Stock Manipulation: The Case of the Taiwan Stock Exchange

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1. INTRODUCTION

Market manipulation is a growing concern in many emerging stock markets, and has also been a concern in developed stock markets such as the U.S. in the past (Khwaja and Mian, 2005; Jiang, et al., 2005; and Aggarwal and Wu, 2006). The possibility that markets can be manipulated is an important issue for both the regulation of trading and the efficiency of the market. Security regulators generally prohibit market manipulations on the grounds that they distort prices, hamper price discovery, and create deadweight losses. In particular, many Asian stock markets where securities are traded thinly are therefore more susceptible to manipulation.

In modern financial markets, manipulations are often done in hidden. While manipulative activities seem to have declined on the main exchanges, they are still a serious issue in the over-the-counter (OTC) market in the U.S. and in emerging financial markets. In particular, in many emerging markets where legal enforcement is weak, manipulation is still rampant. Recent studies such as Khwaja and Mian (2005) and Wu (2004) suggest that manipulation may still be prevalent in emerging markets. Even in the relatively well-regulated U.S. market, Aggarwal and Wu (2006) have documented more than 100 cases of price manipulation in the 1990s.

Although several theories on stock market manipulation have been investigated, empirical evidence about stock manipulation is still scarce. Furthermore, while most of the empirical studies we have looked at examine the impact of manipulation in well-developed countries such as U.S., a few studies examined the impacts on emerging markets. There is a wide disparity in disclosure requirements and securities regulations across nations. The disclosure requirements in U.S. are considered high relative to the rest of the world, while disclosure requirements and securities regulations in emerging markets are less stringent.

In this paper, we undertake an examination of stock manipulation using a unique data set to study the characteristics of manipulated stocks and the impacts they have on market quality. The samples establish some basic facts about stock market manipulation in an emerging market, Taiwan. We have hand-collected data on manipulation cases pursued by Taiwan Securities and Exchange Commission (TSEC) from 1991 to 2005. So far, few studies examine sample cases of prosecution for stock manipulation as a basis for empirical investigation of emerging financial markets. Our findings will provide useful knowledge for regulatory policy as well as the investigation of manipulation cases.

The remainder of the article is organized as follows. In Section 2, we discuss stock manipulation theory and review the literature. In Section 3, we describe the data and sample selection procedures and present a methodology of stock price manipulation. The results of the empirical tests are presented in Section 4. A summary and conclusion are given in the last section.

2. LITERATURE REVIEW

2.1 Types of Manipulation

Stock manipulation behavior takes a variety of forms, from insiders taking actions that influence stock prices to the release of false information or rumors in internet chat rooms, e.g., the accounting and earnings manipulation in the Enron case. Moreover, large block trades can influence prices: A trader places a large number of purchase orders to drive the price up. Allen and Gale (1992) classify manipulation into three types: action-based, information-based, and trade-based. Action-based manipulation involves actions that change the actual or perceived value of the assets. Bagnoli and Lipman (1996) investigate action-based manipulation using takeover bids. In their model, a manipulator acquires stocks in a firm and then announces a takeover bid. This leads to a price run-up of the firm's stock. The manipulator is therefore able to sell his stock at the higher price. Of course, the bid is inevitably dropped.

Information-based manipulation releases false information or spreads false rumors in the stock market. The "trading pools" in the U.S. during the 1920s give examples of information-based manipulation. A group of investors would combine to form a pool, first to buy a stock, then to spread favorable rumors about the firm, and finally to sell out at a profit. Van Bommel (2003) argues that the sources of rumors are small informed investors who manipulate prices to increase their information-based profits. Rumormongers can be skillful amateur analysts, investors with access to serendipitous information such as suppliers or clients, or individuals with access to inside information. A dynamic model with rational profit-maximizing

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traders shows that spreading rumors makes economic sense, as it increases demand for a security and can drive its price beyond the value that the rumormonger privately knows.

Trade-based manipulation is much more difficult to detect and rule out. It occurs when a trader attempts to manipulate a stock simply by buying and then selling, without taking any publicly observable actions to alter the perceived value of the firm or releasing any false information to influence the price. Allen and Gale (1992) built a model showing that trade-based manipulation is possible in a rational-expectations framework. They classify the traders into three types, including rational investor, informed trader, and manipulator. The manipulator is able to achieve a positive profit under certain conditions because a pooling equilibrium can arise in which the investors are uncertain whether a large trader who buys shares is a manipulator or an informed trader.

In this study, our cases are mostly of trade-based manipulation.

2.2 Theoretical and Empirical Evidence

The concern with manipulation of security prices has been growing for the last several years. Some of the most compelling studies have focused on modeling the behaviors of manipulation, and on the empirical implications of manipulation (e.g., Vila, 1989; Allen and Gale, 1992; Jarrow, 1992; Allen and Gorton, 1992; and Bagnoli and Lipman, 1996). In recent years, more attention has been paid to empirical studies of manipulation issues (Wu, 2004; Mei, Wu and Zhou, 2004; Khwaja and Mian, 2005; Jiang, et al., 2005; Allen, et al., 2006; Merrick, et al., 2005; and Aggarwal and Wu, 2006). In this study, we extend this line of the literature by examining the behavior of stock manipulation and its impact on market quality in the context of the TSEC.

There is a growing theoretical literature on market manipulation. Hart (1977), Hart and Kreps (1986), Vila (1989), Allen and Gale (1992), Allen and Gorton (1992), Benabou and Laroque (1992), and Jarrow (1992, 1994) were among the first to study market manipulation. Subsequent contributions include Bagnoli and Lipman (1996), Chakraborty and Yilmaz (2004a, b), and Goldstein and Guembel (2003). Kumar and Seppi (1992) discuss the possibility of futures manipulation with cash settlement. Pirrong (1993) shows how squeezes hinder price discovery and create deadweight losses. Vitale (2000) considers manipulation in foreign exchange markets. Van Bommel (2003) shows the role of rumors in facilitating price manipulation.

