4-25-2017

Global Investigation of Return Autocorrelation and its Determinants

Pawan Jain
University of Wyoming

Wenjun Xue
Department of Economics, Florida International University, wxue@fiu.edu

Global investigation of return autocorrelation and its determinants

Pawan Jain[a,*], Wenjun Xue[b]

[a]*University of Wyoming*

[b]*Florida International University*

ABSTRACT

We estimate global return autocorrelation by using the quantile autocorrelation model and investigate its determinants across 43 stock markets from 1980 to 2013. Although our results document a decline in autocorrelation across the entire sample period for all countries, return autocorrelation is significantly larger in emerging markets than in developed markets. The results further document that larger and liquid stock markets have lower return autocorrelation. We also find that price limits in most emerging markets result in higher return autocorrelation. We show that the disclosure requirement, public enforcement, investor psychology, and market characteristics significantly affect return autocorrelation. Our results document that investors from different cultural backgrounds and regulation regimes react differently to corporate disclosers, which affects return autocorrelation.

Keywords: Return autocorrelation, Global stock markets, Quantile autoregression model, Legal environment, Investor psychology, Hofstede's cultural dimensions

JEL classification: G12, G14, G15

---

*Corresponding author, E-mail: pjain@uwyo.edu; fax: 307-766-5090.

1. Introduction

One of the most striking asset pricing anomalies is the existence of large, positive, short-horizon return autocorrelation in stock portfolios, first documented in Conrad and Kaul (1988) and Lo and MacKinlay (1990). This existence of autocorrelation presents a challenge to the mainstream models in continuous-time finance, which rely on some form of the random walk hypothesis, and is puzzling because it suggests that stock prices are not even weak-form efficient. The evidence of this anomaly is pervasive both across sample periods and across countries, and has attributed to firm size (Lo and MacKinlay, 1990), volume (Chordia and Swaminathan, 2000), volatility (Conard and Kaul, 1998), liquidity (Amihud and Mendelson, 1986; Campbell et al., 1993; Chordia et al., 2000), price limits (Lee and Chung, 1996; Lim and Brooks, 2009; Ryoo and Smith, 2002), and information asymmetry (Hirshleifer and Teoh, 2003).Most explanations of autocorrelation center around the argument that stock prices adjust slowly to aggregate fundamental information and do not reflect all available information instantaneously. Some financial economists have related this lagged price adjustment to investors' irrationality (Daniel et al., 1998), whereas others have focused on transaction costs and other microstructure biases to explain this phenomenon (Mech, 1993).

We extend the literature by showing the existence of return autocorrelation and its determinants in the past 30 years and across 43 countries. We use the quantile autoregression model to test the implications of existing theories to explain return autocorrelation. The quantile autoregression framework helps us understand the differential effect of extreme market conditions, such as market boom and bust, on autocorrelation and its determinants. In addition, instead of relying on artificially constructed portfolios, as is the case with much of the existing empirical literature, we base our analyses on 43 global stock indices that exhibit properties of a well-diversified portfolio. We are among the first to analyze the impact of national culture and legal environment on return autocorrelation.

Our results document significant and positive return autocorrelation in global stock markets from 1980 to 2013. However, the magnitude of autocorrelation declines over time. Additionally, return autocorrelation is not significant in developed markets in the post-2004 period. These findings suggest that global stock markets are becoming more efficient. Our results further document that although return autocorrelation is generally stronger in developing markets than in developed markets, autocorrelation of the two subsets of markets converges over time.

We find that larger, more liquid, and less volatile stock markets have lower information asymmetry and transaction costs, resulting in lower return autocorrelation. We also find that the price limits in most developing stock exchanges increase return autocorrelation as price limits restrict daily stock price movements beyond a prespecified level, resulting in higher momentum. Our results further document that stringent disclosure requirements and stronger public enforcement reduce return autocorrelation by requiring timely dissemination of high-quality information, which reduces information asymmetry. Finally, we find that Hofstede's (2001) cultural dimensions—individualism and uncertainty avoidance—affect return autocorrelation. Investors with high uncertainty avoidance trade cautiously, resulting in higher return autocorrelation during extreme market conditions characterized by large stock price fluctuations. Individualistic investors are quick to react to new information, which significantly reduces return autocorrelation.

2. Literature review

We evaluate the evolution of return predictability over the past three decades in 43 major stock exchanges around the globe. We are among the first to test the differences in return autocorrelation across market characteristics and investor demographics. We also present factors that determine the level of return autocorrelation during different market conditions.

2.1. Historical perspective on return autocorrelation

The efficient market hypothesis can be viewed as the foundation of modern finance literature. Lo (2004) argues that there is no consensus among academics and practitioners regarding stock market efficiency. Most academic researchers argue that markets in general are weak-form efficient (Doran et al., 2009). However, behavioral finance theorists and empiricists disregard the efficient market hypothesis and document irrational investor behaviors, such as underreaction or overreaction and overconfidence leading to predictable stock price movements (see DeBondt and Thaler, 1985).

Yen and Lee (2008) provide a historical survey of the existing literature and find that although the early studies (1960–1987) support market efficiency, the recent literature (1988–2004) report otherwise. Hence, the findings of these surveys suggest that market efficiency varies over time. One of the goals of this study is to present the evolution of autocorrelation in returns over the past 30 years and across 43 countries. We also analyze the difference in autocorrelation across developing and developed stock markets.[1]

Lo (2004) presents the adaptive markets hypothesis, which relates the investor rationality argument of behavioral critics to the efficient market hypothesis. The adaptive markets hypothesis argues that constantly changing market conditions create variability in market efficiency over time. The adaptive markets hypothesis also suggests that return predictability, or autocorrelation, can be attributed to changes in the demographics of investors, financial

---

[1] There is no consensus in the literature on market efficiency in developed markets, such as the United States. Gu and Finnerty (2002) document that the U.S. market has shown improved efficiency since the late 1970s, whereas Lo(2004) reports that the market was more efficient in the 1950s than in the 1990s. Ito and Sugiyama (2009) find that the market was efficient in the 1960s and 1970s, highly inefficient in the 1980s, and then became efficient again around 2000. Harvey (1995) reports that return predictability and serial correlation are higher in emerging markets than in developed markets.

institutions, and market characteristics. Although there is an expanding literature on time-varying stock return predictability (Lim and Brooks, 2009), there is little research on the roles of changing market characteristics and investor psychology in return predictability. This study is a first attempt to evaluate the effect of investor psychology and the legal environment on return autocorrelation. We also analyze factors that explain the level of return autocorrelation across different market conditions.

2.2. Return autocorrelation and legal environment

We proxy for the legal environment with the disclosure requirement of publicly listed firms and the public enforcement of financial market regulation.[2,3] Both measures are provided by La Porta et al. (2006) and used in Kim and Park (2010) and Han et al. (2013). The existing literature on the effects of the legal environment on return autocorrelation is limited and inconclusive. Verrecchia (2001) and Easley and O'Hara (2004) suggest that the public release of corporate information can reduce the risk faced by traders and improve liquidity. Similarly Agrawal and Nasser (2012) argue that public enforcement instills more confidence in the stock market and leads to greater transparency. Higher information disclosure and enforcement aid price discovery and improve informational efficiency, which should in turn decrease return autocorrelation. Conversely, Han et al. (2013) argue that higher information disclosure can attract noise trading and have a negative effect on informational efficiency, which results in an increase in return autocorrelation.

---

[2]The disclosure requirement is obtained by averaging information from the prospectus, the compensation for the issuer's directors and key officers, the issuer's equity ownership structure, the equity ownership of the issuer's shares by its directors and key officers, the issuer's contracts outside the ordinary course of business, and the transactions between the issuer and its directors, officers, or large shareholders.

[3] The public enforcement index averages the supervisor's independence and unique coverage on the stock market (supervisor characteristics index), the supervisor's power to regulate the security market (rule-making power index), and investigation of all possible false and misleading statements (investigative powers index) covering noncriminal (orders index) and criminal sanctions for violations of security (criminal index). To keep the units consistent, we divide the scores of public enforcement, individualism, and uncertainty avoidance by 100.

2.3. The factors in investor psychology

We employ the two widely used dimensions provided by Hofstede (2001) to measure investor psychology: uncertainty avoidance and individualism. Uncertainty avoidance expresses the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity. Individualism measures the preference of individuals to take care of only themselves and their immediate families.

Salter and Niswander (1995) link uncertainty avoidance to preferences for rules, stability, uniformity, conservatism, and risk aversion. Barberis et al. (1998) present a theoretical model where conservative investors exhibit partial response to corporate disclosures. Edwards (1968) also suggests that conservatism is related to underreaction to new information, which in turn decreases return autocorrelation.

Markus and Kitayama (1998) and Jain and Chu (2014) show that investors from countries with high individualism scores reflect overconfidence and lead to a more pervasive self-attribution bias. Van den Steen (2004) finds that people from individualistic cultures are overoptimistic about their predictive precision. Daniel et al. (1998) find that overconfidence can generate excess trading and excess volatility. Therefore, investors with higher individualism scoresmight exhibit stronger responses to new information and, in turn, decrease return autocorrelation.

2.4. Stock market characteristics

Lo and MacKinlay (1990) and Llorente et al. (2002) document a negative relation between firm size and return autocorrelation. Brockman et al. (2009) extend the analysis to an international setting and find that the stock exchange size (total market capitalization) plays an influential role in the liquidity transmission process and that large exchanges have the lower return autocorrelation. Smaller exchanges might have greater nonsynchronous trading and higher information asymmetry, which could result in higher return autocorrelation.

Empirical evidence on the effects of volatility on return autocorrelation is mixed. Gębka and Wohar (2013) document a positive relation between volatility and return autocorrelation caused by a pronounced bid–ask bounce. However, Säfvenblad (2000) attribute their finding of a positive relation between volatility and return autocorrelation to the lower cost of pricing errors and higher trading volume.[4]

Amihud and Mendelson (1986), Campbell et al. (1993), Chordia et al. (2000), and Acharya and Pedersen (2005) find that highly liquid stocks have lower information-driven and liquidity-motivated trades, which lead to lower return autocorrelation. Similarly, Brockman et al. (2009) find a negative relation between liquidity and return autocorrelation, and they relate their findings to reduced transaction costs, as improved liquidity could result in lower return autocorrelation.

Lee and Chung (1996) suggest that price limits bound daily stock price movements, truncatethe distribution of true price changes, and constrain the observed price within a specific range. Ryoo and Smith (2002) find price limits prevent equity prices from following a random walk process and result in market inefficiency. Lee and Chou (2004) extend previous studies by examining the effects of intraday price limits on stock price movements. They find that stocks with price limits exhibit a strong price reversal after the event. This suggests that investors tend to overreact to price limits, resulting in higher return autocorrelation. Shen and Wang (1998) and

[4] The previous literature documents a negative relation between trading volume and return autocorrelation. Campbell et al. (1993) suggest that high trading volume makes aggregate risk aversion more easily observable, reducing the nonsynchronicity of the price and index return autocorrelation. Conrad et al. (1994) find that the existence of a volume effect implies that autocorrelation is lower on high-volume days than on low-volume days. Foster and Viswanathan (1993) also show that high trading volume can increase the informed trader's signal precision, and the consequent price precision, thus decreasing return autocorrelation. Because trading volume has a strong correlation with volatility and liquidity, we do not use trading volume in this article.

Lim and Brooks (2009) find similar results in different markets and periods. Theoretical influences of the determinants on return autocorrelation are provided in Appendix A.

