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Daily serial correlation, trading volume and price limits: Evidence from the Taiwan stock market

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Abstract

The relationship among daily stock return autocorrelation, trading volume, and price limits are investigated in this paper. Twenty-four Taiwan individual stocks are adopted here. We found that increasing the volume reduces the daily autocorrelation for nearly half of the stocks. This negative volume effect is contrary to the positive price-limit effect, which strengthens the autocorrelation. We use OLS, generalized autoregressive conditional heteroscedasticity (GARCH) and generalized method of moment (GMM) to investigate the sensitivity of the estimation results. Our results display robustness across estimation methods. © 1998 Elsevier Science B.V. All rights reserved.

Keywords: Daily stock autocorrelation; Stock trading volume; Price limits

1. Introduction

Recently, some papers have reported evidence that stock returns can be predicted in both the short and long run. Though forecasting long-term stock returns can be based on certain economic variables or past returns, [2] evidence on

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[2] For example, Hodrick (1992) finds that dividend yields are helpful in improving forecasts of future stock returns from 1 month to 4 years. Fama and French (1988) claim that 3- to 5-year stock returns are predictable from past returns.

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the predictability in the short term has largely been based on past returns data due to the scarcity of short-horizon economic data. Hence, predictability in the short term means that the stock returns are autocorrelated. This autocorrelation is widely evidenced. For example, point estimates made by Poterba and Summers (1988) imply positive autocorrelation in returns over short horizons. Conrad et al. (1991) and Lehmann (1990) found significant daily autocorrelation in the returns of individual securities. [3] Conrad et al. (1994) also found strong evidence of a relation between trading activity and subsequent autocovariance. The autocorrelation of stock returns in the short term appears common rather than an exception.

More recent studies claim that this autocorrelation of stock returns may vary with time, rather than being fixed. Specifically, they argue that autocorrelation is affected by trading volume. Campbell et al. (1993) model the interactions between a liquidity investor and a market maker. A liquidity trader sells for exogenous reasons and a risk-averse market maker demands a reward in order to accommodate selling pressure. The model implies that positive first-order daily stock returns autocorrelation tends to decline with volume. Their empirical study confirms this suspicion. Blume et al. (1994) present a model in which traders can learn valuable information about a security by observing both past prices and past volumes. Boudoukh et al. (1994) report similar results. LeBaron (1992) and Sentana and Wadhwani (1992), using volatility to replace volume, also reach a similar conclusion. This price reversal is also documented by Conrad et al. (1994). The existence of the volume effect implies that the autocorrelation is lower on high-volume days than on low-volume days.

This volume effect, in fact, is consistent with a less well-known adage in the technical analysis, that is, an abnormally large change in volume is a signal of price reversals. This adage claims that the serial correlation of stock returns is related to trading volume, and a sudden and substantial movement in volume can change the direction of correlation. [4]

Studies investigating the volume effect on the autocorrelation of stock returns typically use data from non-price-limit markets. No studies, to the best of the authors' knowledge, have examined whether the results also hold true in an imperfect market. In the world of capital markets, both explicit price limits and informal price limits are common. For example, the Tokyo market, the world's second largest stock market, has daily limits imposed on share price movements (Kim and Rhee, 1997). In futures and foreign exchange markets, price limits are the norm. Thus, price limits in the financial market, for the time being, cannot be treated as an exception. Studying the role of the price-limit effect in autocorrela-

[3] Earlier papers, such as Scholes and William (1977), find daily return indexes calculated using close-to-close indexes exhibit substantial positive first-order autocorrelation.

[4] A well-known and related saying in the technical analysis is that ‘‘it takes volume to move price’’. Virtually almost all empirical studies have confirmed the following adage suggested in the technical analysis: volume tends to be higher when stock prices are increasing than when prices are falling.

tion complements our knowledge on time-varying autocorrelation in the non-price-limit markets.

If a market is subject to a price-limit regulation, the shock will not be completely realized in a day; rather, the shock will be accumulated and carried over to the successive trading day(s) (Chiang and Wei, 1995; Chou, 1997). Data containing these limiting observations, therefore, distort the true relationship among stock returns. The estimated serial correlation–volume relationship may thus be spurious if the price limits are ignored.

This paper extends the work of Campbell et al. (1993) to include the price-limit effect, which may be another factor explaining the variance in the autocorrelation of stock returns. In our empirical studies below, the price-limit effect is found to have a stronger impact on the correlation than the trading volume. We use daily Taiwan stock returns for the sample periods from November 14, 1988 to December 31, 1995. The Taiwan Stock Exchange has imposed daily limits since its inception in the 1950s. The purpose of the limits was to prevent stocks from excessive volatility and to protect investors by limiting potential daily losses to a maximum. Price limits were adjusted up or down several times according to market conditions. We use dummy variables to capture the impact of price limits on the autocorrelation. If the closing price hits an up limit on a trading day, this implies that the current closing price does not fully reflect some of the good information. The subsequent price tends to be higher than the 'equilibrium' price. Hence, it would appear that the price following a limit move are more likely to be trended, strengthening the autocorrelation. The autocorrelation of stock returns are not only influenced by trading volume but also by the price limits.

To investigate volume and price limits effects, the conventional OLS method is first attempted. Since conditional heteroscedasticity is common for stock returns in a short-horizon situation (e.g., see Lamoureux and Lastrapes, 1990), the generalized autoregressive conditional heteroscedasticity (GARCH) of Bollerslev (1986) is next implemented. However, because price limits restrict the range of price movement on a given trading day, the true price is unobserved when it moves outside the range. Thus, the conventional methods, either OLS or GARCH, may be biased in estimating the parameters. While many studies have proposed various econometric methods to estimate the parameters under price limits (Kodres, 1988, 1993; Sutrick, 1993; Yang and Brorsen, 1995), Chou (1997) points out that those methods do not correctly specify the carry-out effect. He treats the unobserved true price as a latent variable and estimates the parameters via Gibbs Sampler approach. His approach has been applied by Shen and Chou (1997) to study the weekday effect in the Taiwan stock market and by Chou and Wu (1996) in a study of the cooling-off effect induced by price limits. An alternative method to overcome the bias is derived by Chiang and Wei (1995) using the generalized method of moment (GMM) approach. Their method yields consistent estimates of the true parameters by assuming that the generating process of stock returns are invariant with price limits. The method has been employed by Shen and Lee

(1998) in an event study of accountant opinions. The estimation technique adopted here is Chiang and Wei's GMM technique for its ease of implementation. Furthermore, GMM is a distribution-free method, which may be more appropriate for high frequency data typically characterized by the conditional heteroscedasticity. [5]

The remainder of this paper is organized as follows. The data are described in Section 2 and the regression analysis based on OLS and GARCH is reported in Section 3, followed by a similar analysis using the GMM method in Section 4. Section 5 offers our conclusions.

2. Data and summarized statistics

Individual stock prices are employed in this paper to avoid the nonsynchronous trading effect on the (weighted) stock index. More importantly, the price limits influence can be more suitably dealt with if individual stocks are used. Since it is impossible to examine all stocks, the 24 daily stock series which are used to construct the composite stock index by the Taiwan Stock Exchange are adopted. The sample period covers November 14, 1988 to December 31, 1995, a period which experienced two different price limit levels. The price limit was 5% during the period November 14, 1988 to October 10, 1989 and was 7% thereafter. Altogether, 1967 observations are used in this study.

The turnover is used as a proxy for the volume as suggested by Campbell et al. (1993). The turnover, which is also referred to as the relative volume, is a ratio of the number of shares traded to the number of shares outstanding. Using the turnover avoids the problem that arises when the increase in trading results from an increase in outstanding shares. Also, it helps to reduce the low-frequency variation. However, unlike the trended turnover found in Campbell et al. (1993), turnover in our sample reveals no trend. [6] Thus, no transformation on turnover is made.

Both stock prices and returns are taken from the Taiwan AREMOS data tape available from the Education Department of the government. The stock price is used only to identify the limit-hitting days. Once the limit days are identified, the stock returns, which have been adjusted for dividend, are employed. The trading and outstanding volumes are available in the *Taiwan Economic Journal*. [7]

Table 1 presents summary statistics on the continuously compounded returns series. The first column reports the four-digit number for the stocks used by

[5] The weakness of the Gibbs sampler is their iid assumption imbedded in the residuals. The typical GARCH behavior of stock returns is ignored. The GMM method, however, which makes little assumption on the residuals, is more suitable for the present study.

[6] Figures of all turnovers are available upon request.

[7] *Taiwan Economic Journal* is a private data source company. It was established in April 1990 with a strong commitment to provide the most comprehensive and reliable data base in Taiwan.