In contrast, the empirical literature is quite limited. Although in the U.S stock market, the widespread manipulation through stock pools before the US stock market Crash of 1929 is examined in Mahoney (1999) and Jiang et al. (2005), they find little evidence of price manipulation for the stock pools. In recent years, however, some studies have found evidence of market manipulation after 21st century. For example, Aggarwal and Wu (2006) present a theory and some empirical evidence on stock price manipulation in the U.S. Extending the framework of Allen and Gale (1992), they find that more information seekers imply greater competition for shares in a market with manipulators, making it easier for a manipulator to enter the market and potentially worsen market efficiency. Using a unique dataset from SEC actions in cases of stock manipulation, they find that illiquid stocks are more likely to be manipulated and that this manipulation increases stock volatility. Khwaja and Mian (2005) discover evidence of broker price manipulation by using a unique daily trade level data set from the main stock market in Pakistan. They find that when brokers trade on their own behalf, they earn annual rates of return that are 50-90 percentage points higher than those earned by outside investors. While neither market timing nor liquidity provision offer sufficient explanations for this result, they find compelling evidence for a specific trade-based, "pump-and-dump" price manipulation scheme.

Moreover, Mei et al. (2004) propose a model in which smart money can strategically take advantage of investors' behavioral biases and manipulate the price process to make a profit. They show that due to the behavioral biases of investors and the limitations of arbitrage, the manipulator can profit from a "pump-and-dump" trading strategy by accumulating the speculative asset while pushing the asset price up, and then selling the asset at higher prices. Since nobody has private information, manipulation here is completely trade-based. In an empirical test of the model developed by them, Mei et al. find that "pump-and-dump" operations have led to higher returns, increased volatility, larger trading volume, and short-term price continuation, as well as long-term price reversal during the manipulation period. Moreover, small stocks are found to be more subject to the effects of manipulation.

Relative to the existing literature, this study makes three contributions. First, most of the previous cases of manipulation are in the U.S equity market. We broadened the picture by hand-collecting a unique data set of manipulation cases in an emerging market, Taiwan. Second, we depict the pattern of manipulation behavior on abnormal return, abnormal turnover, and abnormal volatility. Additionally, we investigate the impact of manipulation behaviors on market depth. Last, we compare the difference in market impacts of manipulation between guilty and guiltless verdicts for the manipulated sample.

3. DATA AND METHODOLOGY

3.1. A Unique Sample Set

This study uses a new data set to provide more systematic evidence of stock market manipulation. We hand-collected data on stock market manipulation cases pursued by the TSEC from August 1991 to June 2005. Specifically, through the LAWBANK website, we collected all indictment releases in a legal database that contain the key words "stock manipulation" and "Article 155 of the Securities and Exchange Act"[1]. We then manually constructed a database of all these manipulation cases.

There are a total of 60 cases in our sample; 3 cases involve the spread of rumors, and 57 cases involve trade-based manipulation. The median length of manipulation is 49 days. The maximum is 559 days and the minimum is 6 days. The manipulators are either insiders or large shareholders. There are no brokers or underwriters involved in the manipulation cases. We further divide the samples into Guilty and Guiltless sub-samples. 38 sample cases are classified as Guilty verdicts, while the other 22 samples are guiltless verdicts. Our data sources for daily prices, return, turnover (for liquidity proxy), trading volume, market capitalization (for size proxy) and book-to-market ratio are from the Taiwan Economic Journal (TEJ) database. The prices are all adjusted to account for dividends and other splits.

Fig. 1 shows that average cumulative abnormal return (ACAR) that is nearly zero during the pre-manipulation period, increases during the manipulation period, and then reverses to approach zero 210 days after the end of the manipulation period. We therefore define the manipulation period transparently as the number of days between the start and the end of the manipulation, while the pre- and post-manipulation periods are defined as one month prior the beginning of manipulation and 210 days after the end of the manipulation period, respectively.

3.2. Empirical Model

3.2.1 Definition of Variables

For manipulated stocks, we collect major variables of daily stock return, turnover, and volatility. We calculate daily return as two days' natural log closing price, turnover as trading volume divided by the number of shares outstanding, and volatility as measured by Yang and Zhang (2000).

For volatility measurement, Yang and Zhang (2000) prove that an unbiased variance estimator independent of both the drift and the opening jump must be multi-period based. They construct an estimator that has the minimum variance among all estimators having the same property. Their estimator is given by:

$$\hat{\sigma}_{YZ} = \sqrt{\hat{\sigma}_o^2 + k\hat{\sigma}_c^2 + (1-k)\hat{\sigma}_{RS}^2} \qquad (1)$$

where $\hat{\sigma}_o^2$ and $\hat{\sigma}_c^2$ are the variances estimated by the classical estimator with the use of daily opening and closing prices, respectively. The constant k is set to be:

$$k = \frac{0.34}{1.34 + (m+1)/(m-1)}$$

where m is the number of days. Yang and Zhang (2000) prove that this range estimator reaches its highest efficiency when . Therefore of is used in this study for the measurement of volatility.

3.2.2 Market Model

The market model is applied to establish the abnormal stock return, turnover, and volatility for the manipulated stocks. The stock return, turnover, and volatility are assumed to reflect a linear relationship between the individual stock and the market in the market model. Chatterjee, et al., (2001), Pettengill and Clark (2001), and Cowan and Anne (1996) have demonstrated that the market model can accurately forecast stock prices. The market model of an individual sample's stock return is expressed as follows:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \qquad (2)$$

where $R_{i,t}$ is the natural log return for stock i on date , is market return on date t, and is the error term for stock i on date t. To obtain the optimal estimation function of Eq. (2), this study applies OLS to solve , and optimizes evaluation values $\hat{\alpha}_i$ and β_i evaluation values $\hat{\beta}_i$. The expected return can then be expressed as:

$$E(R_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t} \qquad (3)$$

where $E(R_{i,t})$ is the expected return for stock i on date .

