THE IMPACT OF SHORT SALE RESTRICTIONS ON STOCK VOLATILITY: EVIDENCE FROM TAIWAN

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ABSTRACT

Governments implement policies to stabilize stock markets in times of financial crisis. The most common intervention is to forbid short sales. For instance, around the financial crisis of 2008, eleven governments announced restrictions on naked short sales in their stock markets. In light of the Greek credit crisis in 2010, Germany also disallowed naked short sales. Opinions were widely divided regarding the appropriateness of government to interfere in markets. This paper studies the influence of volatility asymmetries caused by the Taiwanese government's naked short sale restrictions. Intraday data is used to analyze the issue by way of EGARCH models. We find the high liquidity associated with large stocks increases asymmetric volatility. However, asymmetric volatility of middle and small sized stocks decreases around the naked short sale ban.

JEL: C22; C58; G18;

KEYWORDS: Asymmetric volatility, Information exposure, Naked short sale, Firm size, EGARCH

INTRODUCTION

The Greek debt crisis in 2010 caused a variety of financial concerns. In an attempt to stabilize the financial situation, the German Federal Financial Supervisory Authority forbid the naked short sale for Euro zone bonds, and shorting some financial stocks. The rule came into effect on May 19, 2010 until March 31, 2011. In 2008 global financial crisis resulted in global stock market collapse together, It also made every government adopt all kinds of policies to stabilize the stock market, such as limiting or banning the naked short sale in Taiwan, Korea, Belgium, Holland, Canada, German, Ireland, England, America, Australia, and Russia; pausing to trade in Russia, Korea, and Brazil; stopping to trade in Russia, Ukraine, Kuwait and Indonesia.

Limiting or banning naked short sales was the policy nearly every government carried out to stabilize its stock market. The effectiveness of this approach is debated. This paper researches the effects of banning naked short sales in the Taiwan stock market after the financial crisis of 2008. In the past, most research has been based on the closing prices, thereby ignoring changes in intraday volatility. In this paper, we advance the analysis to include intraday volatility. We conclude that the banning naked short sales increases return volatility for large firms, but it can decrease the return volatility for the middle and small sized firms.

This paper is organized into five parts. The following section contains a literature review about short sale restrictions and asymmetric volatility. The third part presents the data and methodology which is based on EGARCH Analysis to assess the influence of short sale bans on intraday data asymmetric volatility in the stock market. The fourth part presents the empirical results, which reveals that interfering policies and the banning naked short sales have certain influences on intraday asymmetric volatility. The paper closes with a summary and some concluding comments.

LITERATURE REVIEW

Limiting or banning naked short sales was a common policy to provide stability to the stock markets around the recessions of 2008. However, the success of this approach remains debatable. Woolridge and Dickinson (1994) studied the relationship between stock prices and securities lending. They found that securities lending couldn't collapse stock prices, those who traded in securities lending were not able to earn super-normal return, and it provided liquidity. Frost and Savarino (1988) found investment limit restrictions could not only help to reduce the estimated error, but also improve portfolio returns. Ho (1996) studied the Singapore stock market, from 1985 to 1986. He found that by forbidding naked short sales affected volatility. He used unconditional fluctuation and conditional fluctuation in his tests and found strictly limiting naked short sales would increase the volatility of the stock market. Hong and Stein (2003) derived a model for the heterogeneous expectations and used limited naked short sales to explain why stock prices showed negative skewness. In other words, stock price declines were an excess volatility phenomena.

Diether, Lee, and Werner（2009）examined 2,485 stocks, 1,352 from the NYSE and 1,133 from the NASDAQ. They explored how naked short sales affect liquidity, volatility and the effects of market quality. While short-selling activity increased both for NYSE and NASDAQ-listed Pilot stocks, returns and volatility at the daily level were unaffected. NYSE-listed Pilot stocks experience more symmetric trading patterns and a slight increase in spreads and intraday volatility after the suspension while there was a smaller effect on market quality for NASDAQ-listed Pilot stocks.

