Stock manipulation and its impact on market quality

Yu Chuan Huang

Professor, Department of Risk Management and Insurance, National Kaohsiung First University of Science and Technology, Kaohsiung 811, Taiwan, ROC.

Roger C.Y. Chen

Professor, Graduate Institute of Business and Management, National Kaohsiung First University of Science and Technology, Kaohsiung 811, Taiwan, ROC.

Yao Jen Cheng

Ph.D. student, Department of Finance, National Kaohsiung First University of Science and Technology, Kaohsiung 811, Taiwan, ROC.

- Name: Yu Chuan Huang
- Address: 2, Juoyue Road, Nantsu, Kaohsiung 811, Taiwan, R.O.C.
- TEL: 886-7-6011000 ext. 4013
- FAX: 886-7-6011041
- Email: <u>ychuang@ccms.nkfust.edu.tw</u>

Stock manipulation and its impact on market quality

Abstract

Using a new hand-collected data set, this study examines the stock price manipulation in the Taiwan Stock Exchange (TSE). We examine the characteristics of the manipulated stocks, and their impacts on market quality. The results show that manipulated stocks tend to be small. The stock prices rise throughout the manipulation period, followed by a price reversal. The average cumulative abnormal return of the manipulated stocks is over 70 percent, which is far higher than that found in the developed markets but similar to emerging market circumstances. In addition, manipulated stocks display increased return continuation conditional on high trading volume, and increased volatility of stock price conditional on high liquidity of market during the manipulation period. Market depth is also worse during the manipulation period. This suggests that stock manipulation can actually create market inefficiency, lead to both abnormally high trading volume and volatility, worsen the market depth, and hence have important impacts on market quality.

JEL classification: G14; G15

Key words: Stock manipulation; Market quality; Depth; Emerging markets

1. Introduction

Market manipulation has been less thoroughly examined in the academic literature but is a growing concern on many emerging stock markets. The possibility that the 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 basis that they distort prices, hamper price discovery, and create deadweight losses. In particular, many Asian stock markets have securities that are thinly traded and therefore more susceptible to manipulation.

In modern financial markets, manipulations are often taken in hidden ways that cannot be easily detected and outlawed. While manipulative activities seem to have declined on the main exchanges, it is 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 could still be quite prevalent in emerging markets. Even in the relatively well-regulated U.S., Aggarwal and Wu (2004) 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. Moreover, most of the empirical evidence on manipulation has focused on well-developed countries such as U.S. Research on emerging markets is scarce. As we are aware, there is a wide disparity in disclosure requirements and securities regulations across nations. The disclosure requirements in USA 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 using a set of unique data 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 from 1991 to 2005. Surprisingly few studies have so far been made at empirical investigation of emerging financial market manipulation using a prosecuting sample of cases. The 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 the manipulation theory and review the literature. In Section 3, we describe the data and sample selection procedures; also we present a methodology of stock price manipulation. The results of the empirical tests are presented in Section 4. A summary and conclusions are given in the last section.

2. Theories and Literature Review

Manipulation can occur in a variety of ways, from insiders taking actions that influence stock prices to the release of false information or rumors in Internet chat rooms, e.g., accounting and earnings manipulation such as in the Enron case. Moreover, it is well known that large block trades can influence prices. For example, by purchasing a large amount of stocks, a trader can drive the price up.

Allen and Gale (1992) classify three types of manipulation: The first kind can be described as action-based manipulation, that is, manipulation based on actions that change the actual or perceived value of the assets. The second kind can be described as information-based manipulation, that is, manipulation based on releasing false information or spreading false rumors. The "trading pools" in the United States 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. There is a third kind of manipulation that is much more difficult to detect and rule out and is referred to as trade-based manipulation. It occurs when a trader tempts to manipulate a stock simply by buying and then selling, without taking any publicly observable actions to alter the value of the firm or releasing false information to change the price.

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 stock 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 dropped eventually.

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

Allen and Gale (1992) build a model showing that trade-based manipulation is possible in a rational expectations framework. The Allen and Gale model has three types of traders, a continuum of identical rational investors, a large informed trader, and a large manipulator who observes whether the informed trader has private information. The manipulator is able to achieve a positive profit under certain conditions because a pooling equilibrium can exist in which the investors are uncertain whether a large trader who buys shares is a manipulator or an informed trader.

