Stock Return Autocorrelations and Predictability in the Chinese Stock Market

—Evidence from Threshold Quantile Autoregressive Models

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This paper applies the threshold quantile autoregressive model to study stock return autocorrelations and predictability in the Chinese stock market from 2005 to 2014. The results show that the Shanghai A-share stock index has significant negative autocorrelations in the lower regime and has significant positive autocorrelations in the higher regime. It attributes that Chinese investors overreact and underreact in two different states. These results are similar when we employ individual stocks. Besides, we investigate stock return autocorrelations by different stock characteristics, including liquidity, volatility, market to book ratio and investor sentiment. The results show autocorrelations are significantly large in the middle and higher regimes of market to book ratio and volatility. Psychological biases can result into return autocorrelations by using investor sentiment proxy since autocorrelations are significantly larger in the middle and higher regime of investor sentiment. The empirical results show that predictability exists in the Chinese stock market.

Keyword: Stock return autocorrelations, Predictability, Chinese stock market, Threshold quantile autoregressive model

JEL Classification: C23; G12; G14

1. Introduction

Fama (1970) proposes the Efficient Market Hypothesis and classifies the efficient markets into three forms, that is, weak form market, semi-strong form market and strong form market. In the weak form market, all the historical information has been contained in the price so that asset return is completely unpredictable or weakly predictable from past prices and no trading strategy which outperforms passive investment strategies, after adjustment for trading costs and risk (Jensen, 1978). However, stock price can not adjust promptly and reflects all the available information because of market frictions, such as limited dissemination channels, transaction cost and nonsynchronous trading (Cohen, Maier, Schwartz and Whitcomb, 1986; Keim and Stambaugh, 1986; Lo and MacKinlay, 1990; Conrad, Gultekin and Kaul, 1997; Lo and MacKinlay, 1997). The information frictions is also an important factor (Hong, Torous and Valkanov, 2007; Rapach, Strauss and Zhou, 2013). Moreover, psychological biases and irrational investment behaviors attribute to stock return autocorrelations and predictability, such as conservatism (Veronesi, 1999), overconfidence and self-attribution bias (De Bondt and Thaler, 1985; Daniel, Hirshleifer and Subrahmanyam, 1998, Barber and Odean, 2001). These factors above lead to information autocorrelations and investor's inadequate response (Glosten, Jagannathan and Runkle, 1993), investor's overreaction to lagged information (Amihud and Mendelson, 1986), sequentially arriving information and acquisition of information by agents (Copeland, 1976; Jennings, Starks and Fellingham, 1981; Holden and Subrahmanyam, 1992).

The Chinese stock market is one of the largest emerging markets in the world. Harvey (1995a, 1995b) thinks that emerging markets have more market frictions because of limited dissemination channels and high transaction cost. Besides, 85 percent of investors (approximately 200 million) in the Chinese stock market are individual investors. They trade more frequently than the investors abroad. Besides, two-thirds of the most new Chinese investors do not graduate from high school and many seem to invest with borrowed money[1]. Eun and Huang (2007) cite Wall Street Journal (August 22, 2001) and note that the Chinese stock market is like casinos, driven by fast money flows in and out of stocks with little regard for their underlying value. It is thought that the factors above attribute the Chinese stock market is full of irrational investment behaviors.

For the causes of irrational investment behaviors in the Chinese stock market, some researchers think individual investors have more psychological biases, compared with institutional investors. Nofsinger and Sias (1999) note that individual investors are less sophisticated and irrational investment behaviors and market anomalies come from their trading. Baker, Coval and Stein (2007) show that large percentage of individual investors are more inertial than logical. Chen et al. (2007) show that Chinese individual investors appear to make worse trading decisions and have more trading mistakes than institution investors. Odean (1998), Ekholm and Pasternack (2008) also confirm that institutional investors' trading decisions are less biased than the individuals in the behavioral aspects.

Some scholars learn about the Chinese investors' investment behaviors and study return autocorrelations and predictability in the Chinese stock market by using financial, industrial and firm predictors, such as Narayan, Narayan and Westerlund (2015), Westerlund, Narayan, Zheng (2015) and Narayan and Sharma (2016). However, the scholars above and other scholars apply the linear models to estimate stock return autocorrelations, such as Poterba and Summers (1988), Shen and Wang (1998), Lehmann (1990), Säfvenblad (2000) and Baur, Dimpfl and Jung (2012). The problem is that the marginal distribution of returns is sometimes skewed and has the asymmetric distribution in the financial time series. Furthermore, some asymmetries and differential effects in the stock behaviors occur in the different market conditions, such as the bull market and bear market (Harvey and Siddique, 1999; Chen, Hong and Stein, 2001; Engle and Patton, 2001; He and Silvennoinen, 2008). Considering the

[1] The features of Chinese individual investors and stock market structure are cited from the Fahey and Chemi (2015)'s report "Three charts explaining China's strange stock market".

issue on fitting this type of data, Tong (1978) and Tong and Lim (1980) think that threshold models are a class of non-linear models and able to reproduce non-linear behaviors often observed on real data in the financial markets, such as cyclical, asymmetric and jump phenomenon.

Therefore, in order to make up for the research deficiencies in the Chinese stock market, this paper aims to apply the threshold quantile autoregressive model proposed by Galvao, Montes-Rojasb and Olmoc (2010) to study the return autocorrelations and predictability in the Chinese stock market from 2005 to 2014. The advantage of this method can both consider the asymmetric and skewed distribution of stock returns so that it has a better capacity to predict stock returns with different distribution features. For instance, the model in the higher (lower) quantile points can perform better to predict stock returns in the market booms (crashes). Therefore, this paper offers a new perspective with the theoretical/econometric strand and makes complements on the literature in the return autocorrelations and predictability in the Chinese stock market[2]. Besides, in the literature, most scholars research the causes of return autocorrelations in theory and some apply the linear models to analyze return autocorrelations and predictability in line with the different proportions of stock characteristics. In this paper, we empirically study how return autocorrelations change, in line with different stock characteristics and investor psychology regimes divided by the threshold model. We believe that this model is more reasonable.

2. Literature Review

2.1 Empirical research on return autocorrelations

Efficient Market Hypothesis (Fama, 1970) is criticized by many researchers because they find the obvious stock return autocorrelations and predictability in their empirical work, which can let investors systematically make abnormal profits. For the relationship with stock return autocorrelations and predictability, Amini, Hudson and

[2] Narayan and Bannigidadmath (2015) summarize two strands of studies in return predictability. One is the issue with the theoretical/econometric concerns in testing for return predictability. The other one focuses on the practical (or rather the economic significance) aspect of return predictability.

Keasey (2010) catch stock return predictability despite low autocorrelations by using 30 stocks traded on the London Stock from 1987 to 2007. Kim, Shamsuddin and Lim (2011) employ some statistic tests to show the overall positive (negative) autocorrelations in stock returns and indicate the presence of statistically significant return predictability by using Dow Jones Industrial Average index from 1900 to 2009. Kinnunen (2013) finds that return autocorrelations is one source of predictability of the Russian aggregate stock market returns during the periods of low information flow from 1999 to 2012. Therefore, we acknowledge that return autocorrelations can reflect predictability, to some degree.

In some empirical research on return autocorrelations, Poterba and Summers (1988) and Conrad and Kaul (1988) find the positive autocorrelations in the short horizon by using the value-weighted and equal weighted NYSE indices and the weekly portfolio in CRSP from 1926 to 1985, respectively. Lo and MacKinlay (1988) find there exists the first-order weekly return autocorrelations of approximately 30% in the CRSP equally-weighted index and notice autocorrelations decrease from 1962 to 1985. Lehmann (1990) uses almost all the securities listed in the NYSE and AMEX to build portfolio and find significant weak autocorrelations. Campbell and MacKinley (1997) find the significant positive autocorrelations of daily, weekly and monthly stock index returns comprised in all the NYSE, AMEX and NASDAQ common stocks from 1963 to 1994. Some scholars employ quantile autoregression models to estimate return autocorrelations. Baur, Dimpfl and Jung (2012) use 30 years of daily, weekly and monthly returns of the stocks comprised in the Dow Jones Stoxx 600 index and find that lower quantiles exhibit positive dependence on past returns while upper quantiles are marked by negative dependence. Gębka and Wohar (2013) use 423 UK stocks and find autocorrelations in lower quantiles are predominantly positive, whereas those in the remaining quantiles are negative.

