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Detecting Price Manipulation in the Korean Stock Market: Application to Recent Suspected Cases*

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Abstract We propose three criteria, including the permanent return ratio, change in permanent price ratio, and floating share ratio, to detect potential stock price manipulation. The permanent return and price ratios capture persistent price movements driven not by firms' fundamental values but primarily by non-fundamental, including manipulative, sources. Manipulators' preferences for information asymmetry favorable to generate manipulative price impacts are captured by the floating share ratio. We apply these criteria to the recent price manipulation-suspected cases in Korea, and find that the criteria can effectively detect the suspected stocks by sorting them into highly manipulation-susceptible groups. The results of the confusion matrix analysis confirm that our suggested criteria perform well in detecting potential price manipulation.

Keywords Stock price manipulation, permanent price ratio, floating share ratio.

JEL Classification G12, G14.

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1. INTRODUCTION

Stock price manipulation is a long-standing research topic of great importance to both market investors and regulators. Theoretical studies such as those of Vila (1989), Allen and Gale (1992), and Allen and Gorton (1992) suggest that profitable manipulation can arise as a rational expectation equilibrium under asymmetric information regarding the existence of manipulators. That is, uninformed manipulators can profit when investors cannot distinguish whether a buy (sell) trade for a stock is made by informed traders who know that it is undervalued (overvalued) or by uninformed traders for manipulative purposes. Benabou and Laroque (1992) suggest that many types of insiders can manipulate public information and asset prices by strategically spreading incorrect information, and that manipulation opportunities will not disappear if the public's learning is limited. Jarrow (1992) shows that market manipulation trading strategies exist when speculators have market power to corner the market and squeeze shorts or create a trend and sell against it. Aggarwal and Wu (2006) show that more arbitrageurs may worsen market efficiency when manipulators exist, and find that liquidity, returns, and volatility tend to be higher for manipulated stocks during the manipulation period from Securities and Exchange Commission (SEC)'s litigation cases.

Jarrell and Poulsen (1989) document patterns of abnormal returns and surges in volume before takeover bids in association with illegal insider trading, where press speculation and rumors in the media are a strong factor to explain the unanticipated premiums and prebid runup. Using trade level data from the Pakistan stock market, Khwaja and Mian (2005) find that brokers who manipulate prices using a specific trade-based scheme earn substantially higher returns than outside investors. Cumming and Johan (2008) examine market surveillance activities to detect manipulative trading practices worldwide and compare the scope and effectiveness of single- and cross-market surveillance, and provide evidence that surveillance efforts can facilitate stock market activity such as trading velocity. Karpoff, Lee and Martin (2008) find that for companies charged with financial misrepresentation by the SEC, the largest penalty is the reputation cost imposed by the market, which leads to losses in their market value by an average of 38% when their misconduct is revealed. King (2009) identifies insider trading from a sample of Canadian public companies' takeover announcements, in which the price-volume dynamics are consistent with the information leakage hypothesis. Cumming, Johan and Li (2011) examine international differences in the integrity-related trading rules of stock exchanges and reveal that rules regarding insider trading and market manipulation significantly affect market liquidity.

Huang and Cheng (2015) examine stock price manipulation in Taiwan and show that manipulated stocks tend to have poorer corporate governance and lower financial reporting credibility than control portfolios. Dyck, Morse and Zingales (2024) detect the proportion of corporate fraud from the increased scrutiny of former clients of the collapsed accounting company Arthur Andersen and estimated that, on average, 10% of large public companies commit securities fraud.[1] And recent studies such as Zhai, Cao and Ding (2018), Liu *et al.* (2021), and Liu, Li and Shi (2024) apply machine-learning algorithms to detect stock market manipulation and conclude that these techniques generally outperform traditional statistical models.

Although these studies provide thorough discussions on the issues of equilibrium models and sources of manipulative trading activities as well as the concomitant impacts of misconduct, price manipulations are in fact difficult to identify in real financial markets.[2] The reasons for this include, but are not limited to, the fact that price manipulations can take forms of a range of trading activities and their legal definitions tend to be intentionally vague to avoid the possibility that manipulators easily circumvent the law. However, Putniņš (2020) highlights that two key elements can help determine whether a certain action is a manipulation: intent and artificiality. That is, manipulative actions can be distinguished from non-manipulative ones when the actions are taken with an impermissible purpose and affect market demand and supply to generate "artificial prices." Artificial prices imply that market prices under manipulation do not reflect the genuine fundamental value. This finding suggests that measuring the degree to which an observed price deviates from its fundamental value may be an effective way to detect manipulative trading activities. However, to the best of our knowledge, no previous study has measured the degree of price deviation to detect manipulation, which is the focus of our study.

We believe that this lack of prior research attributes at least partially to the difficulty in distinguishing whether observed price changes arise from changes in fundamental values through a price discovery process or from non-fundamental sources for manipulative purposes. As Allen and Gale (1992) describe, market participants cannot accurately determine whether price changes are driven by informed traders or uninformed manipulators under information asymmetry. In this study, we use a statistical approach to circumvent this problem. That

[1] Cumming, Dannhauser and Johan (2015) provide a comprehensive review on recent research on financial market misconduct and potential agency conflicts.

[2] Cumming *et al.* (2020) states that "Market manipulation can be difficult to prove, because trading ahead of information announcements may simply be attributable to market anticipation, unusual volatility, or EOD market activity." (page 2)

is, we use the Beveridge-Nelson (hereafter BN) decomposition (Beveridge and Nelson, 1981) to distinguish between fundamental or permanent components and non-fundamental or transitory components of observed prices and focus on their relative movements to detect manipulative price changes. Clearly, a limitation exists in applying the statistical approach because transitory price movements do not necessarily come from manipulative trades, but also from non-fundamental or liquidity shocks. To overcome this limitation, we adopt a supplementary variable that is likely to reflect the degree of information asymmetry in manipulative market environments, and combine it with relative movements of permanent and transitory prices to filter manipulation-suspected stocks more effectively.