3. Methodology

3.1. Regression model

Stock return distribution is characterized by fat tails, asymmetry, and non-normality. Quantile regression (Koenker and Basset, 1978) can analyze asymmetry in stock returns and estimate coefficients across various quantiles of stock returns. Furthermore, some developing stock markets have a daily price limit, which might result in inaccurate conclusions using the traditional ordinary least squares (OLS) estimation technique, as the distribution of stock returns is truncated. To deal with these econometric issues, we employ the quantile autoregression model to estimate return autocorrelation over various quantiles (Koenker and Xiao, 2006).The quantile autoregression model is described as follows:

$$Q(\tau | r_{t,i}) = \theta_{0i}(\tau) + AC_{1i}(\tau) r_{t-1,i} + \varepsilon_{t,i} \;, \tag{1}$$

where $Q(\tau | r_{t,i})$ is the conditional quantile of stock index i 's return, $r_{t,i}$; $AC_{1i}(\tau)$, our measure for return autocorrelation, is the first-order return autocorrelation coefficient for the quantile of stock index *i*; and $\varepsilon_{t,i}$ is the error term.

Then, in the second stage, we employ factors in the stock market, legal environment, and investor psychology to explain the estimated return autocorrelation coefficients using the following model:

$$\begin{aligned} AC_{it} = {} & \mu_i + b_1 SIZE_{it} + b_2 VOLATILITY_{it} + b_3 LIQUIDITY_{it} + b_4 LIMIT_{it} + b_5 ENFORCEMENT_{it} + b_6 DISCLOSE_{it} \\ & + b_7 UNCERTAINTY_{it} + b_8 INDIVIDUALISM_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

where μ_i is the country-specific fixed effect and ε_t is the error term. AC_{it} is the estimated return autocorrelation coefficient, $SIZE_{it}$ is stock market size, $VOLATILITY_{it}$ is volatility of returns,

$LIQUIDITY_{it}$ is liquidity, $LIMIT_{it}$ is price limits, $ENFORCEMENT_{it}$ is the level of public enforcement, $DISCLOSE_{it}$ is the disclosure requirement, $UNCERTAINTY_{it}$ is the score of uncertainty avoidance, and $INDIVIDUALISM_{it}$ is the score of individualism (collectivism). Appendix B provides the source and definition for each variable.

3.2. Data

We use the most representative stock indexes in 43 stock markets to analyze return autocorrelation worldwide. The stock indexes closely reflect price movements in the underlying markets. We divide these 43 stock markets into two groups: one group is composed of 25 developed markets and the other group is composed of 18 emerging markets.[5]The description of the selected stock indexes can be found in Appendix C.

Data on information disclosure and public enforcement are collected from La Porta et al. (2006). Data on investor psychology—uncertainty avoidance and individualism—are collected from the Hofstede's IBM Study (Hofstede, 2001). Stock-market-specific characteristics, such as stock market size, volatility, and liquidity, are collected from the financial sector in World Bank's Global Financial Development Database (GFDD). Data on price limits are collected from Kim and Park (2010).

Table 1 presents country-specific descriptive statistics for the 43 stock markets. *SIZE* is the average market capitalization scaled by gross domestic product (GDP). Hong Kong (3.038) has the largest *SIZE*, followed by Switzerland (1.800) and South Africa (1.798). Venezuela (0.014) has the smallest *SIZE*. *VOLATILTIY*, which is measured as the standard deviation of returns across 360 days, varies significantly across stock markets. Argentina (0.466) has the highest *VOLATILTIY*, followed by Turkey (0.439) and South Africa (0.431). New Zealand

[5] The division standard is in line with the IMF Advanced Economies List (World Economic Outlook, 2016) and the Country and Lending Groups (World Bank, 2015).

(0.114) has the lowest *VOLATILTIY*. South Korea (1.975) has the highest *LIQUIDITY* as measured by the turnover ratio, followed by the United States (1.462). Venezuela (0.010) has the lowest *LIQUIDITY*. Later, Table 3 reports that to suppress extreme price movements, 9 developed markets and 12 emerging markets have price limits.

[INSERT TABLE 1 AROUND HERE]

Table 1 also presents the descriptive statistics for our legal environment variables. The United States (1.000) has the highest information disclosure, followed by Canada (0.917), Hong Kong (0.917), India (0.917), and Thailand (0.917). Singapore (0.100) and Venezuela (0.167) have the lowest disclosure. Australia (0.896) has the highest public enforcement, followed by Hong Kong (0.875), Singapore (0.875), and the United States (0.875). Austria (0.188), Belgium (0.188), Japan (0.000) and Mexico (0.250) have lowest public enforcement.

Finally, Table 1 reports descriptive statistics on the investor psychology variables: *UNCERTAINTY* and *INDIVIDUALISM*. We find that Belgium (0.940), Greece (1.120), and Portugal (1.040) have the highest scores on *UNCERTAINTY*. Denmark (0.230), Singapore (0.080) and Sweden (0.290) have lowest scores. Similarly, Australia (0.900) and the United States (0.910) have highest *INDIVIDUALISM*. Columbia (0.130), Indonesia (0.140), and Venezuela (0.120) have lowest *INDIVIDUALISM*.

Table 2 provides descriptive statistics for the key variables across the subsamples of developed and emerging markets. We find that developed markets have larger stock market size (0.827), lower volatility (0.201), and higher liquidity (0.794) as compared to the emerging markets. We also find that 78% of emerging markets have price limits whereas only 36% of developed markets have price limits. Developed markets also seem to have more stringent disclosure requirements but weaker public enforcements as compared to emerging markets. Later,

Table 4 reports that developed markets have a higher score on individualism (0.618) and a lower score on uncertainty avoidance (0.609) as compared to the emerging markets. Based on these findings, it can be argued that investors in developed markets can be characterized as overconfident with lower risk aversion as compared to investors in emerging markets. The last row in Table 2 reports the *T*-test on differences in means across the two subsamples. We find that the differences between emerging and developed markets across all variables are statistically significant at the 5% level.

[INSERT TABLE 2 AROUND HERE]

4. Empirical Results

4.1. Return autocorrelation in the global stock markets

We estimate return autocorrelation in 43 stock markets from 1980 to 2013, using the quantile autocorrelation estimation techniques outlined in the previous section. Table 3 presents return autocorrelations in the full sample period and across several subsamples. We also divide all stock markets into developed markets and emerging markets. To address time-varying return autocorrelation, we divide the whole sample period into five-year intervals (Campbell et al., 1993; Gębka and Wohar, 2013; Mech, 1993). Finally, we separate the periods by the two recent global financial crises: Asian financial crisis (1997–1999) and global financial crisis (2008–2009).We also employ the automatic variance ratio test and joint Wright's rank and sign test to test the random walk hypothesis in these stock markets. The automatic variance ratio test is a classic parametric test used in the literature as a test for market efficiency (Choi, 1999), and the joint Wright's rank and sign test is a newer nonparametric statistical test for market efficiency.

[INSERT TABLE 3 AROUND HERE]

Table 3 shows that although most developed markets have positive and significant autocorrelation coefficients in the entire sample period, the five-year subsample analysis shows that the significant autocorrelation is driven mostly by the period before 2005. We also find that the return autocorrelation coefficients of developed markets are becoming smaller in magnitude overtime. We find that the results of the automatic variance ratio test and the joint Wright's rank and sign test are consistent with the results of the quantile autocorrelation regression models. Specifically, whenever the coefficient for return autocorrelation from the 50% quantile regression is positive and significant, the automatic variance ratio test and the joint Wright's rank and sign test are also significant. Therefore, we reject the random walk hypothesis using any of the three estimation techniques. We also find that the magnitude and significance of the test statistics are declining over time. These results suggest that although historically most developed markets were not even weak-form efficient, market efficiency has improved in most of these markets since 2005.

Table 3 further documents positive and significant return autocorrelation coefficients in all emerging markets in the entire sample period and across most subperiods. It also reveals that the automatic variance ratio test and the joint Wright's rank and sign test reject the random walk hypothesis in most emerging markets across subperiods. These findings suggest that emerging stock markets are not even weak-form efficient, as investors can apply previous price information to forecast and earn excess profits. In contrast, developed markets have become more efficient over time, as the autocorrelation and random walk tests are rarely significant after 1995. It could be because of declining transaction costs and easier and cheaper access to reliable information in developed markets. Additionally, as we show later, investors in developed markets have fewer cognitive biases, which mitigate underreaction or overreaction to new information and results in improved market efficiency.

Figure 1 shows that the return autocorrelation coefficients in emerging markets are larger than in developed markets. Our results are consistent with the general consensus in the literature that the lack of transparency in emerging markets can lead to significant predictability in returns (Chan and Hameed, 2006).

[INSERT FIGURE 1 AROUND HERE]

Similar to the findings for developed markets, the return autocorrelation coefficients in emerging markets are getting smaller over time. Figure 1 graphically presents these findings. Brockman et al. (2009) regard lower information technology costs and a movement toward deregulation and free trade on the part of national governments as important reasons for gradually diminishing return autocorrelation.[6]Table 3 further reports that the markets in Asia, South America, and Africa have stronger return autocorrelation than do the markets in Europe and North America. Figure 2 graphically reports return autocorrelation in the 50% quantile in the 43 sample countries.

[INSERT FIGURE 2 AROUND HERE]

Columns 8 and 9 in Table 3 report the return autocorrelation coefficients during the two recent financial crises. We find that return autocorrelation is positive and significant in most emerging markets. The increase in information asymmetry during the financial crises coupled

[6] To show the effects of the time trend on return autocorrelation, we generate a time trend variable (1, 2, 3…, 34), run the linear regression model, and find a significant and negative coefficient for time trend. This suggests that return autocorrelation has been declining over time. We further find that the declining trend in autocorrelation is driven by lower trading costs and lower volatility due to efficient and reliable information flow.

with poor firm-specific transparency in the emerging markets can lead to higher return autocorrelation.[7]

4.2. Determinants of return autocorrelation in global stock markets

By using cross-country, time-series panel data and the fixed-effect feasible generalized least square (FGLS) technique, we analyze the determinants of the level of return autocorrelation across countries and during different market conditions. FGLS has several advantages over OLS. In a panel data regression model, the unobserved country-specific effects are a part of the error term, which increases the possibility of correlation between the error term and the explanatory variables and thereby results in biased coefficient estimators. FGLS takes care of this econometric problem. Additionally, FGLS allows for fully unrestricted error covariance structure in every observation group, which addresses intragroup heteroskedasticity and serial correlation.[8]

Table 4 presents estimation results for the FGLS regressions of return autocorrelation on the market characteristics, legal environment, and investor psychology factors. Each model specification adds variables related to these factors to the base model of control variables. The quantile regression method is useful for studying a range of quantiles of the conditional return distribution. We estimate the return autocorrelation coefficients for the 80% quantile, 20% quantile, and 50% quantile. The autocorrelation quantile regression for the 80% quantile is used to estimate return autocorrelation during the market boom periods (good state) ,and the autocorrelation quantile regression for the 20% quantile is used to estimate return autocorrelation during the market bust periods (bad state). The autocorrelation quantile regression for the 50%

[7]Jain (2015) suggests that information asymmetry increases during the financial crisis.

[8]FGLS is a form of the generalized least squares (GLS) estimation method with robust standard errors. In our search for the most appropriate econometric method to address panel-level heteroskedasticity, we find that in addition to FGLS, the HAC estimator (Heteroskedasticity and autocorrelation consistent covariance matrix estimation) and the Eicker–White estimator are acceptable estimation techniques. However, the FGLS estimator is more efficient and is preferred in this setting (Greene, 2003). We test the robustness of our findings using GLS with robust standard errors (HAC estimator) and find consistent results. Because the FGLS estimation technique is more efficient with panel-level heteroscedasticity, we present the results using FGLS.

quantile is used to estimate return autocorrelation during normal market periods, without large fluctuations.

[INSERT TABLE 4 AROUND HERE]

Consistent with Lo and MacKinlay (1990), Llorente et al. (2002), and Brockman et al. (2009), we find negative and significant stock market size coefficients across different regression models. This result suggests that larger stock markets tend to have lower return autocorrelation, which could be driven by factors such as low nonsynchronous trading, low asymmetric information, and a better liquidity transmission process. The stock market size effect is larger in the market boom and smaller in the market bust. The results further document that high volatility lowers return autocorrelation; however, this negative relation depends on market conditions. In the market boom, investors tend to overreact to new information, resulting in a positive relation between volatility and return autocorrelation. In the market bust, investors tend to underreact to new information, resulting in a negative relation between these two variables.