Similarly, the market models for the individual sample's turnover and volatility are expressed as Eq. (4) and (5):

(4)

$$\hat{\sigma}_{YZ,i,t} = \alpha_i + \beta_i \hat{\sigma}_{YZ,m,t} + \varepsilon_{i,t} \qquad (5)$$

where $Tur_{i,t}$ is trading volume divided by the number of shares outstanding for stock i on date , is market turnover on date t, is volatility as measured by Yang and Zhang (2000) for stock i on date , and is market volatility on date t. The expected turnover and volatility can then be expressed as:

(6)

[1] Refer to the website: http://www.lawbank.com.tw/

$$E(\hat{\sigma}_{YZ,i,t}) = \hat{\alpha}_i + \hat{\beta}_i \hat{\sigma}_{YZ,m,t} \tag{7}$$

where $E(Tur_{i,t})$ is the expected turnover for stock i on date t, and is the expected volatility for stock i on date t. We define an abnormal return, turnover, and volatility for manipulated stock on date , as:[1]

(8)

$$AT_{i,t} = Tur_{i,t} - E(Tur_{i,t}) \tag{9}$$

$$AV_{i,t} = \hat{\sigma}_{YZ,i,t} - E(\hat{\sigma}_{YZ,i,t}) \tag{10}$$

3.2.3. Cross-sectional Analysis of Abnormal Returns, Turnover, and Volatility

The models in Jarrow (1992), Allen and Gale (1992), and Aggarwal and Wu (2006) all state that the trades of the manipulators influence prices. In addition, Scheinkman and Xiong (2003) and Mei et al. (2004) also find that turnover is positively correlated with volatility for manipulated stocks. These findings suggest that there are cross-sectional relationships between returns, turnover, and volatility for manipulated stocks. In this section, we examine the cross-sectional relationship of the abnormal returns, turnover, and volatility for the manipulated stocks during the manipulation period and compare it with the pre-manipulation period. First, the cross-sectional relationship of the abnormal return and turnover for the manipulated stocks is estimated using the following regressions:

$$CAR_i = \beta_0 + \beta_1 \cdot CAT_i + \beta_2 \cdot CAT_i \cdot DumG_i + \varepsilon_i \tag{11}$$

where for each manipulated stock i, is the cumulative abnormal return, and CAT_i is the cumulative abnormal turnover from the pre-manipulation period to the manipulation period. The dummy variable $DumG_i$ equals one for the Guilty sub-sample and zero otherwise.

The cross-sectional relationship of the abnormal volatility and turnover for the manipulated stocks is estimated using the following regression:

$$CAV_i = \beta_0 + \beta_1 \cdot CAT_i + \beta_2 \cdot CAT_i \cdot DumG_i + \varepsilon_i \tag{12}$$

where CAV_i is the cumulative abnormal volatility for each manipulated stock i.

3.2.4. The Dynamic Relationships between Abnormal Returns, Turnover, and Volatility

This section describes a simple model designed to shed additional light on the effects of stock manipulation. Llorente et al. (2002) argue that returns generated by risk-sharing liquidity trades tend to reverse, whereas those generated by the manipulator's trades tend to continue. Jiang et al. (2005) examine the dynamic relationship between turnover and returns using the framework developed by Llorente et al. (2002). They argue that return continuation in connection with potentially manipulative trading could also be evidence of price momentum generated by the manipulator. Following Llorente et al. (2002) and Jiang et al. (2005), we estimate a variant model to examine the dynamic relation between returns, turnover, and volatility. Moreover, we compare the dynamic relations between manipulation period and pre-manipulation period. The model is as follows:

(13)

$$AV_{i,t} = \alpha_0 + \sum_{j=1}^{p} (\alpha_j \cdot AV_{i,t-j}) + \beta_1 \cdot AV_{i,t-1} \cdot AT_{i,t-1} + \beta_2 \cdot AV_{i,t-1} \cdot AT_{i,t-1} \cdot Dum_{i,t-1} + \varepsilon_{i,t} \tag{14}$$

where $AR_{i,t-1}$, $AT_{i,t-1}$, and $AV_{i,t-1}$ are the abnormal return, abnormal turnover, and abnormal volatility, respectively for stock i on date . The dummy variable equals one for the manipulation period and zero for the pre-manipulation period. The lagged term of p is determined using the Akaike information criterion (AIC) and the Schwartz Bayesian information criterion (SBC). The sample period is from one month prior to the beginning of the manipulation period to the end of the manipulation period.

In general, trading contains both hedging and speculative elements. The coefficients of are estimated to control the problem of serial correlation. The coefficients of β_1 and β_2 in Eq. (13) and Eq. (14) are of particular interest, depending on the relative importance of the type of trade; they should be positive for informed or speculative trades and negative for liquidity trades. β_2 would be positive if it captures the continuation of incremental abnormal return and abnormal volatility, conditional on abnormal turnover, during the manipulation period. A positive β_2 would be consistent with manipulation of stock price due to manipulated trading. β_1 would be negative if it captures the reversal of abnormal return and abnormal volatility, conditional on abnormal turnover in the pre-manipulation period.

3.2.5. Impact of Manipulation on Market Depth

To examine the impact of stock manipulation on market depth, the two-step procedure depth model presented by Pirrong

[1] The estimation period of the market model is one year prior to Pre-manipulation period. There are nine cases that have been listed on TSEC for less than one year, so their estimation periods are less than one year. Following the methods of Eades, fless and Kin (1985) and Mikkelson and Partch (1986), we utilized one year after the post-manipulation period as the estimation period for the nine cases.