Using these variables, we identify several common features that characterize the movements of manipulated stock prices, distinguished from those of the price discovery process, and suggest a corresponding set of market-based criteria to detect potentially ongoing manipulations. First, manipulated price changes are driven primarily by transitory rather than permanent components. Under well-functioning, non-manipulative market conditions, deviations in prices from their fundamental values tend to disappear quickly through the price discovery process. However, when manipulations are in progress, we conjecture that manipulators try to push prices away from their fundamental values to maximize their profits, leading to large and persistent returns mainly generated by transitory price components. This feature is consistent with the condition for the nonexistence of market manipulation trading strategies proposed by Jarrow (1992), in which the price process is independent of the past sequence of speculators' trades, so prices do not exhibit momentum. This condition suggests that if we observe that transitory price returns account for an increasingly large proportion of total returns for a certain period, this would indicate the existence of manipulation underway.

According to Allen and Gale (1992), there are three types of stock price manipulations: action-, information-, and trade-based. The relative movements of transitory prices against fundamental values are likely to capture the price impacts of potentially manipulative actions or trades behind the observed price changes. To supplement the detection performance of the permanent-transitory decomposition, we also focus on an informational feature of prices. Because transitory price changes are driven by false signals or rumors with little relation to fundamental values under information-based manipulation, we expect manipulative prices to incorporate a large amount of private information. In addition, manipulators may prefer a market environment under which this "privateness" can be sustained, such as a small amount of floating shares for a stock where only limited number of shares is traded among outside investors. This feature suggests that this stock may be a good target for manipulators because it is favorable for maintaining information asymmetry and for generating price impacts as intended, making their manipulation more fruitful.

Based on these features regarding permanent-transitory price movements and preference for privateness under information asymmetry, we come up with a list of criteria, including the ratio of permanent price return out of total return, change in the ratio of permanent price to total price, and the ratio of floating shares. We can then rank the likelihood of price manipulation for individual stocks using these criteria. To evaluate how well our suggested criteria can detect actual manipulations before they are revealed, we apply these criteria to recent suspected stock price manipulation cases that occurred in Korea. In doing so, selecting target manipulation cases based on objective criteria is not an easy task. Aggarwal and Wu (2006) mention potential selection problems such as the cases where manipulations are possible but do not actually happen, or where they occur but are not observed or brought into regulators' actions. In addition, Park, Ahn and Yeo (2013) point out that new types of short-term price manipulation continue to emerge, and examine the cases of closing price manipulation, which involves placing intensive orders at the end of trading days to form artificial closing prices, in the Korean stock market.

In this study, we intend to focus on a more traditional, which is so-called pump-and-dump, type of price manipulation that tends to occur over a relatively long term and still accounts for a significant proportion of overall manipulation, as this type will be a relevant target of our analysis to apply the permanent-transitory price decomposition. Specifically, in April 2023, the prices of eight stocks plummeted to their lower limit following massive sell-offs through Societe Generale Securities Korea (SG) after about a year of steady rise. While these stocks are now being investigated for suspected price manipulations (we call "suspected" because, although the manipulation conviction was upheld in the appellate trial, the Supreme Court trial has not yet concluded), it would have been desirable if they had been closely monitored and controlled by the surveillance authority before the price collapsed, in which case a group of deceived individual investors could have avoided large capital losses. To pursue this possibility, we use data for all component stocks of the Korea Composite Stock Price Index (KOSPI) and Korea Securities Dealers Automated Quotation (KOSDAQ) up to the first quarter of 2023 and check whether the eight stocks currently under investigation are in fact filtered as highly likely cases for ongoing price manipulation by our criteria.

The remainder of this paper is organized as follows. Section 2 discusses the methodology for constructing the main variables used to select the manipulation detection criteria. Section 3 presents the data and basic statistics for the variables used in our study. Section 4 presents the main empirical results of stock ranking based on decile-sort portfolios using the selected criteria. Evaluation of the detecting performance of these criteria based on the confusion matrix is also conducted in this section. Finally, Section 5 concludes the paper.

2. METHODOLOGY

This section presents the main methods used to establish the criteria for detecting potentially manipulated stocks: the permanent return ratio, change in the permanent price ratio, and floating share ratio. To calculate the permanent return and price ratios, we apply the BN decomposition to separate stock prices into permanent and transitory components. Particularly, we follow the state-space approach of Morley (2002) to estimate a bivariate vector error correction model (VECM) in calculating the BN trend and cycle of the form

$$\begin{bmatrix} \Delta p_t - \mu \\ \Delta d_t - \mu \\ p_t - d_t - \alpha \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{11} - \beta_{21} & \beta_{12} - \beta_{22} & 1 + \beta_{13} - \beta_{23} \end{bmatrix} \begin{bmatrix} \Delta p_{t-1} - \mu \\ \Delta d_{t-1} - \mu \\ p_{t-1} - d_{t-1} - \alpha \end{bmatrix} + \begin{bmatrix} \epsilon_{pt} \\ \epsilon_{dt} \\ \epsilon_{pt} - \epsilon_{dt} \end{bmatrix}, \tag{1}$$

which is consistent with that of Cochrane (1994). Equation 1 can be written in simpler form as

$$Y_t = FY_{t-1} + \epsilon_t,$$

where p_t is the natural logarithm of the stock price, d_t is the natural logarithm of a variable that captures the fundamental value, μ is the common mean of Δp_t and Δd_t, and ϵ_{pt} and ϵ_{dt} are the residuals from the Δp_t and Δd_t regressions, respectively. A study by Choi and Park (2013) is an example to apply the state-space model under the restriction of the present-value relation to the Korean stock market. As described by Morley (2002), $\epsilon_t \sim \mathcal{N}(0, \Omega)$ and the eigenvalues of F lie within the unit circle; thus, p_t and d_t are cointegrated with the cointegrating vector of $\begin{bmatrix} 1 & -1 \end{bmatrix}$.[3]

The BN trend, or permanent component, of the stock price is defined as the minimum mean-squared-error forecast of the long-run price level minus the de-

[3]For the observations with zero or negative fundamental values, we set those values to be one so that the logged values would be zero, with the full sample maintained.

