Article

Timely Loss Recognition Helps Nothing

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Abstract: This paper digests the relationship between the manipulation of losses and price reversals in the Chinese stock market. Timely loss recognition is involved in detecting the manipulation of losses, while price reversals are investigated by momentum profit. In addition, two-way sorting momentum portfolios are employed to connect manipulating losses with price reversals. Companies with low timely loss recognition aggressively manipulate their losses, and our results indicate that they generate much more significantly negative momentum profits. As a consequence, they cannot build up any immunity against reversal risks and encounter much higher reversal risks than other companies. Such findings still hold after the risk adjustments using asset pricing models come into play and when controlling for the calendar effect. This research indeed suggests that investors should exercise caution when dealing with companies whose financial information is too positive. Such companies may dress up their financial reports, thereby significantly increasing the risks associated with price reversals.

Keywords: price momentum; price reversal; timely loss recognition

1. Introduction

"The more one wants to bury a scandal, the more it is exposed."

—*The Commentary of Zuo*

According to the China Securities Regulatory Commission, the total market capitalization of the Chinese stock market in 2021 amounts to 81.648 trillion RMB, implying that it is an essential capital market in the world. However, the Chinese market gives rise to severe price reversals as contended by [1,2]. In accordance with the concepts of [3], momentum represents price sustainability, while price reversals imply that past price trends will turn to move in the opposite direction in the future, suggesting that stock price increases (or decreases) are unsustainable.

Reference [4] considered that price reversal challenges market efficiency since the information is not fully reflected in the stock prices. As it is common to see financial manipulation taking place around the world—e.g., [5,6]—we infer that the inefficiency represented by price reversal stems from the low transparency of financial information. These studies convey the message that Chinese-listed companies experience dramatic price decreases after great increases and vice versa, which indicates that the Chinese stock market is characterized by extreme risks. This background inspires us to connect financial manipulation with price reversal.

References [7,8] show that manipulating accounting losses is prevalent in the US and European markets. In addition, refs. [9,10] point out that the managers of listed companies are incentivized to show what they prefer to the public. In the Chinese market, refs. [11–13] prove that the frequent releases of financial information continue to affect the market despite its reliability. Besides, refs. [14,15] suggest that the investors are particularly

sensitive to accounting losses, stimulating the managers to manipulate the companies' losses and further influence price trends in China.

Furthermore, refs. [16–18] reveal that the prevalent manipulation of losses by the Chinese listed companies temporarily masks actual financial information. However, the stock prices may reverse after the disclosure of the manipulation. More importantly, the dominant retail investors in the Chinese market pay much attention to the changes in the directions of price trends—e.g., [19,20]. Motivated by these circumstances in China, this paper seeks to determine the interactions between manipulating losses and price reversals.

In addition to the above background, there are underlying linkages between price reversals and the manipulation of losses. References [21,22] suggested that investors will become aware of fraud and consider listed companies to be dishonest once manipulations of losses are identified. Accordingly, investors will overreact to the news about the listed companies. They will often abruptly or even arbitrarily alter their past investment decisions, thereby increasing the risk of strong price reversals.

By contrast, as clarified by [23,24], if the manipulations of losses are not recognized, listed companies can successfully release positive information that they have made up to the market. It is thus possible that the investors will exhibit delayed reactions to this so-called positive news. Hence, they will not frequently adjust their investments, and price sustainability will occur.

Most studies on manipulating losses intuitively dissect its effect on financial reporting quality. References [25–27] are vivid examples in this stream of research on manipulating losses. Moreover, prior research on price reversals concentrates on the perspectives of market states and company characteristics in the Chinese market, such as [28,29]. Regardless of whether in the field of financial manipulation or price reversal, there are few papers that focus on the impact of manipulating losses on price reversal in China. Our paper fully settles this issue that has been missed in the literature.

The theoretical framework used to detect the effect of manipulating losses on price reversal is outlined as follows: To address price reversal risks in China, we follow [30] to calculate the momentum profit. To be specific, formation and holding periods are required in the procedure to acquire momentum profit. Due to the considerable power of the tests, a rolling and overlapping procedure is applied that complies with [30], who show that a significantly positive momentum profit represents price sustainability while a significantly negative momentum profit suggests price reversal.

Moreover, we use asset pricing models to acquire the risk-adjusted momentum profit. Following [31] in an asset pricing model, the intercept is the part of the momentum profit that remains after it has been explained by risk pricing factors; thus, the intercept is the risk-adjusted momentum profit. It is important to note that existing reversal studies mainly implement the capital asset pricing model of [32,33] and Fama–French three-factor model of [34] for risk adjustments, such as [35,36].

Differing from these studies, our paper includes the commonly used asset pricing models, as well as the Chinese three-factor and four-factor asset pricing models of [37]. The main advantage of [37]'s asset pricing models is that the models consider a vital characteristic regarding backdoor listings in the Chinese market. Consequently, our findings are supposed to be closer to the actual situation in the Chinese market.

We follow [38] to dissect the manipulation of losses using timely loss recognition based on earnings and accruals. In accordance with their concepts, when losses are recognized in time, fewer losses will be manipulated. On the contrary, it is possible that more losses will be manipulated when their recognition is delayed. To extract the influence of manipulating losses on price reversal, we take into account the momentum portfolios using specific sorts.

Prior studies mainly employ any one of sequential, inverse sequential, and simultaneous sorts. For instance, refs. [39,40] use sequential sorts, whereas [41,42] shed light on inverse sequential sorts. Apart from them, refs. [31,43] choose simultaneous sorts in their explorations. Compared to the research mentioned above, we adopt all three of these types of sorts to construct momentum portfolios.

Moreover, we follow [30] to control for the calendar effect since they perceive price reversals to be more likely to occur during the new-year holiday. Apart from the calendar effect, we also propose reversal strength tests in light of [30]'s concept addressing price reversal. In addition, an alternative proxy for timely loss recognition from [44] is also employed to conduct further analysis. These robustness checks confirm whether the empirical findings are strong.

The remainder of this paper is organized as follows: The literature review appears in the next section. The methodology and data are introduced in Section 3. The outcomes of the empirical analyses are presented in Section 4. In Section 5, we show the results of the tests for robustness. Finally, the conclusions are provided in Section 6.

2. Literature Review

A number of studies investigate the origin of manipulation from the perspective of internal pressure. Reference [45], for instance, provides evidence that those managers with obvious narcissism tend to manipulate losses in an effort to demonstrate their leadership and, as a result, are less likely to recognize losses in time. In addition, ref. [26] finds that the managers manipulate losses because they are dedicated to establishing a decent reputation among the shareholders. Since the financial reports of listed companies are available to the public, the managers' salaries are generally based on the firms' financial performance. Hence, refs. [46] finds that managers have the motivation to fine-tune their firms' accounting losses and wish to maximize their salaries.

The manipulation of losses has also been explained in terms of external pressure. Reference [47] perceives that listed companies will manipulate losses in order to avoid being delisted when the companies financially exhibit extreme underperformance. They further reveal that the companies will tend to overstate financial performance when issuing new shares, echoing the financing incentive referred to in [48,49]. Moreover, as argued by [50], listed companies that are carefully followed by analysts are more likely to cook up positive news, since the analysts will come up with misestimations of the companies' bright prospects.

Engaging in the manipulation of losses masks the actual financial performance of the listed companies. Therefore, as discovered by [25–27], these modified financial reports cannot transfer useful news to the market, resulting in very low financial reporting quality. References [51–54] have even confirmed the low financial reporting quality to be followed by weak corporate innovation and investment efficiency while also increasing information uncertainty, etc. In relation to the manipulation of losses, existing research does not examine the subsequent price reversal arising from such manipulation.

By going back at least to [55,56], the authors began to dissect price reversals in terms of investor behaviors. They perceived that the investors were likely to overreact to unexpected information and adjust their trading strategies abruptly. Such behaviors lead to price reversals. Moreover, several studies analyze price reversals from the perspective of informed trading, such as [57–59]. These endeavors indicate that the investor behaviors stimulate price reversals when the investors are uninformed, while it is less likely for price reversals to take place in circumstances where informed investors are considered. Apart from what has already been mentioned, it is recognized that price reversal is one of the outcomes of herding behavior. For instance, refs. [60,61] demonstrate that price reversal is positively related to the strength of herding behavior.

When it comes to the anatomy of price reversal in China, refs. [29,62] investigate price reversal in terms of market states. They find that price reversal can be attributed to the economic downturn in China. By contrast, ref. [28] explains the emergence of price reversal from the perspective of company size. To be specific, small market capitalization contributes to price reversals among listed companies in China. In addition, refs. [63,64] verify that high analyst coverage and strong trading intensity expose the listed companies to price reversals. Likewise, in the field of price reversal, there are few endeavors that shed light on the manipulation of losses.