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 profit. They consider three types of traders, behavior-driven investors who are loss averse (dispositional effect), arbitrageurs, and a manipulator who can influence asset prices. They show that, due to the investors' behavioral biases and the limit 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 high prices. Since nobody has private information, manipulation here is completely trade-based. In an empirical test of the model developed by Mei et al. (2004), they find that "pump-and-dump" operations have led to higher return, increased volatility, larger trading volume, short-term price continuation and also long-term price reversal during the manipulation period. Moreover, small stocks are found to be more subject to the effects of manipulation. This possibility poses a new challenge for regulators. As the manipulator relies on neither inside information nor visible actions his manipulation is difficult to be detected and ruled out.

Hillion and Suominen (2004) present an agency theory-based manipulation model. They suggest that since visible price for a security is its closing price, and since brokers are reliant upon their customer's satisfaction for repeated business, brokers have incentives to manipulate the closing price to alter the customer's inference of his execution quality. According to the theory, the trading volume, hidden orders, and price volatility will increase at market close due to price manipulation. They suggest that the introduction of a closing call reduces manipulation and brings the closing price nearer to the fair value of the asset at close. However, the optimal trading interruption prior to the call should depend on the liquidity of the stock. Numerous stock market manipulation studies are theoretically quantitative model solution, but scarcely empirical studies. Recently, Aggarwal and Wu (2004) has recently collected data on stock market manipulation cases pursued by the U.S. SEC from January 1990 to October 2001. They find that prices, trading volumes, and volatility rise during the alleged manipulation, followed by a price fall,, suggesting that profitable manipulation could have occurred and that stock market manipulation may have important impacts on market quality. Jiang et al. (2005) use a new data set to examine the pre- and post- pool characteristics of the stocks that were subject to pools in the years 1928 and 1929 by the NYSE. They find that the pool stocks are comparable with their associated industry portfolios on measures of size and are more volatile and liquid, on average, than other companies in their industry. During the period of pool activity, the pool stocks experience both abnormally high trading volume and returns, but both effects are small on average.

3. Data and Methodology

3.1. A Unique Sample Set

This study uses a new data set to provide more systematic evidence on stock market manipulation. We hand-collect data on stock market manipulation cases pursued by the Taiwan Stock Exchange (TSE) and over-the-counter (OTC) from January 1991 to June 2005. Specifically, we collect all indictment releases from LAWBANK website of a legal database that contain the key word "stock manipulation". We then manually construct a database of all these manipulation cases. There are 60 cases in total. We further differentiate the samples between guilty and guiltless sub-samples. The 32 guilty samples are defined as certain verdicts, and the other 28 guiltless samples are defined as uncertain guilty or guiltless verdicts. Our data sources for daily prices, turnover and volatility are from the Taiwan Economic

Journal (TEJ) database. The prices are all adjusted to account for dividends and other splits.

We define the manipulation period as the number of days between the start and the end of the manipulation, the pre- and post- manipulation periods are defined as 65 days before and after the manipulation period. For each manipulated stock we also choose one by one industry-size-matched stocks as a benchmark. The average of the five stocks is taken as the value of the benchmark. There are 60 manipulated stocks in total. For the 60 cases, 5 cases involved the spread of rumors, and 55 cases are trade-based manipulation. The median length of manipulation is 57 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.

3.2. Empirical Model

3.2.1. Cross-sectional analysis of abnormal returns, turnover and volatility

The models in Jarrow (1992), Allen and Gale (1992), Aggarwal and Wu (2004) 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 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 by the following regressions:

$$CAR_{i} = \beta_{0} + \beta_{1} \cdot CAT_{i} + \beta_{2} \cdot CAT_{i} \cdot DumG_{i} + \varepsilon_{i}$$
⁽¹⁾

where for each manipulated stock i, CAR_i is the cumulative abnormal return during the entire period of manipulation, CAT_i is the cumulative abnormal turnover, and $DumG_i$ equals one for the guilty sample and zero otherwise.

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

$$CAV_{i} = \beta_{0} + \beta_{1} \cdot CAT_{i} + \beta_{2} \cdot CAT_{i} \cdot DumG_{i} + \varepsilon_{i}$$
⁽²⁾

where for each manipulated stock i, CAV_i is the cumulative abnormal volatility. Volatility is calculated by Parkinson's (1980) measure:

$$\tilde{\sigma}_{i,t} \approx \sqrt{0.361 \left[\ln \left(S_{i,t}^{High} \right) - \ln \left(S_{i,t}^{Low} \right) \right]^2}$$
(3)

where $S_{i,t}^{High}$ and $S_{i,t}^{Low}$ are the highest and lowest prices observed during day t.