Table 1
Basic statistics of data

Code	Mean	Standard error	First autocorrelation	Excess skewness	Excess kurtosis	Up limit	Down limit	Total % hit
1101	−0.0194	2.4112	0.0204	0.05982	1.28764[a]	69	56	6.36
1201	−0.0011	2.8495	−0.0429[c]	0.03938	0.34022[a]	100	68	8.54
1301	−0.0033	2.5587	−0.0032	0.15177[a]	1.03600[a]	73	52	6.35
1304	−0.0388	2.9962	0.0611[a]	0.05168	0.14637	83	76	8.08
1305	−0.0359	2.9377	0.0388[c]	0.02274	0.31007[a]	84	85	8.59
1402	−0.0086	2.5830	0.0411[c]	0.07974	0.85386[a]	69	50	6.05
1407	0.0324	3.0698	0.0724[a]	0.04385	0.06105	91	77	8.53
1408	−0.0070	3.0077	0.0647[a]	0.14001	0.16411	83	39	6.19
1433	−0.0245	2.4863	−0.0170	0.13333[b]	0.95071[a]	57	44	5.14
1504	0.0088	2.5428	−0.0192	0.03773[b]	0.86871[a]	77	52	6.86
1602	0.0044	2.7480	0.0496[b]	0.05138	0.55345[a]	74	66	7.12
1604	−0.0030	2.8287	0.0244	0.02650	0.33524[a]	76	72	7.52
1702	−0.0345	3.1789	0.1573[a]	0.05837	−0.06198	126	109	11.95
1802	0.0145	2.5144	−0.0194	0.04282	0.90158[a]	67	49	5.90
1905	−0.0207	2.9783	0.0401[c]	0.06657	0.22041[b]	84	69	7.78
1907	−0.0341	2.7266	0.0433[c]	−0.03110	0.61449[a]	86	77	8.28
2002	−0.0358	2.7181	0.0042	0.15756[a]	0.57937[a]	90	60	7.63
2103	−0.0058	2.8632	0.0005	0.05743	0.25509[b]	77	59	6.91
2201	−0.0347	2.8894	0.0485[a]	0.09172[b]	0.26100[b]	86	78	8.34
2301	0.0440	3.2747	0.1320[a]	−0.02945	−0.21842[b]	123	106	11.64
2501	0.0041	2.6478	0.0573[a]	0.13143[a]	0.71420[a]	90	72	8.24
2704	−0.0335	2.9507	0.0441[c]	0.08970	0.22212[b]	114	91	10.43
2801	−0.0169	2.7163	0.0637[a]	0.16886[a]	0.68698[a]	69	49	6.00
2903	−0.0148	2.4248	0.0072	0.05910	1.21342[a]	56	43	5.04
Index	−0.1101	2.2807	0.0557[a]	−0.08961	1.15102[a]	na	na	na

[a], [b] and [c]: significant at the 1%, 5% and 10% level, respectively.
The first autocorrelation is the correlation between r_t and r_{t-1}. Excess skewness is the skewness minus its mean zero. Excess kurtosis is the kurtosis minus 3. Up limit is percentage of days in the sample hitting the upper price limit. Down limit is percentage of days in the sample hitting the lower price limit. Total percent is the sum of up limit and down limit. Index is equally weighted index of 24 stocks list.

Taiwan academics. The actual name of the stocks can be easily found in the AREMOS manual. The first statistic is the sample mean of each stock return. Eighteen out of 24 stock returns reveal negative means, suggesting a downward trend in the Taiwan market during the period of study. However, sample means are overwhelmingly insignificantly different from zero. The statistics for the first autocorrelation coefficient of the observed stock returns are mainly positive and 15 out of 24 stocks are significant. The returns exhibit no skewness but reveal strong kurtosis. The sixth and seventh columns show the number of stocks hitting upper and lower price limits, respectively. The total number of stocks hitting these limits ranges from 99 to 235 and appears non-trivial. The last column reports the percentage of days in the sample that the given stock reached the price limit. These percentages range from 5.04 to 11.95. The imposition of price limits is expected to alter the behavior of stock returns.

3. Conventional regression analysis

This section employs two conventional methods, OLS and GARCH, to explore the volume and price-limit effects on the autocorrelation. Although the methods may be biased when hitting percentages are large, each of them has one merit. First, the implications of the OLS method are well-known and easy to follow and thus can function as a benchmark. Second, the GARCH method, which considers a stylized fact in residuals, could increase efficiency substantially. As a consequence, the results provided by the OLS and GARCH methods can be complementary to, rather than be substituted by, the GMM method.

3.1. OLS estimation and results

Investigation of the correlation-volume relationship can be modelled as

$$r_t^* = \beta_0 + \beta_1 r_{t-1}^* + \sum_{i=1}^{5} \alpha_i D_{it} + \varepsilon_t, \tag{1}$$

$$r_t^* = \beta_0 + (\beta_2 + \beta_3 \mathrm{TO}_{t-1}) r_{t-1}^* + \sum_{i=1}^{5} \alpha_i D_{it} + \varepsilon_t, \tag{2}$$

$$r_t^* = \beta_0 + (\beta_4 + \beta_5 \mathrm{PLU}_{t-1} + \beta_6 \mathrm{PLL}_{t-1}) r_{t-1}^* + \sum_{i=1}^{5} \alpha_i D_{it} + \varepsilon_t, \tag{3}$$

$$r_t^* = \beta_0 + (\beta_7 + \beta_8 \mathrm{TO}_{t-1} + \beta_9 \mathrm{PLU}_{t-1} + \beta_{10} \mathrm{PLL}_{t-1}) r_{t-1}^* + \sum_{i=1}^{5} \alpha_i D_{it} + \varepsilon_t, \tag{4}$$

where r_t^* is the true stock returns which is assumed to equal the observed stock returns in this section, PLU_{t-1} and PLL_{t-1} are the price limit dummy variables which equal 1 if the observed price hits the upper or lower limit and zero otherwise, respectively, and TO_t is the turnover at time t. The variables D_{it} $(i=1,\dots,5)$ denote the weekday dummies. [8] Since the stock returns are characterized by positive autocorrelation over a short interval (Poterba and Summers, 1988; Lo and Mackinlay, 1988; Boudoukh et al., 1994), the autocorrelation coefficients β_1, β_2, β_4 and β_7 are expected to be positive in the respective equations. The first concern of this paper is to investigate whether this correlation is lower on high-volume days than on low-volume days. Specifically, if β_2 is positive and β_3 is negative in Eq. (2), the positive daily first autocorrelation of stock returns decreases when the volume increases. The direction of autocorrelation may even be reversed when the trading volume exceeds $-\beta_2/\beta_3$. Similar argument holds for β_7 and β_8.

Whether limit moves intensify the autocorrelation or not is the next concern. Moreover, hitting the upper limit is hypothesized to have stronger effect than hitting the lower limit on the autocorrelation. A simple but unjustified psychological reason to account for this hypothesis is to assume asymmetric feedback traders. Feedback traders purchase when the prices go up and sell when prices drop. Asymmetric behavior means that the degree of response of a feedback trader differs from price increase to decrease. Specifically, when the price hits the upper limit, a feedback trader tends to believe that the price will be higher tomorrow, increasing the autoregressive coefficient. In contrast, when the price hits the lower limit, though the trader thinks that the market will continue going down, the speed of going down is decreased. Thus, lower limit moves may still increase the autocorrelation but the degree of influence is reduced. In other words, the coefficients for PLU_{t-1} and PLL_{t-1} in Eqs. (3) and (4) are both positive, but the former are expected to be larger than the latter.

Table 2 reports the OLS estimation results of models (1) and (2). The models estimated contain weekday dummies, but results change little when the weekday dummies are excluded. The estimated coefficients of β_1 in model 1, shown in the first column, are positive for 20 out of 24 stocks. When the interaction variable, $rto_t = r_{t-1} * TO_{t-1}$ is added into Eq. (2), all autocorrelation coefficients are positive and 13 of them are significant. These positive autocorrelation coefficients are consistent with the findings using US data. Furthermore, among 20 out of 24 stock returns, coefficients on the interaction variable, rto_t, are shown to be negative, suggesting that the autocorrelation coefficient declines when the relative volume increases. In other words, the price pattern is reversed if relative volume increases substantially. However, since only 4 of 20 negative coefficients are significant, the evidence of time-varying autocorrelation is weakened.

Since estimation results of Eq. (3) are similar to those of Eq. (4), only the latter are presented. In Table 3, the volume reduces the autocorrelation for majority

[8] There are six trading days per week in the Taiwan stock market. Thus, only five dummies are used. See Gibbons and Hess (1981) for the use of weekday dummies.