(1996) is used in this study. In the first step, volume is decomposed into expected and unexpected components, because volume shocks may have effects on prices different from those caused by anticipated changes in volume. The expected volumes during a daily time interval are estimated using the following regression equation:

$$Vol_t = a + \sum_{i=1}^{m} \beta_i Vol_{t-i} + \sum_{j=1}^{n} \theta_j \left|\Delta P_{t-j}\right| + \lambda \hat{\sigma}_{YZ,t-1} + \varepsilon_t \qquad (15)$$

where Vol_t is the trading volume in interval t, $|\Delta P_{t-j}|$ is the absolute price change over the lagged $t-j$ time, $\hat{\sigma}_{YZ,t-1}$ is a measure of lagged volatility, and ε_t is an error term. The lagged terms of m and n are determined by the Akaike information criterion (AIC) and the Schwartz Bayesian information criterion (SBC). The volatility is calculated by the Yang and Zhang's (2000) measure. This term, plus the lagged absolute price changes, captures the effect of expected price volatility on volume. The fitted values from this equation serve as estimates for expected volume in a second volatility/depth equation, and the residuals from the volume equation are employed to measure unexpected volume in the second step.

In the second step, market depth is determined by estimating the following price volatility model:

$$|\Delta P_t| = \phi + \delta \cdot EVOL_t + \gamma \cdot UVOL_t + \mu \cdot UVOLPOS_t + \rho \cdot \hat{\sigma}_{YZ,t-1} + \eta_t \qquad (16)$$

where $EVOL_t$ is the expected volume on day t, $UVOL_t = \varepsilon_t$, $UVOLPOS_t = \varepsilon_t$ if $\varepsilon_t > 0$, $UVOLPOS_t = 0$ if $\varepsilon_t \le 0$, and η_t is an error term. The coefficients on the various volume terms are measures of the depth of the market. Positive unexpected volume is included to determine whether the effects of volume shocks on price volatility are asymmetric, as documented in Bessimbinder and Seguin (1993).

Since the expected volume and unexpected volume variables in the volatility equation are generated regressions, an instrumental variable approach is employed to estimate the market depth regressions to reflect this fact.

4. EMPIRICAL RESULTS AND ANALYSIS

4.1. Descriptive Statistics

Table 1 lists the summary statistics for the manipulated stocks and the entire stock market, and their difference during the estimation period. Sample mean, median, and standard deviation for firm size (capitalization), daily returns, turnover, and volatility are computed for the estimation period.

The manipulated sample mean of market-capitalization value is NT $7,178.17 million, which is far smaller than the entire stock market (NT $15,631.21 million). This is consistent with the mean obtained by Aggarwal and Wu (2006), indicating that manipulations are most probable with smaller stocks. The mean return, turnover, and volatility of the manipulated sample in the estimation period are 0.0373%, 1.6723%, and 0.0238, respectively. For the market index in the estimation period, the mean return, turnover, and volatility are 0.0551%, 1.1621%, and 0.0118, respectively. The difference between

Table 1

Sample descriptive statistics

This table reports statistics for market capitalization (proxy for size)\, returns, turnover, and volatility of return in the manipulated sample and market index during the estimation period. The estimation period of the market model is one year prior to pre-manipulation period, or one year after post- manipulation.

	Manipulated sample in estimation period	Market index in estimation period	Difference
Market Capitalization (in millions):			
Mean	$7,178.17	$15,631.21	-$8,453.04 ***
(S.E./t-value)	($1,153.34)	($468.92)	(6.789479)
Median	$4,296.73	$15,244.46	-$10,947.73
Return (%):			
Mean	0.037349	0.055063	-0.017714
(S.E./t-value)	(0.022041)	(0.013590)	(0.684133)
Median	0.000000	0.060000	-0.060000
Turnover (%):			
Mean	1.672317	1.162058	0.510259 ***
(S.E./t-value)	(0.017452)	(0.005085)	(28.07130)
Median	0.940000	1.020000	-0.080000
Volatility:			
Mean	0.023771	0.011783	0.011988 ***
(S.E./t-value)	(0.000101)	(0.000055)	(104.5357)
Median	0.021216	0.010337	0.010879

*** = coefficients is significant at the 1% levels.

manipulated sample and market index is shown in last column of Table 1. The results show that firms which are manipulated are smaller, more liquid, and volatile.

4.2. Characteristics of Manipulated Stocks

Aggarwal and Wu (2006) find that prices, trading volumes, and volatility rise during the alleged manipulation period. Table 2 reports the characteristic statistics of abnormal return, turnover, and volatility of the manipulated stocks from the pre-manipulation to the post- manipulation period. The abnormal return of manipulated stocks is positive and statistically significant during the manipulation period. However, it is negative and statistically significant during the post-manipulation period. This suggests that most of the manipulated stocks are pump-and-dump manipulation cases with the manipulator pumping up the stock price through a series of buying orders and then dumping the stock to make a profit. The abnormal turnover and volatility of manipulated firms is positive and statistically significant for the manipulation period as well as the pre and post manipulation periods. The results indicate that stock manipulation leads to the prices increasing and then decreasing, and also causes large trading volume and price volatility.

Table 2

Summary statistics of abnormal returns, turnover, and volatility

This table reports summary statistics of abnormal return, turnover, and volatility, including mean, standard error, and median, of the 60 manipulated stocks from pre-manipulation to post-manipulation period.