Some scholars find significant return autocorrelations of individual stocks by using CRSP stock returns, such as Lehmann (1990), Conrad, Kaul and Nimalendran (1991), McKenzie and Faff (2005). Besides for the US stock market, Shen and Wang

(1998) employ 24 daily stock series in the Taiwan stock exchange and finds nearly half of the stocks have daily positive autocorrelations. Säfvenblad (2000) selects 62 major stocks traded in the Stockholm Stock Exchange and finds stock returns are strongly positively autocorrelated. De Penya and Gil-Alana (2007) find that the IGBM daily returns have positive and large autocorrelation coefficients from 1966 to 2002. Besides, some scholars find return autocorrelations and predictability are not rare in the Chinese and Indian stock markets by using data in the intraday and other frequencies, such as Narayan et al. (2014), Narayan and Bannigidadmath (2015) and Bannigidadmath and Narayan (2016). In the research on the comparison with the developed and emerging markets, Harvey (1995a, 1995b) reports that return predictability and serial correlation in the emerging stock markets are higher than the developed markets. De Santis and Imrohoroglu (1997) also obtain the significant first lagged return autocorrelations in the emerging markets while individual securities only show weak positive or negative autocorrelations in the developed markets.

In methodology, many scholars above employ the linear models to estimate the return autocorrelations, such as Poterba and Summers (1988), Shen and Wang (1998), Lehmann (1990), Säfvenblad (2000) and Baur, Dimpfl and Jung (2012). However, it is thought that asymmetry and skewness are present in the return series. It is not suitable to fit this type of data by using linear autoregressive models (Tong, 1978; Tong and Lim, 1980). Kahneman and Tversky (1979) confirm the reasons of asymmetric behaviors in stock returns that investors evaluate values from gains and losses with respect to a specific reference, and their utility functions are unbalanced in gains and losses. Therefore, in some empirical work, McMillan (2004) adopts the nonlinear models to explain the asymmetric behaviors of UK stock returns. Chang (2009) finds that predictability of stock returns changes over time by using S&P 500 Composite Stock index. The predictability is stronger in bad times than in good times.

2.2 The causes for return autocorrelations

Boudoukh, Richardson and Whitelaw (1994) summarize the explanations for return autocorrelations from three schools. The first school (The loyalist) believes that return autocorrelations in the short horizon attributes to market frictions, including nonsynchronous trading (Scholes and Williams, 1977; Lo and MacKinlay, 1990), price discreteness or bid-ask spreads. The second school (The revisionist) believes that return autocorrelations is consistent with time-varying economic risk premiums induced by variation in risk factors (Fama and French, 1988; Conrad and Kaul, 1988). In the empirical research, Gębka and Wohar (2013) link observable features of stocks, such as size, trading volume, volatility, etc, with the theoretical determinants of autocorrelations, including nonsynchronous trading, bid–ask-bounce and partial price adjustment effects. They find the features of stocks can significantly affect return autocorrelations. Narayan and Bannigidadmath (2015) and Westerlund, Narayan and Zheng (2015) also use the features of stocks and obtain similar results in Indian and Chinese stock markets, respectively. McKenzie and Kim (2007) apply the M-GARCH model and find the evidence of a relationship between autocorrelations and volatility by using the FTSE100 market index as well as 20 individual stocks listed on the LSE from 1986 to 2003. Anderson, Eom, Hahn and Park (2013) test the contributions of nonsynchronous trading, bid–ask bounce, partial price adjustment and time-varying risk premia to daily return autocorrelations and find partial price adjustment is an important source on return autocorrelations, involving small and medium firms and most large firms. The tests cover both individual stock return autocorrelations and portfolio return autocorrelations.

The third school believes that investors are not rational and psychological factors matter in security pricing. Specifically, return autocorrelations exists because investors either overact or partially adjust to the arriving market information. Psychological biases include conservatism (Veronesi, 1999), overconfidence and self-attribution bias (Daniel, Hirshleifer and Subrahmanyam, 1998). To be specific, Veronesi (1999) reveals that investors are inclined to overreact to the bad news during market booms and underreact to the good news during market depressions. De Bondt and Thaler (1985, 1987) argue that good and bad news can attribute to return autocorrelations because of investors' overreaction and underreaction. Daniel, Hirshleifer and Subrahmanyam (1998) conclude that overconfidence and self-attribution bias are the key reasons for investors to overreact and underreact. They believe that overreaction causes positive return autocorrelations while negative return autocorrelations is the result of reverse adjustment of price. In the empirical work, Bohl and Siklos (2008) find the presence of the positive feedback trading has a significant role on the stock return autocorrelations since this strategy may be caused by some investors' behavioral biases (De Long et al., 1990). Meanwhile, autocorrelations is expected higher in the presence of herding (Gebka et al., 2013). Lewellen (2002) and Baur, Dimpfl and Jung (2012) also empirically confirm the relationship with overreaction (underreaction) and return autocorrelations by researching the US and European stock markets.

Moreover, Glosten, Jagannathan and Runkle (1993) think that information autocorrelations and inadequate price response to the public information can lead to return autocorrelations. Amihud and Mendelson (1986) attribute autocorrelations to the overreaction to the lagged information. Mech (1993) notices that transaction cost and time, which investors need to process and make decisions, let price slowly adjust to the information and lead to return autocorrelations. Copeland (1976) and Jennings, Starks and Fellingham (1981) and Holden and Subrahmanyam (1992) think sequentially arriving information and information acquisition by agents are also the important reasons for return autocorrelations. Hong, Torous and Valkanov (2007) and Rapach, Strauss and Zhou (2013) suggest that the extent of return autocorrelations and predictability across stocks are driven partly by information frictions.

3. Methodology

3.1 Regression model

Quantile regression (Koenker and Basset, 1978) provides an insight into the relationship at different tails of the response distribution on the covariates. Let y be the response variable of interest and x be a p-dimensional vector of covariates. At any given quantile level τ, we define $Q_y(\tau \mid x)$ as the τ th conditional quantile of y given x which is $Q_y(\tau \mid x) = F^{-1}(\tau) = \inf\{t : F(t \mid x) \geq t\}$, where $F(\cdot \mid x)$ is the conditional distribution of y given x. We consider the following conditional quantile regression model as

$$Q_y(\tau \mid x) = x^{'}\beta(\tau),$$

where $\beta(\tau)$ is a unknown p-dimensional regression coefficient. We could gain a more complete picture of the underlying structure of the conditional distribution of y by considering different quantiles (Koenker and Basset, 1978).

Besides, some scholars apply the quantile technique on the time series. Koenker and Xiao (2006) propose the linear quantile autoregressive model, restricting the autoregressive parameters which may vary with quantiles. They also show the asymptotic distribution of the parameter estimators and the limiting distribution of the autoregression quantile process. In order to combine the advantages of the quantile technique and the threshold models (Tong, 1978; Tong and Lim, 1980), Galvao, Montes-Rojasb and Olmoc (2010) consider the threshold quantile autoregressive model and derive the asymptotic normality of the slope parameter estimators.