Studies on the US and European markets indicate that manipulating losses causes stock prices to fall to low levels. For instance, ref. [65] suggests that more frequent attempts to manipulate losses are a sign of more dramatic exposure to stock price crashes, and so stock price crashes can be predicted by the manipulation of losses. Furthermore, big companies are more prone to price crashes as a result of the manipulation. Reference [66] finds that the positive relationship between the manipulation of losses and price crashes is robust in relation to investor heterogeneity and information asymmetries. Reference [67] points out that those companies with positive discretionary accruals, smaller institutional holdings, and fewer regulations will encounter price crashes due to the manipulation. In addition, ref. [68] further confirms that it is more possible for stock prices to decline when the manipulation of losses takes place.

While there is little doubt that the manipulation of losses is related to stock price crashes, the stocks may exhibit price increases once the price crashes disappear. If the investors do not perceive such price reversal, they will mistakenly sell off the stocks. Consequently, the effect of manipulating losses on price reversal is in need of urgent analysis. Prior research, such as [69,70], has found that price momentum prevails in the US and European stock markets, indicating that stock prices will not adjust in opposite directions. However, in China, the anatomy of price reversal suggests that price momentum is absent, and stock prices will easily start to move in the opposite direction. This gives us grounds for considering that price reversal should be an outcome of manipulating losses.

3. Methodology and Data

According to the concepts of [21–24], price sustainability and price reversal are, respectively, caused by delayed reactions and overreactions to news releases. Hence, ref. [38]'s timely loss recognition is used to investigate the manipulation of losses. In addition, we fully present the procedures for acquiring momentum profit that comply with [30]. Following [71], the risk-adjusted momentum profit originates from the intercept of the asset pricing model.

3.1. Earnings-Based Timely Loss Recognition

In compliance with [38], we can make use of the transitory nature of earnings to identify the manipulations when the listed companies delay the recognition of losses to overstate earnings. The earnings-based measure of timely loss recognition (*TLR*) for each stock is estimated by using a piecewise linear model as follows:

$$\frac{\Delta E_t}{TA_t} = a + \varphi_1 D\Delta E_{t-1} + \varphi_2 \frac{\Delta E_{t-1}}{TA_{t-1}} + \varphi_3 \frac{\Delta E_{t-1}}{TA_{t-1}} D\Delta E_{t-1} + u_t \tag{1}$$

where ΔE_t is the change in earnings between period t and $t-1$, ΔE_{t-1} is the change in earnings between period $t-1$ and $t-2$, and $D\Delta E_{t-1}$ takes a value of 1 when the change in earnings is negative and zero otherwise. The magnitude of the timely loss recognition for each stock is the regression slope in the model.

$$TLR_t^E = \begin{cases} |\widehat{\varphi_2}| \times 100\% & \Delta E_{t-1} \geq 0 \\ |\widehat{\varphi_2} + \widehat{\varphi_3}| \times 100\% & \Delta E_{t-1} < 0 \end{cases} \tag{2}$$

3.2. Accruals-Based Timely Loss Recognition

In accordance with [38], it is all the more possible that loss recognition will be delayed once the realized accruals emerge. Hence, a piecewise linear model that includes accruals and cash flow is employed to obtain accruals-based timely loss recognition:

$$\frac{AC_t}{TA_t} = a + \gamma_1 DCF_t + \gamma_2 \frac{CF_t}{TA_t} + \gamma_3 \frac{CF_t}{TA_t} \times DCF_t + u_t \tag{3}$$

where TA_t is total assets in period t, CF_t is cash flow from operations, DCF_t is a dummy variable taking a value of 1 when cash from operations is negative and zero otherwise, and

AC_t is accruals. The degree of timely loss recognition for each stock is measured by the regression slopes.

$$TLR_t^A = \begin{cases} |\widehat{\gamma_2}| \times 100\% & CF_t \geq 0 \\ |\widehat{\gamma_2} + \widehat{\gamma_3}| \times 100\% & CF_t < 0 \end{cases} \tag{4}$$

3.3. Momentum Algorithm

According to [30], the computation of momentum profit requires formation and holding periods. Each pair of formation and holding periods engenders a momentum portfolio. If the length of the formation period covers A periods and the length of the holding period covers B periods, we will obtain a total of $A \times B$ momentum portfolios. The whole procedure to obtain momentum profit is *rolling* and *overlapping* in order to increase the power of the tests in accordance with [30].

In the first screening period t_1, we employ the individual price growth rates in the first formation period S_1 to sort the stocks. $S_1 = \left[s_1^{first}, s_1^{last} \right]$, s_1^{first} is the first period of S_1, and s_1^{last} is the last period of S_1. During the first formation period S_1, the expression for the individual price growth rates r_{i,S_1} is

$$r_{i,S_1} = \left(P_{i,s_1^{last}} - P_{i,s_1^{first}} \right) / P_{i,s_1^{first}} \tag{5}$$

where $P_{i,s_1^{first}}$ is the individual prices in s_1^{first}, and $P_{i,s_1^{last}}$ is the individual prices in s_1^{last} and $s_1^{last} = t_1 - 1$.

We screen $1/Z$ stocks with the highest r_{i,S_1} as the winner portfolio W_{S_1} and the $1/Z$ stocks with the lowest r_{i,S_1} as the loser portfolio L_{S_1}. The value of Z depends on the number of stocks. During the first holding period H_1, we calculate the individual price growth rates r_{i,H_1}:

$$r_{i,H_1} = \left(P_{i,h_1^{last}} - P_{i,h_1^{first}} \right) / P_{i,h_1^{first}} \tag{6}$$

where $P_{i,h_1^{first}}$ is the individual prices in h_1^{first}, h_1^{first} is the first period of H_1, $P_{i,h_1^{last}}$ is the individual prices in h_1^{last}, h_1^{last} is the last period of H_1, and $h_1^{first} = t_1 + 1$.

Then, we compute the returns of the winner portfolio W_{S_1} and the returns of the loser portfolio L_{S_1} in the first holding period.

$$R_{T_1}^{W_{S_1}} = \frac{1}{Q} \sum_{i=1}^{Q} r_{i,H_1}^{w_{S_1}} \tag{7}$$

$$R_{T_1}^{L_{S_1}} = \frac{1}{Q} \sum_{i=1}^{Q} r_{i,H_1}^{l_{S_1}} \tag{8}$$

where Q is the number of stocks within the winner and loser portfolios, $R_{T_1}^{W_{S_1}}$ is the winner portfolio returns in the first holding period, $r_{i,H_1}^{w_{S_1}}$ is the individual price growth rates of the winner stocks in the holding period, $R_{T_1}^{L_{S_1}}$ is the loser portfolio returns in the first holding period, $r_{i,H_1}^{l_{S_1}}$ is the individual price growth rates of the loser stocks in the holding period, and $T_1 = h_1^{last}$.

In the second screening period $t_2 (t_2 = t_1 + 1)$, we use the individual price growth rates in the second formation period S_2 to select the stocks; $S_2 = \left[s_1^{second}, s_1^{last} + 1 \right]$, s_1^{second} is the second period of S_1, and s_1^{last} is the last period of S_1. The individual price growth rates r_{i,S_2} in S_2 can be expressed as

$$r_{i,S_2} = \left(P_{i,s_1^{last}+1} - P_{i,s_1^{second}} \right) / P_{i,s_1^{second}} \tag{9}$$

where $P_{i,s_1^{second}}$ is the individual prices in s_1^{second}, and $P_{i,s_1^{last}+1}$ is the individual prices in $s_1^{last}+1$.

We still select the $1/Z$ stocks with the highest r_{i,S_2} as the winner portfolio W_{S_2} and the $1/Z$ stocks with the lowest r_{i,S_2} as the loser portfolio L_{S_2}. Within the second holding period H_2, we calculate the individual price growth rates r_{i,H_2} as follows:

$$r_{i,H_2} = \left(P_{i,h_1^{last}+1} - P_{i,h_1^{second}} \right) / P_{i,h_1^{second}} \tag{10}$$

where $H_2 = \left[h_1^{second}, h_1^{last}+1 \right]$, $P_{i,h_1^{second}}$ is the individual prices in h_1^{second}, h_1^{second} is the second period in H_1, $P_{i,h_1^{last}+1}$ is the individual prices in $h_1^{last}+1$, and h_1^{last} is the last period of H_1.