	Abnormal return	Abnormal turnover	Abnormal volatility
Pre-manipulation:			
Mean	0.040458	0.354914***	0.002645***
(S.E.)	(0.066553)	(0.067405)	(0.000326)
Median	-0.1	-0.10766	0.000965
Manipulation:			
Mean	0.256515***	1.494604***	0.005986***
(S.E.)	(0.034636)	(0.040508)	(0.000168)
Median	0.054491	0.46313	0.00445
Post-manipulation:			
Mean	-0.26512***	0.386714***	0.003256***
(S.E.)	(0.025699)	(0.022)	(0.000127)
Median	-0.2517	0.015342	0.001377

*** = coefficients is significant at the 1% levels.

We further divide the manipulated stocks into Guilty and Guiltless sub-samples according to the prosecution report. Table 3 shows the difference in abnormal return, turnover, and volatility between manipulation and pre-manipulation periods, and between post and pre manipulation periods, for all the samples. The result shows that the abnormal return during the manipulation period is higher than that during the pre-manipulation period for the entire sample and the Guilty sub-sample, but not for the Guiltless sub-sample. On the contrary, the abnormal return during the post- manipulation period is lower than that during the pre-manipulation period for the entire sample and both of the sub-samples. For the abnormal turnover and abnormal volatility, Table 3 shows that during the manipulation period they are both significantly larger than during the pre-manipulation period for the entire sample and both of the sub-samples. In the post-manipulation period, the abnormal turnover and volatility are significantly higher than in the pre- manipulation period for the Guilty sub-sample only. This may be the main reason why those in the Guiltless sub-sample received a guiltless verdict: They didn't cause abnormal return during the manipulation period, and did not incur large turnover and volatility during the post-manipulation period.

Table 3

Abnormal returns, turnover, and volatility of manipulated stocks

This table reports the abnormal return, abnormal turnover, and abnormal volatility change from pre- manipulation period to manipulation period and post-manipulation period for the Guilty sub-sample, Guiltless sub-sample, and All sample.

	Guilty sub-sample	Guiltless sub-sample	All sample
Abnormal return			
t-value (manipulation – pre)	2.246475 **	1.373859	2.569512 **
t-value (post - pre)	-3.161399 ***	-2.362642 **	-3.931543 ***
Abnormal turnover			
t-value (manipulation – pre)	8.707950 ***	8.498932 ***	11.76866 ***
t-value (post - pre)	3.681297 ***	-3.443223 ***	0.469712
Abnormal volatility			
t-value (manipulation – pre)	4.724300 ***	6.862042 ***	8.175870 ***
t-value (post - pre)	2.160165 **	0.105425	1.596878

, * = coefficients are significant at the 5% and 1% levels, respectively.

4.3. Results of Cross-sectional Analysis of Abnormal Returns, Turnover, and Volatility

Table 4 shows the cross-sectional results of the relationship between the abnormal returns, turnover, and volatility during the manipulation and pre-manipulation periods. Cumulative abnormal returns range from -1.14% to 65.47%, and cumulative abnormal volatility range from -0.003 to 1.752, while cumulative abnormal turnover ranges from 0.310% to 439.85% from the pre-manipulation period to the end of the manipulation period. To investigate the effect of CAT on CAR and CAV for the pre-manipulation and manipulation periods, Eq. (11) and Eq. (12) are employed. For the pre-manipulation period (shown in Panel A), the results show that there is a significantly positive relation between CAR and CAT as well as between CAV and CAT. However, it is insignificant for the dummy of guilty stocks for both models.

Table 4

Results of the cross-sectional model analysis

This table reports the relationship between cumulative abnormal returns (CAR) and cumulative abnormal turnover (CAT) during pre-manipulation period and manipulation periods, with each standard error in parentheses. The regression is estimated by OLS as:

$$CAR_i = \beta_0 + \beta_1 \cdot CAT_i + \beta_2 \cdot CAT_i \cdot DumG_i + \varepsilon_i \tag{11}$$

where $DumG_i$ is the dummy variable of the Guilty sub-sample. It shows relationship between cumulative abnormal volatility (CAV) and CAT during the pre-manipulation period and the manipulation period, with each standard error in parentheses. The regression is estimated by OLS as:

$$CAV_i = \beta_0 + \beta_1 \cdot CAT_i + \beta_2 \cdot CAT_i \cdot DumG_i + \varepsilon_i \tag{12}$$

Panel A: Pre-manipulation period		
Variables	CAR-model	CAV-model
Constant	0.618032	-0.001288
	(1.823943)	(0.016262)
CAT_i	0.142865 **	0.001255 **
	(0.061357)	(0.000547)
$CAT_i \cdot DumG_i$	-0.045275	-0.000391
	(0.089875)	(0.000801)
Adjusted R^2	0.087855	0.085072
Panel B: Manipulation period		
Variables	CAR-model	CAV-model
Constant	13.915330	0.202185
	(7.892584)	(0.251661)
CAT_i	0.052982 **	0.001265
	(0.022657)	(0.000722)
$CAT_i \cdot DumG_i$	0.117422 **	0.004081 **
	(0.055593)	(0.001773)
Adjusted R^2	0.153829	0.128051

**= coefficients is significant at the 5% levels.

For the manipulation period, the results of Panel B show that the relationship between CAR and CAT is significantly positive, and the dummy of guilty stocks is positively related to CAR and CAV. This result shows that guilty-verdict stocks were more likely actually to have been manipulated than not-guilty-verdict ones during manipulation period. We further compare the adjusted R^2 of the CAR and CAV model with the pre-manipulation and manipulation periods. For the manipulation period, the adjusted R^2 of CAR and CAV model are 0.1538 and 0.1281, respectively. For pre- manipulation period, the adjusted R^2 of CAR and CAV model are 0.0879 and 0.0851. The characteristics of manipulation behavior are more significant during the manipulation period since the adjusted R^2 of the CAR and CAV model are higher than in the pre-manipulation period.

These results are consistent with the pumping operation described in Mei et al. (2004) and Jiang et al. (2005) where a deep-pocketed manipulator pushes the stock price up by making large purchases. Holding all else constant, the more stocks the manipulator purchases, the higher the trading volume, price, and volatility will be.

4.4. Results of the Dynamic Relationship between Abnormal Returns, Turnover and Volatility

Table 5 presents the dynamic results of the relationship between the abnormal returns, abnormal turnover, and abnormal volatility for the all sample as well as the Guilty and Guiltless sub-samples.