Table 2
OLS estimation results of models (1) and (2) – (I)

Code	β_1	t-value	β_2	t-value	β_3	t-value
1101	0.0198	(0.8763)	0.0836[a]	(2.1395)	−6.8279[b]	(2.0002)
1201	0.0419[c]	(1.8543)	0.0689[a]	(2.1525)	−1.0957	(1.1911)
1301	−0.0038	(0.1684)	0.0205	(0.5469)	−2.6524	(0.8125)
1304	0.0596[a]	(2.6400)	0.0613[c]	(1.8675)	−0.0988	(0.0746)
1305	0.0378[c]	(1.6765)	0.0487	(1.3295)	−0.4597	(0.3764)
1402	0.0400[c]	(1.7714)	0.0567[c]	(1.7170)	−2.9070	(0.6949)
1407	0.0714[a]	(3.1698)	0.1089[a]	(2.6553)	−1.0971	(1.0942)
1408	0.0647[a]	(2.8702)	0.1061[a]	(2.9580)	−0.8813	(1.4837)
1433	−0.0180	(0.7985)	0.0047	(0.1344)	−3.0374	(0.8545)
1504	−0.0197	(0.8716)	0.0198	(0.5896)	−3.2356	(1.5862)
1602	0.0480[a]	(2.1304)	0.0666[b]	(2.0312)	−1.0132	(0.7806)
1604	0.0235	(1.0422)	0.0695[b]	(1.9728)	−2.4665[c]	(1.6993)
1702	0.1567[a]	(7.0274)	0.1992[a]	(5.7939)	−1.5368	(1.6222)
1802	−0.0207	(0.9169)	0.0487	(1.5040)	−9.4566[a]	(2.9841)
1905	0.0390[c]	(1.7282)	0.0086	(0.2664)	1.4494	(1.3261)
1907	0.0426[c]	(1.8901)	0.1255[a]	(3.3616)	−14.6609[a]	(2.7827)
2002	0.0036	(0.1593)	0.0052	(0.1975)	−0.5063	(0.1186)
2103	−0.0002	(0.0093)	0.0302	(0.7813)	−1.1300	(0.9687)
2201	0.0482[a]	(2.1388)	0.0711[b]	(2.0218)	−1.5931	(0.8484)
2301	0.1321[a]	(5.9040)	0.0868[a]	(2.2451)	0.8981	(1.4391)
2501	0.0568[a]	(2.5188)	0.0524	(1.4503)	0.3489	(0.1575)
2704	0.0431[b]	(1.9102)	0.0797[a]	(2.2543)	−1.1374	(1.3447)
2801	0.0637[a]	(2.8272)	0.0502	(1.3428)	1.7774	(0.4564)
2903	0.0071	(0.3125)	0.0169	(0.5018)	−0.9276	(0.3941)

r_t^* is replaced by observed stock return in estimation. D_{t-i} is the weekday dummies variables.TO_{t-i} is the turnover rate = trading volume/shares outstanding. Coefficients on r_{t-1}^* are the autocorrelation coefficients concerned.
[a], [b] and [c]: significant at the 1%, 5% and 10%, respectively.
Absolute t-value in parenthesis.
Other parameters are not reported to save space.

stocks since coefficients β_7 and β_8 are opposite in sign for 18 out of 24 stock returns. Moreover, 13 β_8s are significant. Furthermore, all but one coefficient on U_{t-1} are positive and 20 of them are significant. Similarly, 22 coefficients for D_{t-1} are positive and 14 of them are significant. Hence, both upper and lower price limits increase the autocorrelation; however, the former exhibits more strength than the latter.

3.2. GARCH estimation and results

Since asset price typically displays heteroscedasticity in high frequency data, the use of OLS may thus be inefficient in estimating the autocorrelation coefficient. This section uses the GARCH method of Bollerslev (1986) to estimate the model. For simplicity, the error terms are assumed to follow a GARCH (1,1) process (i.e., see Eq. (10)).

Table 3
OLS estimation results of model (4) – (II)

Code	β_7	t-value	β_8	t-value	β_9	t-value	β_{10}	t-value
1101	0.060	(1.462)	−10.550[a]	(2.964)	0.220[a]	(3.644)	0.075	(1.228)
1201	0.041	(1.158)	−2.059[a]	(2.145)	0.203[a]	(3.327)	0.074	(1.167)
1301	−0.018	(0.450)	−5.643[c]	(1.686)	0.198[a]	(3.405)	0.146[a]	(2.260)
1304	−0.027	(0.712)	0.022	(0.017)	0.294[a]	(4.998)	0.167[a]	(2.700)
1305	−0.002	(0.054)	−1.516	(1.202)	0.218[a]	(3.546)	0.162[a]	(2.772)
1402	0.046	(1.283)	−7.193[c]	(1.640)	0.191[a]	(3.135)	−0.008	(0.115)
1407	0.065	(1.468)	−1.470	(1.452)	0.144[a]	(2.483)	0.137[a]	(2.283)
1408	0.045	(1.158)	−1.320[a]	(2.196)	0.245[a]	(4.314)	0.176[a]	(2.637)
1433	−0.019	(0.500)	−4.658	(1.293)	0.159[a]	(2.572)	0.063	(0.915)
1504	−0.033	(0.923)	−4.801[a]	(2.272)	0.159[a]	(2.565)	0.266[a]	(4.164)
1602	0.030	(0.839)	−1.748	(1.312)	0.118[c]	(1.853)	0.170[a]	(2.822)
1604	0.048	(1.267)	−3.058[b]	(2.034)	0.113[c]	(1.823)	0.068	(1.090)
1702	0.099[a]	(2.638)	−2.500[a]	(2.575)	0.247[a]	(4.327)	0.310[a]	(5.369)
1802	0.033	(0.963)	−10.573[a]	(3.298)	0.090	(1.430)	0.082	(1.177)
1905	−0.009	(0.253)	1.288	(1.164)	0.041	(0.672)	0.087	(1.380)
1907	0.102[a]	(2.498)	−13.839[a]	(2.554)	−0.006	(0.097)	0.118[c]	(1.919)
2002	−0.011	(0.353)	−0.244	(0.057)	0.003	(0.044)	0.113[b]	(1.666)
2103	−0.020	(0.496)	−2.163[c]	(1.772)	0.197[a]	(3.136)	0.264[a]	(4.127)
2201	0.040	(1.063)	−3.328[c]	(1.724)	0.218[a]	(3.686)	0.053	(0.851)
2301	−0.026	(0.650)	−0.050	(0.079)	0.306[a]	(5.344)	0.426[a]	(7.315)
2501	0.020	(0.535)	−1.308	(0.558)	0.102[c]	(1.693)	0.168[a]	(2.745)
2704	0.028	(0.719)	−1.852[a]	(2.150)	0.220[a]	(3.820)	0.123[b]	(2.045)
2801	0.056	(1.480)	−1.350	(0.326)	0.161[a]	(2.612)	−0.103	(1.537)
2903	0.015	(0.406)	−1.077	(0.452)	0.035	(0.577)	−0.017	(0.257)

PLU_{t-1} and PLD_{t-1} are the dummy variables which = 1 if the observed price hits the upper and lower limit and zero, otherwise, respectively.
Autocorrelation coefficient is affected by TO_{t-1}, PLL_{t-1} and PLD_{t-1}.
[a], [b] and [c]: significant at the 1%, 5% and 10%, respectively.
Absolute t-value in parenthesis.
Other parameters are not reported to save space.

Table 4, which has the same structural form as Table 2, assumes that the errors follow a GARCH (1,1) process. The results obtained are consistent with our expectation. First, positive daily autocorrelation coefficients are more common than negative ones as evidenced in the columns for β_1 and β_2. The sign and magnitude for pure autocorrelation coefficients β_1 differ little from those reported in Table 2. Second, all coefficients for r^*_{t-1} and interacting variables are opposite in sign, suggesting a possible volume effect as 13 of them are significant. [9] The volume effect exists for nearly half of all stocks.

[9] As GARCH modelling increases the efficiency of estimation, 13 coefficients in Table 4 compared to 4 in Table 2 for interacting variables are significant.