3.2.2. 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) model the dynamic volume-return relation. The model assumes that trades are motivated either by risk sharing or stock manipulation. 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) also look at the dynamic relation between turnover and returns using the framework developed by Llorente et al. (2002). They argue that return continuation in connection with potentially manipulator. Following Llorente et al. (2002) and Jiang et al. (2005), we estimate a variant model during from pre-manipulation to end of manipulation period, and separate two part of period that beginning on 65 days before the manipulation period (day -65) to prior one day of manipulation. Second period are beginning on the first manipulation day to the end of manipulation day. An important implication of the model is that returns generated by speculative trades tend to continue, while returns generated by hedging trades tend to reverse. To examine the

effects of the manipulated trades on abnormal returns and volatility, we estimate the following regressions:

$$AR_{i,t+1} = \alpha_0 + \alpha_1 \cdot AR_{i,t} + \alpha_2 \cdot AR_{i,t} \cdot AT_{i,t} + \varepsilon_{i,t+1}$$
(4)

$$AV_{i,t+1} = \beta_0 + \beta_1 \cdot AV_{i,t} + \beta_2 \cdot AV_{i,t} \cdot AT_{i,t} + \varepsilon_{i,t+1}$$
(5)

where $AR_{i,t}$ and $AT_{i,t}$ are the abnormal return and abnormal turnover, respectively for stock *i* on date *t*, $AV_{i,t}$ is the abnormal volatility for *i* stock on date *t*. We define an abnormal return for manipulated stock *i* on date *t*, $AR_{i,t}$, as:

$$AR_{i,t} = R_{i,t} - \frac{\sum_{j=1}^{n} R_{j,t}}{n}$$
(6)

where *n* equals five, which is the number of stocks in the control portfolio corresponding to manipulated stock *i* for which there is a return on date *t*. Similarly, we define an abnormal turnover for manipulated stock *i* on date *t*, $AT_{i,t}$, as:

$$AT_{i,t} = turnover_{i,t} - \frac{\sum_{j=1}^{n} turnover_{j,t}}{n}$$
(7)

The abnormal volatility for manipulated stock i on date t, $AV_{i,t}$, is defined as:

$$AV_{i,t} = volatility_{i,t} - \frac{\sum_{j=1}^{n} volatility_{j,t}}{n}$$
(8)

In principle, trading contains both hedging and speculative elements. The coefficient of α_1 are control variable in series correlation. The coefficient α_2 in Eq. (4) is of particular interest, depends on the relative importance of the type of trade which should be positive for informed or speculated trades and negative for liquidity trades. As it captures the continuation (reversal) of incremental abnormal return, conditional on abnormal volume, during the manipulation period. A positive α_2 would be consistent with manipulation due to manipulated trading.

3.2.3. 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 (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:

$$Vol_{t} = a + \sum_{i=1}^{m} \beta_{i} V_{t-i} + \sum_{j=1}^{n} \theta_{j} \left| \Delta P_{t-j} \right| + \lambda \sigma_{t-1} + \varepsilon_{t}$$

$$\tag{9}$$

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, σ_{t-1} is a measure of lagged volatility, and ε_t is an error term. The lagged term of m and n are determined by Akaike information criterion (AIC) and Schwartz Bayesian information criterion (SBC). The volatility is calculated by the Parkinson's (1980) 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:

$$\Delta P_t = \phi + \delta \cdot EVOL_t + \gamma \cdot UVOL_t + \mu \cdot UVOLPOS_t + \rho \cdot \sigma_{t-1} + \omega \cdot DumG_t + \eta_t$$
(10)

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). $DumG_t = 1$ for a guilty sub-sample, and 0 for the guiltless sub-sample.

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, benchmark portfolios, and the entire stock market. Sample mean, median and, standard deviation for firm size (market capital), daily returns, turnover, and volatility of daily price return of are computed during prior one year of manipulation period. The manipulated sample mean of market-capitalization value is NT \$7,406.26 million N.T dollars, which is close to the match sample (NT \$7,480.55), but far smaller than the entire stock market (NT \$18,067.63 million). This is consistent with that obtained by

Table 1

Matching sample selection descriptive statistics

Mean, Median, and Standard deviations are show for market capital (proxy for size), returns, turnover, and volatility of price for the 60 pool stocks and 60 industry-matched control portfolios over prior one year of manipulation period. Each pool stock is paired with a control portfolio consisting of all companies with the same classified industry.

