Earnings Management and Price Informativeness*

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Abstract

We address the puzzling finding by Carpenter, Lu, and Whitelaw (2021) that stock prices in the Chinese A-share market are as informative about future earnings as those in the U.S. market. Contrary to their interpretation, we argue that, in the presence of prevalent earnings management and less sophisticated investors, firms may manage earnings to align with expectations reflected in their stock valuations. Our analysis reveals that Chinese stocks with higher valuations tend to exhibit higher earnings in the subsequent three years, but this does not translate to increased payouts to shareholders and the higher earnings reverse in the long run. Additionally, we provide evidence of earnings management through non-recurring gains and losses (NRGL), leveraging the 20192020 reform on delisting rules as an exogenous shock to earnings management practices.

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1 Introduction

Bai, Philippon, and Savov (2016) develop a method to gauge price informativeness in stock markets. They run cross-sectional regressions of future earnings on current firm market capitalization, and the predicted variation of market capitalization measures the extent to which stock prices contain information about firms' future profits. Carpenter, Lu, and Whitelaw (2021) apply this method to the Chinese A-share market and find that the Chinese stock prices are as informative as their US counterparts.

Their finding is surprising, given that the Chinese stock market is known for being highly volatile and speculative (e.g., Hu, Pan, and Wang, 2021). Also, previous studies show that Chinese A-share listed firms are subject to severe governance issues (e.g., Allen, Qian, Shan, and Zhu, 2024). In particular, there is ample evidence of earnings management and manipulation suggesting a low quality of financial reports in the Chinese stock market (see, e.g., Piotroski and Wong (2012) for a review).This paper aims to reconcile the tension between the literature and the finding of Carpenter, Lu, and Whitelaw (2021) and provides new insights on the price informativeness of Chinese stocks.

We argue that the price informativeness measure of Bai et al. (2016) can be subject to an alternative interpretation when applied to the Chinese A-share market. One critical assumption of their framework is that reported earnings reflect firms' actual profits. This assumption does not necessarily hold in China, considering the prevalence of earnings management and manipulation documented in the literature. To reconcile the observed empirical patterns, we propose a "manipulate-to-cater" mechanism, which features a corporate manager who wants to maintain high share prices caters to investors' expectation on performance by manipulating future reported earnings. Certainly, our mechanism is not exclusive to the interpretation of Carpenter, Lu, and Whitelaw (2021), but it could potentially contribute to the inflated estimates of the price informativeness in Chinese share prices.

According to the "manipulate-to-cater" mechanism, we should observe a firm's high market capitalization predicts high reported earnings, but not necessarily high payouts. Also, since the managed component of reported earnings is not sustainable, high reported earnings should reverse in the long term. The managed earnings component should predict lower stock returns as investors slowly learn about the degree of earnings management. In this paper, we identify the "manipulate-to-cater" mechanism by testing its unique predictions and find supportive evidence, as summarized below.

We begin with a replication of the main result of Carpenter et al. (2021). We conduct cross-sectional regressions of Chinese firms' future earnings reported in the next one to five years ($E_{t+1}, ..., E_{t+5}$), scaled by current firm asset (A_t), on the log of market capitalization M_t to A_t. Our sample includes all Chinese A-share stocks from 1995 to 2022. For a comparison with US data, we use the sample of S&P500 constitute stocks from 1960 to 2021, following Carpenter et al. (2021) and Bai et al. (2016). We follow the procedure of Carpenter et al. (2021) with two differences. First, to examine the long-term predictability of market prices we conduct regression analysis at even longer horizons, that is, E_{t+6} and E_{t+7}. Second, we conduct the regression at the portfolio level, instead of the individual stock level. At the end of each year, we form 50 stock portfolios by independently sorting stocks on market capitalization into deciles and on book-to-market ratio into quintiles. Within each portfolio, we sum up all stocks' earnings, payouts, market capitalization, and total assets for our empirical work. This portfolio-based approach follows the idea of Fama and French (1995) and can effectively alleviate the impact of extreme values on coefficient estimation.[1]

We show that the main finding of Carpenter et al. (2021) is generally robust during the extended sample period (at the portfolio level). The valuation of Chinese A-share stocks appears to be as informativeness as the US S&P500 stocks in the sense of predicting future firms' earnings. Several new patterns, however, emerge. First, while the predictability is stronger for medium-term earnings, such as 3 to 5 years, than for short-term earnings (1 year), it starts to decline for future earnings in 6 and 7 years in China. By comparison, such overshooting pattern does not appear in the US market. Second, the predictability experiences a reduction in recent years in China (which is beyond the sample period of Carpenter et al., 2021), and as we argue later, the decrease is plausibly related to the delisting rule reform in the A-share market that was implemented in 2020.

Next, we replace future earnings with future total payouts ($D_{t+1}, ..., D_{t+7}$) as the dependent variable and examine whether the higher reported earnings means more actual payoff to

[1] Results of individual stock level regressions are reported in Appendix Section A.3.

shareholders. We do not find the higher reported earnings bring real payoff to investors. Total payout includes cash dividends and share repurchase, and we control for current earnings and payouts. Such a pattern is consistent with our hypothesis that the reported earnings of Chinese firms may reflect earnings management or manipulation, rather than real operational profits paid out in the future. By comparison, the market value of S&P500 stocks contain significant predictive power for future payouts in the US, and this is as strong as its predictive power for future earnings.

While the divergence in the predictability for future earnings and payouts supports our hypothesis, we acknowledge that lower payouts of higher-valuation firms can be due to higher retained profits and greater capital investment. To address this issue, we provide more direct evidence of earnings management in China.

From our "manipulate-to-cater" hypothesis, one unique prediction that can identify our proposed mechanism is earnings reversal i.e., a high market value (M_t) of an individual firm should be associated with high reported earnings in the short term that are reversed in the long term. To formally test this overshooting pattern of reported earnings in response to higher stock prices, we modify the specification of Carpenter et al. (2021) by using the change of earnings in year $t+1$ to t and the change in earnings from year $t+3$ to $t+1$ and from $t+5$ to $t+3$. Like our earlier tests, we use the 50 size by book-to-market ratio portfolios to conduct this analysis. We find that the empirical results are consistent with our conjecture. In a panel regression, a high M_t/A_t is associated with high values of $(E_{t+1} - E_t)/A_t$, insignificant values of $(E_{t+3} - E_{t+1})/A_t$, but low values of $(E_{t+5} - E_{t+3})/A_t$. In contrast, this overshooting pattern in predicting earnings does not show up in the sample of US S&P500 firms.

It is worth mentioning that our "manipulate-to-cater" mechanism is plausibly more relevant to time-series patterns of financial variables for individual firms. In comparison, the price informativeness interpretation of Carpenter et al. (2021) is more about prediction in the cross sectional firm data. Indeed, the overshooting pattern in firms' reported earnings is more pronounced after controlling for portfolio fixed effects, but gets weakened and even turns insignificant if we control for time fixed effects (a setting analogous to the specification of Carpenter et al. (2021)). This suggests that the two economic forces are not mutually exclusive; rather, both contribute to the strong correlation between firms' valuations and future reported earnings that we find in our sample of Chinese firms.

Our main empirical design exploits the 2020 reform on delisting rules regarding Non-Recurring Gain and Loss (NRGL) in Chinese stock market. The previous literature (e.g., Piotroski and Wong, 2012) documents pervasive earnings management behavior among A-share firms through related party transactions, accruals, and so on, mainly to avoid reporting negative earnings. Before the fiscal year of 2020, companies reporting negative net profit for two consecutive years were labeled as ST (special treatment) firms, and the ST stock could be delisted by the exchange if the corresponding firm continues to report losses.[2] According to China's accounting rules, NRGL—which record firms' non-operating and non-recurring incomes such as one-off government subsidies, asset sales, and donations—were included in the calculation of total earnings for delisting-regulation purposes, until the 2020 delisting rule which excluded NRGL from earning calculations. This policy shock motivates us to conduct a series of empirical analyses on China's earnings management based on NRGL.

Anecdotal evidence suggests poorly performing A-share firms frequently used NRGLs as a way to boost reported earnings to avoid reporting losses and the risk of being delisted. We first verify that firms with a high incentive to maintain their listing status were indeed likely to increase reported NRGL (scaled by total assets). Following Lee et al. (2023), for each stock we calculate expected shell probability (ESP), which measures the likelihood of being reverse merged by a private company. We find that high ESP firms are indeed more likely to report higher NRGL, offering new evidence of earnings management in Chinese stock market. In addition, consistent with our hypothesis, firms with high valuation ratios tend to report more NRGL.

Next, we examine if investors can fully see through the managed earnings. If investors understand that high reported earnings largely comes from a high NRGL component of firms' accounts, and that these are unlikely to persist in the future, then rational investors should undo the manipulation in the spirit of Stein (1989), implying no return predictability. Our evidence, however, rejects such mechanism. The level of quarterly NRGL and also the

[2] Piotroski and Wong (2012) show that there are too many firms reporting net profits just above zero and too few companies with earnings just below, suggesting massive earnings management around the cutoff zero.

change in NRGL predict lower stocks returns over the subsequent one to four quarters. A one standard deviation increase in NRGL (the change of NRGL) is associated with 0.68% (0.91%) lower returns over a quarter.