Our results further document that higher liquidity lowers return autocorrelation. Higher liquidity allows information to be quickly incorporated into prices, resulting in lower return autocorrelation. This negative relation between liquidity and return autocorrelation is consistent with the findings in Amihud and Mendelson (1986), Campbell et al. (1993), Chordia et al. (2000), and Acharya and Pedersen (2005). The results further document that the negative effects of liquidity are larger in the market boom and smaller in the market bust. Consistent with Lee and Chung (1996) and Shen and Wang (1998), we find a positive and significant relation between price limits and return autocorrelation. Price limits constrain observed prices within a specific range, which might result in higher return autocorrelation, especially in the market boom.

Table 4 further reports that higher information disclosure and stronger public enforcement can effectively reduce return autocorrelation. Verrecchia (2001) and Easley and O'Hara (2004) document that the public release of corporate information reduces the risk faced by traders, improves liquidity, helps price discovery, and increases informational efficiency. This increase in firm-specific transparency should result in lower return autocorrelation. We extend the literature in a new direction by documenting that this relation reverses during the market boom. Han et al. (2013) show that high information disclosure during bull markets attracts noise trading, leading to lower informational efficiency, which should result in higher return autocorrelation.

Finally in Table 4, we show that investor behavior has a significant influence on return autocorrelation. We proxy for investor behavior using two national culture dimensions provided by Hofstede (2001): individualism and uncertainty avoidance. Our results document that both of these cultural dimensions have a significant and negative impact on return autocorrelation. Investors with a high individualism score tend to be overconfident about their ability to pick stocks. These investors exhibit stronger responses to the arrival of new information, which results in high stock-specific trading and, in turn, lower return autocorrelation. We also find a negative relation between uncertainty avoidance and return autocorrelation. A high uncertainty avoidance score leads to more conservative investment decisions. Barberis et al. (1998) present a theoretical model, in which conservative investors exhibit a partial response to corporate disclosures, which in turn decreases return autocorrelation. These negative relations between uncertainty avoidance and return autocorrelation and between individualism and return autocorrelation become stronger during the market booms and busts. The literature has established that investor behavior and cognitive bias are more prominent during extreme market conditions.

We divide the sample markets into developed and emerging markets, and Table 5 provides regression results for the two subsamples. We find that stock market size has consistent negative effects across the two markets. Larger stock markets offer more symmetrical and transparent economic information and have higher price efficiency, which results in lower return autocorrelation. However, effects are smaller in the market bust. The effects of volatility on return autocorrelation vary across markets. In the market bust, higher volatility lowers return autocorrelation because individuals trade only when their private signals are strong, leading to more stock-specific trading and lower return autocorrelation. In the market boom, the relation between volatility and return autocorrelation is positive in developed markets and negative in emerging markets.

[INSERT TABLE 5 AROUND HERE]

Our results further document a negative relation between liquidity and return autocorrelation, especially in the market boom. Increased resiliency during market booms can lead to a reduction in return autocorrelation (Campbell et al., 1993, Llorente et al., 2002; Wang, 1994). In a normal market, the liquidity coefficient is negative and significant in developed markets but not significant in emerging markets. This result suggests that high liquidity reflects more adequate and symmetrical firm-specific information and reduces return autocorrelation in developed markets (Amihud and Mendelson, 1986; Campbell, Grossman and Wang, 1993; Chordia et al., 2000; Acharya and Pedersen, 2005). Table 6 reports a positive and significant relation between price limits and return autocorrelation in the emerging markets in the market boom and bust. This result documents the trend-chasing behavior of investors in emerging markets during extreme market conditions (Lee and Chung, 1996; Shen and Wang, 1998).

[INSERT TABLE 6 AROUND HERE]

Furthermore, we document a negative and significant relation between return autocorrelation and public enforcement and information disclosure in emerging markets. Public enforcement and information disclosure increase information spread and information quality, and decrease insider trading, which results in lower return autocorrelation. In Table 6, we document that individualism has a negative and significant effect on return autocorrelation, especially in the market boom. A higher individualism score reflects overconfidence in stock-picking abilities, which results in more stock-specific trading and, in turn, lower return autocorrelation.

In Table 6, we analyze the evolution of autocorrelation and its determinants across different market conditions. We divide the sample period into two subperiods: normal market conditions and global financial crises. Most of the results are consistent across subperiods but the effects on return autocorrelation are smaller during the global financial crises, as reflected by smaller coefficients. We find that the coefficients on price limits are not significant across models during the global financial crises. We also find that the markets with price limits have higher return autocorrelation during normal periods. These results could be driven by the fact that global financial crisis periods, marked by higher volatility, experience price reversals whereas normal market periods experience momentum. Hence, price limits exert upward/downward pressure during the normal market conditions and result in higher return autocorrelation. In addition, the effects of the above variables are much more significant in extreme market conditions.

The public enforcement results are generally consistent across regression models. We find that public enforcement has negative and significant coefficients during the global financial crises period. In the market bust, information asymmetry increases and traders trade only when they have reliable information signals. Stronger public enforcement in such market conditions can effectively reduce asymmetric information, resulting in lower return autocorrelation. (Easley and O'Hara, 2004; Verrecchia, 2001).Table 6also reports that information disclosure is positively and significantly related to return autocorrelation. Han et al. (2013) suggest that higher information disclosure can attract noise trading, resulting in an increase in return autocorrelation.

Table 6 further reports that the effects of uncertainty avoidance on return autocorrelation vary across market conditions. Uncertainty avoidance is positively and significantly related to return autocorrelation during the period with global financial crises, and this relation reverses during the period without global financial crises. The behavioral biases become stronger during both extreme markets, which result in under-reaction to news. This partial response to corporate disclosures increases return autocorrelation (Barberis et al., 1998). However, during normal market conditions, investor behavior and cognitive biases are not prominent, which reduces return autocorrelation. Finally, consistent with previous results, we find that individualism is negativelyand significantly related to return autocorrelation. These findings provide further evidence that investors with a high individualism score exhibit stronger responses to the arrival of new information, which results in high stock-specific trading and lower return autocorrelation.

5. Robustness tests

5.1. Economic cycle and return autocorrelation

Velazquez and Smith (2013) argue that stock returns are affected by business cycles. To test whether our results are robust to controlling for business cycles, we add GDP growth rate to the regression model. We divide the sample period into two subsamples: expansion periods, which are periods of yearly GDP growth rate greater than 2%, and contraction periods, which are periods of negative yearly GDP growth rate. Results from this analysis are presented in Table 7.We find that return autocorrelation changes with the business cycle. Specifically, during expansionary periods we find an increase in return autocorrelation. However, during contraction periods, return autocorrelation declines. Within the economic expansion periods, we find that GDP growth significantly increases return autocorrelation during stock market booms (20% quantile) but the effect is not statistically significant for other periods. During the expansionary period, in general, we observe an increase in stock investment, which leads to an increasing trend in stock returns and results in increased return autocorrelation. Positive investor sentiments could also drive return autocorrelation during economic expansions.

[INSERT TABLE 7 AROUND HERE]

The remaining results are consistent with those presented previously. Specifically, the size and direction of the coefficients for stock market size, liquidity, and individualism are consistent with the80% and 20% quantile regression analyses. Consistent with the results presented in Table 4, we find that the effects of size, liquidity, and individualism are larger and more significant during the market boom than during the market bust in both economic expansion and contraction periods.

5.2. Cross-country correlation in autocorrelation changes

We find that return autocorrelations in larger and developed markets are significantly related to autocorrelations in other stock markets. To test whether our results are robust after controlling for cross-country effects, we include return autocorrelations in the United States, United Kingdom, and Japan as additional explanatory variables in the regression models.

Results summarized in Table 8 show that return autocorrelations in the U.S., U.K., and Japanese markets have a positive and significant effect on return autocorrelations in other markets. Moreover, most results for the other variables in Table 8 are consistent with the results in Table 4. We continue to find negative coefficients for market size, volatility, liquidity, information disclosure, uncertainty avoidance, and individualism. Hence, our results are robust to controlling for cross-country correlations.

[INSERT TABLE 8 AROUND HERE]

5.3. Clustered standard errors

The standard errors may be biased because countries are trading partners or simply close to each other. To test the robustness of our findings we estimate our regression model using OLS with the clustered standard errors.

Table 10 shows that the results are very similar as the ones obtained by FGLS. The main differences lie on that the coefficients of volatility, information disclosure and stronger public enforcement not very significant as these variables in FGLS in the OLS, 50% quantile and 80% quantile. The rest of results are very similar as the results in FGLS, including significant negative influences of size, liquidity, individualism and significant positive influences of price limits in different market conditions.

[INSERT TABLE 9 AROUND HERE]

6. Conclusion

We investigate global return autocorrelation and its determinants using the quantile regression model in a sample of 43 stock indexes from 1980 to 2013. The results document that return autocorrelation was significant in global stock markets before 2005. Emerging markets experience larger and more significant return autocorrelation than developed markets across the entire sample period. These findings document price inefficiency in emerging markets, which results from traders who benefit from technical and fundamental analysis. We find a convergence in return autocorrelation between developed and emerging markets, and we find that return autocorrelation has been declining over time. This could be driven by lower information technology costs and a movement toward deregulation and free trade.

By using cross-country, time-series panel data and employing fixed-effect FGLS, we analyze the determinants of return autocorrelation across countries and during different market conditions and business cycles. We divide the determinants of autocorrelation into three broad factors: stock market characteristics, legal environment, and investor psychology.

The results document that larger and liquid stock markets, with lower asymmetric information and transactions costs, have lower return autocorrelation. We also find that price limits in most emerging markets bind daily stock price movements, resulting in higher return autocorrelation. We find that this relation grows stronger during extreme market conditions marked by more binding price limits. We show that the disclosure requirement, public enforcement, investor psychology, market characteristics, and business cycle significantly affec t return autocorrelation. Our results document that investors from different cultural backgrounds and regulation regimes react differently to corporate disclosers, which in turn affects return autocorrelation.

Our results document that return autocorrelation in global stock markets is driven not only by market microstructure, but also by the legal environment and investor psychology across different countries. Finally, our results suggest that weaker price efficiency, especially in emerging markets, supports the notion that positive returns can be generated through technical and fundamental analyses.

Acknowledgments

We thank the Research Center of Financial Information at the School of Economics, Shanghai University for helping us with data collection.

References

Acharya, V., Pedersen, L. H., 2005. Asset pricing with liquidity risk. Journal of Financial Economics 77(2), 375–410.

Agrawal, A., Nasser, T., 2012. Insider trading in takeover targets, Journal of Corporate Finance 18(3), 598–625.

Amihud, Y., Mendelson, H., 1986. Liquidity and stock returns, Financial Analysts Journal 42(3), 43–48.

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics, 49(3), 307–343.

Brockman, P., Chung, D.Y., P'erignon, C., 2009. Commonality in liquidity: A global perspective, Journal of Financial and Quantitative Analysis 44(4), 851–882.

Campbell, J.Y., Grossman, S.J., Wang, J., 1993. Trading volume and serial correlation in stock returns. Quarterly Journal of Economics 108(4), 905–939.

Chan, K., Hameed, A., 2006.Stock price synchronicity and analyst coverage in emerging markets. Journal of Financial Economics 80(1), 115–147.

Choi, I., 1999. Testing the random walk hypothesis for real exchange rates. Journal of Applied Econometrics 14(3), 293–308.

Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity. Journal of Financial Economics 56(1), 3–28.

Chordia, T., Swaminathan, B., 2000.Trading volume and cross-autocorrelations in stock returns. Journal of Finance 55(2), 913–935.