The conditional threshold quantile autoregressive function of y_t can be written as

$$Q_{y_t}(\tau \left| \Im_{t-1} \right.) = \begin{cases} \theta_{01}(\tau) + \theta_{11}(\tau) y_{t-1} + \ldots + \theta_{p1}(\tau) y_{t-p}, & q_t \le \gamma(\tau), \\ \theta_{02}(\tau) + \theta_{12}(\tau) y_{t-1} + \ldots + \theta_{p2}(\tau) y_{t-p}, & q_t > \gamma(\tau), \end{cases} \tag{1}$$

where $\Im_{t-1}$ denotes the $\sigma -$ field generated by $\left\{ y_s, s \le t-1 \right\}$. The threshold variable is q_t. The parameter $\theta(\tau) = (\theta^1(\tau), \theta^2(\tau))^{'}$ is a 2(p+1) dimensional vector, where $\theta^1(\tau) = (\theta_{01}(\tau), \theta_{11}(\tau), \cdots, \theta_{p1}(\tau))$ and $\theta^2(\tau) = (\theta_{02}(\tau), \theta_{12}(\tau), \cdots, \theta_{p2}(\tau))$ represent the parameters in the first and second segment, respectively. The model allows for the different values of the threshold parameter $\gamma(\tau)$ across different quantiles.

For the notation simplicity, the conditional quantile of y_t is then modeled by

$$Q_{y_t}(\tau \left| \Im_{t-1} \right.) = h(\tau, \gamma(\tau))$$

with a piecewise linear process defined by $h(\tau, \gamma(\tau)) = x_t(\gamma(\tau))^{'}\theta(\tau)$, where

$x_t = (1, y_{t-1}, \cdots, y_{t-p})'$ and

$$x_t(\gamma(\tau)) = \begin{pmatrix} I\{y_{t-1} \le \gamma(\tau)\} & I\{y_{t-1} > \gamma(\tau)\} \\ y_{t-1}I\{y_{t-1} \le \gamma(\tau)\} & y_{t-1}I\{y_{t-1} > \gamma(\tau)\} \\ \cdots & \\ y_{t-p}I\{y_{t-1} \le \gamma(\tau)\} & y_{t-p}I\{y_{t-1} > \gamma(\tau)\} \end{pmatrix},$$

with an indicator function $I\{\cdot\}$.

In the following parts, we give a belief description on the threshold estimation and testing procedure (Galvao et al., 2010). In details, we first introduce the estimation method for the threshold effect according to the quantile check loss function, and then describe the testing procedure for the existence of the threshold effect based on the Wald-type statistic.

3.2 Estimation

Some researchers study the estimation procedure in the threshold regression model by using two-stage methods. Chan and Tsay (1998) study the least squares estimators based on a two-stage method in a two-phase threshold autoregressive model, and show their limiting properties. Koenker and Xiao (2006) propose a two-stage estimation procedure for the threshold parameters and the corresponding coefficients in the quantile autoregressive model.

Galvao, Montes-Rojasb and Olmoc (2010) derive an estimation procedure for the parameters $(\theta(\tau), \gamma(\tau))$ by using a similar idea like the two-stage methods above. Galvao, Montes-Rojasb and Olmoc (2010) define

$$S(\theta(\tau), \gamma(\tau)) = \sum_{t=1}^{T} \rho_\tau(y_t - x_t(\gamma(\tau))'\theta(\tau)),$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ is the quantile check loss function. The parameter $(\theta(\tau), \gamma(\tau))$ is estimated by

$$(\hat{\theta}(\tau), \hat{\gamma}(\tau)) = \arg \min_{(\theta(\tau), \gamma(\tau))} S(\theta(\tau), \gamma(\tau)),$$

which is implemented by the two-stage profile procedure as follows. In the first stage, for a given threshold value $\gamma(\tau)$, the parameter $\theta(\tau)$ is estimated by

$$\hat{\theta}(\gamma(\tau)) = \arg\min_{\theta(\tau)} S(\theta(\tau), \gamma(\tau)).$$

In the second stage, considering a grid of $\gamma(\tau)$ values in the real line, the threshold value can be estimated by $\hat{\gamma}(\tau) = \arg\min_{\gamma(\tau)} S\{\hat{\theta}(\gamma(\tau)), \gamma(\tau)\}$. Then the final parameter estimators are given by $(\hat{\theta}(\hat{\gamma}(\tau)), \hat{\gamma}(\tau))$.

3.3 Test for the threshold effect

It is significant to test the existence of the threshold effect in the regression model before we estimate. In line with Galvao, Montes-Rojasb and Olmoc (2010), we propose the supremum Wald test to detect the threshold effect on the space $\gamma(\tau) \in \mathrm{T}$. The composite hypothesis on the linearity of the model is given as

$$H_0 : R\theta_\gamma(\tau) = 0 \; \textit{for all} \; \gamma(\tau) \in \mathrm{T} \quad \textit{v.s.} \quad H_1 : R\theta_\gamma(\tau) \neq 0 \; \textit{for some} \; \gamma(\tau) \in \mathrm{T},$$

where 0 is p-dimension of zeros, $\theta_\gamma(\tau) = \arg\min_{\theta(\tau)} E[\rho_\tau(y_t - x_t(\gamma(\tau))'\theta(\tau))]$, R is a $(1+p)\times(2(1+p))$ full rank matrix.

The null hypothesis is there exists no threshold effect and the alternative hypothesis is there exists one threshold effect. Andrews and Ploberger (1994), Hansen (1996) and Galvao, Montes-Rojasb and Olmoc (2010) propose the supremum Wald test on the space $\gamma(\tau) \in \mathrm{T}$ for the fixed τ to detect the existence of the threshold effect. In addition, they study the consistency and asymptotic normality of the parameter estimators of $\theta_0(\tau)$ in the quantile framework. They show the asymptotic distribution of the test statistic on the regression function's linearity under the null hypothesis. A more comprehensive review of the threshold quantile autoregressive model can be found in Galvao, Montes-Rojasb and Olmoc (2010).

3.4 Data

In this paper, we collect the data of the stock index and individual stocks. The stock index refers to the Shanghai A-share index and the individual stocks are 741 constituent stocks in the Shanghai A-share index[3]. These stocks cover 13 industries in the Industry Classification Guideline made by China Securities Regulatory Commission (CSRC). The data frequency is daily from 2005 to 2014.

In order to analyze the determinants of return autocorrelations, we collect some stock characteristics in line with Gębka and Wohar (2013). The characteristics include size, volatility, trading volume, liquidity, price-earnings ratio (P/E) and market to book value (MB). Meanwhile, we employ investor sentiment to proxy for psychological biases.

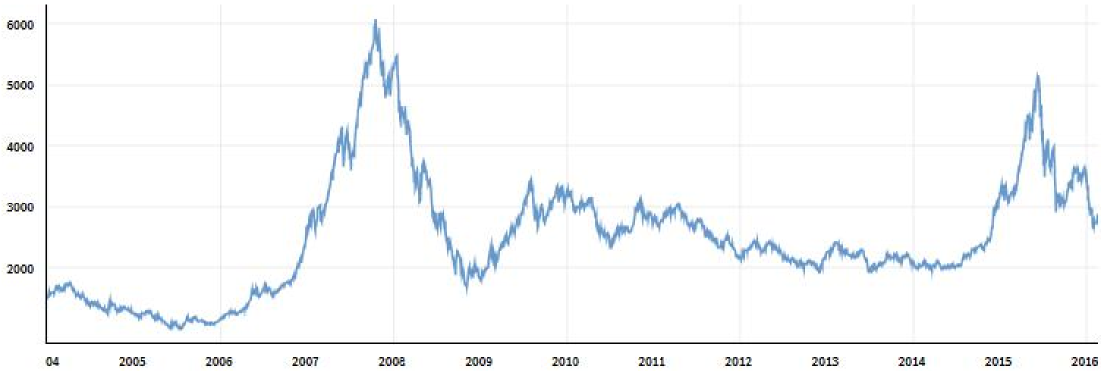

Figure 1 Stock returns in the Shanghai A-share index

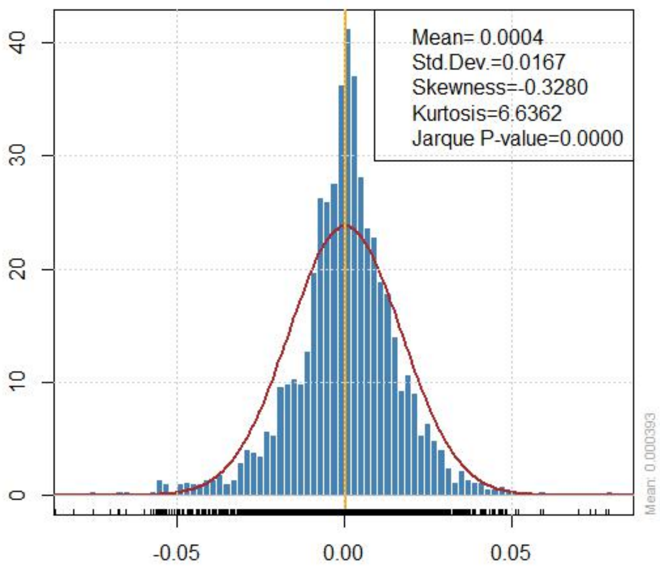

Figure 2 The histogram of stock returns in the Shanghai A-share index

[3] Since some companies are open listed after 2005 and have many missing observations, we do not include these companies in this paper.