The portfolio returns of W_{S_2} and the portfolio returns of L_{S_2} in the second holding period are

$$R_{T_2}^{W_{S_2}} = \frac{1}{Q} \sum_{i=1}^{Q} r_{i,H_2}^{w_{S_2}} \tag{11}$$

$$R_{T_2}^{L_{S_2}} = \frac{1}{Q} \sum_{i=1}^{Q} r_{i,H_2}^{l_{S_2}} \tag{12}$$

where $R_{T_2}^{W_{S_2}}$ is the winner portfolio returns, $r_{i,H_2}^{w_{S_2}}$ is the individual price growth rates of winner stocks, $R_{T_2}^{L_{S_2}}$ is the loser portfolio returns, $r_{i,H_2}^{l_{S_2}}$ is the individual price growth rates of loser stocks, and $T_2 = h_1^{last}+1$.

After rolling n times in $t_n \, (t_n = t_1 + n - 1)$, we apply the individual price growth rates in S_n to sort the stocks; $S_n = \left[s_{n-1}^{second}, s_{n-1}^{last}+1 \right]$, s_{n-1}^{second} is the second period of S_{n-1}, and s_{n-1}^{last} is the last period of S_{n-1}. The individual price growth rates in S_n are expressed by

$$r_{i,S_n} = \left(P_{i,s_{n-1}^{last}+1} - P_{i,s_{n-1}^{second}} \right) / P_{i,s_{n-1}^{second}} \tag{13}$$

where $P_{i,s_{n-1}^{second}}$ is the individual prices in s_{n-1}^{second}, and $P_{i,s_{n-1}^{last}+1}$ is the individual prices in $s_{n-1}^{last}+1$.

We choose the $1/Z$ stocks with the highest r_{i,S_n} as the winner portfolio W_{S_n} and the $1/Z$ stocks with the lowest r_{i,S_n} as the loser portfolio L_{S_n}. The individual price growth rates r_{i,H_n} in H_n are expressed as

$$r_{i,H_n} = \left(P_{i,h_{n-1}^{last}+1} - P_{i,h_{n-1}^{second}} \right) / P_{i,h_{n-1}^{second}} \tag{14}$$

where $H_n = \left[h_{n-1}^{second}, h_{n-1}^{last}+1 \right]$, $P_{i,h_{n-1}^{second}}$ is the individual prices in h_{n-1}^{second}, h_{n-1}^{second} is the second period of H_{n-1}, $P_{i,h_{n-1}^{last}+1}$ is the individual prices in $h_{n-1}^{last}+1$, and h_{n-1}^{last} is the last period of H_{n-1}.

To obtain the portfolio returns of W_{S_n} and L_{S_n} in the holding period, we calculate

$$R_{T_n}^{W_{S_n}} = \frac{1}{Q} \sum_{i=1}^{Q} r_{i,H_n}^{w_{S_n}} \tag{15}$$

$$R_{T_n}^{L_{S_n}} = \frac{1}{Q} \sum_{i=1}^{Q} r_{i,H_n}^{l_{S_n}} \tag{16}$$

where $R_{T_n}^{W_{S_n}}$ is the winner portfolio returns, $r_{i,H_n}^{w_{S_n}}$ is the individual price growth rates of winner stocks, $R_{T_n}^{L_{S_n}}$ is the loser portfolio returns, $r_{i,H_n}^{l_{S_n}}$ is the individual price growth rates of loser stocks, and $T_n = h_{n-1}^{last} + 1$.

Finally, we create long positions for winner portfolios and short positions for loser portfolios. The momentum profit is

$$MP = \frac{1}{n} \sum_{g=1}^{n} \left(R_{T_g}^{W_{S_g}} - R_{T_g}^{L_{S_g}} \right) \tag{17}$$

where price sustainability is represented by a significantly positive momentum profit. By contrast, price reversal is addressed by a significantly negative momentum profit and reflects unsustainable stock prices.

3.4. Risk-Adjusted Momentum Profits

In this section, we follow [71,72] and use asset pricing models to adjust the risks for the momentum profit. The models we use are the capital asset pricing model of [32,33], Fama–French three-factor asset pricing model of [34], and the Chinese three-factor and four-factor asset pricing models from [37]. In accordance with [71,72], the intercept of an asset pricing model stands for the part of the momentum profit that remains after the rest has been explained by the risk pricing factors; thus, the intercept can be considered the risk-adjusted momentum profit.

$$(W - L)_{l,t} = \alpha_{l,C} + \beta_{l,mkt} MKT_t + u_{l,t} \tag{18}$$

$$(W - L)_{l,t} = \alpha_{l,FF} + \beta_{l,mkt} MKT_t + \beta_{l,smb,FF} SMB_{FF,t} + \beta_{l,hml} HML_t + u_{l,t} \tag{19}$$

$$(W - L)_{l,t} = \alpha_{l,CH} + \beta_{l,mkt} MKT_t + \beta_{l,smb,CH} SMB_{CH,t}^{3F} + \beta_{l,vmg} VMG_t + u_{l,t} \tag{20}$$

$$(W - L)_{l,t} = \alpha_{l,CH} + \beta_{l,mkt} MKT_t + \beta_{l,smb,CH} SMB_{CH,t}^{4F} + \beta_{l,vmg} VMG_t + \beta_{l,pmo} PMO_t + u_{l,t} \tag{21}$$

where $(W - L)_{l,t}$ is the time-series of winner-minus-loser return spreads under different levels of timely loss recognition, MKT_t refers to market returns in excess of risk-free rates, $SMB_{FF,t}$ is the size factor of [34], HML_t is the value factor of [34], $SMB_{CH,t}$ is the size factor of [37], VMG_t is the value factor of [37], and PMO_t is the turnover factor of [37]. In these models, the alpha, α_l, is the risk-adjusted momentum profit since the intercept is the part unexplained by the factors. In Appendices A and B, we describe the procedures to obtain the pricing factors from [34,37]. Moreover, we discuss the company characteristics in Appendix C. We also provide the connotations of price sustainability and reversal in Appendix D.

3.5. The Pseudo-Program for the Empirical Analysis

Let r_S be the formation price growth rate, f the asset pricing factor, α the risk-adjusted momentum profit, and I_{ML} the impact of manipulating losses using the judgments on MP and α across the groups based on TLR_t. Algorithm 1 depicts our analysis step by step, which sets up a more intuitive and applicable framework to investigate the effect of manipulating losses on price reversal and price sustainability.

Algorithm 1. The Impact of Manipulating Losses

0: **Begin algorithm.**

1: **For** each stock in the market, **perform**

$$TLR_t^E = \begin{cases} |\widehat{\varphi_2}| \times 100\% & \Delta E_{t-1} \geq 0 \\ |\widehat{\varphi_2} + \widehat{\varphi_3}| \times 100\% & \Delta E_{t-1} < 0 \end{cases}$$

$$TLR_t^A = \begin{cases} |\widehat{\gamma_2}| \times 100\% & CF_t \geq 0 \\ |\widehat{\gamma_2} + \widehat{\gamma_3}| \times 100\% & CF_t < 0 \end{cases}$$

    End for.

2: Perform sequential sorts: Sort the stocks using $TLR_t^E \vee TLR_t^A$ and go to step 5.

3: Perform simultaneous sorts: Sort the stocks using $TLR_t^E \vee TLR_t^A$ and r_S at the same time and go to step 5.

4: Perform inverse sequential sorts: Sort the stocks using r_S and go to step 6.

5: **For** each group based on TLR_t, **perform**

    Procedure a: Perform

$$MP = \frac{1}{n} \sum_{g=1}^{n} \left(R_{W,T_g} - R_{L,T_g} \right)$$

$$R_{W,T_g} - R_{L,T_g} = \alpha + b_1 f_{1,T} + b_2 f_{2,T} + \ldots + b_n f_{n,T} + e_T$$

    Procedure b: **If** $MP > 0$ and $t(MP)$ is significant

            or $\alpha > 0$ and $t(\alpha)$ is significant, **then**

            price sustainability appears.

            Else if $MP < 0$ and $t(MP)$ is significant

            or $\alpha < 0$ and $t(\alpha)$ is significant, **then**

            price reversal occurs.

            End if.

    End for.

6: **For** each group based on r_S, **perform**

    Procedure a: Sort the stocks using $TLR_t^E \vee TLR_t^A$.

    Procedure b: Go to step 5.

    End for.

7: **Return** I_{ML}.