Chelley-Steeley and Steeley (1996), Laopodis (1997), Hu et al. (1997), and Yang (2000) discovered the existence of asymmetric volatility. The phenomenon of asymmetric volatility refers to a situation when new information causes price change. When new information is positive, future price volatility is smaller. When new information is negative, future price volatility is greater. Black (1976) first found that current returns had a negative correlation with future volatility. Christie (1982) and Schwert (1990) later found the same results. Liau & Yang (2008) argued that asymmetric mean reversion and volatility reflect the fact that investors react more strongly to bad news than to good news, confirming the volatility of asymmetry.

This paper researches naked short sale bans in the Taiwan stock market after the global financial crisis in 2008 which affected the degree of volatility. Based on the above studies, we can assume that when new information results in falling stock prices, the financial leverage of companies will rise. In other words, the risk of holding a stock increases, and future returns will be more volatile. On the other hand, when new information causes stock price to rise, the financial leverage of companies will decrease, and fluctuation of future returns will be less volatile. This phenomenon is called the leverage effect. Whether asymmetric volatility of stock returns is caused by leverage effects is still not conclusive. Sentana & Wadhwani (1992) on the other hand assume the asymmetric volatility phenomenon was due to herding behaviors by trader. Lo and MacKinlay (1987) argued that asymmetric volatility resulted from non-synchronous trading.

In the empirical model, when dealing with high-frequency financial data, Engle (1982) established the Autoregressive Conditional Hetroskedasticity Model (ARCH) to solve self-relative and hetroskedasticity problems. Bollerslev (1986) extended this work to the GARCH model (generalized ARCH) to describe the phenomenon of volatility clustering of returns. However, the GARCH model cannot distinguish differences in volatility between positive and negative information (the phenomenon of the violability asymmetries). Nelson (1991) developed the exponential GARCH model (EGARCH) to distinguish this difference. Campbell and Hentschel (1992) distributed the asymmetric volatility by the quadratic GARCH model (QGARCH). Later, Engle & Ng (1993) compared these two models, finding the EGARCH model had a better distribution, and Hafner (1998) proved with empirical data that the EGARCH model was better at distributing the volatility of high-frequency data. The EGARCH model is widely applied to high-frequency data so this research uses the EGARCH model to discuss the asymmetric volatility of stock returns.

Duffee (1995) utilized the daily return square root of the sum to construct the estimated volatility, to study the relations between return and volatility of individual stocks, and return and volatility of the aggregate market. He found positive relations between return and volatility of individual stocks was the primary reason why the stock price fell, return volatility rose. The relationship was stronger for small firms. Kunt and Levine (1996) analyzed the development of stock markets. They found positive relations between development of stock markets and financial agencies , banks and non-banks. He discovered that large scale markets have the low volatility properties.

DATA AND METHODOLOGY

Data and Descriptive Statistics

After the global financial crisis in 2008, the Taiwan stock market introduced the uptick rule on September 22, 2008. Later, naked short sales were banned on October 1, 2008. The uptick rule ban was lifted on January 5, 2009. The policy express in Table 1.

Table 1: The date of Banned the naked short sale in the Taiwan Stock Market

Order	Start	End	Event
1	2005/5/16	2008/9/21	Besides the composition stock of Tai 50 and Tai mid-cap 100 uptick rule
2	2008/9/22	2008/9/30	All stock Uptick rule
3	2008/10/1	2008/12/31	banned the naked short sale
4	2009/1/5		Besides the composition stock of Tai 50 and Tai mid-cap 100 uptick rule

This table presents the period of Banned the naked short sale in the Taiwan Stock Market

This paper studies the influence of banning naked short sales has for the asymmetric volatility of the stock market pre-period, in the period, and post-period in Taiwan markets. Skinner (1989) found that a minimum of five hundred observations is necessary in ensuring reliable estimates with the EGARCH model. Thus we adopt intraday data for each 30 minutes of the TAI 50 and TAI mid-cap 100 indices before, in and after banning naked shorts sale as our data. Data were obtained from the Taiwan Stock Market Exchange. Because the Taiwan stock market doesn't have a small-cap index, we assume the pattern of the TAIEX weighted average index. First, we calculate the market value. The base period is December 28, 2004. The index of the base period is 6000. The index on December 28, 2004 is show in Table 2. The small cap index mode, is computed using Eq. 1.

$$I_s \equiv \frac{\text{market value} - \text{the value of the constituent stock of the TAI 50 and TAI mid cap 100}}{\text{the value of the base period}} * 6000 \qquad (1)$$

Where the base period is December, 28, 2004, and the market value to reduce the value of the composition stock of the TAI 50 and TAI mid-cap 100 is 5283103 thousands.