Conrad, J.S., Hameed, A., Niden, C., 1994. Volume and autocovariances in short-horizon individual security returns. Journal of Finance 49(4), 1305–1329.

Conrad, J., Kaul, G., 1988. Time varying expected returns. Journal of Business 61(4), 409–425.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. Journal of Finance 53(6), 1839–1885.

De Bondt, W.F.M., Thaler, R.T. 1985. Does the stock market overreact? Journal of Finance 40(3), 793–805.

Doran, J.S., Delisle, J., Peterson, D., 2009. Confidence, opinions of market efficiency, and investment behavior of finance professors. Journal of Financial Markets 13(1), 174–195.

Easley, D., O'Hara, M., 2004. Information and the cost of capital, Journal of Finance 59(4), 1553–1583.

Edwards, W., 1968.Conservatism in human information processing, in: Kleinmuntz, B. (Ed.), Formal Representation of Human Judgment. Wiley, New York, pp. 17–52.

Foster, F.D., Viswanathan, S., 1993.Variations in trading volume, return volatility, and trading costs: evidence on recent price formation models. Journal of Finance 48(1), 187–211.

Gębka, B., Wohar, M.E., 2013.The determinants of quantile autocorrelations: evidence from the UK. International Review of Financial Analysis 29(C), 51–61.

Greene, W.H., 2003. Econometric Analysis, fifth ed. Prentice Hall, Upper Saddle River, NJ.

Gu, A.Y., Finnerty, J., 2002. The evolution of market efficiency: 103 years daily data of Dow. Review of Quantitative Finance and Accounting 18(3), 219–237.

Han, B., Liu, Y., Tang, Y., Yang, L., Yu, L., 2013. Disclosure and efficiency in noise-driven markets.Working Paper, MIT Sloan Business School.

Harvey, C.R., 1995.The cross-section of volatility and autocorrelation in emerging stock markets. Finanzmarkt and Portfolio Management 9(1), 12–34.

Hirshleifer, D., Teoh, S.H., 2003.Limited attention, information disclosure, and financial reporting. Journal of Accounting and Economics 36(1-3), 337–386.

Hofstede, G., 2001. Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations across Nations, second ed. Sage Publication, Beverly Hills, CA.

Ito, M., Sugiyama, S. 2009.Measuring the degree of time varying market inefficiency. Economics Letters 103(1), 62–64.

Jain, P., 2015. J-REIT Market quality: impact of high frequency trading and the financial crisis. Paper presented at the 2015 AREUEA/NAREIT conference.

Jain, P., Chu, Q., 2014. Dividend clienteles: A global investigation. Review of Quantitative Finance and Accounting 42(3), 509–534.

Kim, K.A., Park, J., 2010.Why do price limits exist in stock markets? A manipulation-based explanation. European Financial Management 16(2), 296–318.

Koenker, R., Bassett, J.G., 1978. Regression quantiles. Econometrica 46(1), 33–50.

Koenker, R., Xiao, Z., 2006. Quantile autoregression. Journal of the American Statistical Association 101(475), 980–990.

La Porta, R., Lopez-De-Silanes, F., Shleifer, A., 2006. What works in securities laws? Journal of Finance 61(1), 1–32.

Lee, J.H., Chou, R.K., 2004. The intraday stock return characteristics surrounding price limit hits. Journal of Multinational Financial Management 14(4-5), 485–501.

Lee, S.B., Chung, J.S., 1996. Price limits and stock market efficiency. Journal of Business Finance & Accounting 23(4), 585–601.

Lim, K.P., Brooks, R.D., 2009. Price limits and stock market efficiency: evidence from rolling bicorrelation test statistic. Chaos, Solitons and Fractals 40(3), 1271–1276.

Llorente, G., Michaely, R., Saar, G., Wang, J., 2002. Dynamic volume-return relation of individual stocks. Review of Financial Studies 15(4), 1005–1047.

Lo, A., 2004. The adaptive markets hypothesis: market efficiency from an evolutionary perspective. Journal of Portfolio Management 30(5), 15–29.

Lo, A., MacKinlay, C., 1990.When are contrarian profits due to stock market overreaction? Review of Financial Studies 3(2), 175–205.

Markus, H.R., Kitayama, S., 1998. The cultural psychology of personality. Journal of Cross-Cultural Psychology 29(1), 63–87.

Mech, T.S., 1993. Portfolio return autocorrelation. Journal of Financial Economics 34(3), 307–344.

Ryoo, H.J., Smith, G., 2002. Korean stock prices under price limits: Variance ratio tests of random walks. Applied Financial Economics 12(8), 545–553.

Säfvenblad, P., 2000, Trading volume and autocorrelation: Empirical evidence from the Stockholm Stock Exchange, Journal of Banking & Finance 24(8), 1275-1287.

Salter, S.B., Niswander, F., 1995. Cultural influence on the development of accounting systems internationally: A test of Gray's (1988) theory. Journal of International Business Studies 26(2), 379–397.

Shen, C.H., Wang, L.R., 1998. Daily serial correlation, trading volume and price limits: evidence from the Taiwan Stock Market. Pacific-Basin Finance Journal 6(3-4), 251–273.

Verrecchia, R., 2001. Essays on disclosure. Journal of Accounting and Economics 32(1-3), 97–180.

Wang, J., 1994, A model of competitive stock trading volume, Journal of Political Economy 102(1), 127–168.

World Bank, 2015.Country and Lending Groups.

URL: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups

World Economic Outlook, 2016.IMF Advanced Economies List.

URL: http://www.imf.org/external/pubs/ft/weo/2016/02/

Yen, G., Lee, C.F. 2008. Efficient market hypothesis (EMH): Past, present and future. Review of Pacific Basin Financial Markets and Policies 11(2), 305–329.

Table 1

Descriptive statistics on 43 stock markets.

	Beginning year of the stock index	Observations	*SIZE*	*VOLATILITY*	*LIQUIDITY*	*LIMIT*	*DISCLOSE*	*ENFORCEMENT*	*UNCERTAINTY*	*INDIVIDUALISM*
Developed market										
Australia	1993	5313	0.965	0.143	0.686	0	0.750	0.896	0.510	0.900
Austria	1986	6916	0.199	0.203	0.499	1	0.250	0.188	0.700	0.550
Belgium	1991	5819	0.568	0.185	0.321	1	0.417	0.188	0.940	0.750
Canada	1985	7279	0.884	0.145	0.608	0	0.917	0.865	0.480	0.800
Denmark	1990	6000	0.509	0.184	0.661	0	0.583	0.271	0.230	0.740
Finland	1987	6750	0.822	0.250	0.763	1	0.500	0.354	0.590	0.630
France	1988	6552	0.611	0.217	0.748	1	0.750	0.802	0.860	0.710
Germany	1980	8568	0.405	0.210	1.172	0	0.417	0.250	0.650	0.670
Greece	1987	6723	0.401	0.283	0.488	0	0.333	0.354	1.120	0.350
Hong Kong	1980	8398	3.038	0.264	0.683	0	0.917	0.875	0.290	0.250
Ireland	1983	6975	0.528	0.188	0.464	0	0.667	0.271	0.350	0.700
Israel	1992	5390	0.630	0.222	0.533	0	0.667	0.750	0.810	0.540
Italy	1998	4048	0.406	0.231	1.292	1	0.667	0.375	0.750	0.760
Japan	1980	8364	0.791	0.185	0.747	1	0.750	0.000	0.920	0.460
Netherlands	1983	7874	0.890	0.204	0.204	0	0.500	0.375	0.530	0.800
New Zealand	2001	3263	0.373	0.114	0.440	0	0.667	0.396	0.490	0.790
Norway	1996	4500	0.471	0.245	1.024	0	0.583	0.396	0.500	0.690
Portugal	1988	6318	0.305	0.150	0.537	1	0.417	0.500	1.040	0.270
Singapore	2000	3514	1.749	0.203	0.673	0	0.100	0.875	0.080	0.200
South Korea	1980	9248	0.538	0.237	1.975	1	0.750	0.292	0.850	0.180
Spain	1987	6777	0.596	0.211	1.263	1	0.500	0.375	0.860	0.510
Sweden	1987	6750	0.870	0.233	0.852	0	0.583	0.438	0.290	0.710
Swiss	1989	6275	1.800	0.184	0.873	0	0.667	0.208	0.580	0.680
The United Kingdom	1986	7084	1.236	0.160	0.890	0	0.833	0.667	0.350	0.890
The United States	1980	8568	1.092	0.170	1.462	0	1.000	0.875	0.460	0.910
Emerging market										
Argentina	1989	6150	0.249	0.466	0.271	1	0.500	0.500	0.860	0.460
Brazil	1996	4446	0.435	0.349	0.541	0	0.250	0.521	0.760	0.380
Chile	1990	5976	1.293	0.188	0.184	0	0.583	0.542	0.860	0.230
Columbia	2003	2684	0.377	0.125	0.125	0	0.417	0.521	0.800	0.130
Egypt	1994	4520	0.386	0.283	0.315	1	0.500	0.333	NA	NA

Jordan	2000	3416	1.339	0.156	0.382	1	0.667	0.542	NA	NA
India	1980	7718	0.422	0.262	1.039	1	0.917	0.719	0.400	0.480
Indonesia	1984	7290	0.228	0.227	0.497	1	0.500	0.500	0.480	0.140
Malaysia	1980	8364	1.511	0.209	0.391	1	0.500	0.844	0.360	0.260
Mexico	1994	4980	0.279	0.254	0.322	1	0.583	0.250	0.820	0.300
Nigeria	1998	3808	0.167	0.168	0.126	1	0.667	0.281	0.850	0.370
Peru	1990	5952	0.295	0.249	0.181	1	0.333	0.750	0.870	0.160
Philippines	1987	6669	0.469	0.254	0.241	1	0.833	0.813	0.440	0.320
South Africa	1996	4500	1.798	0.431	0.431	0	0.833	0.292	0.490	0.650
Sri Lanka	1985	6902	0.156	0.174	0.158	1	0.750	0.333	0.440	0.320
Thailand	1988	6370	0.534	0.268	0.839	1	0.917	0.667	0.640	0.200
Turkey	1988	6474	0.195	0.439	1.487	1	0.500	0.563	0.850	0.370
Venezuela	1994	4820	0.014	0.263	0.010	1	0.167	0.479	0.760	0.120

Table 1 provides means of the following variables across the entire sample period: stock market size (*SIZE*), volatility (*VOLATILITY*), liquidity (*LIQUIDITY*), price limit (*LIMIT*), disclosure requirement (*DISCLOSE*), public enforcement (*ENFORCEMENT*), uncertainty avoidance (*UNCERTAINTY*), and individualism–collectivism (*INDIVIDUALISM*).

Table 2

Descriptive statistics on developed and emerging markets.

	SIZE	*VOLATILITY*	*LIQUIDITY*	*LIMIT*	*DISCLOSE*	*ENFORCEMENT*	*UNCERTAINTY*	*INDIVIDUALISM*
				Developed market				
Mean	0.827	0.201	0.794	0.360	0.607	0.473	0.609	0.618
Median	0.611	0.203	0.686	0.000	0.667	0.375	0.580	0.690
Std. dev.	0.611	0.041	0.395	0.490	0.214	0.269	0.270	0.220
				Emerging market				
Mean	0.564	0.265	0.419	0.778	0.579	0.525	0.668	0.306
Median	0.382	0.254	0.319	1.000	0.542	0.521	0.760	0.310
Std. dev.	0.531	0.099	0.369	0.428	0.217	0.182	0.196	0.146
Diff. sig.	0.000	0.000	0.000	0.000	0.044	0.000	0.000	0.000

Table 2 provides averages of the variables from the beginning year to 2013 in developed and emerging markets: stock market size (*SIZE*), volatility (*VOLATILITY*), liquidity (*LIQUIDITY*), price limit (*LIMIT*), disclosure requirement (*DISCLOSE*), public enforcement (*ENFORCEMENT*), uncertainty avoidance (*UNCERTAINTY*), and individualism–collectivism (*INDIVIDUALISM*).