8: **End algorithm.**

3.6. Data

This paper investigates the listed companies traded on the Shanghai and Shenzhen stock exchanges. Our data were collected from the China Stock Market and Accounting Research (CSMAR) database, which is a prestigious data provider for academic research on the Chinese stock market and from which we extracted the stock prices and financial reporting data, which are updated on both a daily and quarterly basis, respectively. The sample period ranged from January 2001 to March 2020 with over 3000 companies and covered almost all industries, including the agricultural sector, mining industry, manufacturing industry, energy industry, construction industry, wholesale industry, transportation industry, the financial sector, and real estate, etc.

The Shanghai and Shenzhen stock exchanges were established in the 1990s. At the outset, however, a well-established regulatory system for financial reporting was noticeably absent. According to [37], the listed companies applied their own financial reporting standards, and it was difficult to compare the financial reporting quality across companies. In the 2000s, however, the regulatory system was gradually developed, thereby enabling comparisons of financial reporting quality to take place. Hence, we were able to select our resulting sample.

In Table 1, we show the momentum profits in different testing periods. The classical formation period of the momentum portfolio is 6 months following [30]. Moreover, the holding periods are 6 months, 12 months, 24 months, and 36 months—e.g., [41,42,73].

Table 1. Momentum Profits in Different Holding Periods.

Panel A: Momentum Profits			Panel B: Alphas by 1F		
Holding	*MP*	*t*-stat	Holding	Alpha	*t*-stat
6	−0.053	−6.516	6	−0.054	−6.533
12	−0.079	−6.531	12	−0.079	−6.521
24	−0.171	−8.795	24	−0.173	−8.928
36	−0.252	−11.725	36	−0.252	−11.657
Panel C: Alphas by FF-3F			Panel D: Alphas by CH-3F		
Holding	Alpha	*t*-stat	Holding	Alpha	*t*-stat
6	−0.053	−6.412	6	−0.045	−4.303
12	−0.077	−6.261	12	−0.069	−4.449
24	−0.173	−8.737	24	−0.166	−6.650
36	−0.258	−11.778	36	−0.238	−8.788
Panel E: Alphas by CH-4F					
Holding	Alpha	*t*-stat			
6	−0.046	−3.256			
12	−0.075	−3.945			
24	−0.158	−4.843			
36	−0.228	−6.528			

Table 1 reports the momentum profits in different periods. The formation period of the momentum portfolio is 6 months. Furthermore, the holding period contains 6 months, 12 months, 24 months, and 36 months. We show the momentum profits, risk-adjusted momentum profits (Alphas) from the asset pricing models, and related *t*-statistics. 1F denotes the capital asset pricing model, FF-3F denotes the Fama-French three-factor asset pricing model, CH-3F denotes [37]'s three-factor asset pricing model, and CH-4F is the four-factor asset pricing model from [37].

From Table 1, we can see that the momentum profits of the Chinese stock market are significantly negative regardless of the lengths of the holding periods (the absolute *t*-statistics range from 6 to 12). Moreover, after adjustments for risk, the risk-adjusted momentum profits are also significantly negative since most of the absolute *t*-statistics for the alphas are higher than 3 or even higher than 6, regardless of the specifications of the asset pricing models. In addition, we recognize that longer holding periods elicit more severe price reversals. For instance, in Panel A, the absolute values of the negative momentum profits for the 6-month and 12-month periods are 0.053 and 0.079, respectively. However, the absolute values of the negative momentum profits become 0.171 and 0.252, respectively, for the 24-month and 36-month periods. These patterns prevail across all panels of Table 1 and indicate that the Chinese stock market embodies very severe price reversals. Hence, the later analyses in this paper turn to examining the effect of timely loss recognition on price reversal risks in the Chinese stock market.

4. Empirical Results

According to [47,48], corporate managers exhibit extreme incentives to manipulate losses and thus stabilize stock prices. However, even though the managers may temporarily achieve their goals, the truth will gradually be disclosed as time passes. The actual information will eventually be reflected in the stock prices. Manipulating losses will induce dramatic price increases and decreases. Hence, we contend that the manipulation of losses is supposedly connected to strong price reversals in the Chinese stock market.

In order to test the connection between manipulating losses and price reversal, we calculate the momentum profits as well as the momentum profits after risk-adjustments for various degrees of timely loss recognition. We first adopt sequential and inverse sequential sorts to classify stocks using timely loss recognition and formation price growth rates. In addition, we use simultaneous sorts to screen the stocks using timely loss recognition and formation price growth rates.

4.1. Dissections of Price Reversal Risks Using Sequential Sorts

This section includes the momentum profits under different levels of timely loss recognition. The classical 6-month periods are the lengths of the formation and holding periods for momentum portfolios in accordance with [30]. The stocks are first classified based on timely loss recognition. Within each group from previous sorts, we continue to sort the stocks using formation price growth rates. We perform the momentum algorithm for each group from these sorts to generate the momentum profits.

We use *t*-statistics to examine whether the momentum profit under each level of timely loss recognition differs from zero. In addition, we also employ the *GRS* statistic of [74] to perform joint tests. Hence, our empirical analysis both decodes the effect of timely loss recognition on companies and the market. The formula to compute the *GRS* statistic appears in Appendix E.

Table 2 reports the momentum profits (*MP*) and those after risk adjustments (Alphas) under different levels of timely loss recognition (*TLR*). We use the earnings-based timely loss recognition and accruals-based timely loss recognition of [38]. We first sort the stocks based on timely loss recognition and secondly sort the stocks based on formation price growth rates within the groups from the previous sorts. For each group, we compute the momentum profit and risk-adjusted momentum profit. 1F denotes the capital asset pricing model, FF-3F denotes the Fama-French three-factor asset pricing model, CH-3F denotes [37]'s three-factor asset pricing model, and CH-4F is the four-factor asset pricing model from [37]. We also present the related *t*-statistics and *GRS* statistics for the risk-adjusted momentum profits.

From Table 2, it is clear that timely loss recognition does not alter the reversal risks of the Chinese stock market. No matter how timely loss recognition changes, most of the momentum profits in the Chinese stock market are significantly negative (the absolute *t*-statistics are higher than 2 or even 4). These outcomes also appear among the risk-adjusted momentum profits. For all of the asset pricing models that we use, most of the risk-adjusted momentum profits remain significantly negative (the absolute *t*-statistics for the alphas exceed 2 or 3). Moreover, in Panels A and B, we use two proxies for timely loss recognition based on earnings and accruals in the detection process. One notable finding is that the stocks with low timely loss recognition give rise to the most severe price reversal risks since the absolute values of the negative momentum profits are the highest (the absolute values are 4.3% and 4.9%, respectively, in Panels A and B). These results are maintained after risk adjustments as most of the absolute values for the risk-adjusted negative momentum profits vary around 4%.

Table 2. Momentum Profits from Sequential Sorts.

Panel A: Earnings-Based *TLR* and Momentum Profits			
	High	**Middle**	**Low**
MP	−0.033	−0.024	−0.043
t-stat	−2.684	−2.101	−4.351
1F Alpha	−0.032	−0.024	−0.044
t-stat	−2.656	−2.079	−4.344
GRS		53.463	
FF-3F Alpha	−0.032	−0.023	−0.043
t-stat	−2.601	−2.031	−4.331
GRS		52.780	
CH-3F Alpha	−0.023	−0.012	−0.039
t-stat	−1.364	−0.722	−2.824
GRS		33.256	
CH-4F Alpha	−0.027	−0.012	−0.041
t-stat	−1.570	−0.736	−2.976
GRS		35.853	

Table 2. *Cont.*

	High	Middle	Low
Panel B: Accruals-based *TLR* and Momentum Profits			
MP	−0.044	−0.033	−0.049
t-stat	−3.237	−2.186	−3.599
1F Alpha	−0.044	−0.033	−0.049
t-stat	−3.190	−2.160	−3.605
GRS		247.126	
FF-3F Alpha	−0.044	−0.028	−0.048
t-stat	−3.121	−1.794	−3.355
GRS		287.352	
CH-3F Alpha	−0.012	0.004	−0.019
t-stat	−0.557	0.162	−0.845
GRS		87.853	
CH-4F Alpha	−0.012	0.003	−0.019
t-stat	−0.514	0.131	−0.848
GRS		83.747	

4.2. Dissections of Price Reversal Risks Using Inverse Sequential Sorts

We first sort the stocks according to the formation price growth rates and rank the stocks based on timely loss recognition in each group from prior sorts. Similarly, we run the momentum algorithm for each group from these sorts to compute the momentum profit. The risk-adjusted momentum profits from the asset pricing models are also presented.