These findings are consistent with our proposed mechanism. That is, firms that intend to maintain a high valuation for some reason (such as shell value) are more likely to manipulate their reported earnings through the NRGL component of their accounts. Since the market—especially for Chinese stock market where the majority of trades come from retail investors—cannot fully see through earnings management, inflated valuations can persist. To maintain a high valuation for longer, firms continue to issue high reported earnings projections to boost investors expectations. However, firms' management team cannot manipulate forever; the reported earnings will eventually fall back, leading to a lower return.[3]

As the main identification exercise of our paper, we exploit an important policy change in the Chinese A-share market. Starting in July of 2018, the central government and China's regulatory agency began consultation on policy reforms on the delisting criteria for the Chinese A-share stocks. For a long time, the A-share market featured an extremely low delisting rate (Lee et al. (2023)), because of the high shell values that arose from IPO hurdles and the ease of managing earnings to circumvent delisting criteria.[4] Among other changes, the reform featured a new and detailed delisting rule issued by the Shanghai and Shenzhen Stock Exchanges in December 2020.In a nutshell, the 2020 delisting rules has two critical components: it excluded NRGL from calculations of firms reported earnings for regulatory purposes, and abandoned the sole-criterion of negative earnings for the delisting of firms and added other conditions. Also, shell values fell to almost zero as the number of approved reverse merger cases significantly decreased after 2019. The new rule is effective for 2020 fiscal year financial reports, thus we label 2020 and after as the post-event window.[5]

In this sense, the 2020 delisting rule should prevent firms from using NRGL for earnings management purposes and removed the incentives for shell firms to manage earnings. This

[3]This pattern is analogous to the accrual effects that previous studies have found using US stock data; investors neglect and underreact to the negative information from high accrual firms (e.g., Sloan (1996) and Hirshleifer et al. (2012)).

[4]The Special Treatment (ST) rule solely relied on reported net profit being positive or not before the reform.

[5]See Appendix Section A.2 for more details on the reform.

is supported by several findings. First, we find that high NRGL firms over the pre-event window before 2020 and high ESP firms sharply reduced their NRGL in and after 2020. This finding confirms that the reform effectively limited the useage of NRGL as a way for firms to manage their reported earnings. Also, we also find that the distribution of reported earnings has become more smooth around zero in 2020-2022 than before, suggesting less earnings management behavior.

Furthermore, given that the managed component of reported earnings, NRGL, mostly disappeared after the reform for some firms (e.g., shell stocks), market value (M_t) exhibited a weaker correlation with future reported earnings (E_{t+k}) after 2020 but stronger correlation with future payouts (D_{t+k}). This explains why the price informativeness estimated in our sample, which includes recent years (2017–2022), is lower than that from Carpenter et al. (2021). Again, such pattern does not show up in the US data.

The rest of the paper is organized as follows. Section 3 introduces the data and construction of the variables for empirical tests. Section 4 presents the main results and Section 5 concludes.

2 A Simple Model and Hypothesis Development

In this section, we formally develop our testable hypotheses from the "manipulate-to-cater" mechanism. We argue that with the prevalence of earnings management, a corporate manager who wants to maintain high share prices may cater to investors expectation on performance by manipulating the firm's follow-on reported earnings. But manipulation cannot last forever; eventually true earnings get to revealed and in the long run firm's share price reflect its fundamental value.

More specifically, in Appendix (to be added) we follow Stein (1989) and Hirshleifer and Teoh (2003) to develop a stylized two-period model to capture the "manipulate-to-cater" mechanism. In the model, the firm generates a natural earning E^n at date 1, which is informative about the firm's date-2 dividend V. The manager can manage the date-1 earnings to report $E = E^n + b$ to the market, where b captures (costly) earnings manipulation. Investors form their beliefs based on observed earnings and trade the firm shares in the market, which determines the equilibrium prices M_0 and M_1 in two dates. (By design $M_2 = V$ which is the exogenous liquidating dividends). The manager is given an exogenous compensation contract: we assume that this contract is increasing in the growth of stock prices $M_1 - M_0$; presumably, it is because the manager exerts effort that affects firm fundamentals.

As in Hirshleifer and Teoh (2003), a fraction of investors are inattentive; they blindly believe the firm's true earning e^n is the manager's reported earnings e, based on which they form their demand. The rest of investors are attentive and form rational beliefs about e^n by taking into account the equilibrium manipulation b. The presence of inattentive investors implies that the manager who can manipulate earnings can also manipulate the stock price, at least in the short-run.

Suppose that at date zero a positive signal on firm fundamental pushes up the firm's date-0 share price M_0. Also, suppose that the compensation contract stipulates to fire the manager if $M_1 - M_0$ falls below certain threshold κ. As a result, when M_0 is relatively high, the manager will choose the manipulation b so that M_1 is just enough to hit $M_0 + \kappa$ to avoid layoff. This way, a higher today's stock price M_0 follows with a higher (manipulated) earnings tomorrow. However, the date-1 earnings are inflated; over time the market gets to learn the truth as at date 2 the firm's true fundamental is revealed.

This simple theoretical framework helps us formulate the following testable hypotheses formally.

Hypothesis 1. The correlation between current stock share valuation (M_t) and future reported earnings (E_{t+k}) should be positive for small k, but gets weakened as k becomes large. And such a reversal pattern should be more pronounced when control for firm fixed effects.

Hypothesis 2. The higher the ex ante incentive to manipulate earnings (i.e., high shell stock probability), the greater the managed component of earnings (NRGL in our setting). And, the managed component of earnings should be positively correlated with the current stock share valuation (M_t) but negatively with subsequent stock returns.

Hypothesis 3. Upon a negative shock to the potential benefit of earnings management (i.e., the 2020 delisting rule reform), or equivalently a positive shock to the cost of earnings management (say increasing penalty on accounting manipulations), the level of earnings management should decrease, the correlation between earnings management and market valuation should be weakened, and the correlation between current stock share valuation (M_t) and future reported earnings (E_{t+k}) should be weakened.

3 Data

We have gathered financial information and stock returns of publicly listed Chinese firms from the China Stock Market and Accounting Research (CSMAR) database. Our sample includes only A-share, non-financial firms, excluding those listed on the STAR and ChiNext boards. CSMAR provides firms' annual and quarterly financial variables, including earnings (net profit, E), total assets (A), dividend payouts (D), and total market capitalization (M). D includes cumulative annual cash dividends and net share repurchases. We retain the consolidated financial statements and exclude the parent company's financial statements. E, D, A, and M are adjusted for inflation using the GDP deflator, with the deflator data obtained from CSMAR. We do not fill in missing earnings data.

Following Carpenter et al. (2021), our sample period starts in 1995 and ends in 2022. Since the fiscal year of 2008, the China Securities Regulatory Commission (CSRC) has required public companies to disclose information on non-recurring gains and losses (NRGL) in their financial statements, making NRGL data available only from that year onward. The dataset on reverse mergers is sourced from the Tong Hua Shun iFinD Financial Data Terminal.

For the US data, we obtain annual accounting information from the Compustat database. Following Bai et al. (2016), we focuses on S&P500 companies, excluding financial firms, over the sample period from 1960 to 2021. We also present results using a recent sample from 1995 to 2021. All variables are adjusted for inflation using the GDP deflator from the World Bank. We do not fill in missing earnings data. Table I shows summary statistics of main variables at the stock level. Details on variable construction are provided in Section A.1 of the Online Appendix.

4 Empirical Results

In this section, we explore the relationship between stock valuation measured by the ratio of a stock's market value to asset value (M_t/A_t). We first analyze the predictability of M_t/A_t for the stock's future earnings in the cross-section, following the approach pursued by Carpenter et al. (2021). The essence of this approach is to examine whether stocks with higher valuations tend to have larger earnings in the subsequent years than stocks with lower valuations. We then adopt an alternative approach to examine this predictability in time-series. That is, whether a firm with high valuation in a year tends to report more earnings in subsequent years. We also examine the predictability of M_t/A_t for the stock's future dividend payouts, present evidence of earnings management using NRGL, and exploit the 2019-2020 delisting rule reform as a shock to firms' earnings management behavior.

4.1 Carpenter, Lu, and Whitelaw (2021) revisited

We begin by replicating the main result of Carpenter et al. (2021). We conduct cross-sectional regressions of firms' future earnings reported in the next one to k years ($E_{t+1}, ..., E_{t+k}$), scaled by current firm asset (A_t), on the log of market capitalization (M_t) to A_t. Our sample includes all Chinese A-share stocks from 1995 to 2022. For a comparison, we use the sample of S&P500 stocks following Carpenter et al. (2021) and Bai et al. (2016).

We follow the procedure of Carpenter et al. (2021) with one difference: we conduct the regressions at a portfolio level, instead of at an individual stock level.At the end of each year, we independently sort stocks into deciles based on market capitalization and into quintiles based on the book-to-market ratio, forming 50 portfolios. Within each portfolio, we sum all stocks' current and future earnings ($E_t, ..., E_{t+k}$), dividend payouts ($D_t, ..., D_{t+k}$), market capitalization (M_t), and total assets (A_t) to conduct the regressions. For all variables, we adjust for inflation using the GDP deflator. We use total assets at year t (A_t) to scale and adjust for the size effect. This portfolio approach is in spirit of Fama and French (1995). Compared to conducting the analysis at the individual stock level, portfolios average out firm-level outliers and reduce estimation noises. Additionally, for predicting payouts (D), portfolios can address the issue of too many observations with a value of zero.

Specifically, for each year t, we run the following cross-sectional regression:

$$\frac{E_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma\frac{E_t}{A_t} + \lambda\frac{D_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 7\}. \tag{1}$$

To facilitate the interpretation of the main coefficient β_k of $\log(M_t/A_t)$, we report the coefficient multiplied by the standard deviation $\sigma(log(M_t/A_t))$, that is, predicted variation. We also report the average of the coefficient over the sample years. Differing from Carpenter et al. (2021), we add and control for D_t/A_t (which is related to our analysis later) and examine the predictive power for earnings over horizons longer than 5 years, i.e., $k = 6, 7$. Firms that do not have 7 years of earnings at year t are excluded.

We report the regression results in Table II. For the Chinese market, the table shows the scaled coefficient of $\log(M_t/A_t)$ for each year from 1995 to 2021, as well as the averaged coefficient for the periods 1995-2016 (the sample period of Carpenter et al. (2021)) and 1995-2022. In 1995-2016, the scaled coefficient equals 0.010 (t-stat = 5.0) for $k = 1$ and increases to 0.015 for $k = 3$ (t-stat = 4.2).