Table 3

Results of the median autocorrelation regression models in the 43 stock markets.

	80-85	85-90	90-95	95-00	00-05	05-10	10-13	98-02	08-12	80-13
					Developed market					
Australia			-0.002	-0.018	**-0.083*****	-0.034	0.030	-0.018	-0.034	**-0.024****
			1.319	-0.061	-1.626	-0.694	-0.505	0.479	-0.461	-0.744
			0.384	0.662	1.507	1.090	0.880	0.370	0.727	1.038
Austria		**0.334*****	**0.144*****	-0.007	**0.073****	0.029	0.086	0.015	**0.043****	**0.110*****
		8.609	**5.056**	0.729	0.735	1.011	**1.978**	0.991	1.368	**5.525**
		11.912	**6.936**	1.396	0.816	0.593	0.307	0.847	0.721	**7.836**
Belgium			**0.071*****	**0.115*****	0.020	-0.007	0.033	**0.030***	0.022	**0.045*****
			-0.918	**3.564**	**2.905**	0.949	0.564	**2.436**	0.894	**2.639**
			5.356	**3.855**	1.335	0.789	1.521	**1.872**	0.490	**3.772**
Canada		**0.220*****	**0.253*****	**0.171*****	**0.062****	**-0.052****	0.027	**0.095*****	-0.012	**0.095*****
		2.618	**8.564**	**4.802**	1.215	**-3.182**	0.097	**1.658**	**-2.330**	**1.679**
		6.814	**10.000**	**5.036**	0.205	**2.172**	0.625	1.135	0.606	**5.727**
Denmark			**0.123*****	**0.111*****	**0.062***	0.025	-0.022	**0.052***	0.042	**0.056*****
			3.109	**1.672**	1.008	0.896	1.120	0.973	0.940	**2.198**
			4.917	**3.685**	0.531	0.225	1.407	1.498	0.835	**2.846**
Finland		**0.424*****	**0.173*****	**0.059*****	0.032	0.015	0.002	**0.056*****	0.016	**0.091*****
		3.749	**7.384**	0.729	0.014	-0.270	**1.888**	0.602	0.141	**2.307**
		15.750	**8.196**	0.000	0.020	0.053	0.200	0.155	0.151	**6.670**
France		0.033	0.020	0.003	**-0.109*****	-0.020	**-0.193***	0.003	-0.020	-0.013
		1.481	0.319	0.875	-0.328	-0.836	-1.334	0.738	-0.249	-0.161
		2.454	0.119	0.648	**2.498**	0.934	**3.269**	0.838	0.756	1.590
Germany	0.048	**0.064****	0.003	-0.015	**-0.058*****	-0.026	**0.055****	-0.011	0.008	0.001
	1.085	0.703	0.198	0.234	-0.657	-0.806	1.058	0.726	-0.113	0.177
	0.758	0.442	**1.924**	1.008	0.987	**1.687**	0.334	0.045	0.871	0.241
Greece		**0.370*****	**0.154*****	**0.096*****	**0.065****	**0.048***	0.045	**0.104*****	0.044	**0.128*****
		3.646	**3.314**	**3.774**	**2.040**	1.484	0.458	**3.881**	0.746	**6.106**
		8.272	**4.691**	**5.292**	**2.887**	**2.093**	**1.952**	**4.892**	1.556	**11.303**

Hong Kong	**0.075*****	0.011	0.017	-0.012	0.031	**-0.055*****	-0.011	0.026	-0.020	**0.014*****
	1.227	**2.377**	0.449	0.533	0.562	-1.196	0.687	0.807	-0.535	**1.931**
	2.637	**3.127**	**3.389**	0.890	1.073	0.920	0.048	0.780	0.197	**4.468**
Ireland	**0.182*****	**0.228*****	**0.062****	0.048	0.013	0.036	-0.052	**0.058****	0.004	**0.102*****
	6.191	**4.830**	**4.788**	**2.147**	0.473	0.756	0.650	**2.561**	0.862	**6.188**
	5.961	**8.343**	**5.669**	0.692	1.222	0.636	**1.968**	**1.871**	0.995	**7.816**
Israel			0.038	**0.070****	0.023	-0.033	-0.010	**0.067****	**-0.062*****	**0.023***
			0.898	**2.625**	**1.998**	1.059	-0.869	**2.684**	0.463	**2.499**
			0.963	**3.084**	**2.553**	0.320	0.874	**2.269**	0.062	**2.957**
Italy				0.009	**-0.046***	**0.031*****	-0.190	0.009	**0.031*****	-0.001
				0.660	-0.614	0.410	-0.610	0.660	0.188	-0.061
				0.432	1.390	0.342	**1.832**	0.432	0.248	0.698
Japan	**0.067****	**0.073*****	-0.012	**-0.076*****	-0.015	**-0.048****	**-0.070***	-0.015	**-0.039***	**-0.025*****
	1.016	-0.051	0.383	**-2.348**	-0.435	-0.541	-1.018	-0.593	-0.932	-1.545
	2.260	1.569	0.578	**2.555**	0.726	1.371	1.384	1.636	**1.677**	1.163
Portugal		**0.428****	**0.195*****	**0.085*****	-0.003	**0.068*****	0.002	**0.120*****	**0.068*****	**0.129*****
		8.555	**9.343**	**3.751**	**2.120**	0.884	**1.607**	**2.968**	1.353	**8.177**
		17.591	**10.089**	**5.406**	**2.393**	**1.670**	0.396	**4.769**	**2.101**	**14.247**
New Zealand					0.015	0.060	**0.065***	**-0.035***	**0.060****	**0.041*****
					0.043	0.903	**1.950**	-0.267	0.896	1.568
					0.477	**2.613**	**1.741**	1.494	**2.230**	**2.563**
Netherlands	-0.034	-0.033	0.002	0.041	-0.010	-0.001	0.057	0.041	-0.001	-0.004
	-0.029	-0.736	0.894	0.675	0.0253	-0.315	-0.155	0.794	0.012	0.119
	0.476	0.147	0.471	0.432	0.708	0.290	1.564	0.263	0.234	0.348
Norway				0.036	0.017	**-0.048****	-0.040	0.026	**-0.042***	-0.012
				1.522	1.098	-0.578	0.015	1.021	0.068	0.124
				1.478	0.219	**1.917**	**2.380**	0.290	0.639	1.573
Singapore					-0.037	**-0.068*****	0.005	-0.034	-0.023	**-0.040*****
					0.755	-0.441	**2.017**	0.310	1.168	1.197
					1.313	1.603	1.115	0.378	0.406	0.844
Spain		**0.193*****	**0.145*****	-0.001	-0.012	**0.047****	0.044	-0.012	**0.055****	**0.048*****
		6.139	**2.615**	0.931	-0.550	-0.250	1.419	0.666	0.195	**1.920**

		8.955	**3.320**	0.133	1.290	0.823	0.204	0.681	0.689	**3.220**
Sweden		**0.127*****	**0.063****	**0.065****	-0.027	-0.031	**-0.097***	**0.057***	-0.033	**0.021****
		3.517	**2.383**	0.316	0.503	-1.544	-0.296	0.346	-0.226	0.790
		4.935	**3.178**	0.057	0.255	**2.977**	**2.708**	0.002	**2.421**	0.911
Swiss		-0.015	0.025	0.021	**-0.029***	**0.055*****	0.077	0.023	**0.056*****	**0.014***
		-0.281	**1.688**	0.979	0.100	0.412	0.181	0.755	0.670	0.589
		2.905	0.903	0.403	**2.109**	0.027	0.051	0.881	0.667	1.001
South Korea	**0.184*****	**0.124*****	**0.080*****	**0.188*****	**0.046***	-0.010	-0.033	**0.046***	-0.009	**0.073*****
	3.049	**3.348**	1.560	**3.248**	**1.928**	0.674	0.234	0.726	0.398	**3.743**
	3.350	**5.808**	**3.261**	**4.663**	**2.545**	0.830	0.330	1.554	0.424	**7.825**
the United Kingdom		**0.065****	0.012	**0.058****	-0.041	-0.013	-0.025	0.036	-0.015	0.012
		3.316	**2.266**	**2.016**	-0.386	**-2.770**	0.927	0.312	-0.186	0.758
		1.432	**2.229**	0.880	**2.281**	**2.162**	0.729	0.573	1.349	0.146
the United States	**0.328*****	**0.237*****	**0.226*****	**0.062****	0.028	**-0.036*****	-0.015	0.027	**-0.031***	**0.082*****
	8.064	**10.258**	**6.228**	**2.423**	-0.007	**-3.101**	-1.394	0.452	**-2.624**	1.208
	9.662	**11.771**	**6.833**	**3.342**	0.562	**1.672**	1.180	0.362	**1.699**	**7.032**
Emerging market										
Argentina			**0.064****	**0.077*****	**0.054****	0.011	0.030	**0.050****	**0.040***	**0.041*****
			0.984	1.379	**1.874**	0.305	0.983	1.471	1.539	**4.265**
			1.138	0.884	**2.456**	0.713	**2.378**	**2.370**	**2.071**	**3.974**
Brazil				**0.088*****	0.055	-0.003	0.039	**0.067*****	0.004	**0.042*****
				2.021	1.623	0.188	0.317	1.578	0.065	**1.652**
				2.134	0.402	1.016	0.505	**1.900**	0.139	1.003
Chile			**0.421*****	**0.340*****	**0.304*****	**0.203*****	**0.202***	**0.353*****	**0.180*****	**0.294*****
			14.670	**8.471**	**13.015**	**5.287**	**2.901**	**12.804**	**3.946**	**17.813**
			14.222	**11.019**	**13.079**	**6.873**	**4.975**	**13.435**	**6.083**	**23.031**
Columbia					**0.278***	**0.097****	0.007		**0.091****	**0.138****
					4.256	**1.971**	-0.109		**2.148**	**4.876**
					6.790	**2.635**	0.350		**2.539**	**7.281**
Egypt				**0.314*****	**0.190*****	**0.099*****	**0.137*****	**0.138***	**0.181*****	**0.188*****
				14.258	**4.371**	**4.973**	**4.945**	**3.863**	**4.924**	**11.021**
				15.382	**6.499**	**3.247**	**4.398**	**5.409**	**4.472**	**13.902**