Table 3 reports the momentum profits (*MP*) and those after risk adjustments (Alphas) under different levels of timely loss recognition (*TLR*). We use the earnings-based timely loss recognition and accruals-based timely loss recognition of [38]. We first sort the stocks based on formation price growth rates and secondly sort the stocks based on timely loss recognition within the groups from the previous sorts. For each group, we compute the momentum profit and risk-adjusted momentum profit. 1F denotes the capital asset pricing model, FF-3F denotes the Fama-French three-factor asset pricing model, CH-3F denotes [37]'s three-factor asset pricing model, and CH-4F is the four-factor asset pricing model from [37]. We also present the related *t*-statistics and *GRS* statistics for the risk-adjusted momentum profits.

Table 3. Momentum Profits from Inverse Sequential Sorts.

	High	Middle	Low
Panel A: Earnings-Based *TLR* and Momentum Profits			
MP	−0.033	−0.033	−0.039
t-stat	−2.874	−2.847	−3.698
1F Alpha	−0.033	−0.033	−0.039
t-stat	−2.854	−2.843	−3.714
GRS		39.496	
FF-3F Alpha	−0.032	−0.033	−0.039
t-stat	−2.806	−2.797	−3.660
GRS		37.962	
CH-3F Alpha	−0.023	−0.020	−0.037
t-stat	−1.457	−1.217	−2.475
GRS		22.663	
CH-4F Alpha	−0.026	−0.020	−0.039
t-stat	−1.632	−1.218	−2.651
GRS		25.927	

Table 3. *Cont.*

Panel B: Accruals-based *TLR* and Momentum Profits			
	High	**Middle**	**Low**
MP	−0.024	−0.033	−0.035
t-stat	−1.174	−2.165	−2.130
1F Alpha	−0.025	−0.033	−0.035
t-stat	−1.202	−2.134	−2.114
GRS		160.713	
FF-3F Alpha	−0.020	−0.028	−0.032
t-stat	−1.000	−1.735	−1.934
GRS		137.356	
CH-3F Alpha	0.029	0.003	0.010
t-stat	0.914	0.140	0.396
GRS		31.948	
CH-4F Alpha	0.032	0.002	0.011
t-stat	1.022	0.081	0.421
GRS		41.469	

We report the results from the inverse sequential sorts in Table 3. The results are basically the same as the previous results. Within the two panels, the momentum profits of the stocks with low timely loss recognition have absolute values ranging from 3% to 5% and are significantly negative with absolute *t*-statistics of over 2. Most of the results are maintained after risk adjustments using asset pricing models since the absolute *t*-statistics of the alphas range from 1.9 to 3.714. The findings from both Tables 2 and 3 demonstrate that immunity against price reversal risks cannot be obtained through the manipulation of losses. However, the situation will deteriorate as a result of more drastic reversal risks when the companies become more involved in the process of manipulating losses. This implication also echoes the quote from *The Commentary of Zuo*.

4.3. Dissections of Price Reversal Risks Using Simultaneous Sorts

The previous dissections regarding the effect of manipulating losses on price reversals are based on the sorts on stocks using specific orders, while the empirical results may behave differently if we sort the stocks without any orders. Consequently, in this section, we use simultaneous sorts on timely loss recognition and the formation price growth rates. Within each group from the intersections between these sorts, we employ the momentum algorithm to obtain the momentum profits. The formation and holding periods for the momentum portfolios are still the classical 6-month periods.

Table 4 reports the momentum profits (*MP*) and those after risk adjustments (Alphas) under different levels of timely loss recognition (*TLR*). We use the earnings-based timely loss recognition and accruals-based timely loss recognition of [38]. We simultaneously sort the stocks based on timely loss recognition and the formation price growth rates. For each group resulting from these sorts, we compute the momentum profit and risk-adjusted momentum profit. 1F denotes the capital asset pricing model, FF-3F denotes the Fama-French three-factor asset pricing model, CH-3F denotes [37]'s three-factor asset pricing model, and CH-4F is the four-factor asset pricing model from [37]. We also present the related *t*-statistics and *GRS* statistics for the risk-adjusted momentum profits.

In Table 4, the stocks with low timely loss recognition from Panels A and B still give rise to significantly negative momentum profits and the highest absolute values (the absolute momentum profits are still over 4%), suggesting that these stocks encounter the most severe price reversal risks (many absolute *t*-statistics exceed 2). In addition, the results are maintained after the risk adjustments by the asset pricing models since most of the risk-adjusted momentum profits are also significantly negative and have the highest absolute values. To be specific, the absolute risk-adjusted momentum profits mainly lie between 4% and 4.8%, whereas most of the absolute *t*-statistics for the alphas range from 2 to 4. These findings verify the perceptions from Tables 2 and 3. That is, the listed companies

that aggressively manipulate losses will face more dramatic price reversal risks than other companies.

Table 4. Momentum Profits from Simultaneous Sorts.

	High	Middle	Low
Panel A: Earnings-Based *TLR* and Momentum Profits			
MP	−0.034	−0.026	−0.040
t-stat	−2.859	−2.258	−3.893
1F Alpha	−0.034	−0.026	−0.040
t-stat	−2.842	−2.243	−3.933
GRS		44.810	
FF-3F Alpha	−0.033	−0.026	−0.040
t-stat	−2.801	−2.197	−3.888
GRS		43.621	
CH-3F Alpha	−0.024	−0.010	−0.041
t-stat	−1.462	−0.606	−2.868
GRS		34.708	
CH-4F Alpha	−0.026	−0.011	−0.042
t-stat	−1.624	−0.671	−2.936
GRS		36.111	
Panel B: Accruals-based *TLR* and Momentum Profits			
	High	Middle	Low
MP	−0.041	−0.031	−0.047
t-stat	−3.090	−2.046	−3.585
1F Alpha	−0.041	−0.031	−0.047
t-stat	−3.049	−2.023	−3.561
GRS		249.117	
FF-3F Alpha	−0.041	−0.026	-0.048
t-stat	−2.951	−1.660	-3.422
GRS		325.618	
CH-3F Alpha	−0.007	0.007	−0.019
t-stat	−0.342	0.306	−0.866
GRS		115.843	
CH-4F Alpha	−0.007	0.006	−0.019
t-stat	−0.326	0.241	−0.865
GRS		112.671	

4.4. Summary

Existing studies on the US and European markets, such as [65,67,68], reveal that manipulating losses will induce price crashes. Chinese-listed companies with drastic manipulations of losses are easily disturbed by very severe price reversals, suggesting that price increases may possibly emerge after the crashes (our results of Tables 2–4). Accordingly, the managers of the Chinese-listed companies can achieve the goal of influencing price trends through the manipulation of losses. Moreover, this discussion also documents that the impact of manipulating losses on stock prices greatly differs from that in the US and European markets.

To be specific, by using Table 2 as an example, this paper finds that the listed companies with low timely loss recognition have significantly negative momentum profit (the absolute *t*-statistic is 4.351), and the negative momentum profit has the highest absolute value of 4.3%. Therefore, when considering the manipulation of losses, the stock prices in the Chinese market do not just decrease but exhibit price reversals. From Tables 3 and 4, it is observed that the listed companies with low timely loss recognition have significantly negative momentum profits, with absolute *t*-statistics ranging from 2.13 to 3.893. The absolute values of the negative momentum profits lie between 3.5% and 4.7%, which are always the highest values compared to those for other companies. These results suggest

that companies with aggressive manipulations of losses encounter far more severe price reversals, thereby exposing traders to exceedingly high uncertainty and risk.

In our framework, we employ the Chinese three-factor and four-factor asset pricing models from [37] that consider a characteristic effect regarding backdoor listings in the Chinese stock market. After using these asset pricing models to adjust for risk, our results are not altered. For instance, in Table 2, the risk-adjusted momentum profits of the companies with low timely loss recognition from the Chinese three-factor model are still significantly negative (the absolute *t*-statistic is 2.824). The negative momentum profit has the highest absolute value of 3.9%.

Likewise, from Tables 3 and 4, we see that the risk-adjusted momentum profits of the companies with low timely loss recognition from these two asset pricing models of [39] are significantly negative since the absolute *t*-statistics lie between 2.475 and 2.936. The negative risk-adjusted momentum profits have absolute values ranging from 3.7% to 4.2% and are also the largest. In short, the results from the momentum profits and risk-adjusted momentum profits suggest that great loss manipulation is accompanied by great price reversal.

5. Robustness Tests

We perform the robustness tests by adopting a two-step process in this paper. First of all, we follow [30] to control for the calendar effect in the new year. This procedure confirms whether the impact of manipulating losses on reversal risk remains strong against the calendar effect. Second, we propose individual reversal strength for each stock and then calculate the correlation coefficients between the reversal strength and timely loss recognition.