	· · · · · · · · · · · · · · · · · · ·	Pool sample	Match sample	Market sample
Market Cap. (in millions)	Mean	\$7,406.26	\$7,480.55	\$18,067.63
	Median	\$4,587.18	\$5,722.85	\$18,629.56
	Std. Dev.	\$8,985.50	\$8,556.91	\$4,182.58
Return (%)	Mean	0.0229	0.0181	-0.0084
	Median	0.0466	0.0685	0.0213
	Std. Dev.	0.2108	0.1838	0.1273
Turnover (%)	Mean	1.6317	1.6099	1.0589
	Median	1.4199	1.1995	0.9299
	Std. Dev.	1.0979	1.0646	0.4631
Volatility	Mean	0.0200	0.0207	0.0116
	Median	0.0195	0.0192	0.0104
	Std. Dev.	0.0038	0.0044	0.0051

Aggarwal and Wu (2004), indicating that manipulations are most probable in the case of smaller stocks. The mean return, turnover, and volatility of the manipulated sample are 0.0229%, 1.6317%, and 0.02 respectively. Each variable is also similar with that of the matching benchmark sample but higher than that of the entire stock market.

4.2. Characteristics of Manipulated Stocks

Aggarwal and Wu (2004) find that prices, trading volumes, and volatility rise during the alleged manipulation. Table 2 reports characteristic statistics for the manipulated stocks, the benchmark portfolios, and the difference between the manipulated stocks and benchmark portfolios, which we define as the abnormal measures.

Panel A shows that the mean return during the manipulation period is higher than the mean returns during the pre- and post- manipulation periods. Turnover during the manipulation period is also higher than that in the pre- and post- manipulation periods. Average volatility during the manipulation period is higher than that in the pre-manipulation period. However, it is lower than that in the post- manipulation period. This is not surprising since there is a daily price limit of 7 percent in the TSE. For a manipulated stock, manipulators often pump it into its price limit at the beginning of market opening, and the price is then held until market closes. Panel B presents the characteristic statistics for the benchmark portfolio. It shows that the average return, turnover, and volatility are similar for the manipulation period as well as the pre- and post-manipulation periods. Panel C presents the difference between the manipulated sample and the benchmark portfolio in the three measures. The average return of the manipulated sample is significantly higher than that of the benchmark portfolio during the manipulation. However, it is lower than that of the benchmark portfolio 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 average turnover of the manipulated sample is significantly higher than that of the benchmark portfolio for the manipulation as well as post-manipulation periods. For the volatility measure, Panel C shows that average volatility of the manipulated sample is significantly higher than that of the benchmark portfolio during the manipulation and post-manipulation periods.

We further divide the manipulated stocks into guilty and guiltless sub-sample. For each sub-sample, we compare the return, turnover and volatility of the manipulation period with those of the pre- and post-manipulation periods. Table 3 shows that the abnormal return during the manipulation period is higher than that during the pre- and post-manipulation periods for the entire sample and each sub-sample. For the abnormal turnover and abnormal volatility, Table 3 shows that the abnormal turnover and volatility during the manipulation period is significantly larger than that during the pre-manipulation period for the entire sample and both of the sub-samples.

Table 2Summary statistics of returns, turnover and volatility

This table reports summary statistics for the 50 manipulated stocks, 60 industry-size-matched control portfolios, and the difference between the manipulated stocks and benchmark portfolios, which we define it as the abnormal measures. Panels A to C report the sample mean, standard deviation, skewness and kurtosis coefficients for daily returns, turnover and volatility for the manipulation period, 65 days pre- and 65 days post- manipulation periods, respectively. In addition, Panel C shows the significance test in mean.