Table 1 Descriptive statistics in the Shanghai A-share market[4]

	P/E	MB	Trading volume	Market size	Volatility	Liquidity
Mean	20.585	2.515	909.349	16295.824	24.739	0.672
Standard deviation	11.057	1.254	701.406	7411.145	7.677	0.357
Min	8.900	1.210	36.700	2270.000	15.824	0.144
Max	56.130	7.130	7925.920	35500.000	40.254	3.653

Figure 1 shows the fluctuations of the Shanghai A-share index from 2005 to 2014. We divide the whole period into three stages in line with the market conditions. The first stage comes from 2005 to 2007. The Chinese stock market is in great booms and the Shanghai A-share index rises from about 1251 to the historical highest point 6124. In the second period from 2008 to 2010, the Chinese stock market crashes and the index drops into about 1719. After 2010, the Chinese stock market enters into a long-term recovery period. Figure 2 shows the distribution of the Chinese A-share index returns is not normal, has an obvious asymmetric and fat-tail features in line with some statistics. Therefore, we believe that the threshold quantile autoregressive model employed in this paper is suitable to fit the returns in this type. Table 1 shows the descriptive statistics in the Shanghai A-share market and we find that there exist large fluctuations in the Shanghai A-share market. It is mainly shown by the change of trading volume and market size.

4. Empirical results

4.1 Results of autocorrelations on the endogenous threshold variable

We employ the threshold quantile autoregressive model to estimate return autocorrelations in the Shanghai A-share index from 2005 to 2014. The threshold variable we choose is the first lagged returns RN_{t-1} since we think the first lagged returns RN_{t-1} has a large direct impact on the RN_t. The selection standard on the lagged number is the Akaike information criterion (AIC). The model is showed as:

$$RN_t = \begin{cases} \alpha_1 + \beta_{11}RN_{t-1} + \beta_{12}RN_{t-2} + \beta_{13}RN_{t-3} + \varepsilon_t, & RN_{t-1} \le \gamma, \\ \alpha_2 + \beta_{21}RN_{t-1} + \beta_{22}RN_{t-2} + \beta_{23}RN_{t-3} + \varepsilon_t, & RN_{t-1} > \gamma, \end{cases} \tag{2}$$

where $t = 1,\dots T$, is the number of time. RN_t denotes stock returns at time *t*. RN_{t-2}

[4] The unit of trading volume and market size is billion in RMB.

and RN_{t-3} are the control variables[5]. It is noted that the conditional return autocorrelations in this paper is estimated by the quantile regression method which is regressing y_t on $(x_t \otimes I(y_{t-1} \le \gamma(\tau)), x_t \otimes I(y_{t-1} > \gamma(\tau)))$, where $I(\cdot)$ denotes the indicator function. We define conditional return autocorrelations as the first-order autoregressive parameters in the threshold quantile autoregressive model, that is, β_{11} in the higher regime and β_{21} in the lower regime.

Table 2 shows that the threshold points are very significant in the results of the OLS and quantile regression models. It shows that the influences of the first lagged returns on the current returns should be divided into two regimes. Compared with the lower regime and higher regime, divided by the threshold point 0.001, we find that the first-lagged autoregressive coefficients are significant negative in the lower regime. In the higher regime, the first lagged autoregressive coefficients are significant positive. This result shows that stock returns has a reversal pattern or a momentum pattern in two regimes. In line with Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), Hong and Stein (1999) and Lewellen (2002), they regard that short-run momentum (long-term reversals) is associated with positive (negative) autocorrelations of short-term returns separated by short (long) lags. Pan (2010) thinks price momentum is analogical to positive autocorrelations in stock returns, which could arise because of investors' underreaction or continuing overreaction to news.

Meanwhile, we find that return autocorrelations is large in the higher quantiles. In details, the first-lagged coefficients are -0.247 and 0.371 in the 90% quantile in the lower regime and higher regime, respectively. The larger coefficients in the higher quantiles show the Chinese stock market has an evident overreaction. Veronesi (1999) and Baur, Dimpfl and Jung (2012) explain that a good (bad) state can be associated with the upper (lower) quantiles and the stock market overreacts to bad news in good times and underreacts to good news in bad times. The coefficients in more quantiles can be found in Figure 3.

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[5] Since the results of two thresholds are not very significant, we only choose the model with one threshold.

Table 2 Results of the regression models on the endogenous threshold variable

Quantile	Lower regime				Higher regime				Threshold	Wald-test
	Constant	R(-1)	R(-2)	R(-3)	Constant	R(-1)	R(-2)	R(-3)		
10	-0.032***	-0.233	-0.177	0.352***	-0.018***	-0.011	0.128***	0.045	-0.019***	0.005
	(0.007)	(0.164)	(0.145)	(0.105)	(0.001)	(0.058)	(0.040)	(0.051)		
20	-0.022***	-0.267	-0.139	0.248***	-0.010***	0.058	0.100***	0.048*	-0.019***	0.005
	(0.008)	(0.265)	(0.196)	(0.048)	(0.000)	(0.046)	(0.034)	(0.029)		
30	-0.015***	-0.277**	-0.120	0.258***	-0.006***	0.048	0.058*	0.056**	-0.019***	0.000
	(0.004)	(0.113)	(0.085)	(0.057)	(0.000)	(0.038)	(0.030)	(0.027)		
40	-0.008**	-0.212*	-0.051	0.196**	-0.002***	0.037	0.035	0.038	-0.019**	0.030
	(0.004)	(0.114)	(0.086)	(0.075)	(0.000)	(0.033)	(0.028)	(0.025)		
50	-0.001	-0.137***	-0.002	0.065**	0.0002	0.123**	-0.001	0.064**	0.001**	0.015
	(0.001)	(0.041)	(0.037)	(0.031)	(0.001)	(0.056)	(0.037)	(0.034)		
60	0.001	-0.164***	0.019	0.069**	0.002**	0.129**	-0.039	0.052	0.001***	0.005
	(0.001)	(0.045)	(0.037)	(0.032)	(0.001)	(0.052)	(0.034)	(0.034)		
70	0.006***	-0.145***	0.047	0.061***	0.005***	0.178***	-0.087**	0.029	0.004***	0.000
	(0.001)	(0.045)	(0.033)	(0.031)	(0.001)	(0.058)	(0.040)	(0.035)		
80	0.009***	-0.201***	0.061	0.037	0.009***	0.232**	-0.120***	-0.002	0.004***	0.000
	(0.001)	(0.047)	(0.039)	(0.034)	(0.002)	(0.111)	(0.044)	(0.039)		
90	0.016***	-0.247***	-0.038	-0.005	0.015***	0.371**	-0.211***	-0.010	0.004***	0.000
	(0.001)	(0.042)	(0.043)	(0.048)	(0.002)	(0.150)	(0.043)	(0.052)		
OLS	-0.011***	-0.340***	-0.076	0.178**	0.0002	0.058*	0.004	0.000	-0.019***	0.000
	(0.003)	(0.099)	(0.073)	(0.073)	(0.0004)	(0.035)	(0.026)	(0.029)		

Note: ***, ** and * show the significance at the level of 1%, 5 % and 10%, respectively. Standard error is provided in parentheses. The values in the column of the Wald-test are P-value.