For the All sample, the β_1 in Eq. (13) is negative and statistically significant. The results indicate that the abnormal return tends to reverse conditional on abnormal turnover during the sample period. The coefficient of β_2 is positive and statistically significant at the 1% level, however, indicating that during the manipulation period, the abnormal return tends to continuation conditional on abnormal turnover. For both the Guilty and Guiltless sub-samples, the results are similar to those for all the samples, except that the significant levels of β_2 are lightly different. That is, β_2 is statistically significant at the 1% level for the Guilty sub-sample, and at the 5% level for the Guiltless one. These results show that the manipulation behaviors for the Guiltless sub-sample stocks have less impact on price continuation than for the Guilty sub-sample.

Table 5
Results of the dynamic relationship between abnormal returns and abnormal turnover

This table presents estimates for a variant of the model developed by Llorente et al. (2002) for stock i over the period from one month prior to the beginning manipulation to the end of the manipulation period. The data are run as a panel data regression thus:

(13)

where $AR_{i,t-1}$ and $AT_{i,t-1}$ are the abnormal return and abnormal turnover, respectively, for stock i on date , and is a dummy variable that during the manipulation period equals one and during the prior manipulation period equals zero. The lagged term of p is determined by the Akaike information criterion (AIC) and Schwartz Bayesian information criterion (SBC). Each standard error is given in parentheses.

	Guilty sub-sample	Guiltless sub-sample	All sample
	0.333985 ***	0.280341 ***	0.301305 ***
	(0.089481)	(0.086985)	(0.061156)
$AR_{i,t-1}$	0.206982 ***	0.210980 ***	0.206543 ***
	(0.018463)	(0.018573)	(0.013119)
$AR_{i,t-2}$	0.047016 ***	—	0.051864 ***
	(0.015800)	—	(0.011325)
$AR_{i,t-1} \cdot AT_{i,t-1}$	-0.035157 ***	-0.028002 ***	-0.027617 ***
	(0.010973)	(0.010692)	(0.007689)
$AR_{i,t-1} \cdot AT_{i,t-1} \cdot Dum_{i,t-1}$	0.035893 ***	0.024150 **	0.025010 ***
	(0.011585)	(0.010969)	(0.007967)
Adjusted R^2	0.08409	0.06353	0.07546

, * = coefficients are significant at the 5% and 1% levels, respectively.

Table 6 presents the dynamic results of the relationship between the abnormal returns and abnormal volatility for the All sample as well as the Guilty and Guiltless sub-samples. For the All sample, β_1 in Eq. (14) is negative but insignificant. The coefficient of β_2 in Eq. (14) is positive and statistically significant at the 5% level. During the manipulation period, the results show that abnormal volatility continuation is conditional on abnormal turnover. The results for the Guiltless sub-sample are consistent with those for the All sample. However, in the Guilty sub-sample, the coefficients of β_1 and β_2 in Eq. (14) are positive but insignificant, which is not consistent with our expectation.[1]

[1] This result is not surprising since there is a daily price limit of 7% in the TSEC. Under this limitation, the prices of the manipulated stocks often are pumped (or dumped) to its ceiling (or floor) very early in the trading day and thus open at the ceiling (or floor) price, and the prices do not change before the market close. This phenomenon results in lower volatility. For the Guilty sub-sample, our data shows that trading days with absolute returns larger than 6% accounted for 21.86% of the sample during the manipulation period.

Table 6
Results of the dynamic relationship between abnormal volatility and abnormal turnover

This table presents estimates for a variant of the model developed by Llorente et al. (2002) for stock i over the period from one month prior to the beginning manipulation to the end of the manipulation period. The data are run as a panel data regression thus:

$$AV_{i,t} = \alpha_0 + \sum_{j=1}^{p} (\alpha_j \cdot AV_{i,t-j}) + \beta_1 \cdot AV_{i,t-1} \cdot AT_{i,t-1} + \beta_2 \cdot AV_{i,t-1} \cdot AT_{i,t-1} \cdot Dum_{i,t-1} + \varepsilon_{i,t} \quad (14)$$

where $AV_{i,t-1}$ and $AT_{i,t-1}$ are the abnormal volatility and abnormal turnover, respectively, for stock i on date t, and $Dum_{i,t-1}$ is a dummy variable that during the manipulation period equals one and during the prior manipulation period equals zero. The lagged term of p is determined by Akaike the information criterion (AIC) and Schwartz Bayesian information criterion (SBC). Each standard error is given in parentheses.

	Guilty sub-sample	Guiltless sub-sample	All sample
Constant	0.001007 ***	0.000753 **	0.000860 ***
	(0.000285)	(0.000319)	(0.000198)
$AV_{i,t-1}$	0.988522 ***	1.008739 ***	1.001729 ***
	(0.017364)	(0.017641)	(0.012223)
$AV_{i,t-2}$	-0.644924 ***	-0.689997 ***	-0.661953 ***
	(0.022185)	(0.023668)	(0.016027)
$AV_{i,t-3}$	0.484809 ***	0.526109 ***	0.494573 ***
	(0.023091)	(0.025931)	(0.016843)
$AV_{i,t-4}$	-0.265099 ***	-0.335759 ***	-0.279865 ***
	(0.022142)	(0.026117)	(0.016112)
$AV_{i,t-5}$	0.159920 ***	0.211749 ***	0.154344 ***
	(0.015846)	(0.024113)	(0.011532)
$AV_{i,t-6}$	—	-0.069551 ***	—
	—	(0.017102)	—
$AV_{i,t-1} \cdot AT_{i,t-1}$	0.000634	-0.014515	-0.009114
	(0.014017)	(0.008439)	(0.006553)
$AV_{i,t-1} \cdot AT_{i,t-1} \cdot Dum_{i,t-1}$	0.009886	0.017667 **	0.014381 **
	(0.014199)	(0.008650)	(0.006724)
Adjusted R^2	0.65238	0.59543	0.62630

, * = coefficients are significant at the 5% and 1% levels, respectively.