Table 2: The Index and Market Value

	index	Market Value
TAIEX weighted average index	4521.5	13541728
Tai 50 index	6000.6	6271838
TAI mid-cap 100 index	6053.2	1986787
TAI small-cap	6000.0	5283103

This table presents the index and market value in 2004/12/28

Figure 1 plots the 30 min. stock price movements for the four indexes. The return for each market are calculated as the percent logarithmic difference in the 30 min stock index, i.e., $R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \times 100$,where R_t,P_t,P_{t-1} stand for the market return and price for each 30 min, respectively; ln is the continuous compounding factor. Return' descriptive statistics of three subperiods are exhibited on Table 3. The skewness statistics indicate that all return series are either negatively or positively skewed. The excess kurtosis statistics suggest departure form normality, that is, all series are highly leptokurtic. Hence, the Jarque-Brea statistics rejects the normality for each return series. The Augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) unit root tests revel all the series are stationary.

Figure 1: Taiwan Stock Index of the 30 min

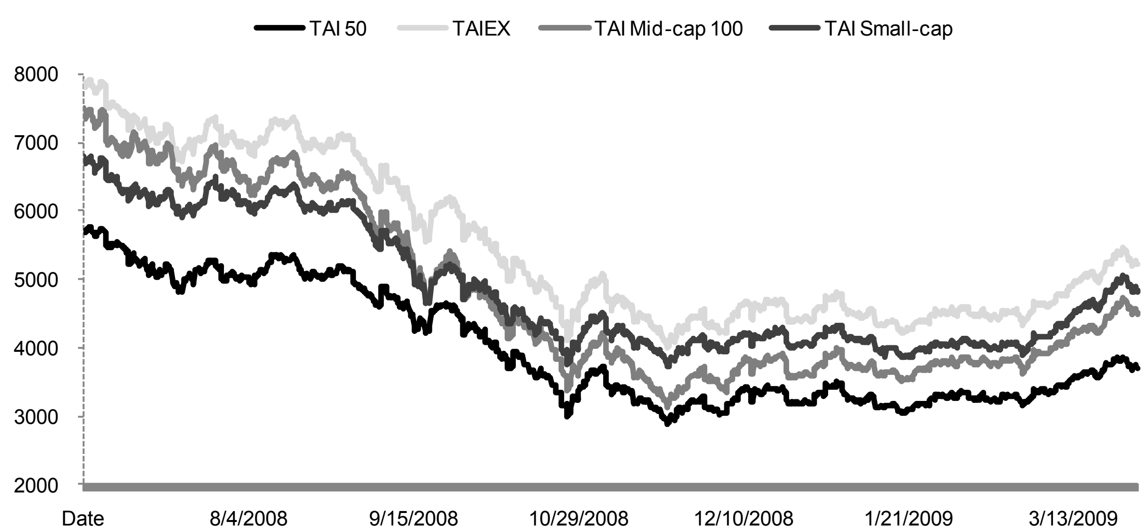

Table 3: Number of Observations

	index	Start	End	Obs.
1	Pre-	2008/6/23	2008/9/21	576
2	In	2008/10/1	2008/12/31	585
3	Post	2009/1/1	2009/3/31	513

This table presents the observation for three sub-periods

This research used return series to analyze asymmetric volatility. The Ljung-Box (LB) statistics for 12 lags applied to residuals and squared residuals indicate significant linear/nonlinear dependence exist.
If the Q statistic of Ljung-Box return series is significant, it shows the autocorrelation phenomenon exists in this series. That is to say, if the Ljung-Box of the square of return series Q statistic is significant, it indcates the series variance exists for the autocorrelation phenomenon. This implies this series contains the heteroskedasticity phenomenon.

The tests of LB(12)、$LB^2(12)$ shown in Table 4 show that most return series and the square of return series all contain the autocorrelation phenomenon. As such, the analysis models should conssider autoregression (AR), and conditional hetrocedesticity (CH). The mean equation of the GARCH Family Model can resolve autocorrelation series, and its variance equation allows the variance to be decided by the pre-variance and disturbance term. So the existence of conditional hetrocedesticity is acceptable. In order to explain the phenomenon, it is optimal to adopt the GARCH Family Models.