Danal A: manipulated sample				
	I allel A. Illa		C1	Ventoria
D 11.	Mean	Sta. Dev.	Skewness	Kurtosis
Pre-manipulation:				
Return	0.059818%	2.602497%	0.139546	3.889182
Turnover	1.576266%	1.864862%	2.701507	13.24678
Volatility	0.020318	0.011076	1.097020	4.604051
Manipulation:				
Return	0.249515%	3.147257%	-0.008154	3.259041
Turnover	2.629963%	3.063899%	2.872598	14.99936
Volatility	0.021444	0.012892	1.046801	4.784399
Post-manipulation:				
Return	-0 593969%	3 490534%	-0.040395	2 830844
Turnover	2 094659%	2 701217%	3 115836	19 63722
Volatility	0.021687	0.01/62/	1 100/50	5 203/18
Volatility	0.021007	Motoh commlo	1.170450	5.205410
	Panel D.		C1	17
	Mean	Std. Dev.	Skewness	Kurtosis
Pre-manipulation:				
Return	0.037869%	2.861525%	0.041226	3.595988
Turnover	1.578616%	1.842297%	2.852974	14.87123
Volatility	0.020624	0.011222	1.341151	6.058802
Manipulation:				
Return	-0.016211%	2.665133%	0.035029	3.768684
Turnover	1.511818%	1.882135%	3.065483	17.22800
Volatility	0.019894	0.010463	1.304935	5.553832
Post-manipulation				
Return	-0.024870%	2 582712%	0 149800	3 871610
Turnover	1 333674%	1 762211%	3 469395	21 17003
Volatility	0.020085	0.010304	1 227555	5 265241
Demol C: Alte	0.020083	0.010394	han alamanla n antfalia	3.203241
Pallel C. Abl	normar measures (man	ipulated sample -)
	Mean	Std. Dev.	Skewness	Kurtosis
Pre-manipulation:				
Abnormal return	0.021949%	3.192321%	0.173273	4.539917
t-value	(0.420246)			
Abnormal turnover	-0.002350%	2.022142%	0.176698	10.88875
t-value	(-0.071036)			
Abnormal volatility	-0.000307	0.013649	-0.083472	5.121999
t-value	(-1.374136)			
Manipulation:				
Abnormal return	0.265726%***	3.343288%	0.101937	4.310181
t-value	(6.271404)			
Abnormal turnover	1 118145%***	3 128143%	1 824019	13 68702
t_value	(28, 20434)	5.1201 1570	1.02 1017	15.00702
Abnormal volatility	0.001551***	0.01/12/	0 211845	1 0130/7
	(8,662208)	0.014124	0.211045	4.913947
l-value	(8.003208)			
Post-manipulation:	0 5 (0 0 0 0 0 / ***	2.0(22210/	0.0(00.45	2 700 400
Abnormal return	-0.569099%***	3.862321%	-0.262045	3./09499
t-value	(-9.23/106)		1.0-0-00	10.0
Abnormal turnover	0.760985%***	2.880112%	1.858760	18.05785
t-value	(16.56391)			
Abnormal volatility	0.001602***	0.016477	0.510844	5.124009
t-value	(6.094425)			

*, **, *** = coefficients are significant at the 10%, 5% and 1% levels, respectively.

Table 3

Abnormal returns, turnover and volatility of manipulated stocks

This table reports the abnormal return, abnormal turnover, and abnormal volatility change from premanipulation period to manipulation period and post- manipulation period for the entire sample, guilty sub-sample, and guiltless sub-sample.

	Entire sample	Guilty	Guiltless
	· · · · · ·	sub-sample	sub-sample
Panel A: Abnormal return			
t-test (manipulation – pre-manipulation)	3.583141***	4.748013***	2.039469**
t-test (post - pre)	-7.283008***	-5.584421***	-4.279500***
Panel B: Abnormal turnover			
t-test (manipulation – pre-manipulation)	19.57658***	13.93985***	7.390215***
t-test (post - pre)	13.36763***	10.27590***	-0.408890
Panel C: Abnormal volatility			
t-test (manipulation – pre-manipulation)	6.435357***	2.276791***	2.769689***
t-test (post - pre)	5.508153***	2.972585***	0.849754

*, **, *** : coefficients are significant at the 10%, 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 period. There is a significantly positive relation between CAR and CAT at the 1% level. For the guilty stocks, there is an even more significant positive relation between CAR and CAT. These results are consistent with the pumping operation described in Mei et al. (2004) wherein 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 and price will be.

Another question is whether manipulation is associated with higher return volatility. The third column in Table 4 presents this result. There is a clear positive relation between CAT and CAV. Conversely, for the guilty stocks, there is a negative significant relation between CAT and CAV. This result is not surprising since there is a daily price limit of 7% in TSE, and it suggests that the prices of the manipulated

stocks are soon pumping (dumping) into its ceiling (flooring) at the market opening and then the prices do not move before market closes¹. It is the reason why the dummy of guilty stocks exhibits negative relationship between CAT and CAV.