Table 3 Results of the regression models on the endogenous threshold variable in the three periods

	2005-2007			2008-2009			2010-2014		
Quantile	Lower regime R(-1)	Higher regime R(-1)	Threshold Wald-test	Lower regime R(-1)	Higher regime R(-1)	Threshold Wald-test	Lower regime R(-1)	Higher regime R(-1)	Threshold Wald-test
10	-0.544***	0.192**	-0.019***	-0.302**	-0.344	0.010***	0.317	0.254***	-0.014**
	(0.146)	(0.097)	(0.000)	(0.151)	(0.344)	(0.000)	(0.656)	(0.078)	(0.015)
20	-0.490***	0.196***	-0.019***	-0.375**	-0.052	-0.005*	0.311	0.204***	-0.014***
	(0.180)	(0.064)	(0.000)	(0.165)	(0.101)	(0.095)	(0.301)	(0.048)	(0.000)
30	-0.490***	0.170***	-0.019***	-0.423***	-0.089	-0.005**	-0.135***	0.092	0.008***
	(0.152)	(0.060)	(0.010)	(0.141)	(0.101)	(0.025)	(0.048)	(0.111)	(0.000)
40	-0.415***	0.107**	-0.019*	-0.255*	-0.146	-0.005	-0.111**	0.098	0.008**
	(0.160)	(0.060)	(0.085)	(0.154)	(0.113)	(0.545)	(0.045)	(0.129)	(0.025)
50	-0.097	0.232**	0.003	-0.284**	-0.140	-0.005	-0.081	0.159***	-0.002*
	(0.090)	(0.093)	(0.450)	(0.133)	(0.114)	(0.800)	(0.077)	(0.059)	(0.065)
60	-0.106*	0.076	0.014	-0.631*	0.025	-0.032	0.011	0.062	-0.014
	(0.061)	(0.152)	(0.290)	(0.377)	(0.083)	(0.935)	(0.152)	(0.043)	(0.390)
70	-0.206**	0.276**	0.003*	-0.179**	-0.166	0.005	-0.055	0.085	0.000
	(0.089)	(0.102)	(0.070)	(0.087)	(0.168)	(0.230)	(0.066)	(0.067)	(0.295)
80	-0.231**	0.192	0.003	-0.254***	-0.187	0.005	-0.147	-0.005	-0.008
	(0.089)	(0.122)	(0.185)	(0.089)	(0.155)	(0.270)	(0.135)	(0.051)	(0.395)
90	-0.201**	0.423***	0.003**	-0.075	0.703	0.027	-0.284	0.073	-0.008***
	(0.098)	(0.143)	(0.025)	(0.070)	(0.464)	(0.150)	(0.190)	(0.077)	(0.005)
OLS	-0.492***	0.084	-0.019***	-0.119	-0.114	0.010	-0.018	0.088**	-0.014***
	(0.116)	(0.051)	(0.000)	(0.074)	(0.185)	(0.030)	(0.117)	(0.041)	(0.000)

Note: ***, ** and * show the significance at the level of 1%, 5 % and 10%, respectively. Standard error of the coefficients and P-value of the Wald-test are provided in parentheses, respectively. We do not report the coefficients of the second and third lagged returns because of the limitations of the space.

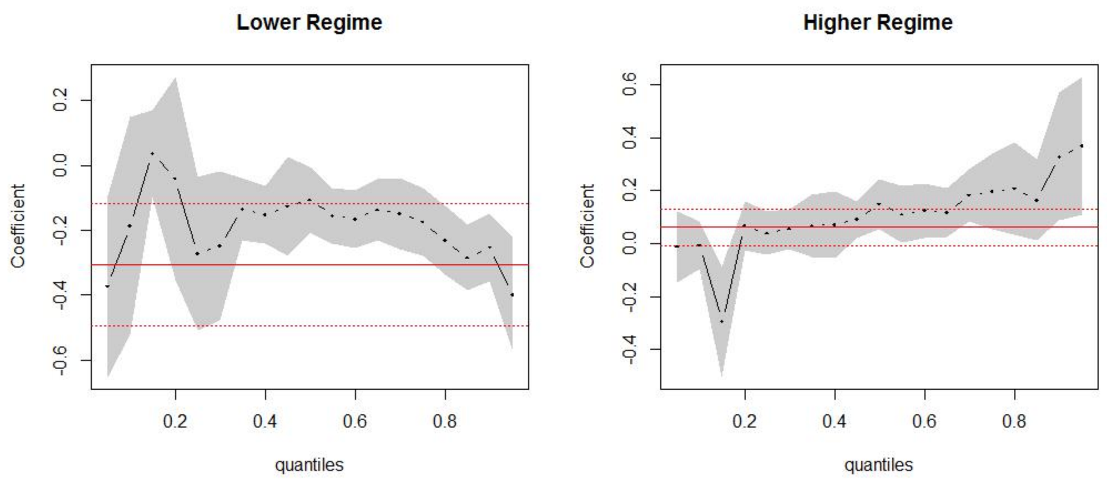


Figure 3 The first-lagged threshold quantile coefficients in two regimes

Note: The first-lagged coefficients in two regimes are estimated by 19 quantiles from 5% to 95%.

Lo and MacKinlay (1990), Moskowitz and Grinblatt (1999), Lewellen (2002), Pan, Liano and Huang (2004), Baur, Dimpfl and Jung (2012), Narayan and Bannigidadmath (2015) and Westerlund, Narayan and Zheng (2015) find the industry effect exists in the autocorrelations and momentum of stock returns. In order to further research the return autocorrelations in the industry effect, we build 13 industries' portfolio in line with the Industry Classification Guideline made by China Securities Regulatory Commission (CSRC). We find that the first-lagged autoregressive coefficients are positive in the higher regime and negative in the lower regime in the most industries. Meanwhile, the positive first-lagged autoregressive coefficients in the higher regime are more significant than the negative autoregressive coefficients in the lower regime. In details, we could find the first-lagged autoregressive coefficients in the higher regime in the financial & insurance industry, real estate industry, agriculture and relevant industry and manufacture industry are significantly large. In the lower regime, the first-lagged autoregressive coefficients in the financial & insurance industry, extractive industry, social service industry and communication & culture industry are significantly large[6].

Table 3 shows the results of the threshold quantile autoregressive models in the three periods. We find the threshold points have large differences. In the 50% quantile, the threshold points are 0.003, -0.005 and 0.025, respectively. From 2005 to 2007, the

[6] Since the limitations of the space, we do not report the specific results in the return autocorrelations in the industry effect in this paper.

threshold points are significant and divide the stock returns into two regimes. In the lower regime, the negative first-lagged autoregressive coefficients are significant. In the higher regime, the positive first-lagged autoregressive coefficients are significant especially in the higher quantiles, which is judged by a good (bad) state associated with the upper (lower) quantiles. We acknowledge that Chinese investors tend to overreact in the extreme market conditions.

In the Chinese stock market clash from 2008 to 2009, the threshold points are not very significant in some quantiles. In the lower regime, most first-lagged autoregressive coefficients are significant but in the higher regime, the autoregressive coefficients are not significant since stock returns falls greatly in this period. From 2010 to 2014, the autoregressive coefficients are not very significant in both regimes since the stock market does not have large fluctuations.

In line with Poterba and Summers (1988), Lehmann (1990) and Conrad and Gultekin, Kaul (1997), we know that return autocorrelations of an index and individual stocks has large differences. We attempt to apply the threshold quantile autoregressive model to estimate the return autocorrelations of individual stocks and calculate their descriptive statistics. Table 4 shows the first-lagged autoregressive coefficients of most individual stocks are significant in the 10% and 90% quantiles but the autoregressive coefficients in the 50% quantile are not very significant. In details, the percent of significant first-lagged autoregressive coefficients in the lower regime is 89.07%, 26.45% and 76.25% in the 10%, 50% and 90% quantiles, respectively. The percent of significant first-lagged autoregressive coefficients in the higher regime are 40.49%, 22.81% and 90.69% in the 10%, 50% and 90% quantiles, respectively. It means that individual stocks have more significant return autocorrelations when the stock market is in the extreme conditions.