Table 4
GARCH (1,1) estimation, models (1), (2), (9) and (10)—(I)

Code	β_1	*t*-value	β_2	*t*-value	β_3	*t*-value
1101	−0.0229	(1.0077)	0.3986[a]	(12.2148)	0.5376[a]	(113)
1201	0.0161	(0.6852)	−0.0258	(0.3606)	0.0152	(0.6155)
1301	−0.0161	(0.6818)	1.5375[a]	(139)	−0.1813[a]	(399)
1304	0.0387[c]	(1.6524)	1.8849[a]	(250)	−0.9984[a]	(929)
1305	0.0091	(0.3958)	1.4146[a]	(308)	−0.2262[a]	(420)
1402	0.0466[b]	(1.9874)	0.1344[b]	(2.0716)	−0.0350[c]	(1.7620)
1407	0.0405[c]	(1.8170)	1.9311[a]	(348)	−1.0717[a]	(1690)
1408	0.0465[b]	(2.0587)	0.4576[a]	(2.3697)	−0.1011[b]	(1.9707)
1433	−0.0215	(0.9897)	0.0057	(0.1164)	−0.0114	(0.5308)
1504	−0.0414[c]	(1.8634)	−0.0484	(0.8334)	0.0029	(0.1246)
1602	0.0366	(1.5915)	0.0841	(1.2934)	−0.0178	(0.7478)
1604	−0.0036	(0.1513)	2.4986[a]	(56788)	−1.0222[a]	(427170)
1702	0.0974[a]	(4.1449)	1.7154[a]	(92.8615)	−0.9185[a]	(560)
1802	−0.0043	(0.1896)	0.0733	(1.2430)	−0.0324	(1.3801)
1905	0.0223	(0.9374)	1.1832[a]	(716772)	−1.0416[a]	(2164606)
1907	0.0204	(0.8927)	1.2472[a]	(55.1328)	−0.0197	(0.8789)
2002	−0.0071	(0.2960)	0.0224	(0.3301)	−0.0112	(0.4534)
2103	−0.0154	(0.6442)	2.1700[a]	(1471189)	−1.0130[a]	(3046742)
2201	0.0135	(0.5624)	−0.0400	(0.6026)	0.0191	(0.8362)
2301	0.0724[a]	(3.3295)	−0.0286	(0.5201)	0.0320[c]	(1.8265)
2501	0.0076	(0.3192)	1.6897[a]	(99.6016)	−0.1499[a]	(24.3893)
2704	0.0214	(0.9168)	0.0024	(0.0334)	0.0066	(0.2759)
2801	0.0244	(0.9998)	0.0045	(0.0624)	0.0075	(0.2923)
2903	0.0218	(0.9431)	0.0884	(1.4142)	−0.0289	(1.1021)

This table is the GARCH version of Table 2. GARCH is estimated by RATS package, BFGS algorithm.
h_t is the conditional variance.
[a], [b] and [c]: significant at the 1%, 5% and 10%, respectively.
Absolute *t*-value in parenthesis.
Other parameters are not reported to save space.

Table 5 is the GARCH version of Table 3. Three phenomena are observed. First, most coefficients for volume-interacted variables are negative, however, only nearly half of them are significant. Second, coefficients for upper limit-interacting variables are overwhelmingly positive and more than half of them are significant 15 are significant here. Third, coefficients for lower limit-interacting variables are also mostly positive but less than the half are significant 9 are significant here.

Numerous papers have documented the fact that stock returns and volatility are related. Campbell et al. (1993), LeBaron (1992) and Sentana and Wadhwani (1992) also consider volatility to examine the volume effect. Hence, in addition to

Table 5
GARCH (1,1) estimation, models (4), (9) and (10) – (II)

Code	β_7	t-value	β_8	t-value	β_9	t-value	β_{10}	t-value
1101	−0.020	(0.610)	−3.909	(1.250)	0.199[a]	(2.358)	0.057	(0.649)
1201	0.018	(0.545)	−1.643[c]	(1.719)	0.230[a]	(3.287)	0.016	(0.189)
1301	−0.017	(0.482)	−5.016	(1.317)	0.178[a]	(2.500)	0.090	(1.099)
1304	−0.017	(0.471)	0.424	(0.291)	0.248[a]	(3.568)	0.110	(1.431)
1305	−0.009	(0.228)	−1.618	(1.156)	0.229[a]	(3.025)	0.116[c]	(1.643)
1402	0.078[a]	(2.121)	−11.175[b]	(1.962)	0.206[a]	(2.850)	−0.032	(0.386)
1407	0.066	(1.517)	−2.114[c]	(1.906)	0.149[a]	(2.196)	0.135[a]	(2.008)
1408	0.045	(1.407)	−1.474[a]	(2.592)	0.263[a]	(3.938)	0.188[a]	(2.406)
1433	−0.012	(0.392)	−4.515	(1.537)	0.125	(1.580)	0.047	(0.480)
1504	−0.038	(1.200)	−3.232	(1.481)	0.117	(1.557)	0.151[c]	(1.932)
1602	0.045	(1.295)	−2.000	(1.313)	0.109	(1.363)	0.110	(1.490)
1604	0.013	(0.350)	−2.383	(1.453)	0.133[c]	(1.767)	0.051	(0.709)
1702	0.064[c]	(1.764)	−2.548[a]	(2.265)	0.299[a]	(4.488)	0.256[a]	(3.781)
1802	0.029	(0.905)	−8.221[a]	(2.642)	0.131[c]	(1.680)	0.054	(0.568)
1905	−0.013	(0.351)	1.516	(1.102)	0.027	(0.372)	0.024	(0.336)
1907	0.048	(1.273)	−10.186[b]	(1.911)	0.056	(0.768)	0.148[b]	(2.035)
2002	−0.012	(0.357)	−2.114	(0.403)	0.025	(0.386)	0.092	(0.967)
2103	−0.006	(0.145)	−2.674[a]	(2.294)	0.214[a]	(3.068)	0.210[a]	(2.809)
2201	0.015	(0.425)	−3.580	(1.420)	0.217[a]	(2.883)	0.055	(0.619)
2301	0.003	(0.083)	−0.762	(1.171)	0.327[a]	(5.324)	0.353[a]	(5.328)
2501	−0.016	(0.445)	−0.589	(0.213)	0.088	(1.149)	0.163[a]	(2.122)
2704	0.039	(1.104)	−2.213[a]	(2.497)	0.198[a]	(3.066)	0.079	(1.063)
2801	0.001	(0.033)	5.365	(1.103)	0.030	(0.384)	−0.152	(1.543)
2903	0.047	(1.457)	−3.217	(1.324)	0.062	(0.715)	−0.055	(0.601)

This table is the GARCH version of Table 3. GARCH is estimated by RATS package, BFGS algorithm.
h_t is the conditional variance.
[a], [b] and [c]: significant at the 1%, 5% and 10%, respectively.
Absolute t-value in parenthesis.
Other parameters are not reported to save space.

the above GARCH models, two extra models (GARCH-M), which add conditional volatility into the mean equation, are employed.

$$r_t^* = \beta_0 + \left(\beta_2 + \beta_3\sqrt{h_{t-1}} \right) r_{t-1}^* + \sum_{i=1}^{5} \alpha_i D_{it} + \varepsilon_t, \tag{5}$$

$$r_t^* = \beta_0 + \left(\beta_2 + \beta_3 \mathrm{TO}_{t-1} + \beta_4\sqrt{h_{t-1}} \right) r_{t-1}^* + \sum_{i=1}^{5} \alpha_i D_{it} + \varepsilon_t, \tag{6}$$

$$r_t^* = \beta_0 + \left(\beta_2 + \beta_3\sqrt{h_{t-1}} + \beta_4 \mathrm{PLU}_{t-1} + \beta_5 \mathrm{PLL}_{t-1} \right) r_{t-1}^* + \sum_{i=1}^{5} \alpha_i D_{it} + \varepsilon_t, \tag{7}$$

$$r_t^* = \beta_0 + \left(\beta_6 + \beta_7 \mathrm{TO}_{t-1} + \beta_8 \sqrt{h_{t-1}} + \beta_9 \mathrm{PLU}_{t-1} + \beta_{10} \mathrm{PLL}_{t-1} \right) r_{t-1}^* + \sum_{i=1}^{5} \alpha_i D_{it} + \varepsilon_t, \tag{8}$$

where h_t is the conditional variance described below. Note that the above models use standard deviation of the conditional variance as the proxy for volatility.[10] The errors of both models are assumed to follow a GARCH (1,1) process as

$$\varepsilon_t | \Omega_{t-1} \sim (0, h_t), \tag{9}$$

$$h_t = \theta_0 + \theta_1 h_{t-1} + \theta_2 \varepsilon_{t-1}^2, \tag{10}$$

where Ω_{t-1} is the information set up to time $t-1$ and θ_i ($i = 0, 1, 2$) are unknown positive coefficients.

