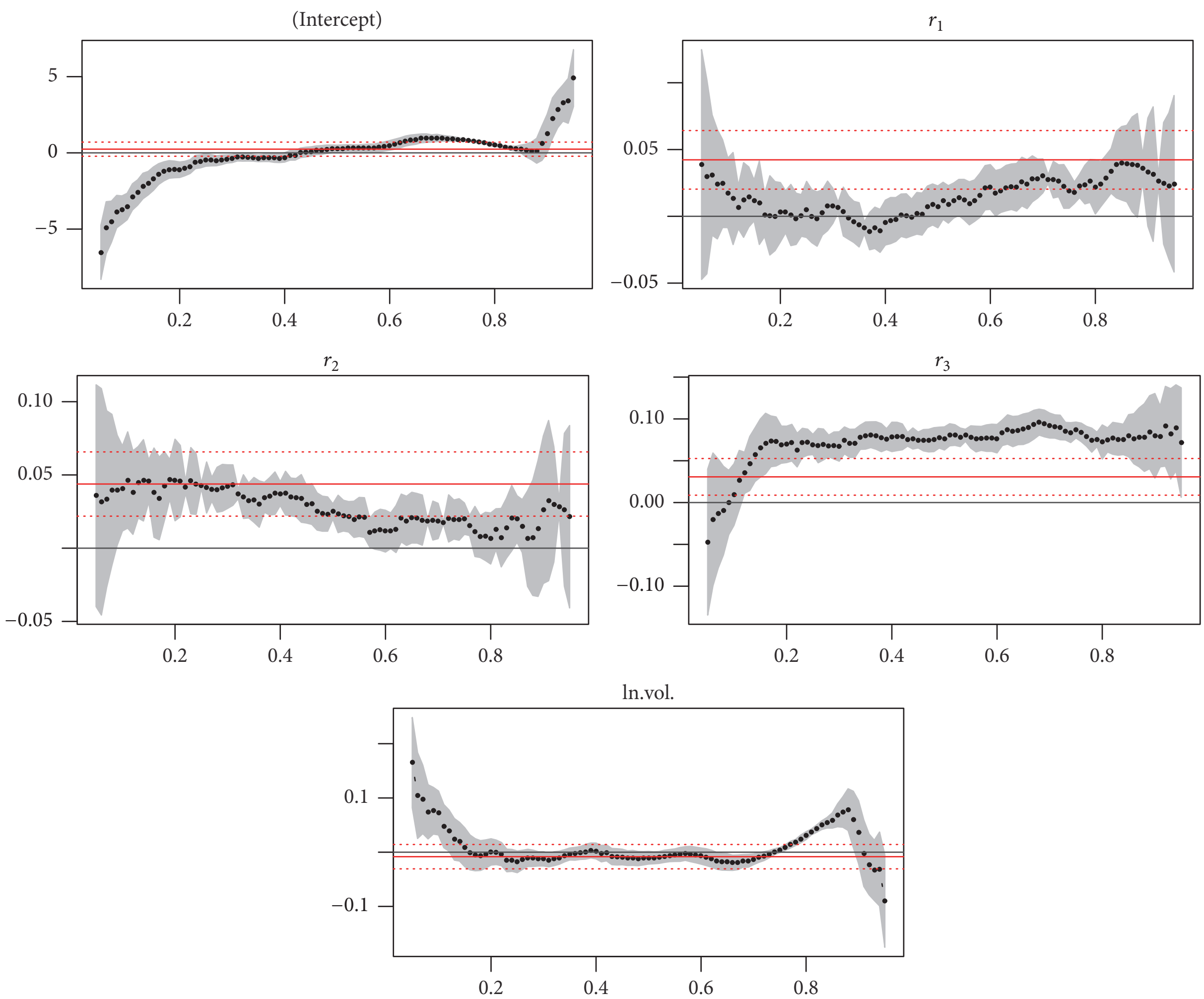

Figure 1: Shanghai Composite Index Quantile Regression Result.

small changes, which can be explained by behavioral factors of overreaction and underreaction.

The coefficient of trading volume is apparently increasing with quantiles. For both upper and lower quantiles, it is clearly outside the confidence interval of OLS estimates. The distinct patterns of coefficients of lagged returns and volume indicate a negative relation between conditional autocorrelation and trading volume (McKenzie and Faff [28]).

Unlike the group of research on the causality between trading volume and returns (e.g., Chuang et al. [21] and Gebka and Wohar [7]), this study focuses on their contemporaneous correlation. Nevertheless, the contemporaneous