terministic trend μ:

$$\tau_t = \lim_{L\to\infty} E_t[p_{t+L} - L\mu] = p_t + \lim_{L\to\infty} \sum_{l=1}^{L} E_t[\Delta p_{t+l} - \mu],$$

which is then calculated from (1) and (2) as

$$\tau_t = p_t + \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} F(I - F)^{-1} Y_t, \tag{2}$$

with the 3×3 identity matrix I. Using the permanent price τ_t, the permanent return ratio is calculated as $pr_t = |r_{\tau t}/r_t|$ in absolute values, where $r_{\tau t} = \Delta\tau_t$ and $r_t = \Delta p_t$. In addition to the permanent return ratio, we calculate the annual change in the permanent price ratio, $cp_t = e^{\tau_t - p_t} - e^{\tau_{t-1} - p_{t-1}}$, which captures the persistent change in the proportion of the permanent component to the total price over a year in our quarterly data frequency. During manipulation periods, stock prices tend to move as intended by manipulators, where most price changes would arise not from permanent components that reflect fundamental values, but primarily from transitory components. In addition, price changes are likely to be gradual and persistent so that they can avoid the market's attention but simultaneously create sizable profits. Thus, we expect that the stock prices under manipulation will have low pr_t at inspection time t, along with low cp_t, to reflect the persistently decreasing proportion of the permanent component to the total price.

The last criterion that is expected to capture a characteristic favorable to information-based price manipulation is the floating share ratio (fs_t), which is the ratio of the number of available shares for trading in open markets to the total number of outstanding shares. Imisiker and Tas (2013) find that companies with higher floating share ratios are manipulated significantly less on the Istanbul Stock Exchange. A stock with a large proportion of closely held or restricted shares would not be appealing to market investors because there is insufficient profit opportunity with high insider ownership and low active trading, which is likely to make this stock an attractive target for manipulators. Khodabandehlou and Golpayegani (2022) describe that, in the pump-and-dump manipulation, manipulators first buy relatively unknown or low-value stocks then try to persuade other investors to buy those stocks by submitting "spoofing" orders to create a false impression of demand trend, which leads to price increases. As a stock with low fs_t is likely to be among those with low levels of attention and involvement of market investors, it would reflect an attractive characteristic to manipulators, which makes fs_t as a useful detecting instrument.

3. DATA

Our sample includes ordinary common stocks listed on the KOSPI and KOSDAQ. We obtain market and industry indices, stock prices, outstanding shares, floating shares, and accounting data from DataGuide for the first quarter of 2013 to the first quarter of 2023, which correspond to the period prior to the sell-offs through SG in April 2023, to avoid a potential ex-post validation problem. To calculate the BN trend or permanent price, as described in Equation 2, we use the quarterly market price and book value of equity on a per-share basis for individual stocks. To alleviate the potential problem owing to corporate actions, we use the adjusted closing price as a measure of the market price. Specifically, a one-quarter lagged book equity value is matched with price data to account for the time required to disclose book information.[4] Using permanent and market prices, we calculate the permanent return and price ratios, as described in the previous section. All variables are winsorized at the 5th and 95th percentiles on a cross sectional basis within each quarter to mitigate the influence of extreme outliers. The BN decomposition applied to individual stock prices may have difficulty in cleanly dividing them into permanent and transitory components because firm-level data is likely to be more affected by idiosyncratic shocks, as well as with shorter time series, than aggregate data. However, given the high level of efficiency in the stock market, we believe that this approach can capture the relative movements of the two price components effectively.

To be included in our sample, an individual stock must have at least 24 observations of the quarterly price and total equity data, which corresponds to 60% of the entire sample period, although the observations need not be consecutive. To avoid our estimation being driven by relatively outdated information after excluding missing observations, we only retain stocks with at least 12 observations over the most recent three-year period in our sample. Furthermore, as of the end of the first quarter of 2023, those stocks that are suspended from trading or designated as administrative issues for investor protection are excluded. After applying the data filtering process, a total of 1,404 individual stocks are included in our sample. The eight stocks that are our main targets as manipulation-suspected cases, which we refer to as Stock A to Stock H rather than revealing their names directly to avoid unnecessary disclosure issues, meet all the qualifications for inclusion. All the individual stocks are then sorted into deciles based on each criterion, from which we give each stock a decile rank. For example, if a stock's

[4] We use book value of equity instead of dividend as a proxy for fundamental value because dividend data is not regularly available on a quarterly basis for a substantial number of firms. Using equity value also helps avoid the negative-value problem in taking a logarithm.

pr_t, cp_t, and fs_t values are low, it will be included in the high-rank deciles of the corresponding criteria.

Table 1 presents the summary statistics for the sample stocks. It is observed in Panel A that the price, size, and book value of equity are positively skewed, with averages much higher than the median (50th-percentile) values, reflecting that KOSDAQ stocks with relatively small sizes are combined with KOSPI stocks in our sample. The average ratio of book value to market value of equity per share is approximately one, and the quarterly returns of the sample stocks were 1.6% during the ten-year period including that of the COVID-19 pandemic. Panel B then provides the correlation table for pr_t, cp_t, and fs_t, which shows that these three variables are not highly correlated. This result suggests that, although pr_t and cp_t are both calculated by the permanent price components, high permanent return ratio at any evaluation time is not necessarily associated with persistent increase in permanent price ratio over the year. Although the full-sample statistics of the three criteria are also presented in Table 1, we focus on the characteristics of these criteria for the period just prior to the price plunges of the suspected stocks in the next section.

4. EMPIRICAL RESULTS

4.1. DECILE RANKS WITH THREE CRITERIA

Table 2 provides the means, standard deviations, and decile breakpoints of the three criteria used to detect potential manipulations, calculated using the data of all KOSPI and KOSDAQ component stocks as of the first quarter of 2023. The average pr_t is 0.971, which means that a substantial fraction of observed price returns is accounted for by variation in the permanent component. Whereas the average cp_t is 0.043 for the full sample as shown in Table 1, it becomes 0.237 in the first quarter of 2023 in Table 2, indicating a marked increase in the permanent component among the sample stocks. The highest 20-percentile breakpoint of cp_t is negative, which indicates that the relative magnitude of the permanent price has decreased because of large increases in the transitory components for non-fundamental reasons for stocks in these deciles. For the floating share ratio, 56.8% of the total number of shares are traded in open markets on average, while the lowest-10%-ranked companies have about 80% floating shares and the highest-10%-ranked companies have 32.8%, indicating that only one-third of the total shares are freely traded.