Table 4: Descriptive Statistics of Three Index Each 30min Stock Return in Four Sample Periods

EVENT	PERIOD	μ	σ	S	K	JB	LB(12)	LB^2(12)	ADF	PP
TAI 50	Per-	-0.04	0.70	0.43	14.15	3002.02	38.14 ***	104.28 ***	-21.86 ***	-21.84 ***
	In-	-0.04	1.02	-0.83	12.89	2450.64	20.59 **	86.33 ***	-24.14 ***	-24.14 ***
	Post-	0.02	0.64	0.30	16.92	4148.83	13.62	23.09 **	-23.97 ***	-23.94 ***
TAI Mid-cap 100	Per-	-0.07	0.81	-0.63	14.93	3453.07	37.74 ***	115.81 ***	-21.75 ***	-21.68 ***
	In-	-0.04	1.04	-0.73	10.90	1574.11	9.67	88.58 ***	-23.54 ***	-23.54 ***
	Post-	0.04	0.65	0.32	12.44	1913.89	14.84	39.60 ***	-24.47 ***	-24.40 ***
TAI Small-cap	Per-	-0.05	0.73	-0.42	19.10	6238.80	35.96 ***	145.70 ***	-25.07 ***	-25.05 ***
	In-	-0.02	0.87	-0.61	11.19	1671.30	5.92	137.94 ***	-24.61 ***	-24.61 ***
	Post-	0.03	0.57	0.49	10.29	1155.59	19.70 **	22.61 **	-25.19 ***	-25.09 ***

Notes：, ** and*** denote significance at the .1, .05 and .01 level, respectively. μ and σ are sample mean and standard deviation; S and K are measures for skewness and excess kurtosis. JB represents Jarque-Bera statistics, testing for normality. LB(12) is are the Ljung-Box test statistics testing for autocorrelation in the residuals and squared residuals up to the twelfth lags, which is distributed as χ^2 with degree of freedom equal to the number of lags. ADF and PP stand for the augmented Dickey-Fuller and Phillips-Perron unit root tests. The critical values of ADF and PP at the .05 and .01 level are -2.86 and -3.43, respectively.*

The autoregressive process is required in describing linear dependent series. We adopt the Akaike information criterion (AIC) to determine the order of the AR(p) and the smallest value of AIC is chosen. As shown in Table 5, the result is show that AR(1) is adopted for all indexes and periods.

The Asymmetric Volatility Model

The diagnostics of higher order autoregressive conditional heteroskedasticity and volatility clustering suggest that a GARCH-class model would be appropriate. Nevertheless, ordinary GARCH models do not distinguish differential impacts of good and bad news on volatility. To examine the asymmetric responses of volatility to positive and negative innovations, the EGARCH model developed by Nelson (1991) is employed. As suggested by Bollerslev, Chou, and Kroner(1992) to use a model that is as parsimonious as possible, we adopt the EGARCH(1,1) model. The model is described as follows：

$$R_t \left| I_{t-1} \sim f\left(\mu_t, \sigma_t^2\right)\right. \tag{2}$$

$$R_t = \beta_0 + \sum_{i=1}^{p} \beta_i R_{t-1} + \varepsilon_t \tag{3}$$

$$\ln\left(\sigma_t^2\right) = \alpha_0 + \alpha_1\left(\left|z_{t-1}\right| - E\left[\left|z_{t-1}\right|\right] + \delta z_{t-1}\right) + \phi \ln\left(\sigma_{t-1}^2\right) \tag{4}$$

Equation 2 expresses the conditional return R at time t, given the information set I at time t-1. With the conditional density function f(•), R_t has the conditional mean $\mu_t=E(R_t|I_{t-1})$ and conditional variance $\sigma_t^2=E(\varepsilon_t^2|I_{t-1})$, where ε_t represents the innovation at time t, i.e., $\varepsilon_t = R_t - \mu_t$. Eq. 3 describes the autoregressive process of order p for the stock returns, with $\sum_{i=1}^{p} \beta_i R_{t-1}$ capturing the autocorrelation. As described in the previous section, the order of AR(p) is decided based on the Akaike information criterion. The selected order for each market in each period is presented in Table 4. The process of conditional variance is expressed by Eq. 4, where the logarithm of the conditional variance is modeled as an asymmetric function of last period's standardized innovation, z_{t-1}, and the logarithm of last period's conditional variance.