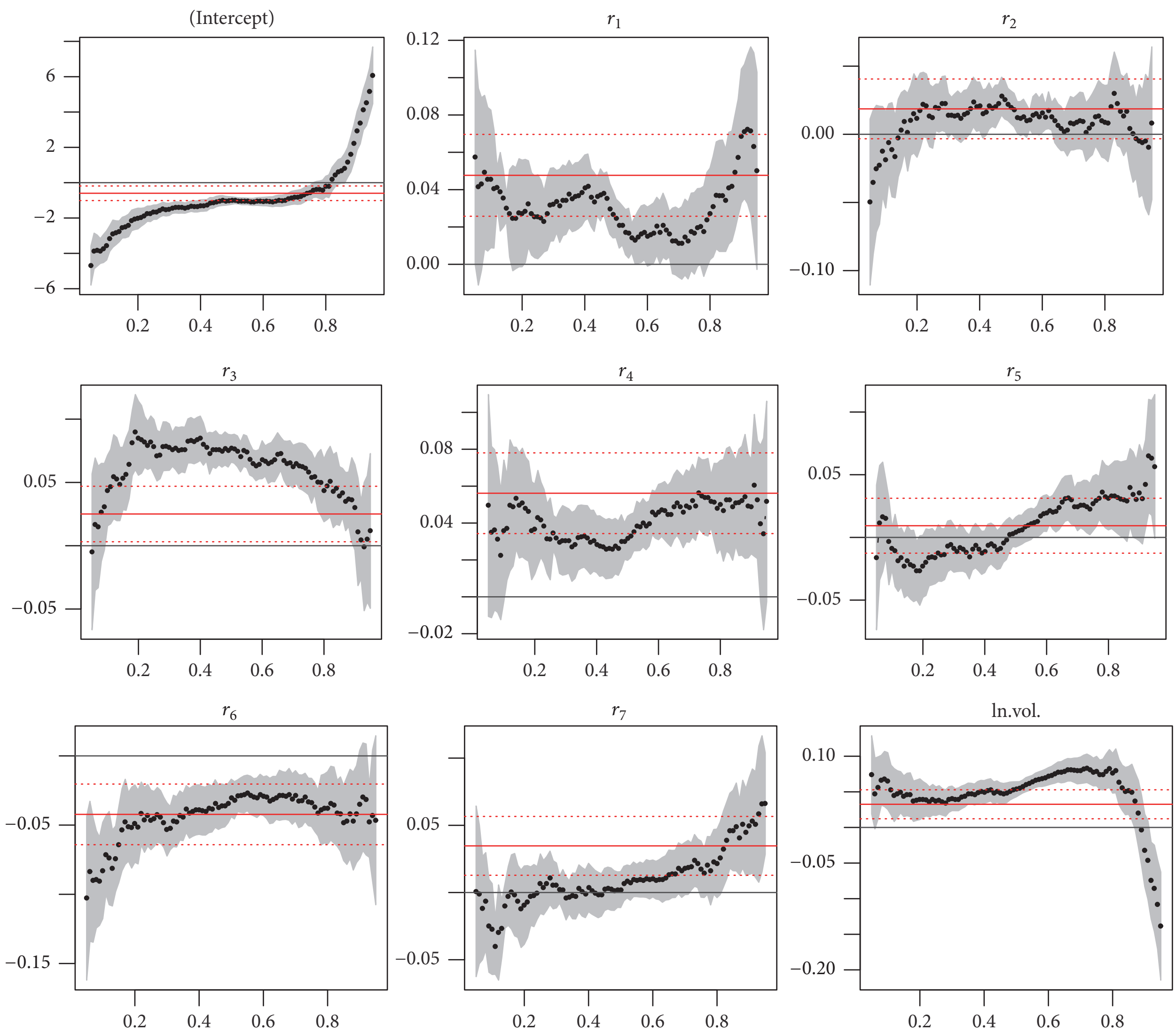

Figure 2: Shenzhen Composite Index Quantile Regression Result.

Table 7: Japan Nikkei 225 Index Quantile Regression Result.

τ	$\theta_1(\tau)$	α
0.05	0.0599	-0.2670^{***}
0.15	0.0123	-0.0828^{**}
0.25	-0.0190	0.0116
0.35	-0.0420^{***}	0.0558^{**}
0.45	-0.0504^{***}	0.0876^{***}
0.55	-0.0659^{***}	0.0930^{***}
0.65	-0.1014^{***}	0.1362^{***}
0.75	-0.1164^{***}	0.1811^{***}
0.85	-0.1012^{***}	0.2706^{***}
0.95	-0.0755^{***}	0.2881^{***}

Note: ***significance at 1% level, **significance at 5%.

Table 8: Italy FTMIB Index Quantile Regression Result.

τ	$\theta_1(\tau)$	α
0.05	0.0770^{**}	-0.4370^{***}
0.15	0.0376	-0.2155^{***}
0.25	0.0315^{**}	-0.1210^{***}
0.35	0.0037	-0.0790^{**}
0.45	-0.0041	-0.0404^{**}
0.55	-0.0238^{*}	-0.0062
0.65	-0.0410^{***}	0.0273
0.75	-0.0316^{**}	0.0683^{***}
0.85	-0.0525^{**}	0.1115^{***}
0.95	-0.0977	0.4191^{***}

Note: ***significance at 1% level, **significance at 5%, and *significance at 10%.

Table 9: U.K. FTSE 100 Index Quantile Regression Result.

τ	$\theta_1(\tau)$	$\theta_2(\tau)$	$\theta_3(\tau)$	$\theta_4(\tau)$	$\theta_5(\tau)$	$\theta_6(\tau)$	α
0.05	0.0876**	0.0339	0.0188	0.1457***	0.0091	−0.0005	−0.4283***
0.15	0.0430*	0.0533**	0.0353	0.0781***	0.0149	−0.0075	−0.1971***
0.25	0.0365**	0.0252*	−0.0000	0.0484***	−0.0028	−0.0230	−0.1172***
0.35	0.0062	−0.0189	−0.0125	0.0319***	−0.0254***	−0.0224*	−0.0766***
0.45	−0.0063	−0.0514***	−0.0139	0.0231**	−0.0278**	−0.0369***	−0.0433***
0.55	−0.0195*	−0.0747***	−0.0195	−0.0043	−0.0435***	−0.0528***	−0.0028
0.65	−0.0421***	−0.0937***	−0.0399***	−0.0182	−0.0480***	−0.0728***	0.0200
0.75	−0.0621***	−0.0980***	−0.0613***	−0.0292**	−0.0661***	−0.0735***	0.0682***
0.85	−0.0901***	−0.1032***	−0.0719***	−0.0508***	−0.0966***	−0.1048***	0.1127***
0.95	−0.1288***	−0.1342***	−0.1419***	−0.0008	−0.1297***	−0.0997***	0.3810***

Note: ***significance at 1% level, **significance at 5%, and *significance at 10%.

Table 10: Comparison of Coefficients of r_{t-1} in QAR Model.