We now examine how the eight manipulation-suspected stocks are ranked among all sample stocks based on the three criteria calculated using available

Panel A. Basic Statistics					
	Avg.	S.D.	Percentile		
			25%	50%	75%
Price	17,580.4	24,286.2	3,360	7,275	19,000
Size	502,168.8	893,839.1	73,760	147,858	388,519
BV	21,676.9	35,696.1	2,949.5	7,293.7	18,363.0
B/M	1.088	0.752	0.508	0.901	1.487
Earnings	13,241.3	23,993.7	628.9	3,818.9	11,211.7
Dividend	432.35	638.8	75.0	175.2	496.9
Return	0.016	0.205	-0.120	-0.010	0.118
pr_t	0.778	1.055	0.164	0.397	0.879
cp_t	0.043	0.340	-0.130	0.042	0.230
fs_t	0.565	0.162	0.449	0.565	0.688

Panel B. Correlation Table			
	pr_t	cp_t	fs_t
pr_t	1		
cp_t	-0.002	1	
fs_t	0.069	0.023	1

Table 1: Summary Statistics. This table presents the summary statistics for 1,404 sample stocks selected in the KOSPI and KOSDAQ for the period from the first quarter of 2013 to the first quarter of 2023. In Panel A, Avg. is the average, S.D. is the standard deviation, and Percentile reports the 25th, 50th (median), and 75th percentile values. Price is the market price, Size is total market value calculated by multiplying the price by the number of outstanding shares, BV is the book value of equity per share, B/M is the ratio of book value to market value per share, Earnings is retained earnings per share, and Dividend is the dividend payment per share. The units are in Korean won (KRW), except for Size, which is measured in million KRW. Return is the quarterly price return in percentage. pr_t is the ratio of permanent return to total return, cp_t is the annual change in the ratio of permanent price to total price, and fs_t is the ratio of the number of floating shares to the total number of outstanding shares. Panel B presents the correlation coefficients among pr_t, cp_t, and fs_t. The data are obtained from DataGuide.

market information. Table 3 presents the pr_t, cp_t, and fs_t values of the suspected stocks and their decile ranks as of the first quarter of 2023. It clearly shows that these eight stocks are mostly included in the high-rank deciles of all the criteria. Notably, according to the cp_t criterion, seven out of eight stocks are in the highest-rank decile, with the largest decrease in the permanent price ratio

	Avg.	S.D.	Decile Breakpoints								
			10%	20%	30%	40%	50%	60%	70%	80%	90%
pr_t	0.971	1.292	0.073	0.159	0.261	0.359	0.489	0.658	0.905	1.319	2.615
cp_t	0.237	0.314	-0.124	-0.021	0.050	0.116	0.186	0.254	0.351	0.455	0.664
fs_t	0.568	0.166	0.328	0.420	0.477	0.524	0.569	0.617	0.665	0.727	0.798

Table 2: Statistics for the Criteria. This table presents the statistics for the three criteria of sample stocks as of the first quarter of 2023. Avg. is the average, S.D. is the standard deviation, and Decile Breakpoints are the values of the criteria used to sort the sample stocks into deciles. pr_t is the ratio of permanent return to total return, cp_t is the annual change in the ratio of permanent price to total price, and fs_t is the ratio of the number of floating shares to the total number of outstanding shares. The data are obtained from DataGuide.

for one year. This result can be confirmed by the fact that the average value of cp_t for these stocks is negative (-0.515) and much lower than that of the full sample (0.237), which is presented in Table 2. For pr_t, three are in the highest, three are in the second-highest, and the remaining two are in the third-highest deciles, suggesting that their quarterly returns are mostly driven by transitory price changes. For fs_t, two stocks are in the highest-rank deciles and four stocks are within the third-highest deciles. The last row presents the quarterly price returns of the suspected stocks for the second quarter of 2023, which show sharp drops that triggered inspection by the surveillance authority. Interestingly, the return on Stock G, whose ranks are lower than the other seven stocks in most criteria, is not as drastic as the others even though it hit the bottom limit.

From the aggregate ranking perspective, two of the eight stocks, Stock D and Stock E, are included in the highest-rank deciles of all three criteria. Stock A is in the highest-rank deciles according to two, pr_t and cp_t, criteria and in the second-highest decile of the remaining fs_t criterion. Stock B and Stock H are in the highest-rank decile of the cp_t criterion and in the second-highest deciles of the pr_t and fs_t criteria. Stock C and Stock F are in the highest-rank decile of the cp_t criterion and within the fourth-highest deciles of the pr_t and fs_t criteria. While Stock G has a relatively large proportion of floating shares, it is in the third-highest deciles of the pr_t and cp_t criteria. Overall, these findings clearly indicate that our suggested criteria are effective in detecting stocks that are suspected of having manipulative price movements.

Figure 1 shows the relative movements of the observed (dashed line) and permanent (solid line) prices of the eight suspected stocks, as well as the KOSPI value (dotted line), which helps us understand the characteristics of permanent price and return ratios in detecting potential manipulations. The common feature is that with stable permanent prices during the past ten years, the observed market prices were also stable before 2020. However, they have begun to persistently increase owing to certain non-fundamental forces, with permanent prices remaining largely unchanged since 2020–2021. These price movements generate low permanent return ratios and persistent decreases in permanent price ratios, by which suspected stocks are included in the high-rank deciles. The only exception is Stock G, of which the permanent price increased while the market price decreased from 2020 to 2021, so that the observed price movement in the first quarter of 2023 looks very much like a discovery process converging to its fundamental value rather than manipulation.