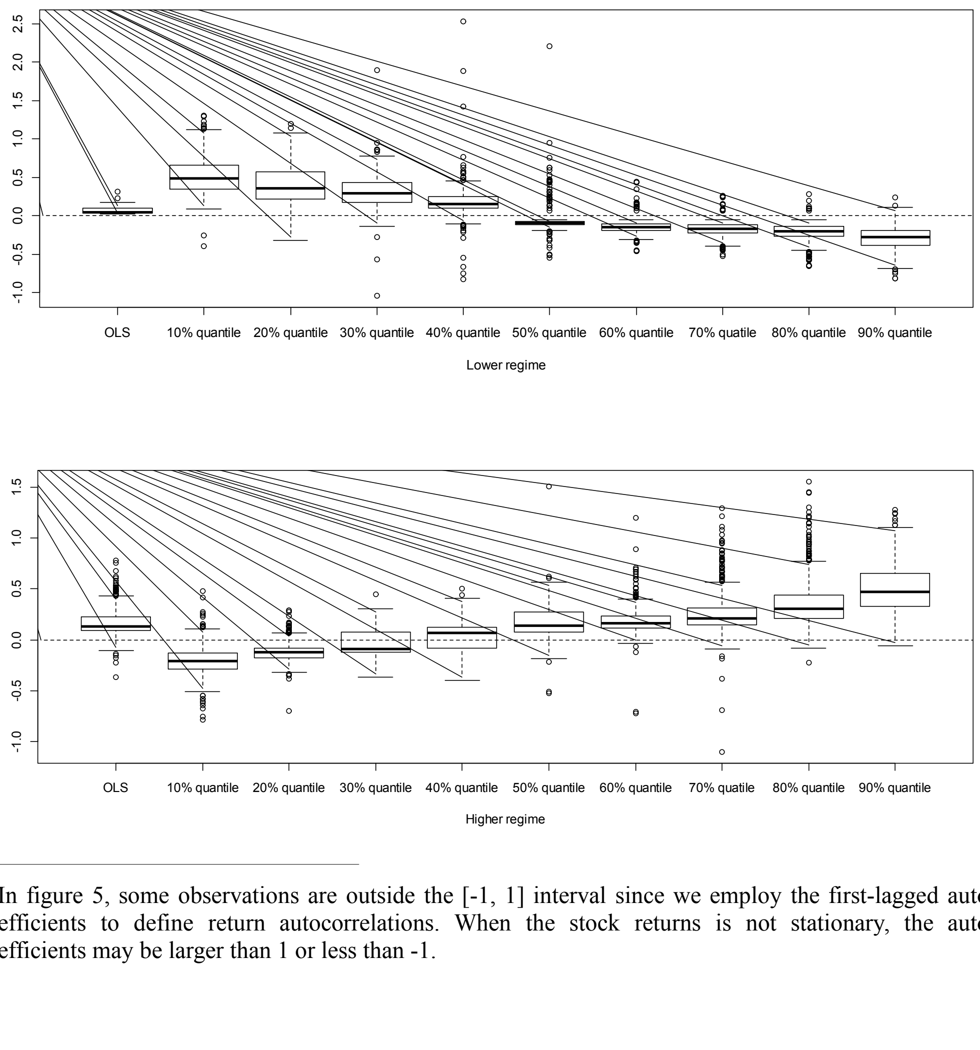
Besides, it is noted that the first-lagged autoregressive coefficients of individual stocks in the higher regime are significant positive and the first-lagged autoregressive coefficients in the lower regime are significant negative in the 50% and 90% quantiles. This finding is similar as the return autocorrelations of the Shanghai A-share index.

Combined with Figure 5[7], we find the first-lagged autoregressive coefficients are significant negative in the higher quantiles in the lower regime. The first-lagged autoregressive coefficients are significant positive in the higher quantiles in the higher regime.

Table 4 Descriptive statistics in the first-lagged autoregressive coefficients of individual stock returns

	OLS		10% quantile		50% quantile		90% quantile	
AC	Lower regime	Higher regime	Lower regime	Higher regime	Lower regime	Higher regime	Lower regime	Higher regime
Mean	0.072	0.176	0.512	-0.200	-0.031	0.181	-0.293	0.504
Standard deviation	0.049	0.136	0.235	0.165	0.261	0.198	0.145	0.225
Min	0.021	-0.365	-0.391	-0.787	-0.545	-0.522	-0.815	-0.054
Max	0.312	0.779	1.308	0.483	2.208	1.507	0.243	1.275
Number	203	456	660	300	196	169	565	672
Percent	27.40%	61.54%	89.07%	40.49%	26.45%	22.81%	76.25%	90.69%

Note: We list the number of individual stocks and the percent of the significant first-lagged autoregressive coefficients in the 10% level. The period is from 2005 to 2014.



[7] In figure 5, some observations are outside the [-1, 1] interval since we employ the first-lagged autoregressive coefficients to define return autocorrelations. When the stock returns is not stationary, the autoregressive coefficients may be larger than 1 or less than -1.

Figure 5 The first-lagged autoregressive coefficients in the different quantiles of return distribution

Note: The first-lagged autoregressive coefficients of the individual stocks are estimated by 741 individual stocks from 2005 to 2014.

Besides, we find the first-lagged autoregressive coefficients in the higher quantiles are larger than the first-lagged autoregressive coefficients in the other quantiles and OLS. In the lower regime, the negative first-lagged autoregressive coefficients in the higher quantiles are much less than the first-lagged autoregressive coefficients in the lower quantiles. In the higher regime, the positive first-lagged autoregressive coefficients in the higher quantiles are much larger than the first-lagged autoregressive coefficients in the lower quantiles. It means that Chinese investors overreact or underreact in the extreme market conditions because of psychological biases and irrational investment behaviors (Veronesi, 1999; Pan, 2010)

4.2 Results of autocorrelations on the exogenous threshold variables

Gębka and Wohar (2013) think stock characteristics can influence return autocorrelations by some transmission channels, including nonsynchronous trading, bid–ask bounce and partial price adjustment. The stock characteristics include size, volatility, trading volume, liquidity, price-earnings ratio (P/E) and market to book value (MB). Narayan and Bannigidadmath (2015), Westerlund, Narayan and Zheng (2015) also apply some similar stock characteristics to research return autocorrelations and predictability. Meanwhile, some scholars regard that overreaction and underreaction caused by conservatism, overconfidence and self-attribution bias can attribute to return autocorrelations (De Bondt and Thaler, 1985, 1987; Daniel, Hirshleifer and Subrahmanyam, 1998; Hong and Stein, 1999; Veronesi, 1999). In order to proxy the psychological factors above, we employ trading volume to be investor sentiment to reflect (Scheinkman and Xiong, 2003). Therefore, in this paper, we apply the stock characteristics and investor sentiment as exogenous threshold variables. The model is shown as[8]

[8] In order to analyze more specific influences of the stock characteristics and psychological factors, we choose to set three regimes in the threshold quantile autoregressive model.

$$RN_t = \begin{cases} \alpha_{11} + \beta_{11} RN_{t-1} + \beta_{12} RN_{t-2} + \beta_{13} RN_{t-3} + \varepsilon_t\,, & Q_t \le \gamma_1\,, \\ \alpha_{21} + \beta_{21} RN_{t-1} + \beta_{22} RN_{t-2} + \beta_{23} RN_{t-3} + \varepsilon_t\,, & \gamma_1 < Q_t \le \gamma_2\,, \\ \alpha_{31} + \beta_{31} RN_{t-1} + \beta_{32} RN_{t-2} + \beta_{33} RN_{t-3} + \varepsilon_t\,, & Q_t > \gamma_2\,, \end{cases} \tag{3}$$

where $t = 1, \ldots T$, is the number of time. RN_t denotes stock returns at time t. Q_t shows the stock characteristics, including liquidity, volatility, MB ratio, and investor sentiment[9]. RN_{t-2} and RN_{t-3} are the control variables.