τ	Shanghai	Shenzhen	Germany	France	Canada	US	Japan	Italy	UK
0.05	0.0388	**0.0575***	**0.1126*****	**0.1118*****	**0.1519*****	**0.1150*****	0.0599	**0.0770****	**0.0876****
0.15	0.0119	**0.0302*****	**0.0586****	**0.0577*****	**0.1383*****	**0.0569*****	0.0123	0.0376	**0.0430***
0.25	0.0052	**0.0254***	**0.0404****	**0.0385****	**0.0846*****	0.01790	−0.0190	**0.0315****	**0.0365****
0.35	−0.0064	**0.0377*****	**0.0259***	**0.0233****	**0.0719*****	−0.0021	**−0.0420*****	0.0037	0.0062
0.45	−0.0009	**0.0372*****	0.0014	−0.0080	**0.0475*****	**−0.0341*****	**−0.0504*****	−0.0041	−0.0063
0.55	0.0125	**0.0140*****	**−0.0268*****	**−0.0333*****	**0.0342*****	**−0.0630*****	**−0.0659*****	**−0.0238***	**−0.0195***
0.65	**0.0217****	**0.0210****	**−0.0456*****	**−0.0411*****	0.0161	**−0.0726*****	**−0.1014*****	−0.0410***	**−0.0421*****
0.75	**0.0193****	0.0166	**−0.0703*****	**−0.0469*****	−0.0102	**−0.1002*****	**−0.1164*****	**−0.0316****	**−0.0621*****
0.85	**0.0397****	**0.0343****	**−0.1101*****	**−0.0565*****	−0.0066	**−0.1079*****	**−0.1012*****	**−0.0525****	**−0.0901*****
0.95	0.0244	0.0501	**−0.1158*****	**−0.1161*****	−0.0473	**−0.1714*****	**−0.0755*****	−0.0977	**−0.1288*****

Note: ***significance at 1% level, **significance at 5%, and *significance at 10%.

volume-return relation for G7 countries (i.e., increasing with quantiles) is similar to (consistent with) the findings on *lag* volume-return relationship as reported in Gebka and Wohar [7] for Asian Pacific nations and in Chuang et al. [21] for NYSE, S&P 500, and FTSE.

4.4. Comparison of Results of All Markets. Although the QAR models come with different orders (between one and seven) for the nine stock indexes, Table 10 collects the coefficients of r_{t-1} for comparison purpose since it is available for every index. The common pattern seems to be that the influence is significant at lower quantiles (with exceptions of Shanghai and Japan) and upper quantiles (with the exception of Canada). It is typically insignificant at medium quantiles.

The figures for Shanghai and Shenzhen Stock Exchanges are quite different from those of G7 countries. The coefficients of QAR display irregular shapes with larger fractions of quantiles within the confidence intervals of OLS estimates. The return autocorrelation is relatively stable (homogeneous) across quantiles for Shanghai and Shenzhen markets. The return autocorrelation is mostly positive across all quantiles. This is consistent with theoretical explanation of underreaction to news, trend chasing, or herding behavior among investors. Trend chasing and herding are quite common in Chinese stock markets (Tan et al. [29], Yao et al. [30], and Huang et al. [31]) since a much higher fraction (approximately 80%) of trading is conducted by less-informed individual investors in Chinese stock market than in developed countries. The positive autocorrelation is also consistent with the finding in Rezvanian et al. [32] that in reaction to both favorable and unfavorable information Chinese equity markets often register an upward trend after the initial adjustment (underreaction to good news but overreaction to bad news).

The consistently positive and significant autocorrelations (especially in Shenzhen) may indicate lower market efficiency. This is in contrast to the finding by Gebka and Wohar [26] that during bull market in UK the autocorrelation seems to be negative and constant across quantiles, but decreasing across quantiles during financial crisis. This result contributes new evidence from a new perspective to the ongoing investigation on market efficiency of Chinese stock market (Chong et al. [33] and Chang et al. [34]).

Table 11 compares the relations between current return and trading volume for the nine stock indexes. In China the relation between trading volume and current stock index return is somewhat different between Shanghai and Shenzhen stock markets. The influence is not significant in the quantile range from 0.15 to 0.55 in Shanghai market, but the relation is always significant in Shenzhen stock market. In Shanghai there is an upswing at lower quantiles, it is fairly horizontal in the middle close to the OLS estimate, and there is strong downswing at the very high end. As for the Shenzhen market,

Table 11: Comparison of coefficients of trading volume.

τ	Shanghai	Shenzhen	Germany	France	Canada	US	Japan	Italy	UK
0.05	**0.1651*****	**0.0738****	**−0.2647*****	**−0.2957*****	**−0.4963*****	**−0.0080*****	**−0.2670*****	**−0.4370*****	**−0.4283*****
0.15	0.0091	**0.0439****	**−0.1504*****	**−0.1254*****	**−0.2572**	**−0.0043*****	**−0.0828****	**−0.2155*****	**−0.1971*****
0.25	−0.0178	**0.0368*****	**−0.0797*****	**−0.0588*****	**−0.1317*****	**−0.0025*****	0.0116	**−0.1210*****	**−0.1172*****
0.35	−0.0033	**0.0476*****	**−0.0381*****	**−0.0463*****	**−0.0542*****	**−0.0014*****	0.0558**	**−0.0790****	**−0.0766*****
0.45	−0.0089	**0.0481*****	**−0.0211****	−0.0160	**−0.0253***	**−0.0005*****	**0.0876*****	**−0.0404****	**−0.0433*****
0.55	−0.0055	**0.0636*****	−0.0056	0.0002	0.0058	0.0001	**0.0930*****	−0.0062	−0.0028
0.65	**−0.0181***	**0.0791*****	**0.0202***	0.0087	**0.0554*****	**0.0008*****	**0.1362*****	0.0273	0.0200
0.75	0.0040	**0.0792*****	**0.0456*****	**0.0311***	**0.1142*****	**0.0015*****	**0.1811*****	**0.0683*****	**0.0682*****
0.85	**0.0585*****	**0.0521****	**0.1012*****	**0.0624*****	0.1646	**0.0030*****	**0.2706*****	**0.1115*****	**0.1127*****
0.95	**−0.0902***	−0.1385***	**0.2242*****	**0.1620*****	0.3723	**0.0068*****	**0.2881*****	**0.4191*****	**0.3810*****

Note: ***significance at 1% level, **significance at 5%, and *significance at 10%.