We additionally provide Figure 2, which depicts the time series evolution of pr_t (dashed line) and cp_t (solid line) for the eight suspected stocks. Although occasional sharp spikes are found, overall the values of pr_t tend to converge toward zero as they approach the first quarter of 2023, which suggests that most of the observed price returns during early 2023 may be explained by changes in the transitory component for these stocks. Except for Stock G, the cp_t series generally stay below zero or fall sharply to negative values as of the first quarter of 2023, implying the persistently reduced contribution of the permanent components to the total prices. These patterns consistently suggest a potential ability of these two criteria to detect manipulation based on the relative movements of the permanent and transitory price components.

	Stock A	Stock B	Stock C	Stock D	Stock E	Stock F	Stock G	Stock H	Avg.
pr_t	0.061	0.079	0.203	0.011	0.005	0.081	0.204	0.120	0.095
	(1)	(2)	(3)	(1)	(1)	(2)	(3)	(2)	
cp_t	-0.286	-1.164	-0.798	-0.422	-0.166	-1.066	0.005	-0.219	-0.515
	(1)	(1)	(1)	(1)	(1)	(1)	(3)	(1)	
fs_t	0.375	0.331	0.453	0.235	0.273	0.494	0.716	0.383	0.408
	(2)	(2)	(3)	(1)	(1)	(4)	(8)	(2)	
23Q2 return	-51.5%	-73.0%	-79.0%	-86.6%	-89.2%	-73.2%	-34.4%	-86.3%	-71.6%

Table 3: CHARACTERISTICS OF EIGHT SUSPECTED STOCKS. This table presents the values of three criteria for the eight manipulation-suspected stocks as of the first quarter of 2023. Avg. is the average values of the eight stocks. pr_t is the ratio of permanent return to total return, cp_t is the annual change in the ratio of permanent price to total price, and fs_t is the ratio of the number of floating shares to the total number of outstanding shares. 23Q2 return is the stock return for the second quarter of 2023. The numbers in parentheses are the decile ranks. The data are obtained from DataGuide.

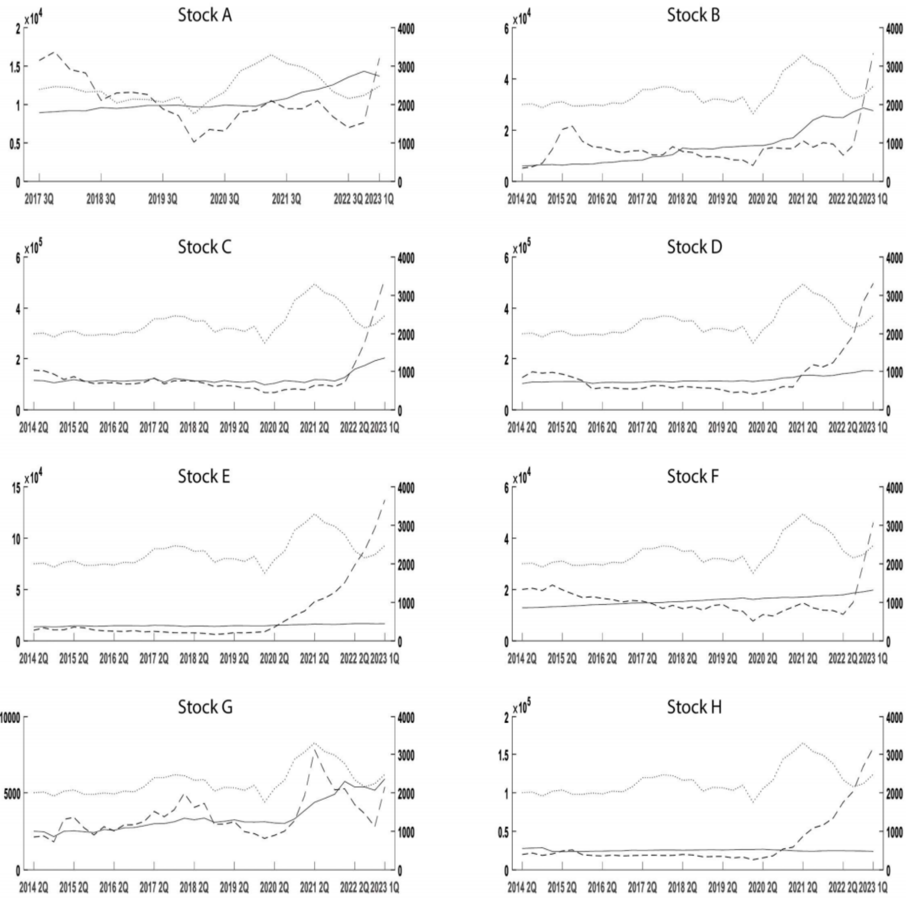

Figure 1: PRICES OF SUSPECTED STOCKS. This figure presents the observed (dashed line) and permanent (solid line) prices of the eight suspected stocks as well as the KOSPI value (dotted line) from the second quarter of 2014 to the first quarter of 2023. Left axis corresponds to the stock prices and right axis corresponds to the KOSPI value. The data are obtained from DataGuide.

4.2. ALTERNATIVE MEASURES OF FUNDAMENTAL VALUES

To calculate the permanent price of an individual stock, we have so far used the book value of equity as a measure of fundamental value. To check the robustness of our results, we use retained earnings plus dividend payments, which are more closely associated with firm profits than the book value of equity, as