The first examination of price reversal using volatility to replace volume is reported in Table 6, which jointly estimates models (5) and (10). For the sake of space, only coefficients for r_{t-1}^* and interacted variables are reported. When the turnover is replaced by the volatility in Eq. (5), the price reversal is observed for 21 stock returns. However, the evidence is weak since only three of them are significant.

Results considering two interacting variables, turnover and volatility, are presented in Table 7, which jointly estimates Eqs. (6) and (10). Though 20 coefficients for the volume-interacting variable are shown to be negative, few of them are significant (4 here). In contrast to the mostly negative coefficients for the volume-interacting variable, only coefficients for the volatility-interacting variable are negative. Furthermore, coefficients for both interacting variables are mainly insignificant, implying that the adding of volatility mitigates the volume effect.

Estimation results of Eqs. (8) and (10) are reported in Table 8.[11] Eleven coefficients for the volume-interacting variables are significantly negative. All, except for the last two stocks, coefficients on the upper limit-interacting variable are positive and ten of them are significant. In contrast, 16 coefficients on the lower limit-interacting variable are negative, though none of them are significant. The GARCH-M estimation reduces the explanatory power of both the volume and the price-limit effects. One reason for this reduction is possibly owing to the multicollinearity between volume and volatility.

In summary, using OLS and GARCH estimation, a mild volume effect exists since slightly less than half of the coefficients are significant. To the contrary, the price-limit effect is found for more than two-thirds of the stocks and the effect

[10] We use standard error of volatility in the mean equation because of the estimation problem. When h_t is used, the estimations explode for many stocks.

[11] Estimation results of Eq. (7) are not reported since it reaches a similar conclusion as that reported in Table 8.

Table 6
GARCH-M estimation, models (5), (9) and (10) – (I)

Code	β_2	t-value	β_3	t-value
1101	−0.0217	(0.6533)	−0.1662	(0.0545)
1201	0.0251	(0.7733)	−0.3986	(0.4327)
1301	−0.0084	(0.2494)	−1.1497	(0.3485)
1304	0.0229	(0.6764)	1.0266	(0.7220)
1305	0.0128	(0.3475)	−0.1889	(0.1480)
1402	0.0786[a]	(2.2226)	−6.3684	(1.2330)
1407	0.0884[b]	(2.0958)	−1.5366	(1.4012)
1408	0.0748[a]	(2.4155)	−0.7242	(1.3035)
1433	−0.0048	(0.1612)	−2.8558	(1.0008)
1504	−0.0250	(0.8005)	−1.7431	(0.8104)
1602	0.0582[c]	(1.7102)	−1.3344	(0.9128)
1604	0.0219	(0.5947)	−1.4835	(0.9756)
1702	0.1164[a]	(3.3981)	−0.8479	(0.7941)
1802	0.0353	(1.1222)	−6.6443[a]	(2.1921)
1905	−0.0084	(0.2411)	1.5986	(1.1835)
1907	0.0647[c]	(1.7894)	−9.2820[c]	(1.7655)
2002	0.0009	(0.0317)	−2.4342	(0.4745)
2103	0.0118	(0.3083)	−1.1929	(1.1001)
2201	0.0262	(0.7534)	−1.1623	(0.5053)
2301	0.0421	(1.2926)	0.7267	(1.1854)
2501	−0.0084	(0.2504)	1.6919	(0.7107)
2704	0.0625[c]	(1.8276)	−1.4931[c]	(1.7344)
2801	−0.0025	(0.0665)	4.7208	(1.0515)
2903	0.0470	(1.4704)	−2.8608	(1.1900)

Autocorrelation coefficient is affected by conditional standard deviation, $\sqrt{h_t}$. Conditional standard deviation is used to replace trading volume.
[a], [b] and [c]: significant at the 1%, 5% and 10%, respectively.
Absolute t-value in parenthesis.
Other parameters are not reported to save space.

induced by hitting the upper limit is stronger than hitting the lower one. Adding volatility to account for the variation of autocorrelation reduces both the volume and the price-limit effects.

4. Regression analysis with price limits

The underlying assumption of the previous section is that the true returns are equal to the observed returns. This is incorrect when the stock price hits the limits. When the hitting percentage is large, the conventional OLS estimates may be seriously biased. For example, because the price limits restrict the movement of stock prices, the trending pattern of stock price may thus disappear. When the price hits the limit, the subsequent price either stays at the limit or bounces back.

Table 7
GARCH estimation, models (6), (9) and (10) – (II)

Code	β_2	t-value	β_3	t-value	β_4	t-value
1101	−0.0957[c]	(1.7572)	−2.8895	(0.9396)	0.0417[c]	(1.8556)
1201	−0.0208	(0.2828)	−0.5412	(0.5854)	0.0178	(0.7192)
1301	−0.0347	(0.5887)	−2.2865	(0.6134)	0.0136	(0.5452)
1304	0.0519	(0.7287)	1.1899	(0.8302)	−0.0108	(0.4553)
1305	0.0004	(0.0056)	−0.2665	(0.2050)	0.0049	(0.2062)
1402	0.1449[a]	(2.1234)	−5.3034	(1.0277)	−0.0286	(1.1049)
1407	0.0318	(0.4563)	−1.8065	(1.6318)	0.0221	(1.0429)
1408	0.0875	(1.4707)	−0.6749	(1.1487)	−0.0050	(0.2329)
1433	0.0086	(0.1618)	−2.5005	(0.8810)	−0.0065	(0.2974)
1504	−0.0476	(0.8157)	−2.1254	(0.9416)	0.0108	(0.4400)
1602	0.0896	(1.3444)	−1.1665	(0.7877)	−0.0128	(0.5323)
1604	−0.1116	(1.3974)	−2.0477	(1.3244)	0.0522[c]	(1.9316)
1702	−0.0587	(0.7446)	−1.9693[c]	(1.7183)	0.0653[a]	(2.5354)
1802	0.0819	(1.3587)	−5,5892	(1.8338)	−0.0221	(0.9229)
1905	0.0741	(0.9759)	1.7645	(1.3038)	−0.0295	(1.2239)
1907	0.0316	(0.5180)	−10.5159[c]	(1.9516)	0.0149	(0.6768)
2002	0.0327	(0.4658)	−2.5641	(0.0511)	−0.0119	(0.4816)
2103	0.0187	(0.2227)	−1.1539	(1.0509)	−0.0028	(0.0988)
2201	−0.0473	(0.7121)	−2.8988	(1.0840)	0.0330	(1.2670)
2301	−0.0283	(0.5141)	0.4060	(0.5511)	0.0266	(1.2607)
2501	−0.1046	(1.6380)	−1.2913	(0.4849)	0.0485[c]	(1.9436)
2704	0.0131	(0.1825)	−1.6963[c]	(1.9323)	0.0190	(0.7822)
2801	0.0115	(0.1602)	5.2314	(1.0608)	−0.0063	(0.2260)
2903	0.0954	(1.5015)	−2.2969	(0.9354)	−0.0232	(0.8673)

Autocorrelation coefficient is affected by conditional standard deviation and turnover rate. Conditional standard deviation $\sqrt{h_t}$ is used to replace trading volume.
[a], [b] and [c]: significant at the 1%, 5% and 10%, respectively.
Absolute t-value in parenthesis.
Other parameters are not reported to save space.

In either case, the observed stock returns become uncorrelated or even negatively correlated even though the true stock returns are not. This section employs the GMM method of Chiang and Wei (1995) to consistently estimate the autocorrelation of stock returns.