In comparison, the US S&P 500 sample shows a larger but similar order of magnitude over this prediction horizon: the predicted variation of $\log(M_t/A_t)$ is 0.021 (0.028) for $k = 1$ and 0.030 (0.033) for $k = 3$ in the sample of 1960–2021 (1995–2021), and all are highly significant. This pattern is fairly aligned with the main results of Carpenter et al. (2021).

When we extend the prediction horizon, however, some differences emerge. For the Chinese market, in 1995–2016, the predicted variation of $\log(M_t/A_t)$ starts to reduce to 0.013 for $k = 5$ (t-stat = 1.98) to 0.009 for $k = 7$ (t-stat = 1.24). In contrast, the estimate for the US market continues to increase in k and equals 0.032 (0.037) for $k = 5$ and 0.037 (0.047) for $k = 7$ and remains statistically significant.

In Figure I, we visualize predicted variation of $\log(M_t/A_t)$ (based on the estimates of β_k) for $k \in \{1, 2, ..., 7\}$ in both markets with 95% confidence intervals. One can see that the magnitude is generally increasing with k in the US market, consistent with Bai et al. (2016). In contrast, price informativeness exhibits an inverted-U shaped pattern as k increases in the Chinese market. This pattern suggests that the predictability for future earnings is partially reversed and becomes insignificant over the long term. The reversal pattern is different from the result of Carpenter et al. (2021), who show that the predictability in earnings increases in k. One of the modifications in our specification leads to the difference: the portfolio approach we use, whereas they estimate β_k on individual stocks (we show the corresponding result in Section A.3 of the Appendix).

Another notable pattern of Table II is that the price informativeness based on the sample between 1995 and 2022 is generally lower than that estimated using the sample period of Carpenter et al. (2021), i.e., 1995 to 2016, for all $k = 1, ..., 7$. This suggests that the estimated magnitude of price informativeness has decreased in recent years; as we discuss in later sections, this is plausibly a consequence of the delisting rule reform in China.

4.2 Predicting dividend payouts

The possibility of earnings being actively managed by firms makes earnings an unreliable measure of firm fundamentals. Dividend payouts to investors are immune to this concern. In this subsection, we examine the predictability of stock valuation for subsequent dividend payouts. We adopt the regression specified in Equation 1, replacing earnings with total dividend payouts ($D_{t+1}, ..., D_{t+7}$). If higher firm earnings bring greater dividend payouts to investors, we should find that stock valuation exhibits similar predictive power for dividend payouts as it does for earnings.

In our data construction, total firm payout includes cash dividends and share repurchases (Appendix Section A.1 details the variable construction procedure for Chinese firms). Specifically, for each year t, we run the following cross-sectional regression:

$$\frac{D_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 7\}. \tag{2}$$

We again multiply the coefficient of $\log(\frac{M_t}{A_t})$ by the standard deviation $\sigma(log(\frac{M_t}{A_t}))$ and calculate the average over our sample period.

The regression results are reported in Table III. We find that in the Chinese market, stock valuation has little predictive power for future payouts. In 1995-2022, the predicted variation of $\log(M_t/A_t)$ is close to zero at short horizons, equalling 0.001 for $k = 1$ (t-stat $=$ 1.6), and increases slightly to 0.002 for $k = 3$ (t-stat $= 3.3$), 0.004 for $k = 5$ (t-stat $= 2.5$), and 0.006 for $k = 7$ (t-stat $= 1.7$). Clearly, the predictability for dividends is much lower than that for earnings shown in Table II.

By comparison, as shown at the bottom of Table III, the market valuation of S&P 500 stocks has significant predictive power for future payouts. The predicted variation of $\log(M_t/A_t)$ ranges from 0.012 (0.006) to 0.040 (0.023) as k increases from 1 to 7 in the sample period of 1995–2021 (1960–2021) and is also statistically significant. Importantly, the magnitudes are highly close to its predictive power for earnings. In Figure **??**, we visualize the predicted variation of $\log(M_t/A_t)$ with 95% confidence intervals for $k \in \{1, 2, ..., 7\}$ in both markets.

The sharp contrast in the predictability of dividend payouts between the Chinese and US markets reinforces the concern that earnings in the Chinese market might be managed and thus not necessarily reflect firm fundamentals. That said, we also acknowledge another possibility: Chinese firms may adopt different payout policies from US firms, making their dividend payouts insensitive to firm fundamentals. In other words, Chinese firms may retain most of their cash flows without paying out to shareholders. If this is the case, the weak predictability of stock valuation for dividend payouts cannot be used as forceful evidence for earnings management either. In the following subsections, we will provide more direct evidence of earnings management.

4.3 Earnings reversal

The previous cross-sectional analysis of earnings predictability suggests the presence of long-run reversal in earnings of Chinese firms. Such reversal provides a channel to examine earnings management by Chinese firms. We now adopt a time-series approach to directly examine whether firms with higher stock valuations tend to exhibit stronger earnings reversal in the long run.

Specifically, we run the following panel regressions of changes in earnings, using the 50 size by market-to-asset ratio portfolios:

$$\frac{E_{j,t+1} - E_{j,t}}{A_{j,t}} = \alpha + \beta^{0\to1} log(\frac{M_{j,t}}{A_{j,t}}) + \gamma \frac{E_{j,t}}{A_{j,t}} + \lambda \frac{D_{j,t}}{A_{j,t}} + \epsilon_{j,t}, \tag{3}$$

$$\frac{E_{j,t+3} - E_{j,t+1}}{A_{j,t}} = \alpha + \beta^{1\to 3} log(\frac{M_{j,t}}{A_{j,t}}) + \gamma \frac{E_{j,t}}{A_{j,t}} + \lambda \frac{D_{j,t}}{A_{j,t}} + \epsilon_{j,t}, \tag{4}$$

$$\frac{E_{j,t+5} - E_{j,t+3}}{A_{j,t}} = \alpha + \beta^{3\to 5} log(\frac{M_{j,t}}{A_{j,t}}) + \gamma \frac{E_{j,t}}{A_{j,t}} + \lambda \frac{D_{j,t}}{A_{j,t}} + \epsilon_{j,t}, \tag{5}$$

Different from Equation 1, the left-hand-side variable in these regressions is the change in earnings over different horizons normalized by the current asset value: from year t to $t+1$, from year $t+1$ to $t+3$, and from $t+3$ to $t+5$. The main variables of interest are $\beta^{1\to 3}$ and $\beta^{3\to 5}$, with negative values indicating long-run earnings reversal predicted by current stock valuation.

We first run these regressions without including any fixed effects, then including portfolio fixed effects (which are essentially time-series regressions), and finally including time fixed effects (which are essentially cross-sectional regressions). We report Driscoll–Kraay standard errors with lag of 1.

We present the regression results in Table IV. Panel A shows the results without including any fixed effects. Consistent with the previous findings, stock valuation ($\log(M/A)$) is associated with higher earnings in the short term ($E_{t+1} - E_t$) with a coefficient of 0.013 (t-stat = 2.5). When looking at the change of earnings from year 1 to year 3 ($E_{t+3} - E_{t+1}$), the coefficient $\beta^{1\to 3}$ is small and insignificant, suggesting that E_{t+3} has a similar level to E_{t+1}. However, we see a significant reversal from year 3 to year 5: the coefficient $\beta^{3\to 5}$ equals -0.013 (t-stat = 3.0). If we compare the point estimates of the coefficients, we find that E_{t+5} has roughly reverted back to the level of E_t.

By comparison, columns (4) to (6) show that there is no earnings reversal in the US market. Firms with higher market valuations tend to report higher earnings at year $t+1$ and remain at the same levels in year $t+3$ and $t+5$, indicating no reversal. This contrast between China and the US highlights the different dynamics of Chinese firms.

If firms manage earnings to meet the market expectations reflected by the current stock valuation, we expect the earnings reversal to be more pronounced in the time-series dynamics of each firm's earnings. This is equivalent to including portfolio fixed effects in our panel regressions. This is indeed the case. In Panel B, we include portfolio fixed effects. The coefficients $\beta^{1\to 3}$ and $\beta^{3\to 5}$ are both significantly negative, with t-stats of 2.1 and 2.4, respectively.

In Panel C, we include time fixed effect instead, which is similar to the original specification of Carpenter et al. (2021) that focuses on the cross-sectional variation. The coefficients $\beta^{0\to1}$ and $\beta^{1\to3}$ are both significantly positive, with t-stats of 5.4 and 2.1, respectively. The coefficient $\beta^{3\to5}$ is negative, albeit insignificant, indicating weak evidence of earnings reversal in the cross section.

Finally, in both panels B and C, the sample of S&P 500 firms in the US market shows a consistent and robust pattern of no long-run reversal in future earnings. That is, the predictability for $(E_{t+1} - E_t)$ is significantly positive, while that for $(E_{t+3} - E_{t+1})$ and $(E_{t+5} - E_{t+3})$ is either positive or insignificant. This lack of reversal in the US market highlights the important difference between the US and Chinese markets in interpreting the results of Bai et al. (2016) and Carpenter et al. (2021).

4.4 Earnings management

In this subsection, we directly examine earnings management by Chinese firms. The accounting literature has documented prevalent earnings management behaviors among Chinese A-share firms through related party transactions, accruals, and other means (see, e.g., Piotroski and Wong (2012) for a review).

To provide a visual illustration of the prevalence of earnings management in the Chinese A-share market, we first follow Piotroski and Wong (2012) and Burgstahler and Dichev (1997) to plot the distribution of reported earnings in China and the US, respectively. Specifically, in Figure III, we plot the distribution of firms' ROA in Panel A for S&P 500 firms in the US market and Panel B for the Chinese A-share firms. In Panel A, the distribution is close to a normal distribution with a modest jump around zero, indicating that S&P 500 firms have managed their earnings around zero. That is, firms might have inflated their earnings at the margin to avoid reporting negative earnings.

In Panel B, we separately plot the distribution of ROA for Chinese A-share firms from 1995-2019 (dark bars) and 2020-2022 (light bars). In contrast to Panel A, there is a sharp jump at zero in Panel B. The jump is particularly large for the period of 1995-2019, from a level close to zero to the peak of the distribution, making the whole distribution roughly a truncated normal curve centered around zero earnings. The jump is moderated in recent years due to a rule change in 2020 (which we will discuss later) but nevertheless remains substantial.