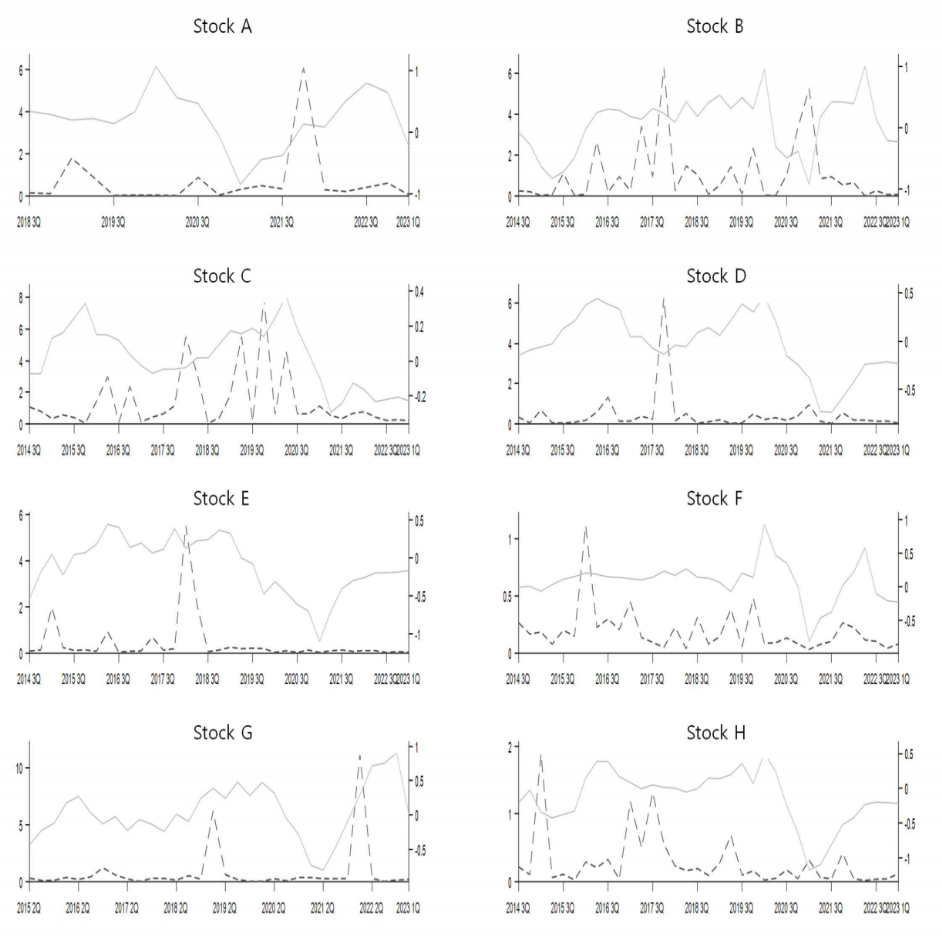

Figure 2: PERMANENT RETURN RATIOS AND ANNUAL CHANGES IN THE PERMANENT PRICE RATIOS OF SUSPECTED STOCKS. This figure presents the permanent return ratios (pr_t, dashed line) and annual change in the permanent price ratios (cp_t, solid line) of the eight suspected stocks from the third quarter of 2014 to the first quarter of 2023. Left axis corresponds to pr_t and right axis corresponds to cp_t. The data are obtained from DataGuide.

an alternative measure of the fundamental value in the BN decomposition. That is, using the observed prices and retained earnings plus dividends per share, we reestimate the permanent and transitory price components in Equation 2 to calculate the corresponding permanent price and return ratios and sort all individual

Panel A. Decile Breakpoints									
	10%	20%	30%	40%	50%	60%	70%	80%	90%
pr_t	0.060	0.206	0.345	0.512	0.682	0.870	1.011	1.372	2.919
cp_t	-0.103	-0.022	0.009	0.051	0.121	0.207	0.302	0.425	0.686

Panel B. Decile Ranks									
	Stock A	Stock B	Stock C	Stock D	Stock E	Stock F	Stock G	Stock H	Avg.
pr_t	0.136	0.204	0.000	0.032	0.067	0.131	0.997	0.102	0.209
	(2)	(2)	(1)	(1)	(2)	(2)	(7)	(2)	
cp_t	-0.281	-0.895	-0.199	-0.424	-0.181	-1.100	-0.010	-0.227	-0.415
	(1)	(1)	(1)	(1)	(1)	(1)	(3)	(1)	

Table 4: Using Retained Earnings Data. This table presents the decile breakpoints in Panel A and the values of two criteria for the eight manipulation-suspected stocks in Panel B as of the first quarter of 2023, calculated using retained earnings and dividend payments as an alternative measure of fundamental value to the book value of equity. Avg. is the average value of the eight stocks. pr_t is the ratio of permanent return to total return, and cp_t is the annual change in the ratio of permanent price to total price. The numbers in parentheses are the decile ranks. The data are obtained from DataGuide.

stocks into deciles accordingly. The results are presented in Table 4, where Panel A shows that the decile breakpoints for the pr_t and cp_t criteria are close to those in Table 2. Panel B provides the values of these two criteria and decile ranks of the eight suspected stocks. We consistently observe that seven stocks, except Stock G, are included in the highest-rank decile according to the cp_t criterion, to indicate the largest decrease in the permanent price ratio. These seven stocks are included in either the first- or second-highest deciles by pr_t, which confirms that their returns in the first quarter of 2023 are mostly driven by transitory components with non-fundamental forces.

To determine the overall ranking performance of our suggested criteria using alternative fundamental value measures, we count the number of sample stocks included in the highest, second-highest, and third-highest deciles by all three criteria. Table 5 presents the results, where Panel A presents the number of samples and suspected stocks within the third-highest deciles. Of the 1,404 individual stocks in our sample, there are 38 stocks included within the highest 30% of all the criteria with permanent prices estimated using book values of equity, and 32 stocks are included using retained earnings plus dividends. Furthermore, 21 stocks are included within the highest 30%, regardless of whether book equity or retained earnings are used, of which six stocks are the suspected ones. We narrow the filtering threshold to 20% and present the results in Panel B. We find that

	Panel A. Highest 30%			Panel B. Highest 20%			Panel C. Highest 10%		
	Equity	Earnings	Both	Equity	Earnings	Both	Equity	Earnings	Both
Total	38	32	21	17	11	8	2	1	1
Suspected	6	6	6	5	5	5	2	1	1

Table 5: Ranking Performance. This table presents the number of stocks included in the highest 30% (Panel A), 20% (Panel B), and 10% (Panel C) by all three criteria (pr_t, cp_t, and fs_t). Total corresponds to the number of included stocks out of all sample stocks, and Suspected corresponds to the number of stocks out of the eight manipulation-suspected stocks. The Equity column corresponds to pr_t and cp_t calculated from the book value of equity, the Earnings column corresponds to those from retained earnings plus dividend payments, and the Both column reports the number of stocks included in both Equity and Earnings. The data are obtained from DataGuide.

seventeen stocks are included within the highest 20% using book equity, eleven stocks are included using retained earnings plus dividends, and eight stocks are included in both groups, of which more than 60% (five stocks) are suspected stocks. Finally, when we narrow the threshold to the highest 10% in all three criteria, the only stock that remains using both book equity and retained earnings plus dividends is one of the suspected stocks (Stock D). Thus, we conclude that our criteria can effectively detect the common characteristics of potentially manipulated stock prices and that these criteria, especially those associated with estimating permanent price components, are robust to using the book values of equity or retained earnings plus dividends as a measure of fundamental value.