4.5. Results of Impacts on Market Depth

The regression results using Eq. (16) for the market depth are presented in Table 7. We compare the market depth of the manipulated stocks during the pre-manipulation period with that during the manipulation period to see how manipulated trading impacts market quality. For the All sample in Panel A, only the coefficient of expected volume is positive and significant at the 5% level during the pre-manipulation period; all other coefficients are insignificant. For the manipulation period, the expected volume and unexpected positive volume have a significantly larger impact on market prices. In addition, lagged volatility magnifies price changes. This suggests that the market is deep before the stocks have been manipulated.

For the Guilty sub-sample in Panel B, during the pre-manipulation period, the market is deep since none of the coefficients are significant. For the manipulation period, the expected volume and unexpected volume have a significantly positive impact on market prices. In addition, lagged volatility magnifies price changes. For the Guiltless sub-sample in Panel C, during the pre-manipulation period, only the coefficient of expected volume is positive and statistically significant at the 5% level; the other coefficients are insignificant. For the manipulation period, only the coefficient of lagged volatility is

Table 7

Results for market depth

In this table, the first step reports the expected volumes during a daily time interval as estimated using the following regression equation:

$$Vol_t = a + \sum_{i=1}^{m} \beta_i Vol_{t-i} + \sum_{j=1}^{n} \theta_j \left|\Delta P_{t-j}\right| + \lambda \hat{\sigma}_{YZ,t-1} + \varepsilon_t \tag{15}$$

where Vol_t is the trading volume in interval t, is the absolute price change over the lagged $t-j$ time, is a measure of lagged volatility, and ε_t is an error term. The lagged terms of m and are determined by AIC and SBC minimum regulation. The second step uses the unexpected trading volume to measure the market depth by estimating the following price volatility model. Eq. (20) is run as a panel data regression thus: (16) $EVOL_t$ is the expected volume in a day interval measured by the fitted value from Eq. (15), $UVOL_t = \varepsilon_t$, $UVOLPOS_t = \varepsilon_t$ if $\varepsilon_t > 0$, $UVOLPOS_t = 0$ if $\varepsilon_t \leq 0_1$, and η_t is an error term. Each standard error is given in parentheses.

Variables	Pre-manipulation period		Manipulation Period	
Panel A: All sample				
Constant	0.877418	**	1.321123	***
	(0.393564)		(0.298378)	
$EVOL_t$	0.000059	**	0.000027	**
	(0.000025)		(0.000011)	
$UVOL_t$	0.000114		0.000018	
	(0.000073)		(0.000025)	
$UVOLPOS_t$	0.000100		0.000074	**
	(0.000105)		(0.000034)	
σ_{t-1}	6.619800		12.826501	***
	(7.178053)		(2.674478)	
Adjusted R^2	0.53667		0.42871	
Panel B: Guilty sub-sample				
Variables	Pre-manipulation Period		Manipulation Period	
Constant	1.057785	**	0.995118	**
	(0.479033)		(0.390574)	
$EVOL_t$	0.000034		0.00011	***
	(0.000035)		(0.000019)	
$UVOL_t$	0.000059		0.000067	**
	(0.000092)		(0.000034)	
$UVOLPOS_t$	0.000088		0.000012	
	(0.000128)		(0.000045)	
σ_{t-1}	2.076422		11.090292	***
	(9.511010)		(4.004975)	
Adjusted R^2	0.46113		0.37317	
Panel C: Guiltless sub-sample				
Variables	Pre-manipulation Period		Manipulation Period	
Constant	0.671683		1.630841	***
	(0.614070)		(0.450204)	
$EVOL_t$	0.000076	**	-0.000023	
	(0.000035)		(0.000013)	
$UVOL_t$	0.000143		0.000011	
	(0.000119)		(0.000037)	
$UVOLPOS_t$	0.000229		0.000067	
	(0.000182)		(0.000054)	
σ_{t-1}	10.806020		12.840957	***
	(10.764571)		(3.527199)	
Adjusted R^2	0.58846		0.49190	

, * = coefficients are significant at the 5% and 1% levels, respectively.

positive and statistically significant at the 1% level. Thus, the results indicate that the manipulation trading of the Guilty sub-sample worsens the market depth, but the trading of the Guiltless sub-sample does not worsen the market depth.

The above results indicate that market depth has deteriorated during the manipulation period, which is consistent with the findings of Mei et al. (2004), in which a manipulator makes sudden purchases in large quantities, creating rising trading volume accompanied by rising prices.

4.6. Price Reversal

The manipulator is typically a large investor who is a price setter rather than a price taker (Allen and Gale, 1992). As a deep-pocket investor, he pumps up the stock price with a series of buying orders and then dumps the stock to make a profit by taking advantage of the disposition effect. The manipulator's strategic action not only brings the manipulator profit, but also brings about higher volatility, larger trading volume, short-term price continuation, and finally price reversal. In this section, we examine whether there is a price reversal after the manipulation period for the manipulated stocks.

Fig. 1 plots the average cumulative abnormal returns (ACAR) for the manipulation cases of the All sample as well as the Guilty and Guiltless sub-samples. As can be seen, the manipulation operations have led to higher cumulative abnormal returns in the manipulation period that reach their peak at the end of the manipulation period, at which time the prices begin to reverse. For the All sample, ACAR appears to be in reversal from "m10" in the manipulation period. Especially for the Guilty sub-sample, the ACAR is over 70% at its highest. It is also far higher than that observed by Jiang et al. (2005), who found an average size of 4% ACAR for the stock pools in the NYSE during the years 1928 and 1929. However, the magnitude of ACAR in the TSEC is similar to that in the Karachi Stock Exchange (KSE), which is the main exchange in Pakistan, where the ACAR is reported at 50-90% (Khwaja and Mian, 2005). The TSEC's ACAR, however, is lower for the Guiltless sub-sample; the highest is about 60%.