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 the manipulation period, and each t-value in parentheses. The regression is estimated as:

 $CAR_i = \beta_0 + \beta_1 \cdot CAT_i + \beta_2 \cdot CAT_i \cdot DumG_i + \varepsilon_i$

where $DumG_i$ is the dummy variable of the guilty sub-sample. The relationship between CAR and cumulative abnormal volatility (CAV) during the manipulation period. The regression is estimated as:

	$CAV_{i} = \beta_{0} + \beta_{1} \cdot CAT_{i} + \beta_{2} \cdot CAT_{i} \cdot DumG_{i} + \varepsilon$	i
Variables	CAR-model	CAV-model
Constant	10.24023***	-0.003141
	(19.59910)	(-0.382745)
CAT	0.009117***	0.002060***
	(3.799496)	(54.64490)
DG*CAT	0.272768***	-0.000650***
	(43.91051)	(-6.659940)
Adjusted R-square	0.257158	0.327687

*, **, *** : coefficients are significant at the 10%, 5% and 1% levels, respectively.

4.4. Results of dynamic relationship between abnormal returns, turnover and volatility

Table 5 presents the dynamic results of the relationship between the abnormal returns and abnormal turnover for the entire sample as well as the guilty and guiltless sub-sample. Panel A shows the results of the pre-manipulated period. The coefficients α_2 for the entire sample and the two sub-samples are not significant. In contrast, the coefficients α_2 for the entire sample and the guilty sub-sample are positive and significant for the manipulation period shown in Panel B, suggesting that the

¹ Our data shows that 21.86% of the absolute returns of the manipulated stock for the guilty sub-sample are larger than 6% during the manipulation period.

manipulated trading increases return continuation conditional on volume during the manipulation period. For the guiltless sub-sample, although the coefficient α_2 is positive, it is not significant. This is probably the reason why the guiltless sample stocks are uncertain verdicts.

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

The table presents estimates for a variant of the model developed by Llorente et al. (2002) for stock \vec{i} over the period from days 65 pre-manipulation to the and of manipulation period:				
stock <i>t</i> over the period from days -65 pre-manipulation to the end of manipulation period: $AR_{t} = \alpha_{t} + \alpha_{t} \cdot AR_{t} + \alpha_{t} \cdot AR_{t} + \varepsilon_{t}$				
where $AR_{i,t}$ and $AT_{i,t}$ are the abnormal return and abnormal turnover, for stock i on date t .				
Panel A: Pre-manipu	lation period			
	Entire sample	Guilty sample	Guiltless sample	
Constan $t_{i,t}$	0.007961	-0.053656	0.077940	
	(0.150292)	(-0.692050)	(1.094970)	
$AR_{i,t}$	0.093952***	0.098894***	0.085224***	
	(5.695149)	(4.356427)	(3.547717)	
$AR_{i,t} \cdot AT_{i,t}$	0.008006	0.005405	0.012166	
	(1.369505)	(0.677812)	(1.411153)	
Panel B: Manipulati	on period			
	Entire sample	Guilty sample	Guiltless sample	
Constan $t_{i,t}$	0.206142***	0.297798***	0.094356*	
	(4.877096)	(4.843028)	(1.635651)	
$AR_{i,t}$	0.145705***	0.149496***	0.126120***	
	(10.71823)	(7.794569)	(6.500662)	
$AR_{i,t} \cdot AT_{i,t}$	0.008732***	0.020030***	0.001077	
	(2.979064)	(4.191266)	(0.296964)	

*, **, *** = coefficients are significant at the 10%, 5% and 1% levels, respectively.

Table 6 presents the dynamic results of the relationship between the abnormal returns and abnormal volatility for the entire sample as well as the guilty and guiltless sub-sample. The coefficients β_2 are all insignificant in pre-manipulation period. For manipulation period, the coefficient β_2 is positive and significant for the guiltless sub-sample, suggesting that the manipulated trading magnifies stock volatility

conditional on volume during the manipulation period. However, for the guilty sub-sample, although the coefficient β_2 is positive, it is not significant. This may due to the daily price limit regulation of the TSE.

Table 6Results of the dynamic relationship between the abnormal returns and abnormalvolatility

The table presents estimates for the dynamic relationship between the abnormal returns and abnormal volatility for stock i over the period from days -65 pre-manipulation to the end of manipulation period:

$$AV_{i,t+1} = \beta_0 + \beta_1 \cdot AV_{i,t} + \beta_2 \cdot AV_{i,t} \cdot AT_{i,t} + \varepsilon_{i,t+1}$$

where $AV_{i,t}$ and $AT_{i,t}$ are the abnormal volatility and abnormal turnover, for stock i on date t.