These patterns are consistent with the findings of Piotroski and Wong (2012) for earlier years. To understand the prevalence of earnings management in the Chinese A-share market, it is useful to note that before 2020, companies reporting negative net profit for two consecutive years would be labeled as ST (special treatment) firms. Moreover, a stock could be delisted from the stock exchange if its earnings remained negative. This delisting policy creates direct incentives for firms to avoid negative earnings.

Next, motivated by anecdotal evidence, we use Non-Recurring Gain and Loss scaled by total assets (NRGL) as a proxy for the degree of earnings management among Chinese A-share listed firms. According to accounting rules in China, NRGL records firms non-operating and non-recurring incomes, such as one-off government subsidies, income from asset sales, and donations. Until the 2020 delisting reforms, main board listed firms were allowed to include NRGL in their reported earnings. Media reports show that poorly performing A-share firms frequently used NRGL as a way to boost reported earnings to avoid reporting losses and the threat of being delisted. Indeed, an important effect of the amended delisting rule in 2020 was to eliminate incentives to manage reported earnings using the NRGL component.

As discussed in Lee et al. (2023), underperforming Chinese firms are strongly incentivized to keep their listed status for its shell value. Because of the high IPO hurdles, some private companies that intend to go public are seeking for alternative ways such as reverse mergers. Through it, unlisted Chinese firms are able to capitalize on the existing framework for listed companies, allowing them to be listed on Chinese markets without undergoing a formal IPO process. Based on the estimates by Lee et al. (2023), the average shell value was about USD500 million between 2008 to 2018. To avoid being delisted, shell companies tend to manage their earnings to show positive values, and one way to do this is through their reported NRGL.

We first verify whether firms with a high incentive to maintain the listing status are likely to increase their reported NRGL. Following Lee et al. (2023), we calculate firms expected shell probability (ESP), the likelihood of being reverse merged by a private company. Specifically, we first run a logit regression model to use observed firm characteristics such as firm size, profitability, ST status, and the proportion of ownership held by the top ten shareholders to predict a reverse merger event. Then, we employ the estimated model and firm characteristics to infer firms' probability of a reverse merger. To avoid look ahead bias, we calculate ESP in a rolling manner: for the computation of ESP_t, we only use data from the years 2007 to $t-1$.

NRGL is calculated as the ratio of non-recurring gains and losses to total asset in the previous year.[6] Consistent with our conjecture, we find that when a company has a high shell probability (ESP), its contemporaneous NRGL exhibits a discernibly positive association. This influence carries over to the NRGL in the subsequent year, albeit with a somewhat attenuated effect compared to the contemporaneous NRGL. The results are in Table V. It is worth discussing that in Table V, the coefficient before $log(M/A)$ is positively correlated with contemporaneous NRGL (t-stat = 4.2) and the subsequent year NRGL (t-stat = 11.5). The patterns are consistent with our "manipulate-to-cater" hypothesis that highly-valued firms tend to manage earnings to align with expectations reflected in their stock valuations.

4.5 Underreaction to managed earnings

Next, we examine whether investors can fully see through the managed component of reported earnings. If investors understand that high earnings arise from high NRGL values, which are unlikely to persist in the future, stock prices should take this into account and contain no significant predictive power for earnings (in the spirit of the rational model of Stein (1989)). Alternatively, if investors cannot fully see through this accounting trick, then stocks could become overvalued when earnings are reported and exhibit low subsequent returns.

To test this conjecture, we use quarterly reports of NRGL, which we think better captures the market reaction to financial reporting. We run Fama-MacBeth regressions of quarterly stock returns on either NRGL or ΔNRGL and control for reported earnings of assets (ROA) and a set of commonly used set of stock characteristics and industrial dummies. ΔNRGL

[6] As non-recurring gains and losses is mandatory to report from 2008. The sample period of this analysis spans from 2008 to 2022.

refers to the difference between NRGL_q and NRGL_{q-4}.

As shown in Table VI, our results are supportive of the case where investors cannot fully see through earnings management via NRGL. Both the level of quarterly NRGL and ΔNRGL predict lower stocks returns over the subsequent one to four quarters. In terms of economic magnitude, a one standard deviation increase in NRGL (the change of NRGL) is associated with 0.68% (0.91%) lower returns over a quarter. This pattern is analogous to the accruals effect in studies using US stock data; investors neglect and underreact to the negative information from high accrual firms (e.g., Sloan (1996) and Hirshleifer et al. (2012)).

4.6 The 2019-2020 reform on delisting rule

To further buttress the identification of our tests, we exploit an important policy change in the Chinese A-share market. Starting in July of 2018, the central government and China's regulatory agency began to a series of policy discussions and reforms on the delisting criteria for the A-share stock market. For a long time, the A-share market featured an extremely low delisting rate (Lee et al. (2023)), mainly because of the high shell value that arises from IPO hurdles and the ease of managing earnings to get around of delisting criteria.The reforms featured a set of new delisting criteria for the Shanghai Stock Exchange's STAR board in March 2019 as a pilot program, a new Security Law passed by the national congress in March 2020, and the new delisting rule formally announced in December 2020 and applied for all main board listed firms in both Shanghai and Shenzhen Stock Exchanges.

In a nutshell, two critical changes were made: (1) NRGL were no longer allowed to be used to calculate earnings for regulatory purposes and (2) abandon the sole-criteria of earnings being negative for ST. Under the 2020 delisting rule, only firms that report losses and have revenue less than 100 million yuan will be labeled as ST. The first fiscal year for the new rule to be effective is 2020. That is, the earnings reported for the fiscal year of 2020 or after should be less likely to be managed through NRGL. Therefore, in our event study, we label 2020 and after as the post-event window. In Appendix Section A.2, we provide more details of the reform timeline and the 2020 new delisting rule.

In Figure IV, we plot the number of delisted firms in each year. The number gradually increased from 2020 onwards reaching around 50 in 2022 and 2023. By comparison, before 2019, the number of delisted firms was less than 10 and even lower between 2008 to 2018 when reverse mergers were common. Figure V shows the number of approved reverse mergers in each year. As part of the reform, reverse mergers were discouraged by the regulator, and the number of approved cases declined to almost zero in and after 2022.

We first examine the reforms of delisting rules on NRGL. We find that high NRGL firms over the pre-event window significantly decreased their NRGL in and after 2020 (see Figure VI), reflecting the rule change that NRGL could no longer be counted in reported earnings for regulatory purposes in the post-event window.

Further, we find that high ESP firms sharply reduce their NRGL in and after 2020. In Table VII, we repeat the regressions in Table V and add an interaction term between ESP and $POST$, where $POST$ is a dummy variable that equals one if the independent variable NRGL is for the fiscal year of 2020 or after. As shown in columns (1) and (3), coefficients before the interaction term are both significantly negative (t-stats above 4). A comparison to the coefficient before ESP itself in column (3) suggests that after the reform, high ESP firms do not report higher NRGL than other firms.

Also, consistent with our hypothesis, in the post-reform period, the correlation between market valuation and NRGL is significantly weakened. In columns (2) and (4), we add an interaction term between $log(M/A)$ and $POST$, and the coefficients before it are significantly negative (t-stats above 3). In terms of economic magnitude, for example, the coefficient before the interaction term is -0.003, whereas the coefficient of $log(M/A)$ equals 0.011, suggesting a 27% reduction in the correlation between stock valuation and subsequent NGRL.

The above-mentioned findings confirm that the 2020 new delisting rule effectively limited the use of NRGL to manage reported earnings after the event window. Indeed, as shown in the lower panel of Figure III, the distribution of reported earnings in 2020 to 2022 (first three fiscal years after the new rule is effective) appears to be less irregular around zero than the period before the reform.

Last but not the least, given that the managed component of reported earnings, NRGL, disappeared after the 2020 rule for some firms (e.g., high ESP stocks), firms' market value (M_t) should exhibit a weaker correlation with future earnings (E_{t+k}) reported after 2020.

To test this conjecture, we modify equation (1) by adding an interaction term between $\log(\frac{M}{A})$ and the dummy variable $POST$, which equals one if $t+k$ is larger than or equal to 2020. To make it analogous to the original setting in Carpenter et al. (2021), we add year fixed effects. That is, we conduct a panel regression of equation (6) as shown below,

$$\frac{E_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \theta_k log(\frac{M_t}{A_t}) * POST + \gamma\frac{E_t}{A_t} + \lambda\frac{D_t}{A_t} + v_t + \epsilon_t, \text{where } k \in \{1, 2, 3\}, \quad (6)$$

where we expect θ to be negative.

Panel A of Table VIII presents the results. The coefficient before the interaction term is significantly negative and equals -0.0131 (t-stat $= 3.9$) for E_{t+1}, which is sizable given that the coefficient before $\log(M/A)$ equals 0.0175. The coefficient before the interaction term changes to -0.00997 (t-stat $= 3.5$) and -0.0092 (t-stat $= 2.2$) for E_{t+2} and E_{t+3}, respectively, whereas the coefficient before $\log(M/A)$ equals 0.0225 and 0.0254. Again, we also conduct the same regressions using the sample of US S&P500 firms and find insignificant results.

We next run the regression of equation (6), where the dependent variable is the level of payouts in Panel B. The coefficient before the interaction term is significantly positive and equals 0.00137 (t-stat $= 2.4$) for D_{t+1}, which is sizable given that the coefficient before $\log(M/A)$ equals 0.00191. The coefficient before the interaction term is 0.00227 (t-stat $= 2.1$) for D_{t+2}, whereas the coefficient before $\log(M/A)$ equals 0.0033. Such patterns suggest an improvement in price informativeness following the 2020 delisting rule reform. By comparison, the result using S&P500 firms shows the opposite.