India	**0.091*****	**0.131*****	**0.234*****	0.038	**0.074****	**0.063*****	**0.071***	**0.051***	**0.072*****	**0.109*****
	0.330	**1.755**	**2.574**	**1.372**	0.756	1.494	1.314	1.277	1.129	**4.074**
	3.644	**2.052**	**3.452**	**3.208**	**2.958**	1.322	**1.609**	**1.929**	**2.127**	**7.379**
Indonesia		**0.064****	**0.266*****	**0.216*****	**0.042***	**0.106*****	-0.022	**0.067*****	**0.024*****	**0.120*****
		-5.037	**9.900**	**5.318**	**3.852**	**2.226**	**3.303**	**3.519**	**3.508**	**11.093**
		9.804	**18.190**	**11.490**	**4.518**	**2.861**	0.378	**4.034**	**1.920**	**15.921**
Jordan					**0.268***	**0.243*****	**0.095*****	**0.255***	**0.215*****	**0.206*****
					4.434	**4.822**	**2.671**	**3.173**	**7.054**	**7.321**
					7.495	**5.817**	**3.059**	**6.369**	**5.264**	**10.420**
Malaysia	**0.226*****	**0.112*****	**0.148*****	**0.118*****	**0.119*****	**0.080*****	**0.114***	**0.077*****	**0.078*****	**0.135*****
	4.154	**3.066**	**4.383**	0.773	**4.916**	**3.335**	**4.040**	0.288	**3.129**	**7.4209**
	6.066	**8.013**	**7.292**	**4.756**	**6.189**	**4.737**	**2.623**	**5.636**	**4.148**	**16.708**
Mexico				**0.078*****	**0.104*****	**0.099****	0.019	**0.071*****	**0.057*****	**0.083*****
				1.816	**2.031**	**1.951**	1.242	**1.998**	1.267	**2.972**
				3.446	**2.722**	0.324	0.374	**2.909**	0.420	**4.004**
Nigeria				**0.475***	**0.342*****	**0.549*****	**0.136***	**0.445*****	**0.532*****	**0.423*****
				11.751	**6.832**	**9.898**	**3.519**	**11.751**	**9.298**	**15.217**
				15.173	**13.246**	**18.148**	**3.864**	**15.173**	**16.386**	**27.353**
Peru			**0.602***	**0.279*****	**0.126*****	**0.260*****	**0.084*****	**0.152*****	**0.127*****	**0.315*****
			29.577	**5.657**	**7.351**	**5.876**	**2.219**	**5.334**	**3.724**	**32.837**
			19.741	**9.797**	**5.503**	**7.455**	**4.614**	**5.375**	**6.029**	**23.935**
Philippines		**0.173*****	**0.193*****	**0.216*****	**0.087*****	**0.073****	**0.118***	**0.154*****	**0.128*****	**0.147*****
		3.149	**5.893**	**4.476**	**2.361**	**3.009**	**1.706**	**2.571**	**3.300**	**7.112**
		6.300	**7.009**	**7.301**	**4.060**	**2.987**	0.594	**5.208**	**3.574**	**12.722**
South Africa				**0.156*****	**0.102*****	0.002	-0.043	**0.056*****	0.016	**0.057*****
				4.060	**3.221**	0.760	-0.073	**4.734**	1.180	**3.327**
				4.615	**3.480**	0.769	1.512	**5.791**	0.770	**2.943**
Sri Lanka		**0.190*****	**0.553*****	**0.480*****	**0.259*****	**0.209*****	**0.252***	**0.290*****	**0.234*****	**0.346*****
		7.145	**17.895**	**14.639**	**3.407**	**3.847**	**8.052**	**4.662**	**7.365**	**19.807**
		13.872	**26.126**	**20.347**	**10.130**	**7.631**	**10.883**	**10.239**	**10.859**	**36.395**
Thailand		**0.087*****	**0.105*****	**0.051****	**0.049***	-0.014	0.036	**0.051****	-0.014	**0.063*****
		2.783	**3.324**	**4.191**	-0.499	**2.458**	0.291	**3.344**	**2.443**	**7.055**

	5.735	**6.188**	**4.000**	**2.638**	**2.139**	0.037	**3.584**	**1.991**	**9.965**
Turkey	**0.228*****	**0.119*****	-0.039	-0.011	0.040	0.023	-0.039	0.040	**0.056*****
	4.460	**4.359**	0.473	-0.080	1.443	-0.983	0.071	1.427	**5.788**
	6.130	**4.731**	**1.861**	0.174	0.610	0.067	1.284	0.050	**6.774**
Venezuela		**0.197***	**0.150*****	**0.141*****	**0.017***	**0.240***	**0.150*****	**0.017***	**0.144*****
		7.030	**2.312**	**4.426**	**6.308**	**2.897**	0.190	**12.061**	**7.030**
		6.857	**4.267**	**8.706**	**4.979**	**4.728**	1.341	**14.675**	**6.857**

In Table 3 we use returns from 43 stock markets to estimate autocorrelation coefficients in five-year intervals in the 50% quantile from 1980 to 2013. We divide all markets into developed markets and emerging markets. Periods with global financial crises and the entire sample period are also considered. The *T*-statistics from the automatic variance ratio test and the joint Wright's rank and sign test are shown in the second and third rows for each country. The null hypothesis is that returns follow a random walk. The alternative hypothesis is that returns do not follow a random walk. *T*-statistics above 1.65 reject the null hypothesis. Boldface indicates that the coefficients and results of the corresponding tests are significant. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4

Results of the autocorrelation regression models in all stock markets.

Variable	OLS				50% quantile				80% quantile				20% quantile			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Constant	0.210***	0.274***	0.273***	0.361***	0.222***	0.162***	0.290***	0.166***	0.264***	0.164***	0.484***	0.392***	0.274***	0.264***	0.374***	0.372***
	(0.014)	(0.020)	(0.018)	(0.023)	(0.020)	(0.031)	(0.044)	(0.052)	(0.020)	(0.037)	(0.042)	(0.052)	(0.014)	(0.021)	(0.032)	(0.042)
SIZE	-0.048***	-0.036***	-0.055***	-0.043***	-0.078***	-0.096***	-0.096***	-0.103***	-0.087***	-0.097***	-0.112***	-0.122***	-0.016***	-0.018***	-0.034***	-0.034***
	(0.010)	(0.010)	(0.009)	(0.010)	(0.017)	(0.018)	(0.022)	(0.021)	(0.013)	(0.015)	(0.014)	(0.015)	(0.006)	(0.007)	(0.009)	(0.009)
VOLATILITY	-0.073*	-0.087*	-0.063	-0.058	0.168**	0.210***	0.181**	0.192**	0.060	0.061	0.112	0.117	-0.182***	-0.179***	-0.197***	-0.195***
	(0.044)	(0.045)	(0.041)	(0.040)	(0.073)	(0.075)	(0.084)	(0.083)	(0.080)	(0.082)	(0.081)	(0.081)	(0.049)	(0.050)	(0.051)	(0.051)
LIQUIDITY	-0.054***	-0.049***	-0.050***	-0.043***	-0.088***	-0.091***	-0.080***	-0.091***	-0.212***	-0.207***	-0.163***	-0.160***	-0.040***	-0.042***	-0.033***	-0.033**
	(0.011)	(0.011)	(0.010)	(0.010)	(0.015)	(0.015)	(0.014)	(0.015)	(0.016)	(0.015)	(0.017)	(0.016)	(0.013)	(0.013)	(0.012)	(0.013)
LIMIT	0.047***	0.044***	0.015	0.015	0.054***	0.048***	0.031*	0.022	0.090***	0.092***	0.038**	0.038**	0.046***	0.047***	0.018	0.018
	(0.009)	(0.009)	(0.010)	(0.011)	(0.015)	(0.015)	(0.019)	(0.018)	(0.017)	(0.018)	(0.017)	(0.017)	(0.010)	(0.010)	(0.012)	(0.012)
ENFORCEMENT		-0.057**		-0.098***		0.060		0.043		0.094**		-0.018		0.004		-0.002
		(0.024)		(0.022)		(0.038)		(0.040)		(0.044)		(0.042)		(0.023)		(0.027)
DISCLOSE		-0.076***		-0.031		0.063		0.149***		0.088*		0.178***		0.014		0.006
		(0.026)		(0.030)		(0.040)		(0.053)		(0.049)		(0.055)		(0.026)		(0.031)
UNCERTAINTY			-0.008	-0.037**			-0.028	0.032			-0.133***	-0.115***			-0.060**	-0.059**
			(0.016)	(0.017)			(0.033)	(0.035)			(0.034)	(0.032)			(0.024)	(0.026)
INDIVIDUALISM			-0.098***	-0.132***			-0.086**	-0.110**			-0.315***	-0.337***			-0.083***	-0.085***
			(0.017)	(0.024)			(0.042)	(0.044)			(0.038)	(0.042)			(0.028)	(0.030)
Observations	313	313	287	287	235	235	217	217	242	242	230	230	334	334	309	309
Wald chi2	95.93	98.36	120.72	138.71	91.83	102.80	91.26	112.09	413.45	451.82	413.45	476.01	56.02	60.04	56.01	57.41
Prob> chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 4 shows results for the determinants of return autocorrelation in 43 stock markets. The regression model is:

$$AC_{it} = \mu_i + b_1 SIZE_{it} + b_2 VOLATILITY_{it} + b_3 LIQUIDITY_{it} + b_4 LIMIT_{it} + b_5 ENFORCEMENT_{it} + b_6 UNCERTAINTY_{it} + b_7 INDIVIDUALISM_{it} + \varepsilon_{it}$$

The return autocorrelation coefficients are estimated year by year using ordinary least squares (OLS), 50% quantile, 80% quantile, and 20% quantile. The estimation method is fixed-effect feasible generalized least squares. Standard errors are in parentheses. ***, **, and *indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Results of the autocorrelation regression models in developed and emerging markets.

Variable	Developed Market				Emerging Market			
	OLS	50% Quantile	80% Quantile	20% Quantile	OLS	50% Quantile	80% Quantile	20% Quantile
Constant	0.430***	0.055**	0.311***	0.348***	0.499***	0.502***	0.535***	0.523***
	(0.056)	(0.068)	(0.076)	(0.063)	(0.077)	(0.095)	(0.102)	(0.083)
SIZE	-0.063***	-0.182***	-0.179***	-0.025***	0.016	-0.108***	-0.030	-0.049***
	(0.009)	(0.034)	(0.023)	(0.009)	(0.020)	(0.030)	(0.019)	(0.016)
VOLATILITY	0.093	0.385***	0.365**	-0.355***	-0.172**	-0.246**	-0.020	-0.209***
	(0.085)	(0.135)	(0.147)	(0.099)	(0.083)	(0.125)	(0.106)	(0.074)
LIQUIDITY	-0.039***	-0.090***	-0.125***	-0.014	-0.026	-0.039	-0.233***	-0.031
	(0.013)	(0.023)	(0.017)	(0.018)	(0.026)	(0.025)	(0.042)	(0.021)
LIMIT	0.017	0.065**	-0.021	0.008	0.114***	0.047	0.178***	0.051**
	(0.016)	(0.026)	(0.028)	(0.020)	(0.028)	(0.034)	(0.035)	(0.024)
ENFORCEMENT	0.078	0.187**	0.124**	0.007	-0.408***	-0.076	-0.292***	-0.116**
	(0.048)	(0.064)	(0.062)	(0.051)	(0.050)	(0.062)	(0.091)	(0.056)
DISCLOSE	-0.139**	0.148*	0.210***	-0.005	-0.183***	-0.312***	0.003	-0.107**
	(0.064)	(0.082)	(0.082)	(0.068)	(0.059)	(0.093)	(0.086)	(0.043)
UNCERTAINTY	-0.128***	0.008	-0.065	-0.033	0.015	-0.089	-0.081	-0.131**
	(0.037)	(0.048)	(0.055)	(0.036)	(0.067)	(0.082)	(0.076)	(0.063)
INDIVIDUALISM	-0.204***	-0.037	-0.407***	-0.054	-0.074	0.441***	-0.361**	-0.005
	(0.038)	(0.072)	(0.077)	(0.040)	(0.100)	(0.152)	(0.181)	(0.083)
Observations	138	97	123	165	149	120	107	144
Wald chi2	106.17	128.85	240.89	26.72	128.94	39.78	120.42	41.95
Prob> chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 5presents results for the determinants of return autocorrelation in 43 stock markets. The regression model is:

$$AC_{it} = \mu_i + b_1 SIZE_{it} + b_2 VOLATILITY_{it} + b_3 LIQUIDITY_{it} + b_4 LIMIT_{it} + b_5 ENFORCEMENT_{it} + b_6 UNCERTAINTY_{it} + b_7 INDIVIDUALISM_{it} + \varepsilon_{it}$$

The return autocorrelation coefficients are estimated year by year by ordinary least squares (OLS), 50% quantile, 80% quantile, and 20% quantile. The estimation method is fixed-effect feasible generalized least squares. Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Results of the autocorrelation regression models in periods with global financial crises and without financial crises.