Panel A: Pre-manipulation period			
	Entire sample	Guilty sample	Guiltless sample
Constan $t_{i,t}$	-0.000307	-0.000851***	0.000408
	(-1.377383)	(-2.593188)	(1.382728)
$AV_{i,t}$	0.258554***	0.302851***	0.175578***
	(16.25134)	(14.01013)	(7.449898)
$AV_{i,t}\cdot AT_{i,t}$	0.006480	0.007821	0.005236
	(1.145470)	(1.051154)	(0.590934)
Panel B: Manipulation period			
	Entire sample	Guilty sample	Guiltless sample
Constan $t_{i,t}$	0.001016***	4.93E-05	0.002165***
	(5.799616)	(0.193246)	(8.989650)
$AV_{i,t}$	0.333482***	0.350609	0.292802***
	(25.34483)	(18.89602)	(15.52431)
$AV_{i,t} \cdot AT_{i,t}$	0.002595	-0.006211	0.010910***
	(0.992472)	(-1.549514)	(3.247886)

*, **, *** = coefficients are significant at the 10%, 5% and 1% levels, respectively.

4.5. Results of impacts on market depth

The regression results for the market depth are presented in Table 7. We compare the market depth of the manipulated stocks during the pre-manipulation period with

Table 7Results of the market depth

Measure the market depth by Pirrong (1996) model. In this table, the first step reports the expected volumes during a daily time interval are estimated using the following regression equation:

$$Vol_{t} = a + \sum_{i=1}^{m} \beta_{i} V_{t-i} + \sum_{j=1}^{n} \theta_{j} \left| \Delta P_{t-j} \right| + \lambda \sigma_{t-1} + \varepsilon$$

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, σ_{t-1} is a measure of lagged volatility, and ε_t is an error term. The lagged term of m and n are determined by AIC and SBC minimum regulation. The m and n are 4 and 5 during the pre-manipulation period. The m and n are 3 and 1 during the manipulation period. It could be acquired unexpected trading volume, ε_t . The second step uses the unexpected trading volume to measure the market depth by estimating the following price volatility model:

$$|\Delta P_t| = \phi + \delta \cdot EVOL_t + \gamma \cdot UVOL_t + \mu \cdot UVOLPOS_t + \rho \cdot \sigma_{t-1} + \omega \cdot DumG_t + \eta$$

*EVOL*_t is the expected volume in a day interval measured by the fitted value from, $UVOL_t = \varepsilon_t$, $UVOLPOS_t = \varepsilon_t$ if $\varepsilon_t > 0$, $UVOLPOS_t = 0$ if $\varepsilon_t \le 0$, and η_t is an error term.

Variable	Pre-manipulation period	Manipulation Period
Constant	0.537751***	0.700019***
	(3.971975)	(7.514516)
$EVOL_t$	0.000208***	0.000014
	(9.314135)	(1.328629)
$UVOL_t$	0.000085	-0.000026
	(1.505572)	(-0.910765)
$UVOLPOS_t$	0.000067	0.000090**
	(0.948033)	(2.429680)
$\sigma_{_{t-1}}$	3.503296	16.89313***
	(0.692634)	(5.337297)
DG	-0.039015	0.334655***
	(-0.351158)	(4.168425)
Adjusted R-square	0.060731	0.013901

*, **, *** = coefficients are significant at the 10%, 5% and 1% levels, respectively.

that during the manipulation period to see how manipulated trading impacts market quality. For the pre-manipulation period, only the coefficient of expected volume is positive and significant at the 1% level; all other coefficients are not significant. This suggests that the market is deep before the stocks have been manipulated. For the manipulation period, the unexpected positive volume has significantly larger impact on market prices. In addition, lagged volatility magnifies price changes. The guilty sample stocks also have additional significant impacts on market volatility. The above results indicate that the market depth has deteriorated during the manipulation period, and it is consistent with the findings of Mei et al. (2004), in which a manipulator purchases suddenly in large quantities, creating rising trading volume accompanied by rising prices.

4.6. Price Reversal

The manipulator is 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 then price reversal. In this section, we examine whether there is a price reversal after the manipulation period for the manipulated stocks.

Figure 1 plots the average cumulative abnormal returns (ACAR) for the manipulation cases of the entire sample as well as the guilty and guiltless sub-samples. As can be seen, the manipulation operations have led to higher cumulative abnormal returns on the manipulation period and reach its peak at the end of the manipulation period when the prices begin to reverse. The ACARs have become negative during the post-manipulation period for all of the samples. In general, the ACAR is the highest for the guilty sub-sample, averaging over 70%. It is also far higher than that of Jiang et al. (2005), who find an average size of 4% ACAR for the stock pools in NYSE during the years 1928 and 1929. However, the magnitude of ACAR in TSE is similar to that in Karachi Stock Exchange (KSE), which is the main exchange in Pakistan, where the ACAR is reported as 50-90% (Khwaja and Mian, 2005). The ACAR of the guiltless sub-sample is lower however, averaging 20%.