5.1. Controlling for the Calendar Effect

Reference [30] dissects how the new-year effect in January, i.e., the January effect, influences the momentum profits in the US. They find that it is more possible to see significantly negative momentum profits in January. In China, the new-year holiday generally comes into its own in the period between late January and some time in February. Besides, the financial data for calculating the timely loss recognition is released quarterly in China. Therefore, we study the calendar effect regarding the period in the first quarter and the period ranging from the second to the fourth quarters. These analyses will help us understand whether the impact of manipulating losses remains after considering the calendar effect.

Table 5 reports the momentum profits (*MP*) and related *t*-statistics considering the calendar effect. The momentum portfolios include those from sequential sorts, inverse sequential sorts, and simultaneous sorts based on past price growth rates and timely loss recognition. We use the earnings-based timely loss recognition and accruals-based timely loss recognition of [38]. After generating the time series of winner-minus-loser return spreads, we then screen out those falling into the first quarter of each year as well as those in the period extending from the second to the fourth quarters. The momentum profits and *t*-statistics are thus calculated.

From Table 5, after controlling for the calendar effect, the stocks with low timely loss recognition still encounter the most severe price reversals, since their significantly negative momentum profits have the highest absolute values. For instance, in Panel A, when considering the first quarter, the momentum profit of these stocks from the sequential momentum portfolio is −0.048 with an absolute *t*-statistic of over 2. However, the absolute values of the negative momentum profits of other stocks in the first quarter from the sequential momentum portfolio are lower than 0.048, and the absolute *t*-statistics are below 1.5. These results remain despite the specifications of the momentum portfolios and the proxies for timely loss recognition.

Table 5. Momentum Profits Considering the Calendar Effect.

Panel A: Earnings-Based *TLR* and Momentum Profits				
		Sequential	Inverse Sequential	Simultaneous
MP with High *TLR*	1st Quarter	−0.029	−0.031	−0.031
	t-stat	−1.165	−1.230	−1.282
	2nd to 4th Quarters	−0.034	−0.034	−0.035
	t-stat	−2.402	−2.579	−2.539
MP with Middle *TLR*	1st Quarter	−0.035	−0.031	−0.030
	t-stat	−1.393	−1.267	−1.267
	2nd to 4th Quarters	−0.021	−0.033	−0.025
	t-stat	−1.633	−2.530	−1.885
MP with Low *TLR*	1st Quarter	−0.048	−0.036	−0.043
	t-stat	−2.269	−1.586	−1.987
	2nd to 4th Quarters	−0.042	−0.040	−0.039
	t-stat	−3.707	−3.317	−3.338
Panel B: Accruals-based *TLR* and Momentum Profits				
		Sequential	Inverse Sequential	Simultaneous
MP with High *TLR*	1st Quarter	−0.019	0.004	0.002
	t-stat	−1.098	0.469	0.118
	2nd to 4th Quarters	−0.046	−0.027	−0.045
	t-stat	−3.143	−1.191	−3.151
MP with Middle *TLR*	1st Quarter	−0.014	−0.014	−0.010
	t-stat	−0.526	−0.480	−0.533
	2nd to 4th Quarters	−0.034	−0.035	−0.033
	t-stat	−2.127	−2.109	−2.001
MP with Low *TLR*	1st Quarter	−0.037	−0.034	−0.039
	t-stat	−0.943	−0.916	−0.839
	2nd to 4th Quarters	−0.050	−0.035	−0.048
	t-stat	−3.438	−1.980	−3.439

In addition, Table 5 reveals a different calendar effect from that of [30]. That is, the price reversal becomes weaker and insignificant in the holiday period during the first quarter in the Chinese stock market. In Panel A, most of the absolute *t*-statistics for the negative momentum profits are between 1.165 and 1.586 in the first quarter. By contrast, within the periods ranging from the second to the fourth quarters, the majority of the absolute *t*-statistics exceed 2 or even 3. These outcomes persist in Panel B. However, the study by [30] for the US market is indicative of significant price reversal in January. Consequently, our findings demonstrate that there is a distinct difference between the Chinese and US markets.

5.2. Alternative Timely Loss Recognition and Reversal Strength

Note that the proxies for timely loss recognition in the previous analyses come from models of [38]. In this section, we implement an alternative proxy for timely loss recognition from [44] to check the robustness of the findings. We recognize that the effect of manipulating losses on price reversal risk is insensitive to the choice of the proxy for timely loss recognition. The detailed results are shown in Appendix F.

In accordance with the concepts of [30] that address price reversal, we propose reversal strength to further verify the previous findings. Reversal strength is an individual measure for each stock since timely loss recognition is a firm-specific variable. Hence, the correlation analysis between reversal strength and timely loss recognition can be performed.

Let $r_{i,S}$ denote the individual price growth rates over a formation period and $r_{i,H}$ be the individual price growth rates over a holding period. Based on a rolling procedure, the individual reversal strength (*RS*) is defined as follows:

$$RS_{i,H} \begin{cases} r_{i,S} - r_{i,H}, \text{ If } r_{i,S} > 0 \wedge r_{i,H} < 0 \\ r_{i,H} - r_{i,S}, \text{ If } r_{i,S} < 0 \wedge r_{i,H} > 0 \\ -(r_{i,S} + r_{i,H}), \text{ If } r_{i,S} > 0 \wedge r_{i,H} > 0 \\ r_{i,S} + r_{i,H}, \text{ If } r_{i,S} < 0 \wedge r_{i,H} < 0 \end{cases} \tag{22}$$

where a higher value of *RS* suggests more severe individual reversal strength, and the lengths of the formation and holding periods follow the classical 6-month periods of [30,75].

After obtaining the time-series of individual reversal strength for each stock, we continue to calculate the time-series of timely loss recognition for every stock. We calculate the time-series average of individual reversal strength and timely loss recognition for each stock. The stocks are sorted into 30 groups based on average timely loss recognition or individual reversal strength. Within each group from the sorts on timely loss recognition or individual reversal strength, we calculate the cross-section correlation coefficient between the timely loss recognition and reversal strength in each group. The results are shown in Figure 1.
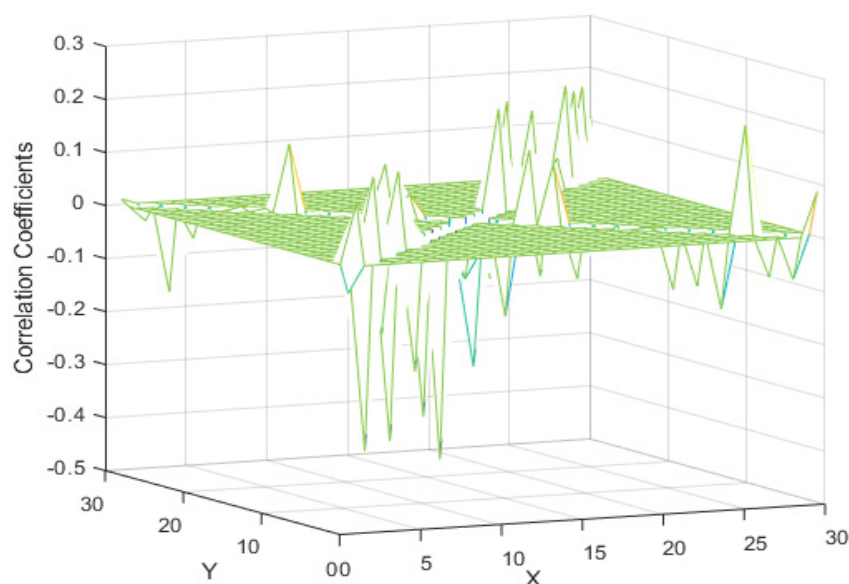

Figure 1. Correlation Coefficients between Timely Loss Recognition and Reversal Strength. The values above or below the positive 45° angle line are the correlation coefficients of the groups from the sorts on timely loss recognition. The values above or below the negative 45° angle line are the correlation coefficients of the groups from the sorts on reversal strength. X denotes the groups from the sorts on reversal strength, and Y denotes the groups from the sorts on timely loss recognition.

From Figure 1, we can see that most of the correlation coefficients within the groups from the sorts on timely loss recognition are negative, suggesting that timely loss recognition and individual reversal strength are negatively correlated and that stocks with low timely loss recognition are very likely to encounter price reversals. When it comes to the coefficients within the groups from the sorts on individual reversal strengths, it is also found that some of them are negative. The negative correlation between timely loss recognition and individual reversal strength demonstrates that greater manipulations of losses cause more drastic price reversals. As in the research of [76,77], what we perceive in this section implies that manipulating losses contributes to the uncertainty in the Chinese market. In addition, since sustainability is a crucial issue in financial economics research—e.g., [78–81]—this finding suggests that manipulating losses impedes the sustainable development of the Chinese market.