Variable	Periods with Global Financial Crises				Periods without Global Financial Crises			
	OLS	50% Quantile	80% Quantile	20% Quantile	OLS	50% Quantile	80% Quantile	20% Quantile
Constant	0.291^{***}	0.203^{***}	0.189^{***}	0.301^{***}	0.476^{***}	0.248^{***}	0.515^{***}	0.391^{***}
	(0.028)	(0.052)	(0.067)	(0.035)	(0.038)	(0.054)	(0.052)	(0.055)
SIZE	-0.016^{***}	-0.032	-0.072^{***}	0.006	-0.083^{***}	-0.187^{***}	-0.139^{***}	-0.050^{***}
	(0.008)	(0.020)	(0.007)	(0.015)	(0.014)	(0.030)	(0.019)	(0.011)
VOLATILITY	-0.262^{***}	-0.059	0.072	-0.230^{***}	-0.098^{*}	0.061	0.0003	-0.166^{**}
	(0.038)	(0.049)	(0.122)	(0.063)	(0.057)	(0.095)	(0.048)	(0.067)
LIQUIDITY	-0.009	-0.044^{***}	-0.093^{***}	-0.038^{***}	-0.097^{***}	-0.136^{***}	-0.221^{***}	-0.053^{***}
	(0.005)	(0.010)	(0.014)	(0.010)	(0.018)	(0.024)	(0.021)	(0.017)
LIMIT	-0.008	-0.024	0.022	-0.003	0.029^{**}	0.035	0.040^{*}	0.040^{**}
	(0.006)	(0.023)	(0.030)	(0.012)	(0.015)	(0.022)	(0.023)	(0.018)
ENFORCEMENT	-0.111^{***}	-0.052	0.024	-0.116^{***}	-0.089^{***}	0.130^{***}	-0.047	0.062^{**}
	(0.024)	(0.040)	(0.057)	(0.024)	(0.031)	(0.046)	(0.050)	(0.030)
DISCLOSE	0.065^{***}	0.115^{***}	0.251^{***}	0.139^{***}	-0.090^{**}	0.092	0.125^{**}	-0.045
	(0.019)	(0.039)	(0.063)	(0.027)	(0.045)	(0.058)	(0.061)	(0.035)
UNCERTAINTY	0.047^{**}	0.093^{***}	0.003	0.041	-0.098^{***}	-0.011	-0.123^{***}	-0.097^{***}
	(0.018)	(0.029)	(0.048)	(0.026)	(0.029)	(0.038)	(0.041)	(0.037)
INDIVIDUALISM	-0.151^{***}	-0.085^{***}	-0.443^{***}	-0.146^{***}	-0.130^{***}	-0.106^{**}	-0.305^{***}	-0.052
	(0.022)	(0.021)	(0.063)	(0.029)	(0.037)	(0.049)	(0.048)	(0.044)
Observations	98	69	71	123	189	148	159	186
Wald chi2	214.97	276.64	2768.10	175.27	268.48	204.50	469.99	64.61
Prob> chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 6 shows results for the determinants of return autocorrelation in 43 stock markets. The regression model is:

$$AC_{it} = \mu_i + b_1 SIZE_{it} + b_2 VOLATILITY_{it} + b_3 LIQUIDITY_{it} + b_4 LIMIT_{it} + b_5 ENFORCEMENT_{it} + b_6 UNCERTAINTY_{it} + b_7 INDIVIDUALISM_{it} + \varepsilon_{it}$$

The return autocorrelation coefficients are estimated year by year by ordinary least squares (OLS), 50% quantile, 80% quantile ,and 20% quantile. The estimation method is fixed-effect feasible generalized least squares. Standard errors are in parentheses. ***, **, and *indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Results of the autocorrelation regression models in periods of economic expansion and contraction.

Variable	Periods of Economic Expansion				Period sof Economic Contraction			
	OLS	50% Quantile	80% Quantile	20% Quantile	OLS	50% Quantile	80% Quantile	20% Quantile
Constant	0.296^{***}	0.192^{***}	0.435^{***}	0.435^{***}	0.349^{***}	0.147	0.501^{***}	0.245^{***}
	(0.030)	(0.065)	(0.053)	(0.042)	(0.101)	(0.247)	(0.120)	(0.066)
GDP	1.057^{***}	0.398	0.283	0.544^{**}	-0.340	-1.644^{*}	-0.687^{*}	-1.379^{*}
	(0.312)	(0.377)	(0.401)	(0.238)	(0.465)	(0.904)	(0.415)	(0.859)
SIZE	-0.038^{***}	-0.149^{***}	-0.088^{***}	-0.040^{***}	0.006	0.098^{**}	-0.223^{**}	-0.003
	(0.010)	(0.029)	(0.015)	(0.008)	(0.031)	(0.040)	(0.108)	(0.029)
VOLATILITY	-0.158^{***}	0.288^{**}	0.021	-0.206^{***}	-0.028	-0.148	-0.006	-0.109
	(0.056)	(0.113)	(0.071)	(0.053)	(0.108)	(0.192)	(0.051)	(0.137)
LIQUIDITY	-0.048^{***}	-0.085^{***}	-0.200^{***}	-0.016	-0.020	-0.176^{**}	-0.074^{**}	-0.101^{***}
	(0.012)	(0.016)	(0.020)	(0.010)	(0.018)	(0.067)	(0.030)	(0.029)
LIMIT	0.022^{*}	0.045^{*}	0.085^{***}	0.002	0.020	0.051	-0.063^{*}	0.018
	(0.012)	(0.026)	(0.020)	(0.014)	(0.026)	(0.044)	(0.037)	(0.034)
ENFORCEMENT	-0.117^{***}	0.002	-0.123^{***}	-0.046^{*}	-0.055	0.258^{**}	0.264^{***}	-0.024
	(0.020)	(0.052)	(0.037)	(0.027)	(0.066)	(0.108)	(0.082)	(0.036)
DISCLOSE	-0.073^{***}	0.060	0.110^{*}	-0.031	-0.109	-0.306	-0.120	0.163^{***}
	(0.027)	(0.060)	(0.063)	(0.030)	(0.100)	(0.203)	(0.141)	(0.046)
UNCERTAINTY	0.008	0.005	-0.095^{**}	-0.114^{***}	-0.053	0.217	-0.165^{**}	0.027
	(0.021)	(0.042)	(0.037)	(0.029)	(0.065)	(0.132)	(0.069)	(0.043)
INDIVIDUALISM	-0.063^{**}	-0.060	-0.293^{***}	-0.088^{***}	-0.095	0.045	-0.237^{**}	-0.170^{**}
	(0.028)	(0.057)	(0.047)	(0.030)	(0.073)	(0.157)	(0.101)	(0.071)
Observations	212	161	157	219	36	21	34	32
Wald chi2	215.15	127.52	678.5	77.28	22.29	54.78	126.26	329.77
Prob> chi2	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.000

Table 7 shows results for the determinants of return autocorrelation in 43 stock markets. The regression model is:

$$AC_{it} = \mu_i + b_1 SIZE_{it} + b_2 VOLATILITY_{it} + b_3 LIQUIDITY_{it} + b_4 LIMIT_{it} + b_5 ENFORCEMENT_{it} + b_6 UNCERTAINTY_{it} + b_7 INDIVIDUALISM_{it} + \varepsilon_{it}$$

The return autocorrelation coefficients are estimated year by year by ordinary least squares (OLS), 50% quantile, 80% quantile, and 20% quantile. The estimation method is fixed-effect feasible generalized least squares. Standard errors are in parentheses. ***, **, and *indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Results of the autocorrelation regression model controlling for cross-country autocorrelation.

Variable	OLS	50% Quantile	80% Quantile	20% Quantile
Constant	0.407***	0.217***	0.424***	0.335***
	(0.031)	(0.052)	(0.044)	(0.042)
SIZE	-0.035**	-0.073***	-0.080***	-0.034***
	(0.014)	(0.020)	(0.016)	(0.009)
VOLATILITY	-0.088*	0.056	-0.033	-0.180***
	(0.048)	(0.082)	(0.068)	(0.050)
LIQUIDITY	-0.063***	-0.081***	-0.116***	-0.030**
	(0.015)	(0.014)	(0.017)	(0.013)
LIMIT	0.028**	0.010	0.018	0.014
	(0.012)	(0.016)	(0.018)	(0.012)
ENFORCEMENT	-0.101***	0.013	-0.060	0.003
	(0.028)	(0.038)	(0.040)	(0.026)
DISCLOSE	-0.072*	0.152***	0.160***	0.007
	(0.040)	(0.050)	(0.050)	(0.031)
UNCERTAINTY	-0.042*	0.020	-0.060*	-0.044
	(0.024)	(0.032)	(0.031)	(0.027)
INDIVIDUALISM	-0.142***	-0.163***	-0.353***	-0.094***
	(0.028)	(0.037)	(0.042)	(0.030)
ACUS	-0.024	0.195**	0.147**	0.086**
	(0.017)	(0.081)	(0.069)	(0.033)
ACUK	0.152**	0.280***	0.497***	0.112**
	(0.061)	(0.086)	(0.088)	(0.043)
ACJAPAN	-0.001	0.296**	0.216**	0.105**
	(0.091)	(0.116)	(0.094)	(0.049)
Observations	248	217	230	309
Wald chi2	182.71	170.4	693.72	69.29
Prob> chi2	0.000	0.000	0.000	0.000

Table 8 shows results for the determinants of return autocorrelation in 43 markets using the following regression model:

$$AC_{it} = \mu_i + b_1 SIZE_{it} + b_2 VOLATILITY_{it} + b_3 LIQUIDITY_{it} + b_4 LIMIT_{it} + b_5 ENFORCEMENT_{it} + b_6 UNCERTAINTY_{it} + b_7 INDIVIDUALISM_{it} + b_8 ACUS_t + b_9 ACUK_t + b_{10} ACJAPAN_t + \varepsilon_{it}$$

The return autocorrelation coefficients are estimated year by year by ordinary least squares (OLS), 50% quantile, 80% quantile, and 20% quantile. The estimation method is fixed-effect feasible generalized least squares. Standard errors are in parentheses. ***, **, and *indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Results of the autocorrelation regression models in all the stock markets with the clustered robust standard errors

Variable	OLS				50% quantile				80% quantile				20% quantile			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Constant	0.216***	0.278***	0.311***	0.390***	0.237***	0.195**	0.339***	0.273**	0.233***	0.125*	0.517***	0.392***	0.297***	0.280***	0.441***	0.433***
	(0.037)	(0.051)	(0.073)	(0.072)	(0.049)	(0.072)	(0.082)	(0.105)	(0.051)	(0.073)	(0.072)	(0.075)	(0.031)	(0.036)	(0.047)	(0.063)
Size	-0.057***	-0.048**	-0.065***	-0.057**	-0.104***	-0.112***	-0.128***	-0.130***	-0.092***	-0.109***	-0.128***	-0.135***	-0.025	-0.028	-0.053***	-0.054***
	(0.019)	(0.020)	(0.020)	(0.021)	(0.035)	(0.035)	(0.042)	(0.044)	(0.029)	(0.030)	(0.028)	(0.029)	(0.018)	(0.020)	(0.015)	(0.015)
Volatility	-0.057	-0.076	-0.091	-0.089	0.232	0.251	0.211	0.220	0.061	0.072	0.030	0.034	-0.204**	-0.195**	-0.220**	-0.212**
	(0.103)	(0.098)	(0.105)	(0.102)	(0.193)	(0.181)	(0.183)	(0.184)	(0.117)	(0.113)	(0.089)	(0.081)	(0.093)	(0.087)	(0.093)	(0.089)
Liquidity	-0.075***	-0.072**	-0.066**	-0.065**	-0.110***	-0.111***	-0.101***	-0.105***	-0.180***	-0.184***	-0.139***	-0.148***	-0.064***	-0.065***	-0.052***	-0.053***
	(0.026)	(0.029)	(0.027)	(0.029)	(0.029)	(0.032)	(0.027)	(0.029)	(0.043)	(0.039)	(0.042)	(0.037)	(0.019)	(0.021)	(0.017)	(0.018)
Limit	0.058**	0.057**	0.019	0.023	0.054	0.053	0.020	0.009	0.102**	0.104**	0.039	0.026	0.055***	0.055***	0.026	0.023
	(0.025)	(0.026)	(0.028)	(0.024)	(0.041)	(0.039)	(0.047)	(0.043)	(0.041)	(0.040)	(0.044)	(0.043)	(0.019)	(0.018)	(0.019)	(0.018)
Enforcement		-0.051		-0.072		0.042		0.030		0.107		0.044		0.002		-0.016
		(0.080)		(0.082)		(0.078)		(0.080)		(0.102)		(0.094)		(0.064)		(0.058)
Disclose		-0.063		-0.045		0.037		0.085		0.105		0.165		0.025		0.028
		(0.081)		(0.089)		(0.086)		(0.106)		(0.089)		(0.103)		(0.058)		(0.064)
Uncertainty			-0.015	-0.049			-0.041	-0.008			-0.162**	-0.109			-0.100**	-0.095**
			(0.072)	(0.061)			(0.067)	(0.073)			(0.076)	(0.075)			(0.042)	(0.045)
Individualism			-0.123**	-0.124**			-0.102	-0.130*			-0.304***	-0.334***			-0.111**	-0.118**
			(0.051)	(0.050)			(0.077)	(0.075)			(0.074)	(0.075)			(0.043)	(0.045)
Observations	313	313	287	287	235	235	217	217	242	242	230	230	334	334	309	309
R-square	0.214	0.231	0.234	0.251	0.284	0.289	0.302	0.312	0.461	0.482	0.523	0.542	0.147	0.148	0.202	0.203
F Statistic	6.000	7.510	7.660	5.960	9.290	7.980	6.180	6.130	17.140	15.290	18.130	16.090	5.570	5.360	6.220	5.580
Prob> F	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000