4.1. Features of price limits

This subsection first explains the structure of the stock price subject to price limits. We begin by noting that under a (daily) price limit regulation, the price during each trading day cannot be above the previous *settlement price* plus an upper limit, or below the previous settlement price minus a lower limit. Furthermore, the price limits are assumed not to have any impact on the underlying asset's true price generating process. If the settlement price at day t hits the upper

Table 8
GARCH-M estimation – with turnover, models (8), (9) and (10)

Code	β_6	t-value	β_7	t-value	β_8	t-value	β_9	t-value	β_{10}	t-value
1101	−0.068	(1.187)	−5.121	(1.639)	0.171[c]	(1.935)	0.022	(0.233)	0.028	(1.083)
1201	0.008	(0.103)	−1.661[c]	(1.737)	0.228[a]	(3.175)	0.012	(0.133)	0.004	(0.164)
1301	−0.021	(0.354)	−5.182	(1.259)	0.178[a]	(2.461)	0.088	(1.042)	0.002	(0.085)
1304	0.082	(1.121)	1.012	(0.690)	0.267[a]	(3.707)	0.145[c]	(1.787)	−0.040	(1.525)
1305	0.032	(0.447)	−1.385	(0.980)	0.236[a]	(3.051)	0.129[c]	(1.737)	−0.017	(0.651)
1402	0.174[a]	(2.554)	−10.102[c]	(1.782)	0.231[a]	(3.106)	0.005	(0.059)	−0.043	(1.629)
1407	0.067	(0.941)	−2.111[c]	(1.901)	0.149[a]	(2.079)	0.135[c]	(1.940)	−0.000	(0.019)
1408	0.130[a]	(2.191)	−1.189[b]	(1.996)	0.280[a]	(4.032)	0.216[a]	(2.654)	−0.035	(1.567)
1433	0.025	(0.454)	−3.668	(1.269)	0.137[c]	(1.657)	0.070	(0.672)	−0.019	(0.778)
1504	−0.024	(0.403)	−3.046	(1.352)	0.120	(1.565)	0.158[c]	(1.872)	−0.007	(0.255)
1602	0.132[c]	(1.926)	−1.673	(1.095)	0.137	(1.623)	0.147[c]	(1.903)	−0.037	(1.442)
1604	−0.098	(1.210)	−2.741[c]	(1.658)	0.113	(1.490)	0.021	(0.286)	0.045	(1.619)
1702	−0.020	(0.253)	−3.070[a]	(2.580)	0.290[a]	(4.318)	0.231[a]	(3.232)	0.033	(1.201)
1802	0.107[c]	(1.749)	−6.954[a]	(2.257)	0.164[b]	(2.042)	0.097	(0.972)	−0.038	(1.525)
1905	0.083	(1.086)	1.682	(1.221)	0.041	(0.550)	0.051	(0.692)	−0.036	(1.416)
1907	0.058	(0.926)	−9.864[c]	(1.807)	0.061	(0.782)	0.155[c]	(1.928)	−0.005	(0.198)
2002	0.048	(0.674)	−2.254	(0.430)	0.041	(0.618)	0.119	(1.208)	−0.024	(0.927)
2103	0.075	(0.885)	−2.316[b]	(2.003)	0.229[a]	(3.199)	0.231[a]	(3.029)	−0.034	(1.151)
2201	−0.036	(0.538)	−4.702[c]	(1.711)	0.208[a]	(2.731)	0.033	(0.351)	0.024	(0.882)
2301	0.080	(1.452)	−0.468	(0.626)	0.340[a]	(5.557)	0.377[a]	(5.399)	−0.031	(1.372)
2501	−0.080	(1.241)	−2.215	(0.818)	0.073	(0.927)	0.132	(1.627)	0.033	(1.265)
2704	0.040	(0.555)	−2.210[a]	(2.467)	0.199[a]	(2.992)	0.079	(1.022)	−0.000	(0.015)
2801	−0.017	(0.228)	4.851	(0.947)	0.026	(0.330)	−0.161	(1.538)	0.008	(0.276)
2903	0.103	(1.550)	−2.787	(1.138)	0.085	(0.901)	−0.024	(0.254)	−0.028	(0.944)

Same as Table 7 except that the upper and down limits are added.
Conditional standard deviation $\sqrt{h_t}$ is used to replace trading volume.
[a], [b] and [c]: significant at the 1%, 5% and 10%, respectively.
Absolute t-value in parenthesis.
Other parameters are not reported to save space.

(lower) limit, then in general it is the case that the closing price is not the equilibrium or ‘true’ price and there remains some unrealized demand (supply). In particular, the ‘true’ price $P_{i,t}^*$ is expected to be greater (smaller) than the closing price if the closing price (i.e., the observed price, $P_{i,t}$) hits the upper (lower) limit.

The relation among the observed return, $r_{i,t}$, the actual and observed stock prices is

$$r_{i,t} = \begin{cases} l_\mathrm{u} & \text{if } \log(P_{i,t}^*/P_{i,t-1}) \geqslant l_\mathrm{u}, \\ \log(P_{i,t}^*/P_{i,t-1}) & \text{if } l_\mathrm{d} < \log(P_{i,t}^*/P_{i,t-1}) < l_\mathrm{u}, \\ l_\mathrm{d} & \text{if } \log(P_{i,t}^*/P_{i,t-1}) \leqslant l_\mathrm{d}, \end{cases} \tag{11}$$

where $r_{i,t} = \log(P_{i,t}/P_{i,t-1})$, $l_\mathrm{u} = \log(1+L_\mathrm{u})$ and $l_\mathrm{d} = \log(1+L_\mathrm{d})$ and L_u and L_d are the upper and lower-price limits, respectively. Clearly, whether one observes a limit move or not depends on whether $\log(P_{i,t}^*/P_{i,t-1})$ lies within the limit range rather than on the magnitude of the true stock return $r_{i,t}^* = \log(P_{i,t}^*/P_{i,t-1}^*)$. The relationship between $r_{i,t}$ and $r_{i,t}^*$ when the price does not hit the limit is

$$\begin{aligned} r_{i,t} &= \log(P_{i,t}^*/P_{i,t-1}) = \log(P_{i,t}^*/P_{i,t-1}^*) + \log(P_{i,t-1}^*/P_{i,t-1}) \\ &= r_{i,t}^* + \mathrm{LO}_{i,t-1}, \end{aligned}$$

where $\mathrm{LO}_{i,t} \equiv \log(P_{i,t}^*/P_{i,t})$, is the difference between the true and the observed stock prices at time t, which essentially reflects the unrealized demand/supply when $P_{i,t}$ hits a limit. $\mathrm{LO}_{i,t}$ is called ‘leftover’ by Yang and Brorsen (1995). If the price at time t hits the upper (lower) limit, $\mathrm{LO}_{i,t}$ is positive (negative). A nonzero $\mathrm{LO}_{i,t}$ represents an ‘overflow’ or spill-over term from trading day t. If day t does not hit the limits, then $P_{i,t}^* = P_{i,t}$ and $\mathrm{LO}_{i,t} = 0$.

The relationship in Eq. (11) indicates that the observed future price change at time t reflects shocks related to current information (i.e., r_t^*), and some unrealized shock carried over from the previous day (i.e., $\mathrm{LO}_{i,t-1}$) if $t-1$ is a limit move. ‘$\mathrm{LO}_{i,t}$’ represents the leftover that is going to carry over to the next day if day t hits a limit. Hence, the extreme values exceeding 7% are eliminated and this will cause the stock return to be truncated. Since the variations of $r_{i,t}$ are mitigated, the estimated OLS coefficients are underestimated if the non-price limit exogenous variable is used. The GMM approach of Chiang and Wei (1995) is an ideal tool to reduce this bias.

Some fundamental properties of stock price subject to the price limits are introduced before we explain the method of Chiang and Wei (1995). To simplify the notations below, subscript i will be suppressed for simplicity. Assuming that the stock price reaches the price limit at time t, but it does not hit the limit at time $t-1$ and $t+1$ namely, $P_t * \neq P_t$, $P_{t-1}^* = P_{t-1}^*$, and $P_{t+1}^* = P_{t+1}$, thus

$$\begin{aligned} r_{t+1}^* + r_t^* &= \log(P_{t+1}^*/P_t^*) + \log(P_t^*/P_{t-1}^*) \\ &= \log(P_{t+1}^*/P_{t-1}^*) \\ &= r_{t+1} + r_t = z_{t+1}. \end{aligned} \tag{12}$$

That is, the two-day true returns ($z_{t+1} = r^*_{t+1} + r^*_t$) can be evaluated even if the r^*_{t+1} and r^*_t are not observed. The expected value of z_{t+1} is 2μ, where μ is the mean of r^*_t. Similarly, the two consecutive days that the prices reach the limits imply that the three-day true returns are

$$r^*_{t+2} + r^*_{t+1} + r^*_t = r_{t+2} + r_{t+1} + r_t = z_{t+2}. \tag{13}$$

The expected value of z_{t+2} is 3μ. The analysis is easily extended to the n limits case. This unique feature of price limits enables Chiang and Wei (1995) to derive the GMM estimators of $\hat{\mu}_t$, $\hat{\sigma}^2_t$ (estimated mean and variance of the true stock return, respectively), $\widehat{\mathrm{Cov}}(r^*_t, x_t)$, $\widehat{\mathrm{Cov}}(r^*_t, x^*_t)$, $\hat{\rho}(r^*_t, r^*_{t-1})$ and the estimated variance σ^2_{GMM} of the regression residual when r^*_t is regressed on r^*_{t-1}, where x_t and x^*_t are the exogenous variables without and with being subject to the price limits, respectively. See Appendix A for detailed formulae of the above estimators.

4.2. Econometric model under price limits and results

We use Eq. (2) to illustrate how the GMM method of Chiang and Wei (1995) is implemented. The same approach can be applied to Eqs. (1), (3) and (4).