6. Conclusions

This paper determines the important connection between the manipulation of losses and price reversals in the Chinese stock market. Our results imply that companies with low timely loss recognition give rise to the most significantly negative momentum profit of −0.049 and *t*-statistic of −3.599 as shown in Table 2. Tables 3 and 4 again show that these companies produce the most significantly negative momentum profits, and most of the absolute *t*-statistics exceed 2 or even 3. These statistics of our data indicate that the companies with low timely loss recognition are characterized by far more severe price reversals than other companies. These companies aggressively manipulate their losses and do not recognize the losses at the appropriate time. However, manipulating the financial information cannot attenuate the price reversals but induces more obvious price risks.

Studies by [65,67,68] on the US and European markets suggest that manipulating losses elicits price crashes. However, they do not realize that latent price reversals may exist. As clarified by the outcomes in Table 3, intensive manipulations result in a much more negative momentum profit of −0.039 with an absolute *t*-statistic of over 3.6. Hence, it is very possible for stock prices to increase after the crashes disappear, indicating the presence of price reversals. This finding further enriches the effect of manipulating losses on stock prices.

To confirm the robustness of our results, we apply asset pricing models from [34,37] to adjust the risks for the negative momentum profits. Our empirical inference remains the same since the negative risk-adjusted momentum profits for the companies with low timely loss recognition are significant with absolute *t*-statistics ranging between 2 and 4. These outcomes indicate that the influence of manipulating losses on price reversal remains stable in spite of the risk adjustments.

Reference [30] finds that price reversals are more evident during the new-year holiday. Therefore, we follow them by examining whether the finding is maintained when controlling for this calendar effect. After considering the calendar effect, our finding still exists, because the absolute *t*-statistics of the negative momentum profits for these companies exceed 2 or even 3.

In addition, we also discover that the companies with high timely loss recognition still cannot be free from price reversals, although they tend to engage in fewer manipulations of losses. The companies with high timely loss recognition have a significantly negative momentum profit of −0.034 with an absolute *t*-statistic of −2.859, shown in Table 4. The magnitudes of their reversals are smaller than those of the companies with low timely loss recognition. Furthermore, the alphas from Chinese three-factor and four-factor asset pricing models further show that the less aggressive manipulation of losses results in less severe price reversals. Consequently, timely loss recognition is negatively related to the magnitudes of the price reversals.

One issue remaining in this paper concerns the perspective of industry. For instance, listed companies in the high-technology industry are required to devote more resources to R&D activities—e.g., [82–85]. Compared to other companies, there is an increasing likelihood that these companies will encounter accounting losses and thus seek to manipulate those losses—e.g., [86–89]. Hence, an investigation regarding the effect of manipulating losses in different industries would certainly be valuable for future research.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Size and Value Factors

According to [34], in June of each year t, we sort the stocks into big and small groups based on company size. Synchronously, we sort the stocks into high, middle, and low groups based on the book-to-market at the end of year $t-1$. The intersections between these sorts generate six value-weighted portfolios. We calculate the monthly value-weighted returns for these portfolios from July of year t to June of year $t+1$. The Fama–French size and value factors are calculated as follows:

$$SMB_{FF,t} = \frac{R_{p,t}^{S,HBM} + R_{p,t}^{S,MBM} + R_{p,t}^{S,LBM}}{3} - \frac{R_{p,t}^{B,HBM} + R_{p,t}^{B,MBM} + R_{p,t}^{B,LBM}}{3} \tag{A1}$$

$$HML_t = \frac{R_{p,t}^{HBM,S} + R_{p,t}^{HBM,B}}{2} - \frac{R_{p,t}^{LBM,S} + R_{p,t}^{LBM,B}}{2} \tag{A2}$$

where $R_{p,t}$ denotes value-weighted returns, S denotes small size, B denotes big size, HBM denotes high book-to-market, MBM denotes middle book-to-market, LBM denotes low book-to-market, $SMB_{FF,t}$ is the size factor, and HML_t is the value factor.

Appendix B. Size, Value, and Turnover Factors

The asset pricing models in [37] include three-factor and four-factor models. In their three-factor model, the size and value factors are constructed as follows. In each month $t-1$, we use company size to sort the stocks into big and small groups. We synchronously classify the stocks into high, middle, and low groups based on earnings-to-price. Since earnings are released semi-annually or quarterly in China, we use the most recent data prior to month $t-1$. We divide the most recent earnings by company size for month $t-1$ to obtain the earnings-to-price in month $t-1$. The above sorts give rise to six groups through their intersections. According to [37], the size and value factors for the three-factor model are calculated as follows:

$$SMB_{CH,t}^{3F} = \frac{R_{p,t}^{S,HEP} + R_{p,t}^{S,MEP} + R_{p,t}^{S,LEP}}{3} - \frac{R_{p,t}^{B,HEP} + R_{p,t}^{B,MEP} + R_{p,t}^{B,LEP}}{3} \tag{A3}$$

$$VMG_t = \frac{R_{p,t}^{HEP,S} + R_{p,t}^{HEP,B}}{2} - \frac{R_{p,t}^{LEP,S} + R_{p,t}^{LEP,B}}{2} \tag{A4}$$

where $R_{p,t}$ refers to the value-weighted returns, S is small size, B is big size, HEP is high earnings-to-price, MEP is middle earnings-to-price, LEP is low earnings-to-price, $SMB_{CH,t}^{3F}$ is the size factor of the three-factor model, and VMG_t is the value factor of the three-factor model.

To acquire the factors for the four-factor model, the stocks are classified in the same manner as those for the three-factor model. The stocks are also classified based on company size into two groups in month $t-1$. Moreover, we synchronously sort them into three groups based on the 1-month abnormal turnover of month $t-1$. The intersections again engender six groups, and we arrive at the following equations:

$$SMB_{CH,t}^{AT} = \frac{R_{p,t}^{S,HAT} + R_{p,t}^{S,MAT} + R_{p,t}^{S,LAT}}{3} - \frac{R_{p,t}^{B,HAT} + R_{p,t}^{B,MAT} + R_{p,t}^{B,LAT}}{3} \tag{A5}$$

$$PMO_t = \frac{R_{p,t}^{LAT,S} + R_{p,t}^{LAT,B}}{2} - \frac{R_{p,t}^{HAT,S} + R_{p,t}^{HAT,B}}{2} \tag{A6}$$

$$SMB_{CH,t}^{4F} = \frac{SMB_{CH,t}^{3F} + SMB_{CH,t}^{AT}}{2} \tag{A7}$$

where *HAT* is high 1-month abnormal turnover, *MAT* is middle 1-month abnormal turnover, *LAT* is low 1-month abnormal turnover, $SMB_{CH,t}^{4F}$ is the size factor of the four-factor model, and PMO_t is the turnover factor of the four-factor model. The value factor in the four-factor model is the same as that in the three-factor model.

Appendix C. Company Characteristics

We recall from the previous sections addressing the asset pricing models that we obtain size, value, and turnover factors from [34,37]. Hence, this section provides the definitions of firm characteristics for the generation of factors. First of all, company size is the product of the stock price and the number of shares outstanding. Second, there are two value metrics, including earnings-to-price and book-to-market. We divide earnings by company size to calculate the earnings-to-price, and earnings are net profit in excess of nonrecurring gains or losses. Book-to-market is the ratio of shareholder equity to company size. Third, 1-month abnormal turnover is used to acquire the turnover factor. The average of daily turnover in the past 20 days is divided by the average of daily turnover in the past 250 days to produce 1-month abnormal turnover.

Appendix D. The Connotations of Price Sustainability and Reversal

The momentum profit of [30] is calculated as

$$MP = \frac{1}{n} \sum_{g=1}^{n} \left(R_{W,T_g} - R_{L,T_g} \right) \tag{A8}$$

where R_{W,T_g} refers to the future price growth rates of winner stocks and R_{L,T_g} to the future price growth rates of loser stocks. The winner stocks are characterized by price increases in the past, while loser stocks exhibit price decreases in the past.

From the formula for momentum profit, a significantly positive momentum profit suggests that the winner stocks will continue to experience price increases in the future, and the loser stocks will still be characterized by price decreases. That is, a significantly positive momentum profit indicates price sustainability.

By contrast, a significantly negative momentum profit represents the future price decreases of winner stocks and the price increases of loser stocks. In other words, a significantly negative momentum profit implies price reversal.