Table 5: Values of AIC

EVENT	PERIOD	Values of AIC 1	2	3	4	5	6
TAI 50	Per-	**2.1179**	2.1224	2.1262	2.1292	2.1303	2.1349
	In-	**2.8792**	2.8807	2.8839	2.8873	2.8901	2.8933
	Post-	**1.9372**	1.9397	1.9415	1.9395	1.9434	1.9471
TAI Mid-cap 100	Per-	**2.4066**	2.4118	2.4121	2.4128	2.4098	2.4147
	In-	**2.9193**	2.9194	2.9228	2.9262	2.9292	2.9324
	Post-	**1.9920**	1.9954	1.9981	1.9943	1.9979	2.0011
TAI Small-cap	Per-	**2.2130**	2.2181	2.2211	2.2237	2.2259	2.2285
	In-	**2.5566**	2.5574	2.5603	2.5635	2.5663	2.5689
	Post-	**1.7111**	1.7133	1.7170	1.7163	1.7195	1.7218

Note: bold number represents the minimum value.

The standardized innovation, z_t is defined as ε_t/σ_t^2 such that a positive z_t implies an unexpected increase in stock returns whereas a negative z_t implies an unexpected decrease. Thus the second term in Eq. 3 allows conditional variance process to respond asymmetrically to rises and falls in stock price. Specifically, the term $|z_t|$-E$|z_{t-1}|$ represents the size effect of the innovation, that is, providing α_1 is positive, a past innovation then a positive (negative) impact on $\ln(\sigma_t^2)$ when the magnitude of z_{t-1} is larger (smaller) than its expected value. The term δz_{t-1} on the other hand captures the sign effect; that is, when the coefficient δ is significantly negative (positive), then negative (positive) innovation increases volatility more than does a positive (negative) innovation of the same magnitude. In essence, to examine the presence of asymmetric volatility is present, the impact of positive innovation on $\ln(\sigma_t^2)$ is equal to$\alpha_1(1-|\delta|)|\ z_{t-1}|$ and the impact of a negative innovation is $\alpha_1(1+|\delta|)|\ z_{t-1}|$.

Given the data for the return series R_t, estimates of the parameters in Eq. 3 and Eq. 4 (namely β_0, β_1, α_0, α_1, δ, ψ) can be derived by maximizing the log-likelihood of the returns over the sample period. Diagnostic test for appropriateness of the models are performed on the standardized residuals and squared residuals via Ljung-Box test and Lagrange multiplier test. Specifically, the Ljung-Box test applied to the standardized residuals tests for remaining serial correlation in the mean equation, whereas the Ljung_Box test as well as the Lagrange multiplier test applied to the squared standardized residuals checks the specification of the variance equation.

EMPIRICAL RESULTS

This paper mainly examines banning naked short selling in the Taiwan Stock Market. The paper uses intraday data for each 30 minutes, and applies them to the above EGARCH(1,1) Model. Table 6 shows the resulting analysis. First, we divide the data into three sub-periods—the pre-period, in the period, and the post-period, to assess whether the samples in Taiwan Stock Market have the Asymmetric Volatility phenomenon in each stage. This paper compares the difference of the asymmetric volatility for the three periods and discusses if δ value differs dramatically among the three sub-periods.

Asymmetric volatility exists when volatilities caused by positive information and negative information are in different ranges. When δ is negative, negative information will increase future volatility more than that of positive information. Likewise, if δ is positive, positive information will increase future volatility more than that of negative information. For example TAI Mid-cap 100 banning short sale period, the EGARCH(1,1) Model estimate of the result would be as follows:

$$R_t = -0.0066 + 0.0333R_{t-1} + \varepsilon_t$$
$$\ln\left(\sigma_t^{\;2}\right) = 0.0677 + 0.1478\left(\left|z_{t-1}\right| - E\left[\left|z_{t-1}\right|\right] - 0.0559 z_{t-1}\right) - 0.9404\ln\left(\sigma_{t-1}^{\;2}\right)$$