Rewriting Eq. (2) into a matrix form yields

$$r^*_t = x'_t\theta + \varepsilon_t, \tag{14}$$

where $x_t = (x^*_{1t}, x_{2t})'$, and $x^*_{1t} = (r^*_{t-1}, \mathrm{rto}^*_t)'$, $x_{2t} = (1, D_{1t}, \ldots, D_{5t})'$, $\mathrm{rto}^*_t = r^*_{t-1} \times \mathrm{TO}_t$ and $\theta = (\beta_2, \beta_3, \beta_0, \alpha_1, \ldots, \alpha_5)$. In short, vector x^*_{1t} denotes those variables being subject to the price limits and x_{2t} denotes the vector of variables of no price limits. The estimators of θ and its variance are identical to conventional OLS estimators, i.e.,

$$\hat{\theta} = (\Sigma x_t x'_t)^{-1}(\Sigma x_t r^*_t), \quad \mathrm{Var}(\hat{\theta}) = \hat{\sigma}^2(\Sigma x_t x'_t)^{-1}.$$

Although the formulae are equivalent to the OLS estimators, calculations of elements in the formulae are different. Since the true x^*_{1t} and r^*_t are not completely observed, using conventional methods based on the observed data yields biased parameters estimates. The consistent estimators can be obtained through the previous four theorems. We decompose $(\Sigma x_t x'_t)$ and $(\Sigma x_t r^*_t)$ into the following elements of variances and covariances:

$$\Sigma x_t x'_t = T\begin{bmatrix} \mathrm{Var}(r^*_{t-1}) & \mathrm{Cov}(r^*_{t-1}, r\mathrm{to}^*_t) & \mathrm{Cov}(r^*_{t-1}, x_{2t}) \\ \cdot & \mathrm{Var}(\mathrm{rto}^*_t) & \mathrm{Cov}(\mathrm{rto}^*_t, x_{2t}) \\ \cdot & \cdot & \mathrm{Var}(x_{2t}) \end{bmatrix}, \tag{15}$$

$$\Sigma x_t y_t = T\begin{bmatrix} \mathrm{Cov}(r^*_t, r^*_{t-1}) \\ \mathrm{Cov}(r^*_t, \mathrm{rto}^*_t) \\ \mathrm{Cov}(r^*_t, x_{2t}) \end{bmatrix}, \tag{16}$$

where Var$(\cdot)$ denotes the variance and Cov$(\cdot)$ denotes the covariance. The calculations of the variances and covariances are biased using the conventional approaches. Instead, the variances and covariances in Eqs. (15) and (16) should be calculated based on the four theorems described in Appendix A. Once these variance and covariance terms are yielded, the consistent estimates of θ and Var(θ) are obtained by substituting them back into Eqs. (15) and (16).

4.3. Estimation results

Table 9 has exactly the same structure as Table 2, but here the estimation procedure is based on the GMM method. The 18 estimated coefficients β_1

Table 9
GMM-Price limit estimation results, models (1) and (2) – (I)

Code	β_1	t-value	β_2	t-value	β_3	t-value
1101	0.0439[a]	(2.1313)	0.0366[a]	(10.2007)	8.0818[a]	(2.4902)
1201	0.0459[a]	(2.2469)	0.0856[c]	(1.6772)	12.6212[a]	(7.9879)
1301	0.0400[b]	(1.9052)	0.0410[a]	(10.1423)	−1.0798	(0.2985)
1304	0.0426[a]	(2.0771)	0.0585[a]	(15.6891)	−8.2975[a]	(5.1181)
1305	0.0469[a]	(2.3134)	0.0502[a]	(12.5504)	−1.3606	(0.9616)
1402	0.0385[c]	(1.8333)	0.0304[a]	(8.0285)	12.6855[a]	(2.5980)
1407	0.0495[a]	(2.4888)	0.0654[a]	(13.0048)	−4.5204[a]	(3.4477)
1408	0.0460[a]	(2.2684)	0.0504[a]	(13.0403)	−0.9223	(1.3330)
1433	0.0321	(1.4923)	0.0347[a]	(9.7808)	−3.4089	(0.9217)
1504	0.0297	(1.3828)	0.0228[a]	(6.9955)	5.7289[a]	(2.8046)
1602	0.0437[a]	(2.1179)	0.0420[a]	(12.0688)	0.8957	(0.6177)
1604	0.0406[c]	(1.9507)	0.0400[a]	(11.3546)	0.3179	(0.2119)
1702	0.0586[a]	(3.1802)	0.0625[a]	(14.5992)	−1.3781	(1.0079)
1802	0.0300	(1.3831)	0.0318[a]	(10.1734)	−2.5009	(0.8110)
1905	0.0417[b]	(2.0117)	0.0316[a]	(10.2573)	4.7136[a]	(4.4125)
1907	0.0438[a]	(2.1429)	0.0444[a]	(13.9188)	−1.0597	(0.2252)
2002	0.0426[b]	(2.0445)	0.0491[a]	(20.1167)	−20.9676[a]	(5.1175)
2103	0.0360[c]	(1.6998)	0.0306[a]	(7.8536)	2.0142[c]	(1.6466)
2201	0.0472[a]	(2.3371)	0.0381[a]	(9.9592)	6.0514[a]	(2.7861)
2301	0.0544[a]	(2.8983)	0.0544[a]	(28.9828)	0.0000	(NA)
2501	0.0438[a]	(2.1510)	0.0272[a]	(7.2701)	12.8483[a]	(5.2727)
2704	0.0463[a]	(2.3049)	0.0442[a]	(13.0495)	0.6793	(0.7955)
2801	0.0453[a]	(2.2111)	−0.0350	(−0.6724)	58.2329[a]	(10.1985)
2903	0.0370[c]	(1.7350)	0.0337[a]	(10.8048)	3.1490	(1.4646)

The true stock return is no longer replaced by the observed stock return but is estimated on the rule, e.g., $r_t^* + r_{t+1}^* = r_t + r_{t+1}$ if p_t hits the limit.
[a], [b] and [c]: significant at the 1%, 5% and 10%, respectively.
Absolute t-value in parenthesis.
Other parameters are not reported to save space.

obtained here are larger than those obtained from Table 2. Furthermore, the previous four negative autocorrelation coefficients β_1 become positive. The limits restrict the movements of the observed stock price making its returns serially uncorrelated or even negatively correlated. Once the consistent estimator is attempted here, the correlation becomes positively correlated. When the volume-interacted variables are considered, all but one autocorrelation coefficient remains positive. Eleven estimated coefficients β_3 are negative and only five of them are significant, suggesting weak volume effect.

The GMM estimation results of Eq. (4) are presented in Table 10. The specification of Eq. (4) together with GMM method yield results most favorable to both effects. For example, the volume effect exists for 17 stock returns. Next, the

Table 10
GMM-Price limit estimation results, model (4) – (II)

Code	β_7	t-value	β_8	t-value	β_9	t-value	β_{10}	t-value
1101	0.235[a]	(6.364)	−5.138[c]	(1.772)	1.606[a]	(28.587)	1.227[a]	(23.035)
1201	94.459[a]	(2.890)	−1915.811[a]	(2.880)	96.379[a]	(2.909)	59.789[a]	(2.864)
1301	0.197[a]	(4.956)	−2.380	(0.759)	1.538[a]	(29.000)	1.108[a]	(20.756)
1304	0.786[a]	(14.187)	−21.056[a]	(11.623)	2.066[a]	(29.175)	1.806[a]	(25.990)
1305	0.671[a]	(12.833)	−13.157[a]	(8.938)	1.603[a]	(26.913)	1.939[a]	(29.324)
1402	0.155[a]	(4.114)	−18.050[a]	(4.064)	1.193[a]	(22.939)	1.100[a]	(19.527)
1407	1.243[a]	(14.044)	−22.812[a]	(12.595)	1.910[a]	(24.616)	2.158[a]	(24.965)
1408	0.946[a]	(15.332)	−9.211[a]	(11.228)	2.256[a]	(29.345)	2.078[a]	(24.861)
1433	0.112[a]	(3.262)	0.414	(0.130)	1.368[a]	(25.304)	1.162[a]	(19.863)
1504	0.147[a]	(4.952)	2.334	(1.336)	1.232[a]	(24.335)	1.387[a]	(25.788)
1602	0.229[a]	(6.263)	−5.711[a]	(4.468)	1.379[a]	(24.876)	1.409[a]	(25.724)
1604	0.159[a]	(4.483)	−2.298[c]	(1.724)	1.224[a]	(23.908)	1.395[a]	(25.360)
1702	0.011	(0.205)	−7.125[a]	(4.778)	1.374[a]	(20.439)	1.010[a]	(11.671)
1802	−0.055[c]	(1.894)	10.081[a]	(3.732)	1.131[a]	(20.825)	0.985[a]	(16.849)
1905	0.106[a]	(3.424)	−4.970[a]	(5.307)	1.119[a]	(21.967)	1.075[a]	(20.535)
1907	0.165[a]	(4.956)	−6.119	(1.467)	1.188[a]	(24.391)	1.528[a]	(27.461)
2002	0.110[a]	(3.879)	−1.614	(0.456)	1.312[a]	(26.560)	1.295[a]	(22.571)
2103	0.309[a]	(7.948)	−3.084[a]	(2.823)	1.429[a]	(26.349)	1.577[a]	(26.819)
2201	0.744[a]	(12.873)	−25.462[a]	(10.022)	2.115[a]	(26.880)	1.485[a]	(20.762)
2301	8.648[a]	(10.999)	−1.671[a]	(2.678)	15.858[a]	(11.612)	17.433[a]	(11.717)
2501	0.206[a]	(6.082)	−5.943[a]	(2.923)	1.345[a]	(27.577)	1.313[a]	(26.389)
2704	0.462[a]	(11.387)	−3.355[a]	(4.211)	1.903[a]	(31.938)	1.393[a]	(25.481)
2801	4.984[a]	(10.083)	−398.735[a]	(9.581)	6.378[a]	(11.850)	0.171	(0.563)
2903	−0.007	(0.217)	1.732	(0.908)	1.091[a]	(21.388)	1.026[a]	(18.889)