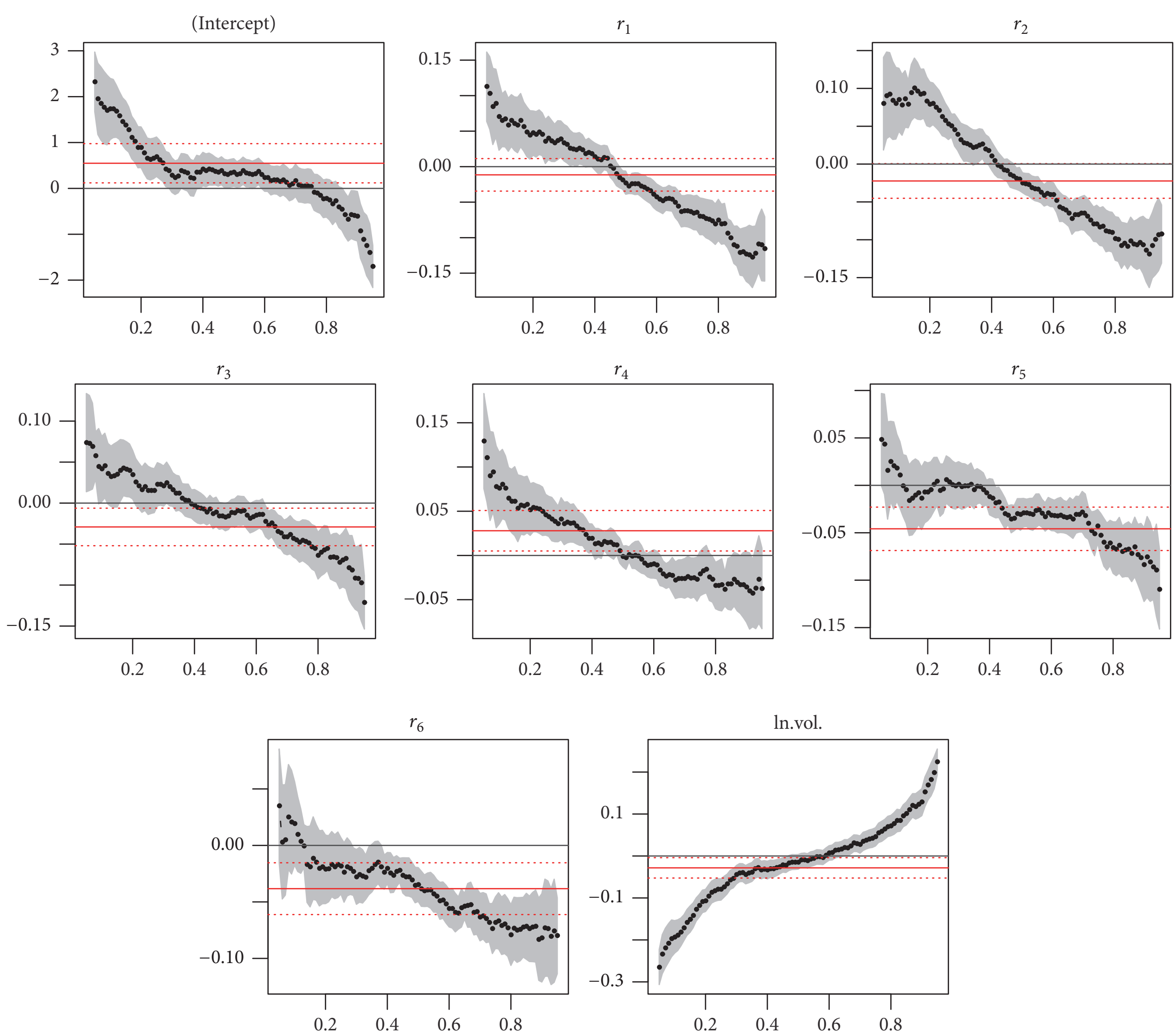

Figure 3: Germany DAX Index Quantile Regression Result.