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

Table 9 shows results for the determinants of return autocorrelation in 43 stock markets. The regression model is:
$$AC_{it} = \mu_i + b_1 SIZE_{it} + b_2 VOLATILITY_{it} + b_3 LIQUIDITY_{it} + b_4 LIMIT_{it} + b_5 ENFORCEMENT_{it} + b_6 UNCERTAINTY_{it} + b_7 INDIVIDUALISM_{it} + \varepsilon_{it}$$
The return autocorrelation coefficients are estimated year by year using ordinary least squares (OLS), 50% quantile, 80% quantile, and 20% quantile. The regression models are estimated by OLS clustered with country robust standard errors. Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix A

Theoretical influences of the determinants on the return autocorrelation.

Variable	Theoretical Influence	Literature
SIZE	−	Lo and MacKinlay (1990), Llorente et al. (2002), Brockman et al. (2009)
VOLATILITY	+(−)	Conrad and Kaul (1988), Säfvenblad (2000)
LIQUIDITY	−	Amihud and Mendelson (1986),Campbell et al. (1993), Chordia et al. (2000), Acharya and Pedersen (2005), Brockman et al. (2009)
LIMIT	+	Lee and Chung (1996), Shen and Wang (1998), Ryoo and Smith (2002), Lee and Chou (2004), Lim and Brooks (2009)
DISCLOSE	+(−)	Hirshleifer and Teoh (2003), La Porta et al. (2006)
ENFORCEMENT	−	La Porta et al. (2006), Agrawal and Nasser (2012)
UNCERTAINTY	+	Edwards (1968), Salter and Niswander (1995), Barberis et al. (1998)
INDIVIDUALISM	−	Markus and Kitayama (1998), Daniel et al. (1998), Jain and Chu (2014), Van den Steen (2004)

Appendix B

Definition of variables and data source.

Variable	Definition	Data Source
SIZE	Stock market size is calculated by stock market capitalization over GDP. Market capitalization is the share price times the number of shares outstanding.	Global Financial Development Database (GFDD)
VOLATILITY	Stock price volatility is the 360-day standard deviation of the return on the national stock market index.	GFDD
LIQUIDITY	Stock market turnover ratio is the total value of shares traded during the period divided by the average market capitalization for the period. Average market capitalization is calculated as the average of the end-of-period values for the current period and previous periods.	GFDD
LIMIT	Price limit is an established amount in which a price may increase or decrease in any single trading day from the previous day's settlement price.	Kim and Park (2010)
DISCLOSE	The disclosure requirement is obtained by averaging information from the prospectus, compensation for the issuer's directors and key officers, issuer's equity ownership structure, equity ownership of the issuer's shares by its directors and key officers, issuer's contracts outside the ordinary course of business, and transaction between the issuer and its directors, officers, or large shareholders. It reflects the degree of information disclosure.	La Porta et al. (2006)
ENFORCEMENT	The public enforcement index averages the supervisor's independence and unique coverage on the stock market (supervisor characteristics index), the supervisor's power to regulate the security market (rule making power index), investigation of all possible false and misleading statements (investigative powers index), covering the noncriminal (orders index) and criminal sanctions for violations of security (criminal index). It reflects the power of the supervisor in charge of the security market.	La Porta et al. (2006)
UNCERTAINTY	Uncertainty avoidance expresses the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity.	Scores in the Hofstede IBM study (Hofstede, 2001)
INDIVIDUALISM	Individualism can be defined as a preference for individuals to take care of only themselves and their immediate families. Its opposite, collectivism, represents a preference for relatives or members of a particular in-group to take care of individuals within the group.	Scores in the Hofstede IBM study (Hofstede, 2001)

Appendix C
Main stock indexes in 43 stock markets.

Developed Market	Stock Index	Emerging Market	Stock Index
Australia	S&P/ASX 200	Argentina	Buenos Aires Stock Exchange Merval Index
Austria	Austrian Traded Index	Brazil	Sao Paulo Stock Exchange Index
Belgium	BEL 20 Index	Chile	IGPA Santiago De Chile Index
Canada	S&P/TSX Composite Index	Columbia	Colombia COLCAP Index
Denmark	OMX Copenhagen 20 Index	Egypt	Hermes Stock Index
Finland	OMX Helsinki Index	Jordan	Amman Stock Exchange General Index
France	CAC 40 Index	India	SENSEX Index
Germany	Deutscher Aktien Index	Indonesia	Jakarta Stock Exchange Composite Index
Greece	Athens Stock Exchange General Index	Malaysia	Kuala Lumpur Composite Index
Hong Kong	Hang Seng Index	Mexico	Mexican Bolsa IPC Index
Ireland	Irish Stock Exchange Overall Index	Nigeria	Nigerian Stock Exchange All Share Index
Israel	Tel Aviv 100 Index	Peru	Bolsa De Valores De Lima General Sector Index
Italy	FTSE MIB Index	Philippines	Philippines Stock Exchange PSEi Index
Japan	Nikkei 225Index	South Africa	FTSE/JSE Africa All Share Index
Netherlands	Amsterdam Exchange Index	Sri Lanka	Sri Lanka Colombo Stock Exchange All Share Index
New Zealand	New Zealand Exchange 50 Gross Index	Thailand	Thailand SET Index
Norway	OBX Index	Turkey	Borsa Istanbul 100 Index
Portugal	PSI All Share Index Gross Return	Venezuela	Venezuela Index
Singapore	Straits Times Index		
South Korea	KOSPI Index		
Spain	IBEX 35 Index		
Sweden	OMX Stockholm 30 Index		
Swiss	Swiss Market Index		
United Kingdom	FTSE 350 Index		
United States	Nasdaq Composite Index		

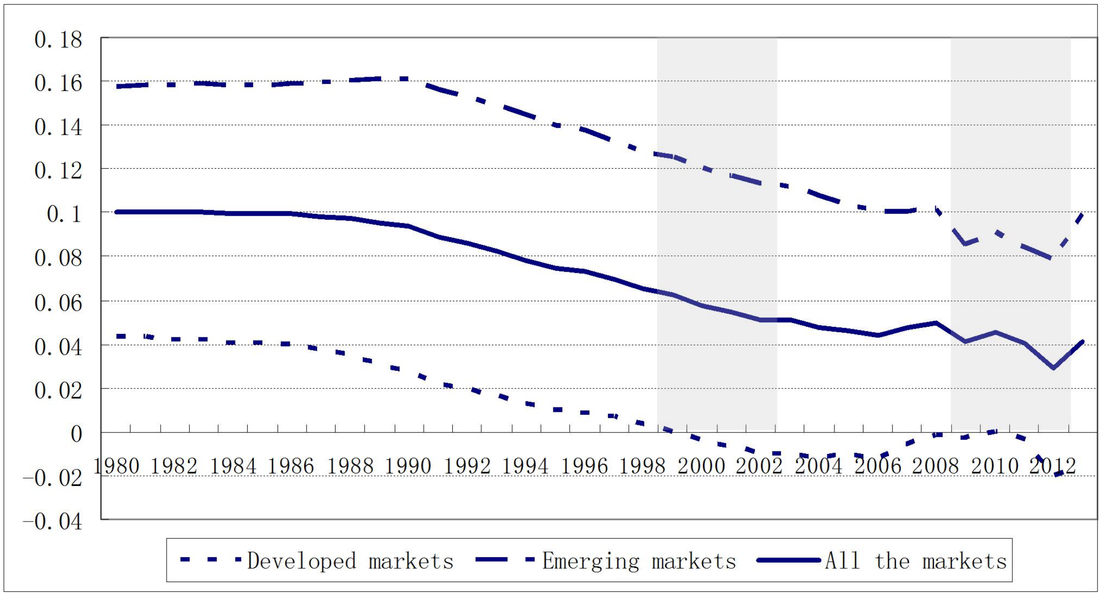

Figure 1
The trend of autocorrelation coefficients in the 50% quantile of stock markets from 1980 to 2013.

In Figure 1, we use the returns from 43 stock markets to estimate autocorrelation coefficients year by year in the 50% quantile from 1980 to 2013. We then calculate their averages for developed, emerging, and all markets. The two shaded parts show the two global financial crises.

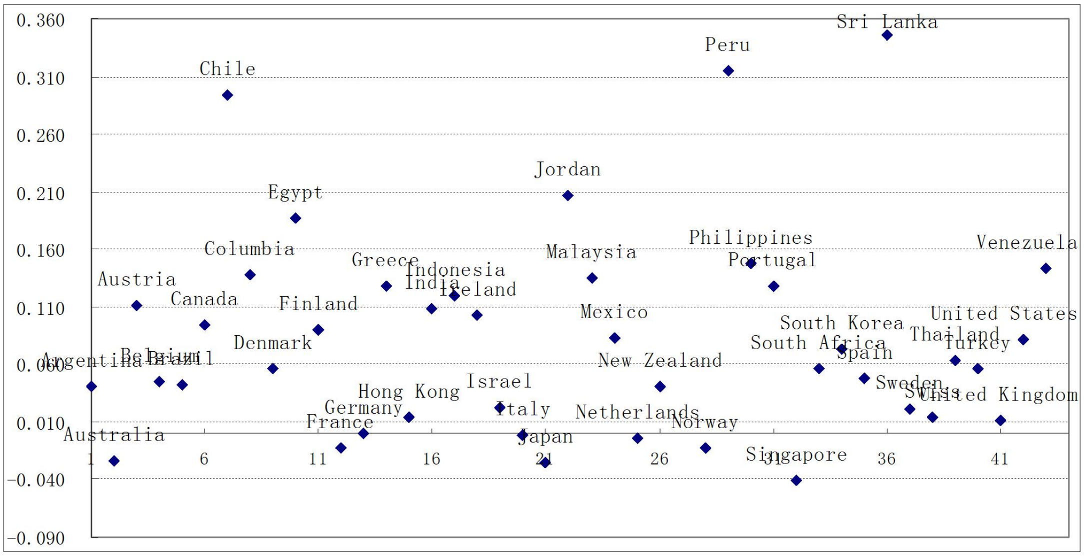

Figure 2
Return autocorrelation coefficients in 43 stock markets.

In Figure 2, we use returns from 43 stock markets to estimate autocorrelation coefficients in the 50% quantile from 1980 to 2013. We find that the autocorrelation coefficients have large differences among these countries.