The true stock return is no longer replaced by the observed stock return but is estimated based on the rule, e.g., $r_t^* + r_{t+1}^* = r_t + r_{t+1}$ if p_t hits the limit.
[a], [b] and [c]: significant at the 1%, 5% and 10%, respectively.
Absolute t-value in parenthesis.
Other parameters are not reported to save space.

upper price-limit effect exists for all stock returns (all coefficients are positive and significant) and the lower price-limit effect for 22 stock returns.

5. Conclusion

Numerous papers have documented the evidence that daily stock returns are autocorrelated. However, less attention has been paid to the fact that the correlation may vary with time. Specifically, we argue that the correlation is negatively affected by the trading volume and positively affected by price limits. Studies of the US market indicate that the autocorrelation is related only to trading volume. No research, however, has been conducted to explore whether or not this phenomenon holds true in an imperfect market, the Taiwan stock market, due to price limits.

Using two conventional methods, OLS and GARCH, the mild positive first daily autoregressive coefficient of stock returns is found for most stock return; for example, all autoregressive coefficients are positive in Table 2 ($:\beta_2$) and only half of them are significant. The volume effect on the autocorrelation is sensitive to the model specification. The GARCH model shows the strongest support for the volume effect and the GARCH-M model is the weakest. On average, the hypothesis that the increasing volume reduces this autocorrelation holds for nearly half of the stocks. For these stocks, prices tend to turn direction when a substantial increase of volume occurs. The price-limit effects, on the other hand, exist for almost all stocks and display robustness across estimation methods. Among the two different price limits effects, the upper hitting limit demonstrates a stronger positive effect than the lower hitting limit. When the stock price hits either limit today, the stock return tends to be positive tomorrow.

Since the daily price limits may bias the conventional econometric methods, it is natural to ask whether or not the results hold true when the GMM consistent estimators are adopted. The volume and the price limits effects obtained by the GMM method are both stronger than those of the OLS and GARCH methods. The price-limit effect displays an even stronger influence on the autoregressive coefficients. The investment strategy suggested is that the current price will be above its equilibrium price if it hits the (upper) limit yesterday. Hence, the trend of stock returns is magnified by the limits' movement and has approximately a 50% chance of being by the trading volume.

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Appendix A

Theory 1. Assuming $r_t * \sim \text{iid}\, N(\mu, \sigma^2)$, then the GMM estimators of μ and σ^2 are

$$\hat{\mu} = \frac{\sum_{r_t \in S_1} z_t + \sum_{r_t \in S_2} z_{t+1} + \cdots + \sum_{r_t \in S_{n+1}} z_{t+n}}{T}, \tag{17}$$

$$\hat{\sigma}^2 = \frac{\sum_{r_t \in S_1} (z_t - \hat{\mu})^2 + \sum_{r_t \in S_2} (z_{t+1} - 2\hat{\mu})^2 + \cdots + \sum_{r_t \in S_{n+1}} [z_{t+n} - (n+1)\hat{\mu}]^2}{T}, \tag{18}$$

respectively, where n is the n consecutive hitting days, and S_{n+1} is the set of n consecutive hitting price.

Theory 2. Assuming r_t^* is subject to the price limit but x_t is not, then the GMM estimator of covariance of r_t^* and x_t is

$$\begin{aligned}\widehat{\text{Cov}}(r_t^*, x_t) = \Bigg[& \sum_{r_t \in S_1} (r_t - \hat{\mu})(x_t - \hat{\mu}_x) \\ & + \sum_{r_t \in S_2} (z_{t+1} - 2\hat{\mu})(x_t + x_{t+1} - 2\hat{\mu}_x) + \cdots \\ & + \sum_{r_t \in S_{n+1}} (z_{t+n} - (n+1)\hat{\mu})(x_t + x_{t+1} + \cdots \\ & + x_{t+T-1} - (n+1)\hat{\mu}_x) \Bigg] / A_1,\end{aligned}$$

where $A_1 = T_1 + 2T_2 + 3T_3 + \cdots + nT_n$, T_i is the number of observations in the S_i and $\hat{\mu}_x$ is the expected value of x.

Theory 3. Assuming that both r_t^* and x_t^* are subject to the price limits, than the GMM-based estimator of covariance is

$$\begin{aligned}\widehat{\text{Cov}}(r_t^*, x_t^*) = \Bigg[& \sum_{r_t, x_t \in S_1} (r_t - \hat{\mu})(x_t - \hat{\mu}_x) \\ & + \sum_{\text{either or both } r_t, x_t \in S_2} (z_{t+1} - 2\hat{\mu})(x_t + x_{t+1} - 2\hat{\mu}_x) \\ & + \sum_{r_t, x_{t+1} \in S_2, \text{ or } r_{t+1}, x_t \in S_3} (z_{t+2} - 3\hat{\mu}) \\ & \times (x_t + x_{t+1} + x_{t+2} - 3\hat{\mu}_x) + \cdots \Bigg] / A_2,\end{aligned}$$

where $A_2 = T_1 + 2T_2 + 3T_3 + \cdots + nT_n$.

Theory 4. If r_t^* is first-order autocorrelated, then the GMM estimator of ρ and variance are

$$\hat{\rho} = \Bigg[\sum_{r_t, r_{t+1} \in S_1} (r_t - \hat{\mu})(r_{t+1} - \hat{\mu})$$

$$+ \sum_{r_t \in S_1, r_{t+1} \in S_2} (r_t - \hat{\mu})(r_{t+1} + r_{t+2} - 2\hat{\mu})$$

$$+ \sum_{r_t \in S_2, r_{t+2} \in S_1} (r_t + r_{t+1} - 2\hat{\mu})(r_{t+2} - \hat{\mu})$$

$$+ \sum_{r_t \in S_1, r_{t+1} \in S_3} (r_t - \hat{\mu})(r_{t+1} + r_{t+2} + r_{t+3} - 3\hat{\mu})$$

$$+ \sum_{r_t \in S_3, r_{t+3} \in S_1} (r_t + r_{t+1} + r_{t+2} - 3\hat{\mu})(r_{t+3} - \hat{\mu})$$

$$+ \cdots \Bigg] \Big/ \left(A3 \cdot \sigma^2_{\mathrm{GMM}} \right), \tag{19}$$

$$\sigma^2_{\mathrm{GMM}} = \frac{\Sigma_{r_t \in S_1} (z_t - \hat{\mu})^2 + \Sigma_{r_t \in S_2} (z_{t+1} - 2\hat{\mu})^2 + \cdots + \Sigma_{r_t \in S_{n+1}} [z_{t+n} - (n+1)\hat{\mu}]^2}{T_1 + (2+2\rho)T_2 + (3+4\rho)T_3 + \cdots + [(n+1) + 2n\rho]T_{n+1}}, \tag{20}$$

where $A3 = (T_1 + T_2 + \cdots + T_{n+1} - 1)$ and $\hat{\mu}$ is defined in Theorem 1.Once the consistent estimator is obtained, the hypothesis can be investigated.

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