4.3. CONFUSION MATRIX ANALYSIS

In this section, we evaluate how well our suggested criteria could detect the eight manipulation-suspected stocks by adopting the confusion matrix analysis, which specifies correct and incorrect detections made by the pr_t, cp_t, and fs_t criteria. We use both pr_t and cp_t with the book value of equity and those with retained earnings plus dividends per share as a measure of the fundamental value for this analysis. Specifically, for each filtering threshold, we calculate the four dimensions of the confusion matrix: true positive (TP) that is a correct classification of one of the eight suspected stocks as positive (for convenience, we refer to the manipulation-suspected stocks as “positive”), false negative (FN) that is an incorrect classification of a suspected stock as negative (unsuspected), false positive (FP) that is an incorrect classification of an unsuspected stock as positive, and true negative (TN) that is a correct classification of an unsuspected stock as negative. We also calculate the precision (PRC) as $PRC = TP/(TP + FP)$, true positive ratio (TPR) as $TPR = TP/(TP + FN)$, and false positive ratio (FPR) as $FPR = FP/(TN + FP)$. Based on these ratios, we consider a widely used measure of classification performance, the F1 score, derived as the harmonic mean of PRC and TPR given their tradeoff relationship: $F1 = 2 \times PRC \times TPR/(PRC + TPR)$. We further calculate the confusion matrices across the full filtering thresholds from the highest 0% to 100% in all criteria to construct the Receiver Operating Characteristic (ROC) curve that plots the pairs of TPR and FPR, from which another key performance measure of a classification model, the Area Under Curve (AUC) value, is derived as the area under the ROC curve.

The results of the confusion matrix analysis are presented in Panel A of Table 6. With the component ratios of the confusion matrices across the full thresholds, the $F1$ column shows that the 20% screening threshold for our suggested criteria generate the F1 score of 0.625. This result indicates that setting the screening threshold as the highest 20% of the suggested criteria can generate a reasonable balance between what percentage of total detected stocks are actual suspected stocks (PRC) and what percentage of total suspected stocks are actually detected (TPR), so that it is considered to provide a good classification performance. Furthermore, at the bottom of Panel A, it is also reported that the AUC value is as high as 0.953. With the AUC value of 1 for a perfect classification model and 0.5 for a random classification model, our result of the AUC value that is fairly close to 1 consistently suggests that the pr_t, cp_t, and fs_t criteria may be able to effectively detect potential price manipulations in advance in the Korean stock market.

While our approach is relatively free from an issue of statistical uncertainty of performance measures because we do not rely on any statistical model to estimate a manipulation likelihood but take a simple and intuitive approach to sort all individual stocks based on the selected criteria, we perform an additional exercise to check the sensitivity of our results by applying the confusion matrix analysis to all different combinations of the three criteria and comparing with the results with those reported in Panel A of Table 6. While the full results are not reported here to save space, the combination of pr_t and cp_t (excluding fs_t) generates the AUC value of 0.958, which is nearly the same as the value (0.953) reported in Panel A. However, the maximum F1 score was 0.444 with the 10% threshold, which is lower than the score (0.625) in Panel A, which leads us to conclude that combination of the three variables would collectively provide credible detecting performance. This result suggests that, in line with the findings of Chan, Chan

Threshold	TP	TN	FP	FN	PRC	TPR	FPR	$F1$
Panel A. pr_t, cp_t, and fs_t								
10%	1	1396	0	7	1	0.125	0	0.222
20%	5	1393	3	3	0.625	0.625	0.002	0.625
30%	6	1381	15	2	0.286	0.750	0.011	0.414
40%	7	1363	33	1	0.175	0.875	0.024	0.292
50%	7	1303	93	1	0.070	0.875	0.067	0.130
60%	7	1198	198	1	0.034	0.875	0.142	0.066
70%	7	1025	371	1	0.019	0.875	0.266	0.036
80%	8	786	610	0	0.013	1	0.437	0.026
90%	8	454	942	0	0.009	1	0.675	0.017
100%	8	0	1396	0	0.006	1	1	0.011
$AUC = 0.953$								
Panel B. pr_t, cp_t, fs_t, and R^2								
10%	1	1396	0	7	1	0.125	0	0.222
20%	3	1394	2	5	0.600	0.375	0.001	0.462
30%	5	1386	10	3	0.333	0.625	0.007	0.435
40%	6	1375	21	2	0.222	0.750	0.015	0.343
50%	6	1337	59	2	0.092	0.750	0.042	0.164
60%	6	1261	135	2	0.043	0.750	0.097	0.081
70%	6	1119	277	2	0.021	0.750	0.198	0.041
80%	7	898	498	1	0.014	0.875	0.357	0.027
90%	8	549	847	0	0.009	1	0.607	0.019
100%	8	0	1396	0	0.006	1	1	0.011
$AUC = 0.902$								

Table 6: Confusion Matrix Analysis. This table presents the confusion matrices and the resulting performance metrics for detecting manipulation using the criteria pr_t, cp_t, and fs_t in Panel A, and pr_t, cp_t, fs_t, and R^2 in Panel B across different filtering thresholds. TP denotes true positives, TN true negatives, FP false positives, and FN false negatives. PRC is precision, TPR is the true positive rate, FPR is the false positive rate, $F1$ is the F1 score, and AUC is the area under the curve. The data are obtained from DataGuide.

and Fong (2004) and Ding, Ni and Zhong (2016) that there is a positive relationship between stock market liquidity and free float, fs_t is likely to capture an additional liquidity dimension in detecting manipulation.