5 Conclusion

We address the puzzling finding by Carpenter, Lu, and Whitelaw (2021) that stock prices in the Chinese A-share market are as informative about future earnings as those in the U.S. market. Contrary to their interpretation, we argue that, in the presence of prevalent earnings management and less sophisticated investors, firms may manage earnings to align with expectations reflected in their stock valuations. Our analysis reveals that Chinese stocks with higher valuations tend to exhibit higher earnings in the subsequent three years, but this does not translate to increased payouts to shareholders and the higher earnings reverse in the long run. Additionally, we provide evidence of earnings management through non-recurring gains and losses (NRGL), leveraging the 2019–2020 reform on delisting rules as an exogenous shock to earnings management practices.

References

F. Allen, J. Qian, C. Shan, and J. L. Zhu. Dissecting the long-term performance of the chinese stock market. *The Journal of Finance*, 79(2):993–1054, 2024.

J. Bai, T. Philippon, and A. Savov. Have financial markets become more informative? *Journal of Financial Economics*, 122(3):625–654, 2016.

D. Burgstahler and I. Dichev. Earnings management to avoid earnings decreases and losses. *Journal of Accounting and Economics*, 24(1):99–126, 1997. ISSN 0165-4101. doi: https://doi.org/10.1016/S0165-4101(97)00017-7. URL https://www.sciencedirect.com/science/article/pii/S0165410197000177. Properties of Accounting Earnings.

J. N. Carpenter, F. Lu, and R. F. Whitelaw. The real value of chinas stock market. *Journal of Financial Economics*, 139(3):679–696, 2021.

E. F. Fama and K. R. French. Size and book-to-market factors in earnings and returns. *The journal of finance*, 50(1):131–155, 1995.

E. F. Fama and K. R. French. Disappearing dividends: changing firm characteristics or lower propensity to pay? *Journal of Financial economics*, 60(1):3–43, 2001.

D. Hirshleifer and S. H. Teoh. Limited attention, information disclosure, and financial reporting. *Journal of accounting and economics*, 36(1-3):337–386, 2003.

D. Hirshleifer, K. Hou, and S. H. Teoh. The accrual anomaly: risk or mispricing? *Management Science*, 58(2):320–335, 2012.

G. X. Hu, J. Pan, and J. Wang. Chinese capital market: An empirical overview. *Critical Finance Review*, 10(2):125–206, 2021.

C. M. Lee, Y. Qu, and T. Shen. Gate fees: The pervasive effect of ipo restrictions on chinese equity markets. *Review of Finance*, 27(3):809–849, 2023.

J. D. Piotroski and T. Wong. Institutions and information environment of chinese listed firms. In *Capitalizing China*, pages 201–242. University of Chicago Press, 2012.

R. G. Sloan. Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting review*, pages 289–315, 1996.

J. C. Stein. Efficient capital markets, inefficient firms: A model of myopic corporate behavior. *The quarterly journal of economics*, 104(4):655–669, 1989.

Table I. Summary Statistics

This table report summary statistics of key variables at the stock level in our analysis. The sample period is 1995 to 2022 for Panel A, 2008 to 2022 for Panel B, and 1960 to 2021 for Panel C. Variable definitions are in Appendix A.1.

Panel A: China annual variable

	Mean	SD	P10	P25	P50	P75	P90	N
E_t/A_t	0.05446	1.9661	-0.01623	0.00962	0.03248	0.06568	0.10760	27577
E_{t+1}/A_t	0.08973	4.7621	-0.01934	0.00912	0.03326	0.07199	0.12700	27577
E_{t+3}/A_t	0.11072	5.6810	-0.02582	0.00865	0.03396	0.07843	0.14708	27577
E_{t+5}/A_t	0.11451	6.2757	-0.03190	0.00835	0.03466	0.08493	0.16760	27577
E_{t+7}/A_t	0.20238	14.855	-0.04968	0.00761	0.03837	0.10644	0.24457	27577
D_t/A_t	0.01394	0.04618	0.00000	0.00000	0.00446	0.01790	0.03792	27577
D_{t+1}/A_t	0.01629	0.06662	0.00000	0.00000	0.00469	0.01932	0.04205	27577
D_{t+3}/A_t	0.02027	0.11260	0.00000	0.00000	0.00484	0.02085	0.04812	27577
D_{t+5}/A_t	0.02480	0.17669	0.00000	0.00000	0.00512	0.02250	0.05418	27577
D_{t+7}/A_t	0.04888	0.91396	0.00000	0.00000	0.00521	0.02825	0.07690	27577
$\log(M_t/A_t)$	0.99277	0.51563	0.41703	0.62111	0.92243	1.27443	1.63821	27577
NRGL	0.01208	0.02722	-0.00024	0.00128	0.00499	0.01252	0.02998	27219
ESP	0.01059	0.01779	0.00014	0.00074	0.00361	0.01225	0.02907	27219
SIZE	22.3113	1.3461	20.7393	21.4173	22.1710	23.0957	24.1020	27219
LEVERAGE	0.49071	0.23288	0.20247	0.32738	0.48649	0.63907	0.76005	27219
P/B	3.78427	5.12197	1.00590	1.55363	2.50903	4.19427	7.14290	27219
ROE	0.05038	0.21186	-0.06020	0.02099	0.06587	0.12226	0.19562	27219

Panel B: China quarterly variable

	Mean	SD	P10	P25	P50	P75	P90	N
RET	0.03077	0.25479	-0.22168	-0.11921	-0.00937	0.13278	0.32516	133076
NRGL	0.00492	0.01280	-0.00010	0.00029	0.00163	0.00509	0.01226	133076
ΔNRGL	-0.00023	0.01900	-0.00722	-0.00168	0.00000	0.00160	0.00687	122832
$\log(M)$	8.72642	1.01225	7.55957	8.00610	8.58474	9.31230	10.11258	133076
B/M	0.47872	0.36213	0.14256	0.23760	0.38821	0.61274	0.92824	133076
TURNOVER	1.45973	1.42354	0.31090	0.54122	1.00444	1.86353	3.15033	133076
ROA	2.23938	4.78656	-0.87493	0.43286	1.73263	4.00533	7.06206	133076
ΔROA	-0.26573	4.42036	-2.96319	-1.02147	-0.07813	0.62438	2.19766	124970

Panel C: US S&P500 annual variable

	Mean	SD	P10	P25	P50	P75	P90	N
E_t/A_t	0.07252	0.07396	0.01450	0.03904	0.06417	0.10136	0.14677	15884
E_{t+1}/A_t	0.07642	0.15613	0.01275	0.03886	0.06663	0.10844	0.15954	15884
E_{t+3}/A_t	0.08064	0.17423	0.01071	0.03843	0.06834	0.11422	0.17256	15884
E_{t+5}/A_t	0.08344	0.35240	0.00921	0.03834	0.06982	0.12002	0.18550	15884
E_{t+7}/A_t	0.08468	0.85987	0.00835	0.03814	0.07193	0.12619	0.19915	15884
D_t/A_t	0.04279	0.06347	0.00000	0.00791	0.02531	0.05118	0.10467	15884
D_{t+1}/A_t	0.04760	0.07075	0.00000	0.01088	0.02769	0.05672	0.11392	15884
D_{t+3}/A_t	0.05253	0.07899	0.00000	0.01326	0.03021	0.06229	0.12403	15884
D_{t+5}/A_t	0.05888	0.10284	0.00000	0.01535	0.03278	0.06828	0.13609	15884
D_{t+7}/A_t	0.06531	0.11246	0.00000	0.01727	0.03516	0.07432	0.14912	15884
$\log(M_t/A_t)$	0.80737	0.51087	0.28989	0.43023	0.68432	1.06387	1.47197	15884

Table II. Stock Price Informativeness about Future Earnings

For each year t, stocks are sorted independently 10×5 portfolios based on size (M_t) and book-to-market ratio (B/M), respectively. Earnings (E_{t+k}), payouts (D_{t+k}), and assets (A_t) are summed up within each portfolio, where $k \in \{0, 1, ..., 7\}$, to conduct regressions. The table shows predicted variation $\hat{\beta}_k \sigma(log(M_t/A_t))$ and White-heteroscedasticity-consistent t-statistics (in parentheses) from the following portfolio-level cross-sectional regressions using the sample of Chinese A-share stocks,