If the t-1 period contains negative information to make εt-1 become negative, $z_{t-1}=\varepsilon_{t-1}/\sigma_{t-1}^2$ should be negative, then z_{t-1} in each unit will make $\ln(\sigma_t^2)$ increase 0.1478(1-0.0559) in the next period (t period), it is equal to 0.1473. On the contrary, if there is positive information, each t-1 period will contain positive information, then each z_{t-1} will make $\ln(\sigma_t^2)$ increase 0.1478(1+0.0559) in the next period, which is equal to 0.1561. So, compared to the positive and negative information, the volatility caused by the former will be 1.0597 times by the latter. That is to say the higher the absolute value of δ become, the more volatile the asymmetric volatility will be. In other word, the degree of asymmetry can be measured by (1+|δ|)/(1-|δ|) (Koutmos and Saidi (1995)). Because the degree of asymmetry is measured by (1+|δ|)/(1-|δ|) and a higher absolute value of δ implies a higher degree of asymmetry, we can simply compare the absolute values of δ between the three sub-periods to examine whether is a change in the extent of asymmetry.

Table 6: Maximum Likehood Estimates of the EARCH

Event		**TAI 50**			**TAI Mid-cap 100**			**TAI Small-cap**	
Period	**Pre**	**In**	**Post**	**Pre**	**In**	**Post**	**Pre**	**In**	**Post**
AR(p)	**AR(1)**	**AR(1)**	**AR(1)**	**AR(1)**	**AR(1)**	**AR(1)**	**AR(1)**	**AR(1)**	**AR(1)**
β_0	-0.0036	0.0431	0.0282	-0.0626	-0.0066	0.0306	-0.0258	0.0081	0.0314
	(0.7969)	(0.0000) ***	(0.0317) **	(0.0028) ***	(0.6335)	(0.0671) *	(0.0930) *	(0.5704)	(0.0185) **
β_1	0.0334	0.0342	-0.0086	0.0969	0.0333	-0.0514	0.0201	0.0136	-0.0424
	(0.1233)	(0.0000) ***	(0.6560)	(0.0002) ***	(0.0023) ***	(0.0617) *	(0.5322)	(0.3338)	(0.1832)
α_0	0.0077	-0.0139	-0.3031	-0.0225	-0.0677	-0.3219	-1.1968	-0.0260	-1.5035
	(0.4360)	(0.8447)	(0.1325)	(0.2402)	(0.7386)	(0.1078)	(0.0004) ***	(0.1594)	(0.0002) ***
α_1	-0.0379	-0.0098	-0.0799	0.0077	0.1478	-0.0295	0.4985	0.0301	0.4468
	(0.0271) **	(0.9249) **	(0.3695) **	(0.7787) **	(0.0016) **	(0.7451) **	(0.0000) **	(0.2431) **	(0.0030) **
Δ	-0.0935	0.1599	-0.0838	-0.0876	-0.0559	-0.1177	0.0572	-0.0484	-0.1843
	(0.0000) ***	(0.0943) *	(0.2137)	(0.0005) ***	(0.0425) **	(0.0813) *	(0.4184)	(0.0133) **	(0.0674) *
Ψ	0.9866	0.6452	0.6936	0.9742	-0.9404	0.6691	0.0599	0.9926	0.0710
	(0.0000) ***	(0.0270) ***	(0.0001) ***	(0.0000) ***	(0.0000) ***	(0.0002) ***	(0.8541)	(0.0000) ***	(0.7920)
Log L	-469.3761	-643.7005	-368.3761	-574.0872	-710.3047	-422.2639	-489.3824	-609.6951	-346.1007
LB(12)	11.6940	23.5770	13.3000	21.7180	8.5151	13.9660	30.2410	5.6073	18.0450
$LB^2(12)$	18.5520	79.0390	22.7030	39.1540	38.2890	36.4190	74.2730	76.4490	23.0960
LM(6)	4.0819	4.3606	3.8951	3.4458	4.0335	4.0316	2.0894	9.1180	6.2808
$\frac{1+\lvert\delta\rvert}{1-\lvert\delta\rvert}$	1.2063	1.3806	1.1829	1.1920	1.1185	1.2669	1.1213	1.1017	1.4518