Table 4 shows the return autocorrelations of the Shanghai A-share index. We find the first-lagged autoregressive coefficients are not very significant in the higher regime of market liquidity but the first-lagged autoregressive coefficients are significant negative in the small and middle regimes of market liquidity in the higher quantiles. It means that high market liquidity can significantly decrease return autocorrelations since liquidity-motivated trades can obtain more information and result in lower autocorrelations (Amihud and Mendelson, 1987; Chordia and Swaminathan, 2000; Acharya and Pedersen, 2005). We also employ volatility as the exogenous threshold variable and find the first-lagged autoregressive coefficients are not significant when volatility is in the higher regime. However, the first-lagged autoregressive coefficients are significant when volatility is in the small and middle regimes. It supports that high volatility can reflect the large changes in fundamental value and potential losses from nonsynchronous trading. It results in less likely nonsynchronous trading and weaker return autocorrelations (Ho, 1983; O'Hara and Oldfield, 1986).

Besides, we use MB ratio as the exogenous threshold variable. We find the first-lagged autoregressive coefficients are very significant in the higher regime of MB ratio in the high quantiles. In the middle and lower regimes of MB ratio, the first-lagged autoregressive coefficients are not very significant. Vassalou (2003) explains that the firms with high MB ratio contain a large amount of news related with the future GDP growth. Growth stocks can generate much news. The consequent

[9] We do not report the results of stock size and P/E ratio since we find their influences are not significant after running the regression models. In the causes of insignificant effects of stock size and P/E ratio on the return autocorrelations in the Chinese stock market, we think that the degree of asymmetric information of the different stock size is very close. Chinese investors put more weights on the stock price spread and have more short-term investment behaviors. Besides, we notice that heterogeneous predictability caused by industrial sector and MB ratio in the Chinese stock market has a large similarity with the Indian stock market.

trade reduces the probability of nonsynchronous trading and implies the weak return autocorrelations. Furthermore, we use investor sentiment as the threshold variable. We find the first-lagged autoregressive coefficients are very significant in the middle and higher regimes of investment sentiment but the first-lagged autoregressive coefficients are not significant in the lower regimes of investment sentiment. It means that investment sentiment can result into return autocorrelations because of investor sentiment may be caused by conservatism, overconfidence and self-attribution bias (De Bondt and Thaler, 1985, 1987; Daniel, Hirshleifer and Subrahmanyam, 1998; Hong and Stein, 1999; Veronesi, 1999).

Table 5 Results of the regression models on the exogenous threshold variables

Quantile	Market liquidity					Market volatility				
	Lower regime	Middle regime	Higher regime	Low threshold	High threshold	Lower regime	Middle regime	Higher regime	Low threshold	High threshold
	R(-1)	R(-1)	R(-1)	Wald-test	Wald-test	R(-1)	R(-1)	R(-1)	Wald-test	Wald-test
10	-0.097^{**}	0.146^{**}	0.076	0.533	1.028	0.117^{*}	0.160^{*}	0.045	24.18	33.16
	(0.041)	(0.065)	(0.252)			(0.066)	(0.086)	(0.081)		
20	-0.024	0.053	0.184^{**}	0.520	0.676	0.081	0.104^{*}	-0.010	16.89	25.65
	(0.045)	(0.083)	(0.072)			(0.105)	(0.057)	(0.048)		
30	-0.063	-0.057	0.064	0.387	0.676	0.080^{**}	-0.003	0.004	26.25	36.48
	(0.053)	(0.035)	(0.067)			(0.038)	(0.051)	(0.093)		
40	-0.073	-0.084^{**}	0.024	0.387	0.693	0.029	0.051	-0.060	22.05	26.25
	(0.055)	(0.035)	(0.050)			(0.033)	(0.069)	(0.038)		
50	-0.082	-0.050	-0.009	0.375	0.744	0.010	-0.024	-0.025	22.95	30.12
	(0.050)	(0.035)	(0.046)			(0.032)	(0.051)	(0.047)		
60	-0.121^{**}	-0.042	-0.055	0.375	0.744	0.027	-0.039	-0.019	22.95	30.12
	(0.051)	(0.034)	(0.043)			(0.031)	(0.054)	(0.046)		
70	-0.094^{**}	-0.061^{*}	-0.049	0.442	0.744	0.035	-0.059	-0.062	22.95	30.12
	(0.038)	(0.036)	(0.035)			(0.028)	(0.042)	(0.045)		
80	-0.139^{***}	-0.151^{***}	-0.060	0.375	0.744	0.060^{*}	-0.055	0.007	22.95	37.81
	(0.039)	(0.040)	(0.040)			(0.033)	(0.041)	(0.070)		
90	-0.136^{***}	-0.114^{***}	-0.125^{***}	0.350	0.744	0.153^{**}	-0.039	-0.028	17.59	24.18
	(0.050)	(0.036)	(0.041)			(0.072)	(0.046)	(0.044)		
OLS	-0.075^{*}	-0.049	0.007	0.375	0.723	0.012	0.011	-0.026	27.47	37.15
	(0.043)	(0.041)	(0.048)			(0.031)	(0.065)	(0.060)		

Note: ***, ** and * show the significance at the level of 1%, 5 % and 10%, respectively. Standard error is provided in parentheses. The values in the columns of the

Wald-test are T-statistics. We do not report the coefficients of the second and third lagged returns because of the limitations of the space.

Table 5 (Cont'd) Results of the regression models on the exogenous threshold variables

	Market MB ratio					Investor sentiment				
Quantile	Lower regime	Middle r egime	Higher regime	Low threshold	High threshold	Lower regime	Middle regi me	Higher regime	Low threshold	High threshold
	R(-1)	R(-1)	R(-1)	Wald-test	Wald-test	R(-1)	R(-1)	R(-1)	Wald-test	Wald-test
10	0.262***	-0.026	0.088	1.73	3.15	-0.032	0.496***	0.012	1164	1594
	(0.060)	(0.052)	(0.160)			(0.038)	(0.138)	(0.108)		
20	0.059	0.087	0.025	2.44	3.15	0.061	-0.159***	0.321***	573	1027
	(0.043)	(0.084)	(0.073)			0.047	(0.054)	(0.056)		
30	0.033	-0.013	0.031	2.36	3.00	0.047	-0.124***	0.164**	549	1027
	(0.036)	(0.054)	(0.077)			(0.047)	(0.034)	(0.069)		
40	0.026	0.041	-0.049	2.32	3.08	0.067	-0.111***	0.070	549	1027
	(0.033)	(0.047)	(0.052)			(0.041)	(0.035)	(0.050)		
50	-0.022	0.044	-0.028	2.48	3.75	-0.050	0.030	-0.010	998	1442
	(0.031)	(0.052)	(0.053)			(0.031)	(0.049)	(0.075)		
60	0.009	0.033	-0.070**	2.22	3.31	-0.027	-0.011	-0.067	767	1375
	(0.033)	(0.047)	(0.048)			(0.038)	(0.036)	(0.049)		
70	-0.012	0.075*	-0.104**	2.48	3.31	-0.018	-0.057	-0.064	767	1375
	(0.029)	(0.046)	(0.041)			(0.039)	(0.039)	(0.039)		
80	0.067	0.019	-0.080*	1.73	3.31	0.000	-0.092**	-0.078*	767	1538
	(0.041)	(0.035)	(0.046)			(0.038)	(0.045)	(0.043)		
90	0.046	-0.002	-0.091*	1.73	2.46	-0.025	-0.197***	-0.024	767	1100
	(0.058)	(0.049)	(0.053)			0.046	0.049	0.042		
OLS	0.118***	-0.003	0.025	1.48	4.00	0.023	-0.103**	0.076	549	1027
	(0.047)	(0.032)	(0.064)			(0.042)	(0.041)	(0.052)		

Note: ***, ** and * show the significance at the level of 1%, 5 % and 10%, respectively. Standard error is provided in parentheses. The values in the columns of the Wald-test are T-statistics. We do not report the coefficients of the second and third lagged returns because of the limitations of the space.