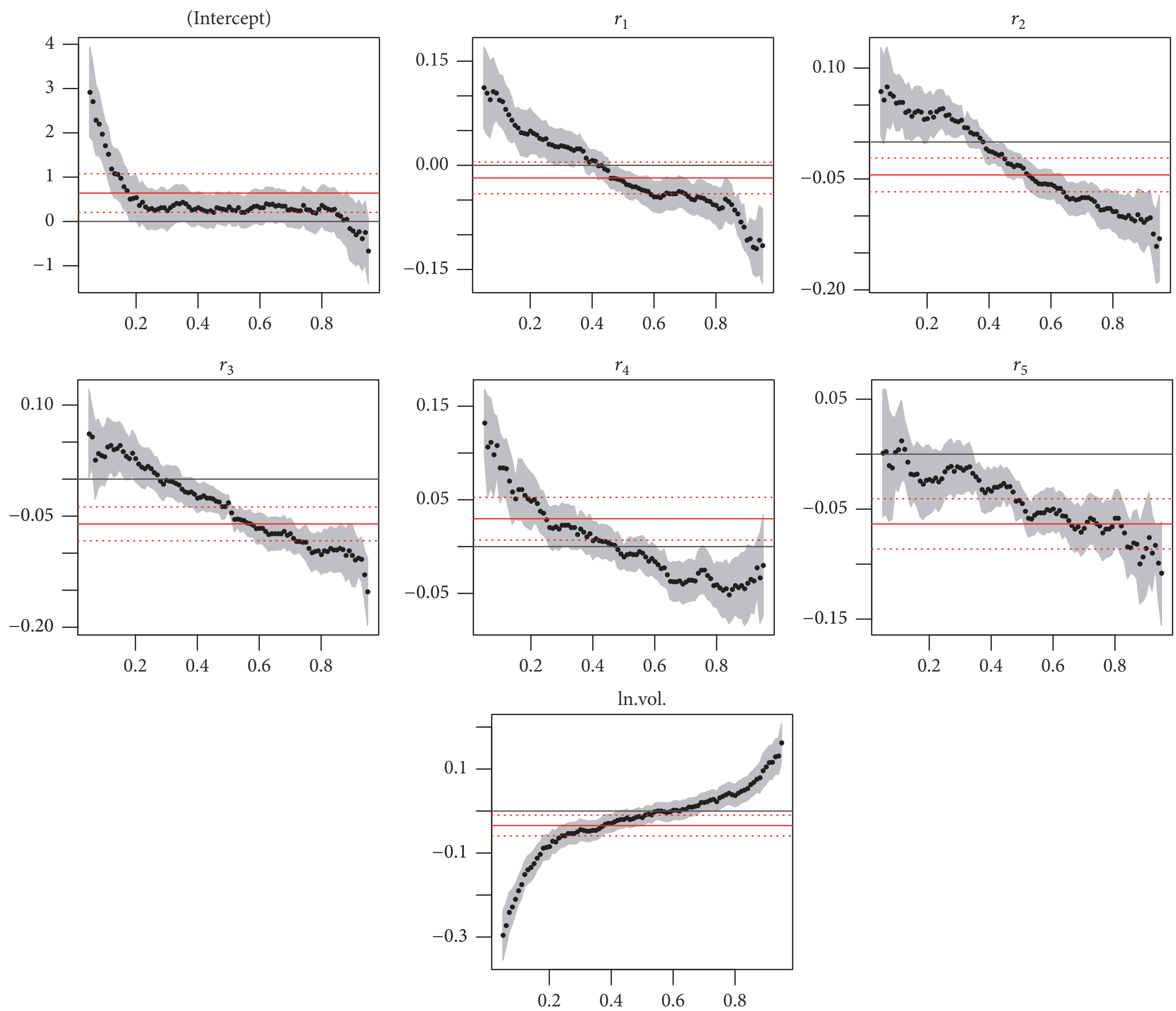

Figure 4: France CAC 40 Index Quantile Regression Result.

it shares the swings at both ends but shows a slight yet steady upward trend in the middle range, slightly above the OLS estimate.

For both Chinese stock exchanges, the majority (especially around the middle) of the volume coefficient is relatively flat (largely within OLS confidence interval for Shanghai) but has an explosive upward tail (positive) at low quantiles and a downward tail (negative) at high quantiles, which is unique compared to other stock exchanges. Such tails can be explained by the daily price fluctuation limits (10%) adopted by both Chinese stock exchanges. In very good states (high quantiles) many stocks' return may reach the 10% upper limit for a trading day (thus their trading will be very limited), so the volume will shrink (compared to the situation without fluctuation limits). In very bad states (low quantiles) many stocks' return may approach the −10% lower limit, so the trading volume will shrink, thus creating the positive correlation between return and volume. Such findings provide evidence against the magnet effect that trading volume may increase when the price change approaches the daily limit in either direction. For both stock exchanges, Shenzhen in particular, the relation between return and volume is generally significantly positive at medium or high quantiles (except the tail), but not as strong as the relation in most exchanges in G7 countries, which is increasing way outside the OLS intervals. At lower quantiles (except the tail), the relation in Chinese stock exchanges is either positive, which suggests that as the return declines the trading volume shrinks, or insignificant. This is in sharp contrast to other exchanges. Such a pattern may be explained by the lack of short selling mechanism at Chinese stock exchanges. (On March 31, 2010, China launched a pilot scheme, allowing 90 constituent stocks on a designated list to be sold short and/or purchased on margin.) As stock prices decline, investors with pessimistic views or negative information are mostly sidelined, thus reducing the trading volume.

The finding on the return-volume relation at tail quantiles in Chinese stock market complements and enriches the