$$\frac{E_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 7\}$$

for China. The time series averages are reported in the bottom rows, with t-statistics based on Newey-West standard errors lag of one year in parentheses. The corresponding statistics from the sample of US S&P500 stocks are also reported. Variable definitions are in Appendix A.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Year	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$		$k=6$		$k=7$	
	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat
1995	0.002	0.760	0.014	4.359	0.030	4.447	0.020	3.429	0.034	3.537	0.014	0.862	0.001	0.067
1996	0.018	4.191	0.028	2.726	0.026	3.027	0.031	3.388	0.017	1.031	0.005	0.517	-0.008	-0.432
1997	0.020	3.201	0.019	1.831	0.025	2.701	0.012	0.774	0.002	0.137	-0.022	-1.100	-0.048	-3.288
1998	0.009	3.844	0.008	1.597	0.011	1.859	-0.004	-0.428	-0.004	-0.497	-0.011	-1.075	-0.031	-2.917
1999	0.016	3.983	0.012	2.419	0.003	0.672	-0.001	-0.140	-0.015	-1.938	-0.019	-2.831	-0.007	-1.169
2000	-0.003	-0.879	-0.004	-1.355	-0.008	-1.869	-0.019	-3.702	-0.018	-3.463	-0.010	-2.664	-0.008	-1.237
2001	0.000	-0.151	-0.003	-1.150	-0.005	-0.830	-0.011	-2.280	-0.008	-2.400	-0.002	-0.334	0.006	0.735
2002	0.002	0.761	-0.004	-0.773	-0.001	-0.235	-0.002	-0.509	0.003	0.600	0.010	1.112	0.011	2.188
2003	0.003	0.879	0.003	1.272	0.002	1.209	0.012	3.281	0.018	3.420	0.015	3.253	0.019	4.045
2004	0.004	1.780	0.005	2.085	0.014	3.067	0.019	2.542	0.019	3.527	0.024	4.382	0.037	4.321
2005	0.007	2.465	0.014	2.771	0.021	3.076	0.020	5.883	0.021	6.146	0.029	5.709	0.035	5.045
2006	0.014	3.258	0.022	4.886	0.028	3.726	0.029	4.329	0.034	6.050	0.033	6.141	0.040	5.289
2007	0.011	3.231	0.010	2.544	0.012	3.207	0.010	1.441	0.020	4.140	0.010	1.355	0.014	1.711
2008	0.010	3.250	0.017	5.165	0.024	5.010	0.024	6.596	0.028	5.646	0.024	4.049	0.034	5.154
2009	0.013	3.791	0.023	3.566	0.026	6.915	0.026	5.566	0.016	3.665	0.027	7.328	0.043	6.828
2010	0.009	2.732	0.021	2.917	0.026	2.346	0.014	4.668	0.019	3.344	0.032	4.814	0.041	4.713
2011	0.013	4.747	0.020	3.343	0.011	1.872	0.024	3.775	0.040	4.153	0.046	2.876	-0.010	-0.976
2012	0.016	1.936	0.010	2.614	0.019	4.626	0.030	4.384	0.026	2.651	-0.014	-0.950	-0.014	-1.613
2013	0.014	3.274	0.017	9.505	0.027	6.836	0.019	2.488	-0.030	-3.657	-0.034	-3.152	-0.014	-1.352
2014	0.014	7.322	0.022	7.731	0.017	2.943	-0.013	-2.106	-0.013	-1.649	-0.003	-0.321	-0.001	-0.065
2015	0.013	6.016	0.010	3.509	-0.011	-2.102	-0.012	-1.492	-0.002	-0.337	0.002	0.346	0.013	2.012
2016	-0.002	-1.160	-0.002	-1.024	-0.001	-0.323	0.000	-0.132	-0.002	-0.547	0.009	1.075		
2017	-0.005	-2.104	-0.002	-1.646	0.005	1.960	0.004	1.171	0.008	2.332				
2018	0.005	1.619	0.010	4.304	0.010	2.900	0.011	4.035						
2019	0.003	0.651	0.008	2.184	0.013	3.328								
2020	0.003	0.567	0.007	1.818										
2021	0.005	1.699												
Averages China														
1995 to 2016-k	0.010		0.013		0.015		0.013		0.013		0.010		0.009	
	(5.032)		(4.816)		(4.233)		(2.653)		(1.981)		(1.589)		(1.238)	
1995 to 2022-k	0.008		0.011		0.013		0.010		0.009		0.008		0.007	
	(6.026)		(4.827)		(4.392)		(2.989)		(2.587)		(2.007)		(1.293)	
Averages US S&P500														
1960 to 2021-k	0.021		0.029		0.030		0.032		0.032		0.032		0.037	
	(12.994)		(18.940)		(17.033)		(18.410)		(19.168)		(11.795)		(11.278)	
1995 to 2021-k	0.028		0.033		0.033		0.037		0.037		0.038		0.047	
	(10.898)		(14.626)		(14.913)		(22.678)		(17.104)		(7.166)		(7.591)	

Table III. Stock Price Informativeness about Future Payouts

For each year t, stocks are sorted independently 10×5 portfolios based on size (M_t) and book-to-market ratio (B/M), respectively. Earnings (E_{t+k}), payouts (D_{t+k}), and assets (A_t) are summed up within each portfolio, where $k \in \{0, 1, ..., 7\}$, to conduct regressions. The table shows predicted variation $\hat{\beta}_k \sigma(log(M_t/A_t))$ and White-heteroscedasticity-consistent t-statistics (in parentheses) from the following portfolio-level cross-sectional regressions using the sample of Chinese A-share stocks,

$$\frac{D_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 7\}$$

for China. The time series averages are reported in the bottom rows, with t-statistics based on Newey-West standard errors lag of one year in parentheses. The corresponding statistics from the sample of US S&P500 stocks are also reported. Variable definitions are in Appendix A.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Year	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$		$k=6$		$k=7$	
	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat
1995	-0.001	-0.541	-0.002	-0.764	-0.001	-0.687	0.000	-0.176	0.007	2.804	0.006	2.930	0.004	1.840
1996	-0.002	-1.266	0.001	0.477	0.001	0.862	0.008	3.319	0.003	1.450	0.002	0.798	-0.001	-0.333
1997	-0.001	-0.593	-0.001	-0.489	0.002	1.139	0.003	0.999	-0.001	-0.419	-0.004	-1.039	-0.007	-1.656
1998	0.000	-0.491	0.003	2.434	0.002	1.866	0.002	1.701	-0.002	-1.010	-0.002	-0.837	-0.001	-0.620
1999	0.002	2.681	0.002	2.548	0.002	1.720	0.000	-0.253	0.000	-0.139	-0.001	-0.394	0.000	0.081
2000	0.000	-0.836	-0.002	-2.549	-0.002	-2.019	-0.003	-1.899	-0.004	-2.490	-0.003	-1.755	-0.003	-1.552
2001	0.000	0.362	-0.001	-1.148	-0.001	-1.745	-0.002	-2.496	-0.002	-1.868	-0.002	-2.221	0.000	0.139
2002	0.000	0.090	0.000	-0.350	0.000	-0.317	-0.001	-0.776	0.000	0.289	0.003	2.067	0.003	1.658
2003	0.001	1.741	0.000	0.767	0.000	0.722	0.001	1.119	0.003	3.227	0.002	1.704	0.004	2.661
2004	0.001	1.406	0.001	1.544	0.001	0.994	0.003	3.380	0.004	2.094	0.005	3.361	0.010	2.930
2005	0.000	0.736	0.001	1.001	0.003	3.903	0.004	3.089	0.005	4.600	0.007	4.607	0.009	5.508
2006	0.000	1.205	0.002	3.523	0.003	2.613	0.003	3.101	0.005	3.533	0.007	4.598	0.007	3.709
2007	0.001	2.825	0.002	2.485	0.002	2.105	0.002	1.970	0.005	3.351	0.002	1.105	0.001	0.856
2008	0.000	-0.599	0.000	-0.305	0.003	2.209	0.003	2.826	0.003	2.937	0.003	2.776	0.005	2.993
2009	0.001	1.263	0.005	2.481	0.006	3.041	0.003	2.375	0.004	3.083	0.004	2.927	0.008	3.566
2010	0.002	2.073	0.002	3.104	0.002	1.790	0.002	2.711	0.004	4.039	0.005	4.140	0.008	4.224
2011	0.001	3.710	0.001	1.746	0.002	2.947	0.004	3.291	0.006	4.401	0.010	2.830	0.027	4.182
2012	0.000	0.777	0.001	2.729	0.003	3.794	0.005	3.371	0.007	3.425	0.015	2.906	0.023	3.480
2013	0.000	0.934	0.001	2.076	0.003	2.987	0.006	3.621	0.010	4.409	0.016	3.504	0.009	2.772
2014	0.002	3.726	0.005	3.054	0.005	4.994	0.008	4.304	0.012	2.516	0.008	2.954	0.013	2.519
2015	0.001	2.038	0.002	2.307	0.004	3.540	0.015	2.608	0.007	2.618	0.008	1.780	0.013	3.072
2016	0.000	-0.120	0.002	1.553	0.003	1.822	0.001	0.478	0.002	1.012	0.004	1.406		
2017	0.001	1.709	0.002	2.130	0.002	2.004	0.003	2.055	0.004	3.159				
2018	0.002	2.257	0.003	3.186	0.003	2.053	0.006	4.465						
2019	0.002	3.284	0.004	3.099	0.005	3.981								
2020	0.001	0.493	0.004	3.125										
2021	0.004	4.252												
Averages China														
1995 to 2016-k	0.000		0.001		0.002		0.003		0.002		0.002		0.002	
	(2.648)		(3.670)		(4.600)		(3.539)		(3.445)		(2.935)		(2.777)	
1995 to 2022-k	0.001		0.001		0.002		0.003		0.004		0.004		0.006	
	(1.626)		(2.502)		(3.269)		(2.838)		(2.494)		(1.904)		(1.709)	
Averages US S&P500														
1960 to 2021-k	0.006		0.014		0.017		0.019		0.021		0.024		0.023	
	(3.458)		(7.964)		(9.089)		(8.470)		(7.986)		(8.019)		(7.508)	
1995 to 2021-k	0.012		0.024		0.027		0.030		0.035		0.039		0.040	
	(7.563)		(16.818)		(15.363)		(11.362)		(10.025)		(13.049)		(11.572)	

Table IV. Earnings Reversal

For each year t, stocks are sorted independently 10×5 portfolios based on size (M_t) and book-to-market ratio (B/M), respectively. Earnings (E_{t+k}), payouts (D_{t+k}), and assets (A_t) are summed up within each portfolio, where $k \in \{0, 1, ..., 7\}$, to conduct regressions. The table shows the results from the following panel regressions at the portfolio level,

$$\frac{E_{j,t+1} - E_{j,t}}{A_{j,t}} = \alpha + \beta^{0\to 1} log(\frac{M_{j,t}}{A_{j,t}}) + \gamma \frac{E_{j,t}}{A_{j,t}} + \lambda \frac{D_{j,t}}{A_{j,t}} + \epsilon_{j,t},$$

$$\frac{E_{j,t+3} - E_{j,t+1}}{A_{j,t}} = \alpha + \beta^{1\to 3} log(\frac{M_{j,t}}{A_{j,t}}) + \gamma \frac{E_{j,t}}{A_{j,t}} + \lambda \frac{D_{j,t}}{A_{j,t}} + \epsilon_{j,t},$$

$$\frac{E_{j,t+5} - E_{j,t+3}}{A_{j,t}} = \alpha + \beta^{3\to 5} log(\frac{M_{j,t}}{A_{j,t}}) + \gamma \frac{E_{j,t}}{A_{j,t}} + \lambda \frac{D_{j,t}}{A_{j,t}} + \epsilon_{j,t},$$

This analysis is conducted for both China and the US S&P 500 samples. The data spans from 1995 to 2022 for China and from 1960 to 2021 for the US S&P 500. Panel A shows the result of regressions without any fixed effects, Panel B with portfolio fixed effects, and Panel C with year fixed effects. Driscoll-Kraay standard errors with lag of 1 are calculated, and the corresponding t-statistics are reported in parentheses.