Fig. 1. The Average Cumulative Abnormal Returns of All, Guilty, and Guiltless Sample

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

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 on many emerging stock markets, there is scant evidence on 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 pursued by the SEC of an emerging market, Taiwan, from 1991 to 2005. By comparing manipulated stocks with industry- and size-matched portfolios, we find that, during the manipulation period, abnormal return, abnormal turnover, and abnormal volatility are higher for manipulated stocks than for the matched sample. The vast majority of manipulation cases involve attempts to increase the stock price rather than to decrease the stock price, consistent with the idea that short-selling restrictions make it difficult to drive the price downwards. The average cumulative abnormal return reaches over 70% for the guilty sub-sample. It is similar to the emerging market of Karachi Stock Exchange, (KSE) which is the main exchange in Pakistan 50-90% (Khwaja and Mian, 2005).

For our entire sample, 91.67% of all cases are trade-based manipulations. Manipulated stocks tend to be small. 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 model of Mei et al. (2004). The abnormal turnover and volatility of the manipulated stocks are still higher for the post-manipulation period. This is consistent with the findings of Aggarwal and Wu (2004). There are also important differences among the manipulated stocks. The guilty sub-sample stocks do not experience abnormally high volatility during the manipulators often pump the stock prices up into its ceiling at the beginning of the market opening and then the prices remain unchanged before market close. On the other hand, the guiltless sub-sample stocks do not experience abnormally high return during the manipulation period, and this is the reason why they are not guilty verdicts.

Overall, the above results indicate that manipulation can actually create market inefficiency, by distorting the stock prices away from their fundamental value. Moreover, the manipulation operations have led to both abnormally high trading volume and volatility, thus worsening the market depth, and hence the market quality. This suggests a strong role for government regulation to discourage manipulation. It also poses a new challenge for regulators. Since most of the manipulators rely on neither inside information nor visible actions, their manipulations are difficult to be detected and ruled out.

References

- Aggarwal, R., G. Wu, 2004. Stock market manipulation---theory and evidence. Unpublished Working Paper, University of Michigan.
- Allen, F., D. Gale, 1992. Stock-price manipulation. The Review of Financial Studies 5, 503-529.
- Bagnoli, M., and B.L. Lipman, 1996. Stock price manipulation through takeover bids. Journal of Economics 27, 124-147.
- Bessimbinder and Seguin, 1993. Price volatility, trading volume, and market depth: evidence from futures markets. Journal of Financial and Quantitative Analysis 28, 21-40.
- Hillion, P., and Suominen, M., 2004. The manipulation of closing price. Journal of Financial Markets 7, 351-375.
- Jarrow, R., 1992. Market manipulation, bubbles, corners and short squeezes. Journal of Financial and Quantitative Analysis 27, 311-336.
- Jiang, G., P.G. Mahoney, and J. Mei., 2005. Market manipulation: a comprehensive study of stock pools. Journal of Financial Economics 77, 147-170.
- Khwaja, A. I., and Mian, A., 2005. Unchecked intermediaries: Price manipulation in an emerging stock market. Journal of Financial Economics 78, 203-241.
- Llorente, G., R. Michaely, G. Saar, J. Wang, 2002. Dynamic volume-return relation of individual stocks. Review of Financial Studies 15, 1005-1047.

- Mei, J., G. Wu, C. Zhou, 2004. Behavior based manipulation: theory and prosecution evidence. Unpublished Working Paper, New York University.
- Parkinson, M. 1998. The extreme value method for estimating the variance of the rate of return. Journal of Business 53, 61-65.
- Pirrong, C., 1996. Depth on computerized and open outcry trading systems: a comparison of DTB and LIFFE bund contracts. The Journal of Futures Markets 16, 519-543.
- Scheinkman, J.A., and W. Xiong, 2003. Overconfidence and speculative bubbles. The Journal of Political Economy 111, 1183-1219.
- Van Bommel, J., 2003. Rumors. Journal of Finance 58, 1499-1520.
- Wu, G., 2004. A detailed analysis of a stock manipulation case. Unpublished working paper, University of Michigan.