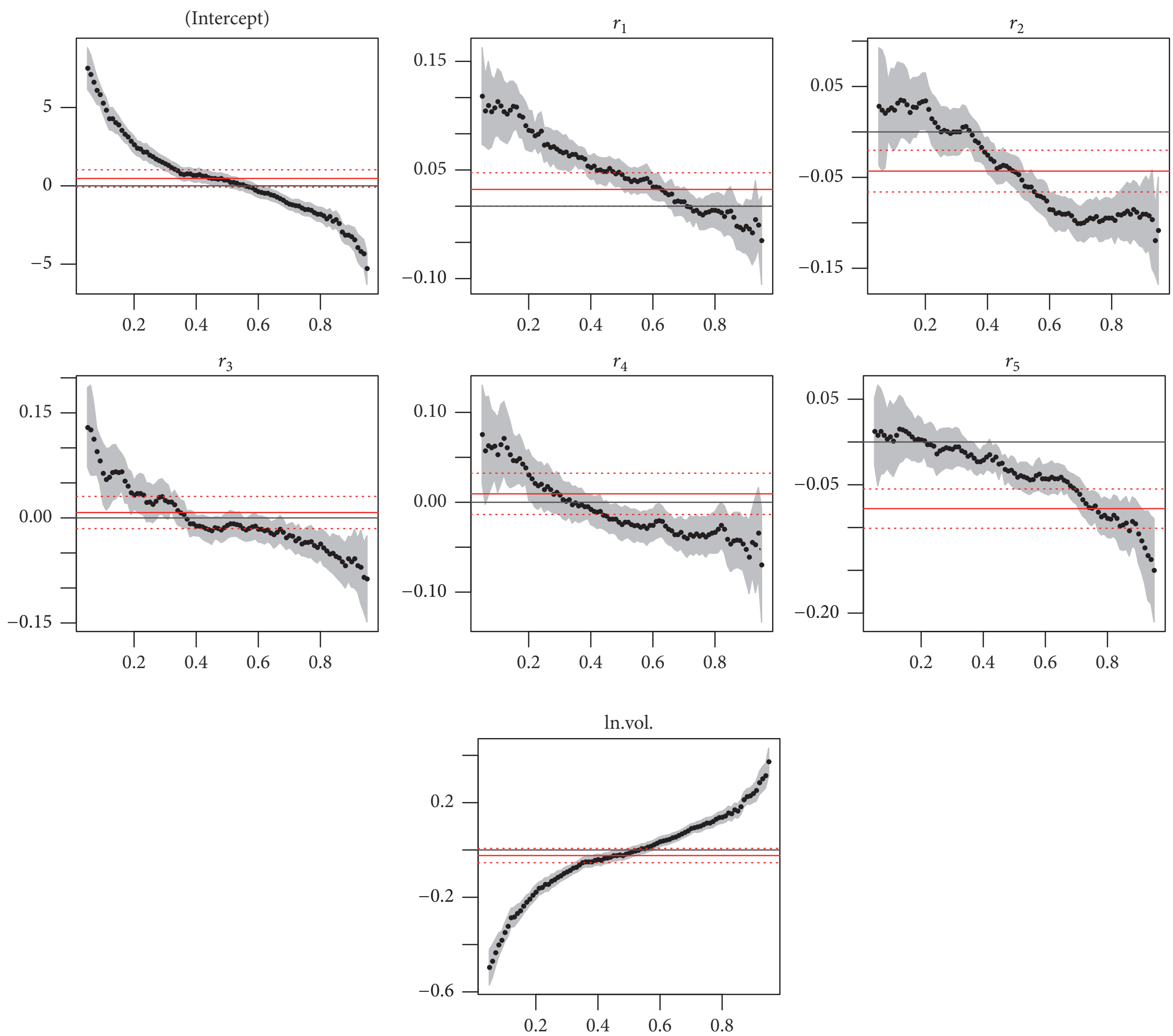

FIGURE 5: Canada S&P-TSX Index Quantile Regression Result.

literature on the effects of price limit. Although widely adopted by many stock exchanges worldwide, the effects of price limit are still inconclusive. Many studies reveal negative impact of imposing price limits such as volatility spillover, delayed price discovery, and trading interference (e.g., Kim and Rhee [35]), but recent studies on Chinese stock market have reported positive effects of price limits (Kim et al. [36] and Li et al. [37]). Our results complement this growing literature by finding no evidence of the magnet effect, which is consistent with Kim et al. [36].

For stock markets outside China, the general pattern seems to be that at lower quantiles the influence of volume on current return is significantly negative. It is often insignificant at medium quantiles, but at upper quantiles the influence turns significantly positive (except Canada).

Karpoff [22] provides an excellent survey of research on the contemporaneous volume-return relation up to mid-1980s (since then research focus has partially shifted to causal relation). Based on a synthesis of previous research Karpoff proposes an asymmetric volume-price change relation in which volume is positively related to the *absolute value* of price change. Moreover, this correlation is somewhat stronger for positive price change (Figure 1 in his paper).

Karpoff's model seems to be supported by the QAR results of all G7 countries. For all these markets the index return is related to volume in an almost monotonic increasing fashion. The correlation is negative at lower quantiles and turns positive at upper quantiles. For upper quantiles the relation is convex and for lower quantiles it is concave. This observation is visually clear and strong for all G7 markets except the Japanese market (still true but not as strong). Such a relation indicates that trading volume explodes when the return is large in both directions since large absolute returns often accompany new information and some investors may trade for rebalancing purpose. Large returns in either direction may also trigger some preset program trading thus raising the