Overall, the above results are consistent with such theoretical models of manipulation as those of Allen and Gale (1992), Scheinkman and Xiong (2003), Mei et al. (2004), and Aggarwal and Wu (2006).

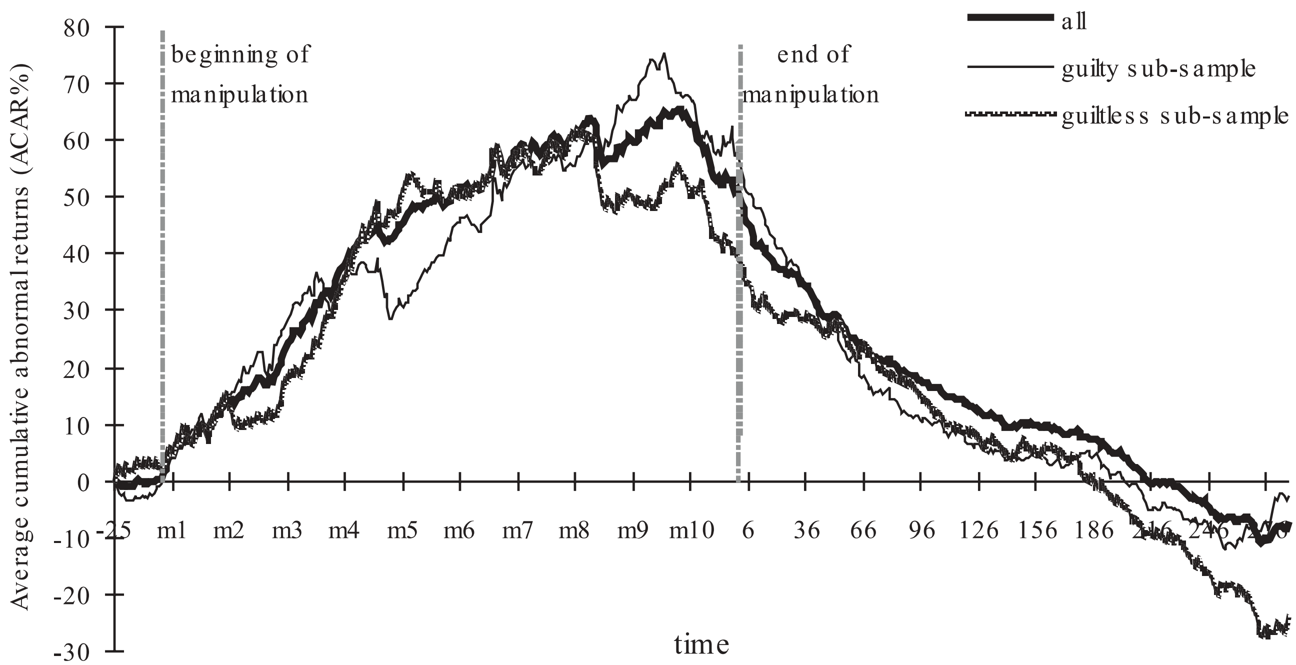

Fig. 1. Average cumulative abnormal returns (ACAR) of manipulation

The Average cumulative abnormal returns (ACAR) for the All sample as well as the Guilty and Guiltless sub-samples are exhibited here over the period from one month prior to the beginning manipulation to the one year after the end of the manipulation period. They are presented over a grid showing different stages of the manipulation. For example, m1 represents the beginning of the manipulation period, m5 represents the middle, and m10 represents the end of the manipulation.

5. CONCLUSIONS

Stock manipulation is an important issue for both the regulation of trading and the efficiency of the market. Although it is a growing concern in many emerging stock markets, there is scant evidence of stock price manipulations and their impacts on market quality. This paper examines the characteristics of manipulated stocks and the impacts they have on market quality using a hand-collected dataset on manipulation cases prosecuted by regulators in an emerging market, Taiwan, from 1991 to 2005. We find that the abnormal return, abnormal turnover, and abnormal volatility are higher for manipulated stocks during the manipulation period than during the pre-manipulation period. The average cumulative abnormal return reaches over 70% for the Guilty sub-sample. This is similar to the effect seen in the emerging market of the Karachi Stock Exchange (KSE) (Khwaja and Mian, 2005).

In addition, returns, trading volumes, and volatility rise during the manipulation period. Manipulated stocks display increased return continuation and the returns reverse at the end of the manipulation period. This is consistent with the manipulation models of Mei et al. (2004) and Jiang, et al. (2005). The abnormal turnover and volatility of the manipulated stocks are higher still for the post-manipulation period. This is consistent with the findings of Aggarwal and Wu (2006). There are also important differences among the manipulated stocks. The Guilty sub-sample stocks do not experience abnormally high volatility during the manipulation period. This may be due to the daily price limit of 7% in the TSEC. The manipulators often pump the stock prices up to its ceiling at the opening of the market and then the prices remain unchanged until the markets close. On the other hand, the Guiltless sub-sample stocks do not experience abnormally high return and turnover during the manipulation period, and this may be the reason why those cases do not generate guilty verdicts.

We utilize various models to compare the Guilty and Guiltless sub-samples. The results indicate that guilty or guiltless verdicts depend on the impact of manipulation on market quality and depth, and accordingly we find that the Guilty sub-sample has a larger impact on market quality than the Guiltless one. Overall, the above results indicate that manipulation can actually create market inefficiency by distorting the stock prices in relation to their fundamental value. Moreover, manipulation behaviors have led to abnormally high trading volume and volatility, thus worsening the market depth, and hence the market quality. This suggests the need for strong government regulation to discourage manipulation. It also poses a new challenge for regulators, since most of the manipulators rely neither on inside information nor visible actions; thus, their manipulations are difficult to detect and rule out.

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