Panel A: with no fixed effect

	China (1995-2022)			US SP500 (1960-2021)		
	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$
$\log(M_t/A_t)$	0.013	0.002	-0.013	0.058	0.013	0.011
	(2.52)	(0.28)	(-2.97)	(8.03)	(1.27)	(1.08)
D_t/A_t	1.378	-0.521	0.376	-0.032	0.065	0.050
	(3.75)	(-1.29)	(0.81)	(-0.47)	(1.21)	(0.79)
E_t/A_t	-0.760	-0.125	-0.196	-0.525	-0.211	-0.072
	(-8.48)	(-1.45)	(-2.31)	(-7.67)	(-4.50)	(-1.27)
Portfolio FE	No	No	No	No	No	No
Year FE	No	No	No	No	No	No
N	1050	1050	1050	2602	2602	2602

Panel B: with group fixed effect

	China (1995-2022)			US SP500 (1960-2021)		
	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$
$\log(M_t/A_t)$	0.005	-0.018	-0.018	0.043	0.014	0.007
	(0.63)	(-2.15)	(-2.41)	(5.22)	(1.02)	(0.45)
D_t/A_t	0.755	-0.218	0.289	-0.025	0.061	0.045
	(2.94)	(-0.55)	(0.58)	(-0.36)	(1.13)	(0.72)
E_t/A_t	-0.723	0.077	-0.207	-0.567	-0.204	-0.067
	(-7.45)	(1.06)	(-2.01)	(-8.59)	(-4.74)	(-1.20)
Portfolio FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
N	1050	1050	1050	2602	2602	2602

Panel C: with time fixed effect

	China (1995-2022)			US SP500 (1960-2021)		
Variable	$E_{t+1}-E_t$	$E_{t+3}-E_{t+1}$	$E_{t+5}-E_{t+3}$	$E_{t+1}-E_t$	$E_{t+3}-E_{t+1}$	$E_{t+5}-E_{t+3}$
$\log(M_t/A_t)$	0.020	0.012	-0.007	0.070	0.010	0.017
	(5.42)	(2.08)	(-1.12)	(8.65)	(1.20)	(2.29)
D_t/A_t	1.671	-0.713	-0.033	0.048	0.101	0.021
	(4.37)	(-1.86)	(-0.07)	(0.48)	(1.39)	(0.33)
E_t/A_t	-0.798	-0.094	-0.098	-0.626	-0.170	-0.098
	(-9.60)	(-1.45)	(-1.24)	(-8.57)	(-3.42)	(-1.87)
Portfolio FE	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1050	1050	1050	2602	2602	2602

Table V. Expected Shell Probability (ESP) and NRGL

This table presents the estimated coefficients from firm-level regressions that examine the impact of ESP on the ratio of non-recurring gains and losses to total assets, both in the current year (NRGL_t) and the following year (NRGL_{t+1}). Firm characteristics at year t such as market-to-assets ratio (M/A), log of total assets (log(A)), LEVERAGE, price-to-book ratio (P/B), return on equity (ROE), and past three-year average of NRGL are included as controls. Year, industry, and firm fixed effects are added. Standard errors are clustered by stock and the corresponding t-statistics are in parentheses below each coefficient. The sample period is from 2008 to 2022.

	(1) NRGL_t	(2) NRGL_{t+1}
ESP	0.241	0.106
	(6.62)	(3.10)
log(M/A)	0.00486	0.00914
	(4.20)	(11.51)
log(A)	0.000718	-0.00485
	(0.91)	(-7.35)
LEVERAGE	0.0120	0.0426
	(2.73)	(10.52)
P/B	0.000152	-0.000532
	(1.03)	(-4.47)
ROE	0.0241	-0.00968
	(8.20)	(-4.62)
$\text{NRGL}_{(t-3,t-1)}$	-0.0573	
	(-2.43)	
$\text{NRGL}_{(t-2,t)}$		-0.0869
		(-4.00)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Firm FE	Yes	Yes
R2	0.211	0.255
N	26357	27884

Table VI. Return Predictability of Non-Recurring Gains and Losses (NRGL)

This table presents the results from quarterly Fama-MacBeth stock-level regressions evaluating the predictive power of NRGL_q and its quarterly changes (ΔNRGL) on future stock returns up to four quarter. Controls include log of market value ($\log(M)$), book-to-market ratio (B/M), past quarter and year returns (RET_q and $RET_{(q-12,q-1)}$), turnover rate (TURNOVER), and return on assets (ROA), along with industry dummies. Newey-West standard errors with lag of three quarters are calculated and the corresponding t-statistics are in parentheses below each coefficient. The sample period is from 2008 to 2022. Variable definitions are in Appendix A.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RET_{q+1}	$RET_{(q+1,q+2)}$	$RET_{(q+1,q+3)}$	$RET_{(q+1,q+4)}$	RET_{q+1}	$RET_{(q+1,q+2)}$	$RET_{(q+1,q+3)}$	$RET_{(q+1,q+4)}$
NRGL_q	-0.529	-0.807	-1.100	-1.550				
	(-4.58)	(-3.68)	(-3.61)	(-3.93)				
ΔNRGL_q					-0.484	-0.690	-1.092	-1.417
					(-5.43)	(-4.14)	(-4.99)	(-5.44)
$\log(M)$	-0.0200	-0.0337	-0.0461	-0.0606	-0.0174	-0.0300	-0.0411	-0.0543
	(-3.36)	(-3.31)	(-3.04)	(-2.91)	(-2.84)	(-2.85)	(-2.62)	(-2.51)
B/M	0.00225	0.00806	0.0103	0.0156	0.00206	0.00792	0.00933	0.0126
	(0.24)	(0.48)	(0.42)	(0.50)	(0.23)	(0.48)	(0.38)	(0.40)
RET_q	-0.0293	-0.0132	0.000276	0.00454	-0.0290	-0.0134	-0.00332	0.00491
	(-2.21)	(-0.66)	(0.01)	(0.19)	(-2.19)	(-0.68)	(-0.16)	(0.21)
$RET_{(q-12,q-1)}$	-0.00107	-0.00231	-0.00515	-0.00574	-0.000324	-0.00134	-0.00381	-0.00414
	(-0.42)	(-0.49)	(-0.73)	(-0.58)	(-0.11)	(-0.24)	(-0.46)	(-0.37)
TURNOVER	-0.0143	-0.0226	-0.0299	-0.0376	-0.0141	-0.0222	-0.0293	-0.0372
	(-9.46)	(-10.34)	(-10.25)	(-10.57)	(-8.93)	(-9.66)	(-9.80)	(-10.45)
ROA	0.00225	0.00303	0.00363	0.00542				
	(2.62)	(1.77)	(1.50)	(1.70)				
ΔROA					0.00352	0.00455	0.00564	0.00504
					(5.85)	(4.10)	(3.74)	(2.94)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.119	0.125	0.132	0.135	0.114	0.119	0.127	0.130
N	118704	114777	110904	107104	116696	112820	108994	105231

Table VII. The Impact of the 2020 Delisting Rule: ESP and NRGL

This table presents the estimated coefficients from firm-level regressions that examine the impact of ESP on NRGL, both in the current year ($NRGL_t$) and the following year ($NRGL_{t+1}$), with an interaction term between ESP and POST in columns (1) and (3) and between log(M/A) and POST in columns (2) and (4). POST is a dummy variable that equals one if the left-hand variable is observed in or after 2020. Firm characteristics at year t such as market-to-assets ratio (M/A), log of total assets (log(A)), LEVERAGE, price-to-book ratio (P/B), return on equity (ROE), and past three-year average of NRGL are included as controls. Year, industry, and firm fixed effects are added. Standard errors are clustered by stock and the corresponding t-statistics are in parentheses below each coefficient. The sample period is from 2008 to 2022. Variable definitions are in Appendix A.1.

	(1)	(2)	(3)	(4)
	$NRGL_t$		$NRGL_{t+1}$	
ESP∗POST	-0.159		-0.191	
	(-4.17)		(-5.16)	
$\log(M/A) * \text{POST}$		-0.002		-0.003
		(-3.04)		(-7.28)
ESP	0.280	0.230	0.176	0.113
	(6.87)	(6.35)	(4.59)	(3.36)
$\log(M/A)$	0.005	0.005	0.009	0.011
	(4.04)	(4.39)	(11.26)	(12.19)
$\log(A)$	0.001	0.001	-0.005	-0.004
	(0.74)	(1.04)	(-7.75)	(-6.81)
LEVERAGE	0.012	0.012	0.042	0.043
	(2.73)	(2.83)	(10.40)	(10.63)
P/B	0.000	0.000	-0.001	-0.001
	(1.24)	(1.11)	(-4.39)	(-4.69)
ROE	0.024	0.023	-0.009	-0.010
	(8.17)	(8.07)	(-4.52)	(-4.64)
$NRGL_{(t-3,t-1)}$	-0.055		-0.090	
	(-2.35)		(-4.16)	
$NRGL_{(t-2,t)}$		-0.056		-0.088
		(-2.37)		(-4.09)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Adj. R-sq	0.119	0.118	0.175	0.174
N	26392	26392	27884	27884

Table VIII. The Impact of the 2020 Delisting Rule: Price Informativeness

For each year t, stocks are sorted independently 10×5 portfolios based on size (M_t) and book-to-market ratio (B/M), respectively. Earnings (E_{t+k}), payouts (D_{t+k}), and assets (A_t) are summed up within each portfolio, where $k \in \{0,1,2,3\}$, to conduct regressions. This table examines the impact of the 2020 delisting rule on the informativeness of the market-to-assets ratio $\log(M_t/A_t)$ for predicting future earnings and payouts in the Chinese A-share and US S&P 500 stock. Panel A presents the result of the following panel regressions at the portfolio level with time fixed effects,

$$\frac{E_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \theta_k log(\frac{M_t}{A_t}) * POST_t + \gamma\frac{E_t}{A_t} + \lambda\frac{D_t}{A_t} + v_t + \epsilon_t, \text{where } k \in \{1,2,3\}$$

$POST_t$ is a dummy variable that equals one if E_{t+k} is observed in 2020 or after. Panel B report the same regressions with replace the dependant variable to D_{t+k}/A_t. Standard errors are clustered by portfolio, and corresponding t-statistics are reported in parentheses. The data ranges from 1995 to 2022 for China and from 1995 to 2021 for the US.