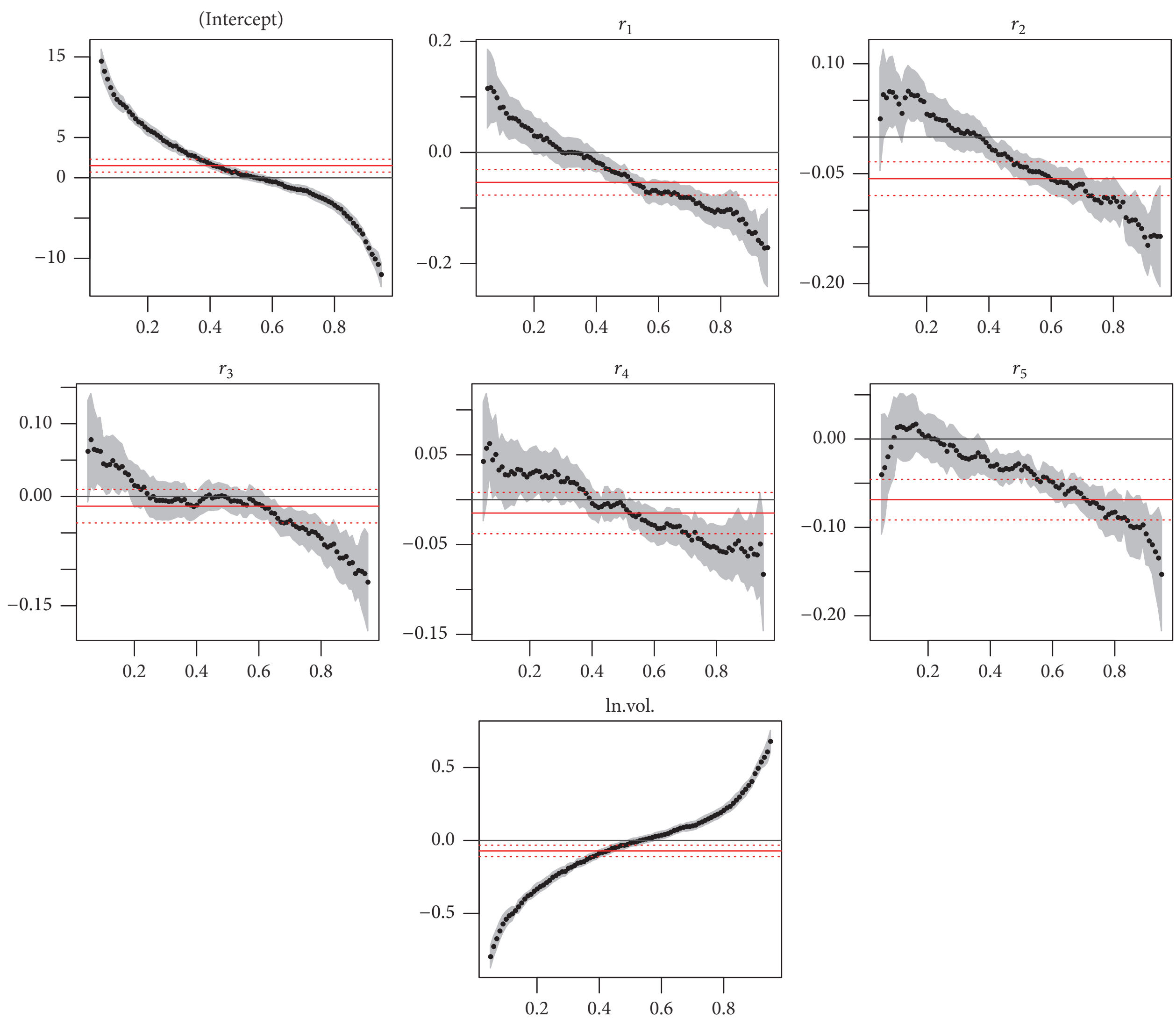

Figure 6: United States S&P 500 Index Quantile Regression Result.

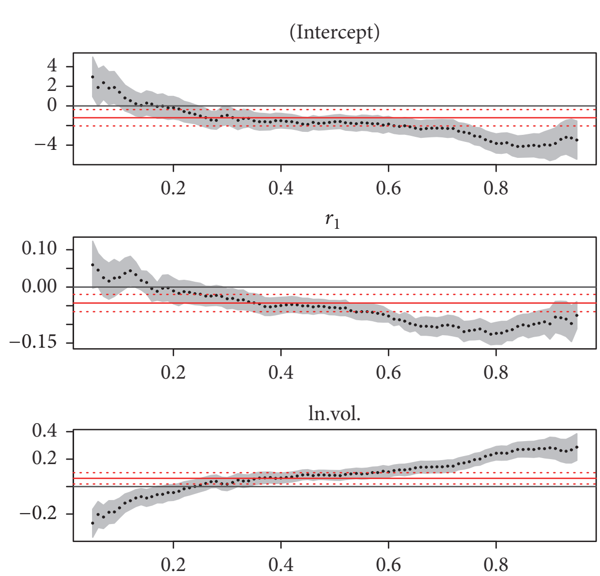

Figure 7: Japan Nikkei 225 Index Quantile Regression Result.

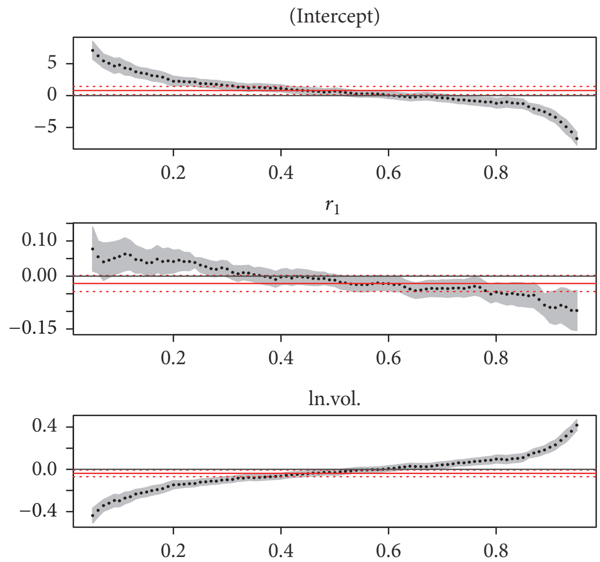

Figure 8: Italy FTMIB Index Return Quantile Regression Result.