Momentum profit is an intuitive tool for exploring price sustainability and reversal. However, its computation does not consider the role of asset risks, which requires a suitable model to adjust risks. According to [31], the multifactor asset pricing model plays a useful role in obtaining the risk-adjusted momentum profit. By letting $f_{1,T}$, $f_{2,T}$, ..., $f_{n,T}$ be the risk pricing factors, the risk-adjusted momentum profit is derived from the model

$$R_{W,T_g} - R_{L,T_g} = \alpha + b_1 f_{1,T} + b_2 f_{2,T} + \ldots + b_n f_{n,T} + e_T \tag{A9}$$

where $R_{W,T_g} - R_{L,T_g}$ is the basis of [30]'s momentum profit. If $R_{W,T_g} - R_{L,T_g}$ is explained by the risk factors and the intercept is significantly different from zero, there will be unexplained momentum profit. Accordingly, α can be the risk-adjusted momentum profit—e.g., [31,71].

Appendix E. *GRS* Tests

In this paper, the intercept in the asset pricing model is the risk-adjusted momentum profit, and the *t*-statistic dissects whether it is different from zero for each level of timely loss recognition. Therefore, we implement the *GRS* statistic of [74] to test whether the risk-adjusted momentum profits under all levels of timely loss recognition jointly differ from zero. The calculations for the *GRS* statistic are as follows:

$$GRS = \left(\frac{T}{N}\right)\left(\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{\alpha}'\widehat{\Sigma_{\hat{u}}}^{-1}\hat{\alpha}}{1+\overline{\psi}'\widehat{\Omega}^{-1}\overline{\psi}}\right] \sim F(N, T-N-L) \tag{A10}$$

where T is the length of the sample period, N is the number of winner-minus-loser return spreads series, L is the number of pricing factors, $\hat{\alpha}$ is an $N \times 1$ vector of regression intercepts, $\widehat{\Sigma_{\hat{u}}}$ is an $N \times N$ covariance matrix of regression residual, $\overline{\psi}$ is an $L \times 1$ vector of factor means, and $\widehat{\Omega}$ is an $L \times L$ covariance matrix of factors.

Appendix F. Timely Loss Recognition

This appendix describes the timely loss recognition from [44] and reports the results of momentum portfolios from sequential, inverse sequential, and simultaneous sorts. The model for timely loss recognition of [44] proceeds in the following period-by-period piecewise linear cross-section regression.

$$\begin{aligned}
\frac{E_{i,t}}{ME_{i,t-1}} = a_{1,t} + \quad & a_{2,t}DR_{i,t} + R_{i,t}\left[\delta_{1,t} + \delta_{2,t}ln(TA_{i,t}) + \delta_{3,t}\frac{ME_{i,t}}{BE_{i,t}} + \delta_{4,t}\frac{LTD_{i,t}}{TA_{i,t}}\right] \\
& + \left[\phi_{1,t} + \phi_{2,t}ln(TA_{i,t}) + \phi_{3,t}\frac{ME_{i,t}}{BE_{i,t}} + \phi_{4,t}\frac{LTD_{i,t}}{TA_{i,t}}\right] \\
& + \left[\xi_{1,t}ln(TA_{i,t}) + \xi_{2,t}\frac{ME_{i,t}}{BE_{i,t}} + \xi_{3,t}\frac{LTD_{i,t}}{TA_{i,t}} + \xi_{4,t}DR_{i,t}ln(TA_{i,t})\right. \\
& \left. + \xi_{5,t}DR_{i,t}\frac{ME_{i,t}}{BE_{i,t}} + \xi_{6,t}DR_{i,t}\frac{LTD_{i,t}}{TA_{i,t}}\right] + u_{i,t}
\end{aligned} \tag{A11}$$

$$\widehat{a_{3,t}} = \widehat{\delta_{1,t}} + \widehat{\delta_{2,t}}ln(TA_{i,t}) + \widehat{\delta_{3,t}}\frac{ME_{i,t}}{BE_{i,t}} + \widehat{\delta_{4,t}}\frac{LTD_{i,t}}{TA_{i,t}} \tag{A12}$$

$$\widehat{a_{4,t}} = \widehat{\phi_{1,t}} + \widehat{\phi_{2,t}}ln(TA_{i,t}) + \widehat{\phi_{3,t}}\frac{ME_{i,t}}{BE_{i,t}} + \widehat{\phi_{4,t}}\frac{LTD_{i,t}}{TA_{i,t}} \tag{A13}$$

$$TLR_{i,t}^{KW} = \begin{cases} |\widehat{a_{3,t}}| & R_{i,t} \geq 0 \\ |\widehat{a_{3,t}} + \widehat{a_{4,t}}| & R_{i,t} < 0 \end{cases} \tag{A14}$$

where $E_{i,t}$ is earnings of stock i in period t, $ME_{i,t-1}$ is the lagged market capitalization, $TA_{i,t}$ is total assets, $BE_{i,t}$ is book equity, $LTD_{i,t}$ is long-term debt, $R_{i,t}$ is cumulative returns, and $DR_{i,t}$ is the dummy variable taking value of 1 when cumulative returns are negative and zero otherwise.

The momentum profits and risk-adjusted momentum profits from asset pricing models are reported in Table A1. We confirm the previous findings using the timely loss recognition of [44].

Table A1 reports the momentum profits (*MP*) and those after risk adjustments using asset pricing models (Alphas). The proxy for timely loss recognition originates from [44]. 1F denotes the capital asset pricing model, FF-3F denotes the Fama–French three-factor asset pricing model, CH-3F denotes [37]'s three-factor asset pricing model, and CH-4F is the four-factor asset pricing model from [37]. We also present the related *t*-statistics and *GRS* statistics for the risk-adjusted momentum profits.

From Table A1, we can see that the stocks with low timely loss recognition still give rise to significantly negative momentum profits regardless of the momentum portfolios using sequential, inverse sequential, and simultaneous sorts. For instance, in Panel A, the stocks with low timely loss recognition have a significantly negative momentum profit of −0.032 with an absolute *t*-statistic of 2.282. In addition, the risk-adjusted momentum profits from the Chinese asset pricing models of [37] remain significantly negative and have the highest absolute value. To be concrete, the risk-adjusted momentum profit from the Chinese three-factor model is −0.045 with a *t*-statistic of −2.482. Furthermore, the risk-adjusted momentum profit from the Chinese four-factor model is also −0.045 (the absolute *t*-statistic is higher than 2).

Table A1. The Momentum Profits under Different Levels of Timely Loss Recognition.

Panel A: Sequential Sorts				Panel B: Inverse Sequential Sorts			
	High	**Middle**	**Low**		**High**	**Middle**	**Low**
MP	−0.036	−0.026	−0.032	*MP*	−0.039	−0.028	−0.031
t-stat	−2.823	−1.793	−2.282	*t*-stat	−2.721	−1.841	−2.377
1F Alpha	−0.036	−0.026	−0.032	1F Alpha	−0.039	−0.028	−0.030
t-stat	−2.799	−1.794	−2.261	*t*-stat	−2.690	−1.855	−2.342
GRS		43.731		*GRS*		41.053	
FF-3F Alpha	−0.038	−0.029	−0.034	FF-3F Alpha	−0.040	−0.030	−0.033
t-stat	−2.850	−1.940	−2.417	*t*-stat	−2.698	−1.986	−2.548
GRS		46.822		*GRS*		44.333	
CH-3F Alpha	−0.029	−0.027	−0.045	CH-3F Alpha	−0.026	−0.036	−0.044
t-stat	−1.648	−1.386	−2.482	*t*-stat	−1.344	−1.761	−2.591
GRS		40.470		*GRS*		51.071	
CH-4F Alpha	−0.035	−0.033	−0.045	CH-4F Alpha	−0.037	−0.044	−0.044
t-stat	−2.073	−1.684	−2.439	*t*-stat	−2.002	−2.168	−2.529
GRS		41.067		*GRS*		47.777	

Panel C: Simultaneous Sorts		
	High	**Middle**	**Low**
MP	−0.040	−0.025	−0.030
t-stat	−2.970	−1.677	−2.212
1F Alpha	−0.040	−0.025	−0.030
t-stat	−2.940	−1.672	−2.181
GRS		47.746	
FF-3F Alpha	−0.041	−0.027	−0.032
t-stat	−2.963	−1.845	−2.333
GRS		49.192	
CH-3F Alpha	−0.029	−0.026	−0.043
t-stat	−1.623	−1.324	−2.442
GRS		39.509	
CH-4F Alpha	−0.039	−0.033	−0.045
t-stat	−2.289	−1.649	−2.513
GRS		44.639	

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