We further test robustness of our results by considering an additional surveillance variable that are likely to capture a potentially manipulation-specific pattern. Comerton-Forde and Putniņš (2014) find that stocks with high information asymmetry and low idiosyncratic volatility are more prone to closing price manipulation due to the risk of unfavorable price movements as well as regulators' attention. Thus, in addition to the three suggested variables, we also consider the R-squared value, which is calculated by $R^2 = 1 - Var(e_t)/Var(r_t)$ from the following regression:

$$r_t = a + b_m r_{m,t} + b_j r_{j,t} + e_t,$$

where r_t is an individual stock return, $r_{m,t}$ is the overall stock market index return, $r_{j,t}$ is the industry index return when the firm is included in industry j, and e_t is the residual term. Given that $Var(e_t)$ represents the idiosyncratic volatility, the R^2 measure has been widely used as a measure of price informativeness, that is, the amount of private information incorporated in prices, by prior studies such as Roll (1988), Morck, Yeung and Yu (2000) and Jin and Myers (2006). The results of confusion matrix analysis applied to the combination of the four variables including R^2 are presented in Panel B of Table 6, where the maximum F1 score is 0.462 with the 20% threshold and the AUC value of 0.902. This performance is inferior to the combination of the suggested three variables without R^2, which consistently indicates that the three variables are effective instruments to detect stock price manipulations.

4.4. ANOTHER MANIPULATION CASE

While our suggested criteria are found to be useful in detecting the eight suspected stock in the SG sell-off incident in 2023, a concern can be raised regarding the difficulty in disentangling firm-specific predictors from time-specific macroeconomic shocks because the eight cases occurred simultaneously within the same time period. To address this concern, we consider another more recent case that was announced by the financial regulator. In September 2025, the joint response team on stock manipulation launched by the Financial Services Commission, the Financial Supervisory Service, and the Korea Exchange announced that it uncovered a case where a group of wealthy individuals colluded to carry out manipulation worth of 100 billion Korean Won. In this section, we examine the three criteria of the stock that is known as a target in comparison with those of the two largest stocks, Samsung Electronics (SS) and SK Hynix (SK), whose price rises might be also driven by transitory components over the past year, as benchmarks. Specifically, we calculate pr_t, cp_t, and fs_t of the target and two benchmark stocks using the five-year data up to the second quarter of 2025 (prior to the authority's detection at the end of the third quarter) to compare their decile ranks.

We find that the target stock is included in the highest 30% decile of pr_t and the highest 10% decile of cp_t, which indicates that this stock is one of those with increasing proportion of the transitory component by the greatest amount during the past year. Unlike the target stock, the two benchmarks show relatively low decile ranks, that is, in the highest 40% decile of pr_t and the highest 90% decile of cp_t for SS, and in the highest 80% decile of pr_t and the highest 60% decile of cp_t for SK. In terms of fs_t criterion, the target stock turns out to have high proportion of floating share, so this criterion does not contribute to detecting manipulation in this case. However, the two criteria based on the permanent-transitory decomposition of stock prices are still likely to be useful in detecting price manipulation for the target stock. One caveat is that, if we select the evaluation period until the fourth quarter of 2025 in which the KOSPI showed a strong upward trend, SS is found to be highly ranked in these two criteria, indicating that a large portion of the SS return was generated by the transitory component even if the stock market surge was driven by semiconductor super cycle. We think that this result is associated with an issue of estimating permanent and transitory prices especially when a fundamental change occurs rapidly in the stock market, which will be an important topic for future study.

5. CONCLUSION

Although stock price manipulation is an important research topic for both market investors and regulators, relatively few studies focus on detecting potential manipulation using the characteristics of price movements. In this study, we consider several features that stock price manipulations are likely to have in common and suggest three criteria for detecting manipulative stock price movements. The first feature is that manipulative price changes are driven not by fundamental values but primarily by non-fundamental sources such as manipulative trades or false information. To utilize this characteristic to detect manipulation, we apply the BN decomposition to distinguish permanent and transitory components from observed prices. Using the decomposed prices, we calculate the permanent return ratio, which is the ratio of permanent price return to total return in absolute value, and the annual change in the permanent price ratio, which is the ratio of permanent price to observed market price. We expect stocks under manipulation to have low permanent return ratios and persistently decreasing permanent price ratios; therefore, we consider these two variables as our criteria. In addition, manipulative prices are likely to incorporate a large amount of private information and manipulators may prefer a market environment favorable for sustaining this privateness to maximize their profits. To capture these preferences, we select an additional criterion, the floating share ratio, which is the proportion of floating shares traded in open markets to the total number of outstanding shares. We expect that manipulators would prefer stocks with low floating share ratios as their potential targets.

We then apply these three criteria to recent price manipulation-suspected cases that occurred in the Korean stock market, where the prices of eight stocks plummeted to their lower limits due to massive sell-offs in April 2023 after persistent rises. Specifically, we use stock market data up to the first quarter of 2023 to determine whether our suggested criteria can detect these suspected stocks out of all the individual components of the KOSPI and KOSDAQ by sorting them into deciles based on these criteria and assigning decile ranks. We find that the eight suspected stocks are mostly included in the high-rank deciles, indicating that they can be classified as stocks highly likely to be manipulated before they are revealed. Our findings indicate that by capturing the features of permanent and transitory price movements and privateness, the suggested criteria can effectively detect potentially ongoing manipulations. We further conduct the confusion matrix analysis to evaluate the detecting performance of these criteria, which consistently support the ability to detect potential price manipulations in advance. This result has important policy implications by suggesting that market surveillance authorities should focus on the dimensions suggested by our criteria to detect stocks that are susceptible to manipulation and closely monitor them before these stocks cause unfair capital losses to general investors. We believe that these criteria will also be helpful for the internal monitoring systems of stock exchanges for self-regulatory purposes.

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