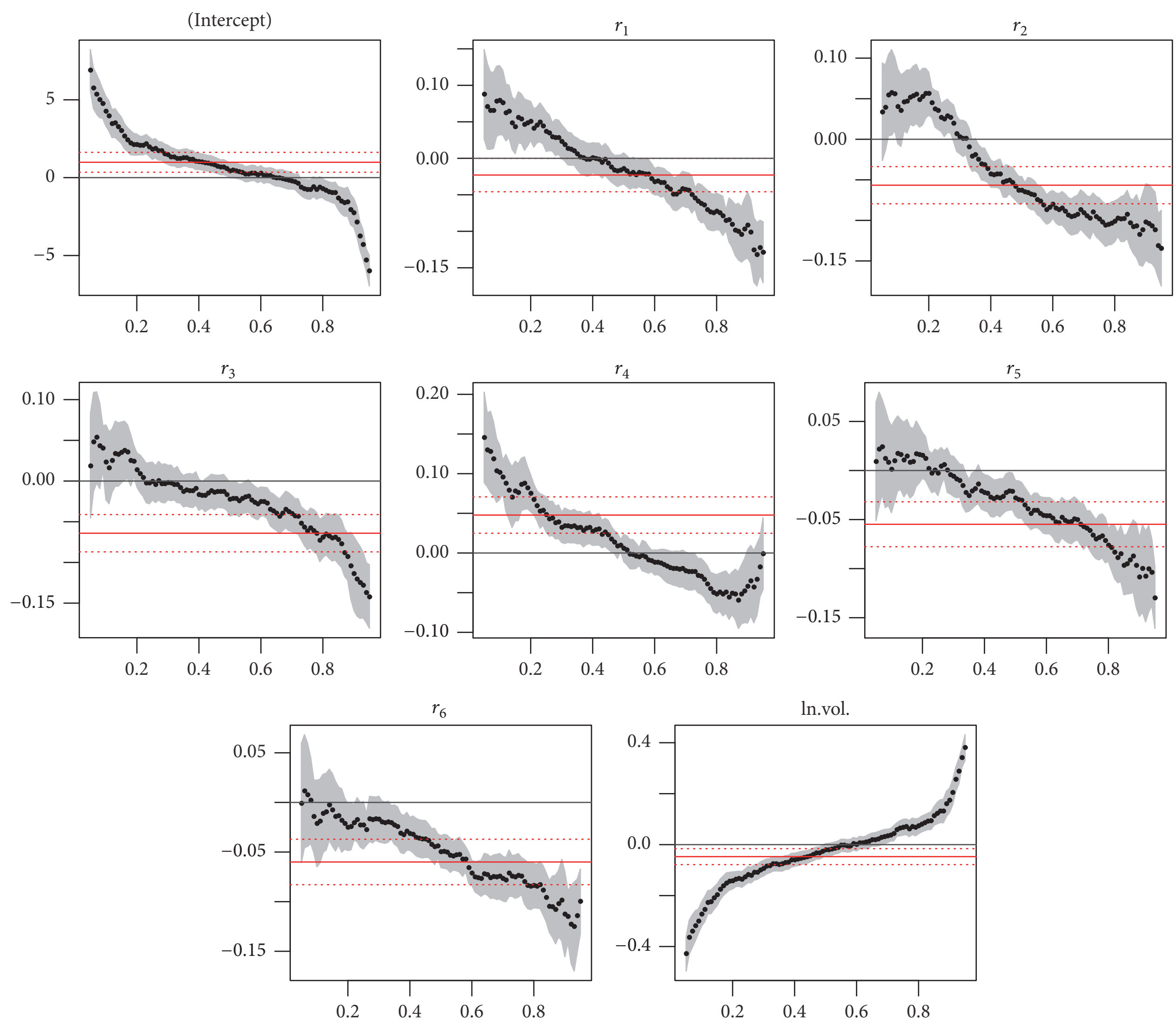

Figure 9: UK FTSE 100 Index quantile regression result.

trading volume. At lower quantiles (bad states) the increase in trading volume is associated with even lower returns; at upper quantiles (good states) the increase in volume is associated with even higher returns. In contrast, the OLS estimates are barely distinguishable from zero (insignificant). To summarize, all these results demonstrate that stock index autocorrelation and return-volume relation are better understood in a state-dependent framework. Focusing solely on the mean of variables, as in OLS regressions, can overlook valuable information.

5. Conclusion

We apply the QAR model to study the dynamics and predictability across all quantiles with stock index data from G7 countries and China. In general, the stock markets in G7 countries share many common characteristics, but the Chinese stock market is distinctly different. For the stock markets in the seven developed economies, the autoregressive parameters generally follow a decreasing pattern across the quantiles with significant portions outside the OLS estimate intervals. At low quantiles the autocorrelation is positive and it gradually turns to negative at high quantiles. For Shanghai and Shenzhen Stock Exchanges in China, however, the autocorrelation pattern across quantiles is irregular but largely homogeneous, often falling into the OLS estimate intervals. As for the contemporaneous relation between return and trading volume, the pattern is also evidently different between stock markets in G7 countries and China. For the seven developed economies, the stock index return is related to trading volume in a monotonically increasing fashion. It is negative at low quantiles and turns positive at high quantiles, with most part clearly outside the OLS estimate intervals. For both Chinese stock exchanges, the most (especially middle) part of the volume coefficient is relatively flat but has an explosive upward tail (positive) at the low end of quantiles and a downward tail (negative) at the high end. While these two tails may be explained by the daily price limits in Chinese stock market, other distinctive characteristics of Chinese stock market as identified in this paper call for further exploration.

Competing Interests

The authors declare that they have no competing interests.

Acknowledgments

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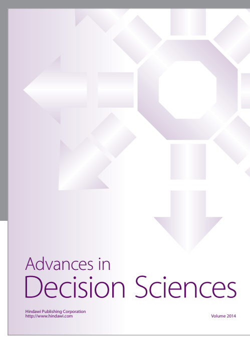

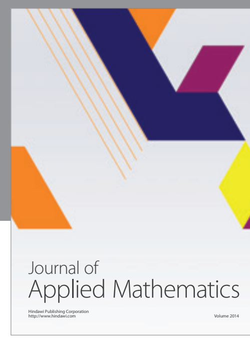

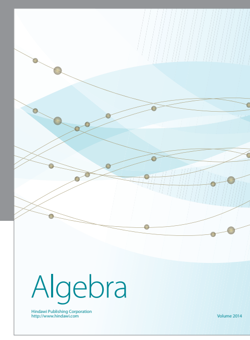

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