*Notes: ** and*** denote significance at the .05 and .01 level, respectively. Numbers in parentheses are standard errors. As the order of AR(p) is different for each event, to save space the estimates of the conditional mean equations are shown. LB(12) and $LB^2(12)$ are the Ljung-Box test statistics testing for autocorrelation in the standardized residuals and standardized squared residuals for the EGARCH model up to the twelfth lags, which is distributed as χ^2 with degree of freedom equal to the number of lags. LM(6) represents the Lagrange multiplier test statistics examining whether the standardized residuals exhibit additional ARCH up to the sixth lags, which is distributed as χ^2 with degree of freedom equal to the order. (1+|δ|)/(1-|δ|) measures the degree of asymmetry.*

This paper found it wasn't significant for the Tai 50 pre-period and Tai Small cap post-period. However, the others were significant, and the maximum and minimum of |δ| were 0.1843, and 0.0484, respectively, showing that the asymmetric volatility existed in the intraday data. We compared the pre-period to the post-period. Except the volatility change ((1+|δ|)/(1-|δ|)) of the TAI 50 was the biggest in the period of the banning naked short selling (1.2063,1.3806,11829, respectively), the others (TAI Mid-cap 100, TAI Small-cap) significantly decreased in the period of the naked short selling ban (1.1920→1.1185), (1.1213→1.1017)). Upon lifting the naked short selling ban, the asymmetric volatility was rose significantly (1.1213→1.1017), (1.1017→1.4518)), as is shown in Table 7.

Table 7: T-Test of δ for the Period

Event	Period	Obs.	δ	significance	σ	t-value	
TAI 50	pre	576	-0.0935	***	0.0160	16.5655	***
	in	585	0.1599	*	0.0956		
	pre	576	-0.0935	***	0.0160	-3.1883	***
	post	513	-0.0838		0.0674		
	in	585	0.1599	*	0.0160	-24.9726	***
	post	513	-0.0838	***	0.0674		
TAI Mid-cap 100	pre	576	-0.0876	***	0.0252	-55.4353	***
	in	585	0.0016	**	0.0276		
	pre	576	-0.0876	***	0.0252	9.5356	***
	post	513	-0.1177	*	0.0676		
	in	585	0.0016	**	0.0276	36.3741	***
	post	513	-0.1177	*	0.0676		
TAI Small-cap	pre	576	0.0572		0.0706	-2.8673	***
	in	585	-0.0484	**	0.0196		
	pre	576	0.0572		0.0706	23.8302	***
	post	513	-0.1843	*	0.1008		
	in	585	-0.0484	**	0.0196	30.0479	***
	post	513	-0.1843	*	0.1008		

*Note : * , **and *** denote significance at the .1 ,.05 and .01 level*

SUMMARY AND CONCLUSIONS

Asymmetric volatility has received more research attention recently, but research on intraday volatility is limited. This paper uses the EGARCH model to research asymmetric volatility. The Taiwan stock market restricted short sales for three months, so this paper uses 30 minutes intraday data to research intraday volatility. Most researchers adopted the last trade price of each day to study asymmetric volatility. However, ignoring intraday volatility resulted in different conclusions. This paper is based on intraday data to analyze asymmetric volatility and long-run and short-run effects. Based on our research, we concluded that intraday asymmetric volatility also exists.

The policy of banning short selling was mainly to prevent investors' excessively panic moods from making unreasonable decisions. This paper found banning naked short selling was effective at decreasing asymmetric volatility for mid-cap and small-cap stocks. It was not effective for decreasing asymmetric volatility for large firms. On the contrary, the asymmetric volatility was increased. We argue it is easy to acquire information of large firms so that the investor analyze rationally. The policy resulted in increasing the asymmetric volatility of the stock market. This study supports the findings of Hogan, Melvin (1994) and Tse and Tsui (1997). The lemma of heterogeneous expectations is that the heterogeneous expectation would be more serious if government interference was expanded or increased. However, it was not easy to acquire the information of mid-cap and small scale of firms. The results were similar to those of Greenwald and Stein (1991) that researched the America stock market. They find the interposed policy provides the opportunity to calm investors, reduced trading noise, and volatility. We close the paper with a fall for more research to more fully understand the affects of intraday asymmetric volatility.

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