Table 6 Descriptive statistics in the first-lagged coefficients of individual stock returns on the liquidity threshold

	OLS			10% quantile			50% quantile			90% quantile		
AC	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime
Mean	0.012	-0.019	-0.027	0.111	0.049	0.063	-0.096	-0.130	-0.102	-0.092	-0.012	0.036
Standard deviation	0.153	0.104	0.142	0.189	0.158	0.231	0.168	0.157	0.142	0.102	0.157	0.148
Min	-0.171	-0.193	-0.237	-0.214	-0.252	-0.476	-0.511	-0.596	-0.355	-0.242	-0.249	-0.407
Max	0.645	0.451	0.405	0.525	0.506	0.551	0.988	0.507	0.341	0.987	0.610	0.405
Number	297	310	229	124	267	322	218	264	196	405	233	156
Percent	40.24%	42.01%	31.03%	16.80%	36.18%	43.63%	29.54%	35.77%	26.56%	54.88%	31.57%	21.14%

Note: We list the number of individual stocks and the percent of significant autocorrelations at the level of 10%.

Table 7 Descriptive statistics in the first-lagged coefficients of individual stock returns on the volatility threshold

	OLS			10% quantile			50% quantile			90% quantile		
AC	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime
Mean	0.041	0.104	0.119	0.112	0.134	0.150	-0.118	0.045	0.106	0.081	0.112	0.136
Standard deviation	0.128	0.107	0.095	0.138	0.156	0.173	0.204	0.230	0.181	0.111	0.098	0.105
Min	-0.206	-0.280	-0.243	-0.244	-0.229	-0.243	-0.512	-0.480	-0.322	-0.361	-0.921	-0.344
Max	0.340	0.479	0.388	0.407	0.494	0.523	0.411	0.697	0.491	0.306	0.375	0.621
Number	125	180	184	156	226	244	99	149	86	276	374	350
Percent	16.80%	24.19%	24.73%	20.97%	30.38%	32.80%	13.31%	20.03%	11.56%	37.10%	50.27%	47.04%

Note: We list the number of individual stocks and the percent of significant autocorrelations at the level of 10%.

Table 8 Descriptive statistics in the first-lagged coefficients of individual stock returns on the MB ratio threshold

	OLS			10% quantile			50% quantile			90% quantile		
AC	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime
Mean	0.041	0.104	0.119	0.112	0.134	0.150	-0.118	0.045	0.106	0.081	0.112	0.136
Standard deviation	0.128	0.107	0.095	0.138	0.156	0.173	0.204	0.230	0.181	0.111	0.098	0.105
Min	-0.206	-0.280	-0.243	-0.244	-0.229	-0.243	-0.512	-0.480	-0.322	-0.361	-0.921	-0.344
Max	0.340	0.479	0.388	0.407	0.494	0.523	0.411	0.697	0.491	0.306	0.375	0.621
Number	125	180	184	156	226	244	99	149	86	276	374	350
Percent	16.91%	24.36%	24.90%	21.14%	30.62%	33.06%	16.78%	25.25%	14.58%	37.40%	50.68%	47.43%

Note: We list the number of individual stocks and the percent of significant autocorrelations at the level of 10%.

Table 9 Descriptive statistics in the first-lagged coefficients of individual stock returns on the investor sentiment threshold

	OLS			10% quantile			50% quantile			90% quantile		
AC	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime	Lower regime	Middle regime	Higher regime
Mean	-0.005	0.066	0.037	0.107	0.135	0.085	-0.098	-0.056	-0.032	-0.124	0.069	0.099
Standard deviation	0.114	0.098	0.141	0.159	0.137	0.196	0.088	0.213	0.171	0.085	0.101	0.146
Min	-0.168	-0.187	-0.251	-0.240	-0.226	-0.377	-0.517	-0.633	-0.323	-0.326	-0.234	-0.381
Max	0.357	0.336	0.496	0.477	0.501	0.539	0.366	0.541	0.402	0.459	0.545	0.424
Number	246	232	200	115	232	324	126	201	139	380	356	203
Percent	33.33%	31.44%	27.10%	15.58%	31.44%	43.90%	17.72%	28.27%	19.55%	51.49%	48.24%	27.51%

Note: We list the number of individual stocks and the percent of significant autocorrelations at the level of 10%.

We also apply the threshold quantile autoregressive model to estimate the first-lagged coefficients of 741 individual stocks and calculate their descriptive statistics. In Table 6, we choose liquidity as the exogenous threshold variable and find number of individual stocks and the percent of the significant first-lagged autoregressive coefficients at the level of 10% is less in the middle and higher regimes. The significant percent is 31.05% (OLS), 43.63% (10% quantile), 26.56% (50% quantile) and 21.14% (90% quantile), respectively. It shows high liquidity can significantly decrease the degree of return autocorrelations. Besides, the autocorrelations of individual stocks in higher regime are less, especially in 10%, 50% and 90% quantiles.

Besides, in Table 7, we choose volatility as the exogenous threshold variable. We find the percent of significant autoregressive coefficients at the level of 10% is large in the lower regime. The significant percent is 16.8% (OLS), 20.97% (10% quantile), 13.31% (50% quantile) and 37.10% (90% quantile), respectively. It shows that low volatility can significantly decrease the degree of return autocorrelations, which is not consistent with the results of the Shanghai A-share index. The return autocorrelations in the lower regime is less than that in the middle and higher regimes. In Table 8, the similar results are found by choosing MB ratio as the threshold variable. The percent of significant autoregressive coefficients at the level of 10% is large in the lower regime. The significant percent is 16.91% (OLS), 21.14% (10% quantile), 16.78% (50% quantile) and 37.40% (90% quantile), respectively. The return autocorrelations in the lower regime is less than that in the middle and higher regimes.

In Table 9, we find the first-lagged autoregressive coefficients are very significant in the middle and higher regimes of investor sentiment in the 10% and 90% quantiles. It means that investor sentiment can significantly increase return autocorrelations of individual stocks in the extreme conditions. However, this pattern is not very significant in the results of the OLS and 50% quantile. In sum, we find the most results of individual stocks are similar as the result of the Shanghai A-share index.

5. Conclusion

This paper employs the threshold quantile autoregressive model to study the return autocorrelations and predictability in the Chinese stock market by using the Shanghai A-share index and 741 constituent individual stocks. The results show that the first-lagged autoregressive coefficients are better estimated in two regimes. In the lower regime, the first-lagged autoregressive coefficients are negative and show a pattern of reversal. In the higher regime, the first-lagged autoregressive coefficients are positive and show a pattern of momentum. Meanwhile, we find that the first-lagged autoregressive coefficients are larger in the higher quantiles and smaller in the lower quantiles, respectively. It reflects that investors tend to overreact when the market is in the extreme conditions. This finding is also supported by the results by using individual stocks, that is, the first-lagged autoregressive coefficients are significant negative in the higher quantiles in the lower regime and the first-lagged autoregressive coefficients are significant positive in the higher quantiles in the higher regime. It means that stock returns have a reversal pattern in the lower regime and a momentum pattern in the higher regime. It means that the behavioral biases of Chinese investors can further result in return predictability.

We also use the exogenous threshold variables to divide the influences of first lagged returns on current returns into three regimes. The exogenous threshold variables include liquidity, volatility, MB ratio and investor sentiment. In the higher regime of liquidity, MB ratio and volatility, we find the first-lagged autoregressive coefficients are not very significant. It shows that large liquidity, MB ratio and volatility can significantly increase return autocorrelations and predictability. Besides, the first-lagged autoregressive coefficients are very significant in the middle and higher regimes of investor sentiment. It shows that psychological biases can cause return autocorrelations and predictability. This is supported by the results of individual stocks. We believe this paper reveals the autocorrelations, dynamic patterns, predictability of stock returns in the Chinese stock market. The investors would take advantage of this return dynamics, design reasonable investment strategies and earn profits in the Chinese stock market.

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