Panel A: predicting earnings

	China			US S&P500		
	E_{t+1}/A_t	E_{t+2}/A_t	E_{t+3}/A_t	E_{t+1}/A_t	E_{t+2}/A_t	E_{t+3}/A_t
$\log(M_t/A_t) *$ POST	-0.0131	-0.00997	-0.00924	-0.0112	0.00394	0.00428
	(-3.91)	(-3.49)	(-2.24)	(-1.65)	(0.60)	(0.68)
$\log(M_t/A_t)$	0.0175	0.0233	0.0254	0.0697	0.0847	0.0847
	(5.85)	(6.07)	(5.01)	(9.29)	(10.05)	(15.75)
D_t/A_t	1.350	1.489	1.169	0.108	0.147	0.0997
	(6.88)	(8.47)	(5.27)	(1.75)	(2.53)	(1.85)
E_t/A_t	0.313	0.116	0.0957	0.281	0.0699	0.103
	(4.37)	(1.53)	(1.44)	(6.22)	(2.06)	(3.33)
N	1349	1299	1249	1283	1217	1158
adj. R2	0.551	0.419	0.299	0.655	0.612	0.608

Panel B: predicting payouts

	China			US S&P500		
	D_{t+1}/A_t	D_{t+2}/A_t	D_{t+3}/A_t	D_{t+1}/A_t	D_{t+2}/A_t	D_{t+3}/A_t
$\log(M_t/A_t) *$ POST	0.00137	0.00227	0.00206	-0.0111	-0.0116	-0.0179
	(2.38)	(2.08)	(1.23)	(-2.07)	(-2.56)	(-2.13)
$\log(M_t/A_t)$	0.00191	0.00330	0.00494	0.0382	0.0666	0.0704
	(5.37)	(5.84)	(7.73)	(4.98)	(15.17)	(14.91)
D_t/A_t	0.792	0.763	0.816	0.440	0.227	0.292
	(13.44)	(9.57)	(8.51)	(4.24)	(3.76)	(4.79)
E_t/A_t	0.0357	0.0380	0.0257	0.0902	0.0703	0.0658
	(3.96)	(3.11)	(2.68)	(4.36)	(3.55)	(2.68)
N	1349	1299	1249	1283	1217	1158
adj. R2	0.706	0.522	0.525	0.705	0.699	0.713

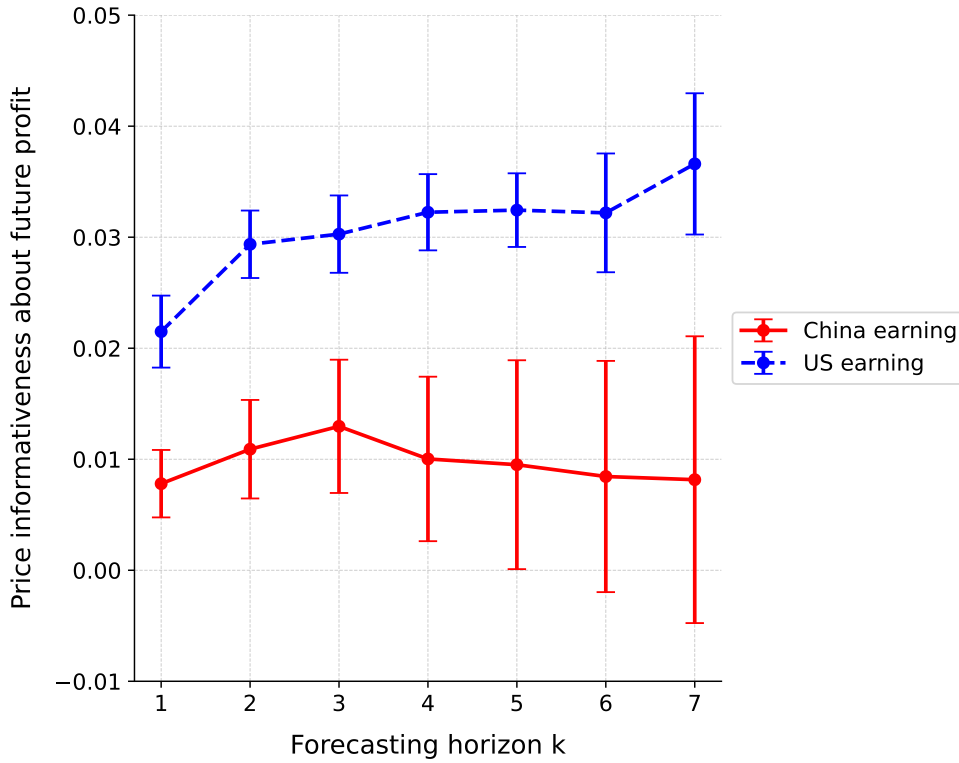

Figure I. Stock Price Informativeness about Future Earnings

This figure presents portfolio-level time-series averages of the predicted variation $\hat{\beta}_k\sigma(\log(M_t/A_t))$ (with 95% confidence intervals) from the annual cross-sectional regressions below:

$$\frac{E_{t+k}}{A_t} = \alpha + \beta_k \log\left(\frac{M_t}{A_t}\right) + \gamma\frac{E_t}{A_t} + \lambda\frac{D_t}{A_t} + \epsilon_t,$$

where k ranges from 1 to 7. For each year t, stocks are sorted independently 10×5 portfolios based on size (M_t) and book-to-market ratio (B/M), respectively. Earnings (E_{t+k}), payouts (D_{t+k}), and assets (A_t) are summed up within each portfolio, where $k \in \{0, 1, ..., 7\}$, to conduct regressions. This analysis includes Chinese A-share stocks from 1995 to $2016 - k$ and US S&P 500 stocks from 1960 to $2021 - k$. Detailed definitions of variables and additional methodological details are delineated in Appendix A.1.

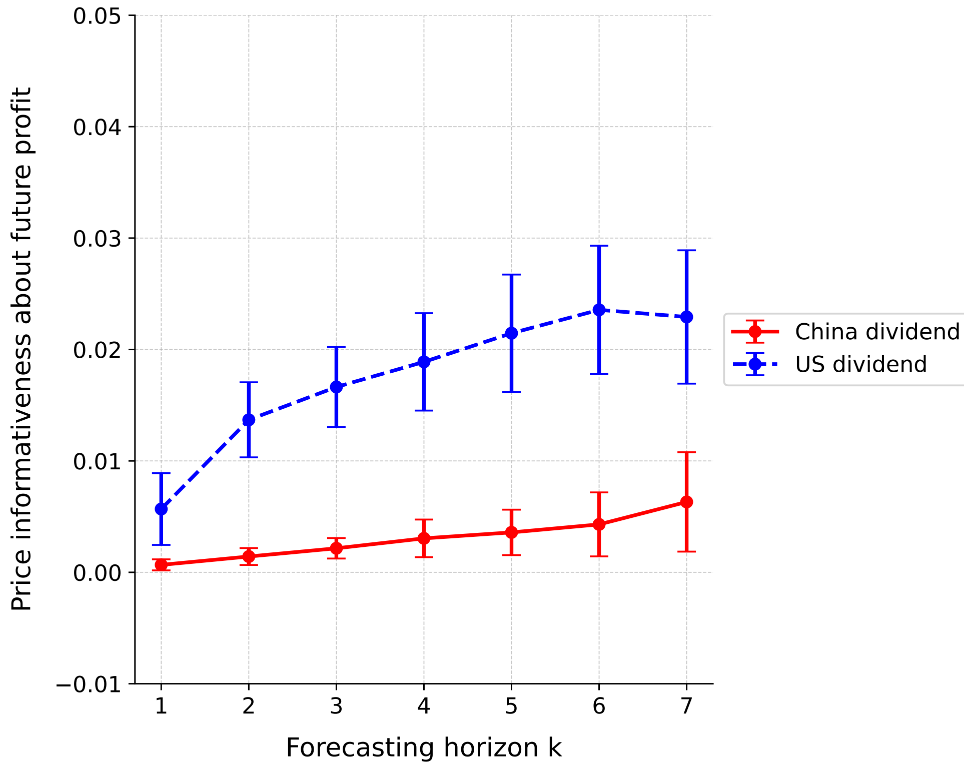

Figure II. Stock Price Informativeness about Future Payouts

This figure presents portfolio-level time-series averages of the predicted variation $\hat{\beta}_k \sigma(\log(M_t/A_t))$ (with 95% confidence intervals) from the annual cross-sectional regressions below:

$$\frac{D_{t+k}}{A_t} = \alpha + \beta_k \log\left(\frac{M_t}{A_t}\right) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \epsilon_t,$$

where k ranges from 1 to 7. For each year t, stocks are sorted independently 10×5 portfolios based on size (M_t) and book-to-market ratio (B/M), respectively. Earnings (E_{t+k}), payouts (D_{t+k}), and assets (A_t) are summed up within each portfolio, where $k \in \{0, 1, ..., 7\}$, to conduct regressions. This analysis includes Chinese A-share stocks from 1995 to $2016 - k$ and US S&P 500 stocks from 1960 to $2021 - k$. Detailed definitions of variables and additional methodological details are delineated in Appendix A.1.

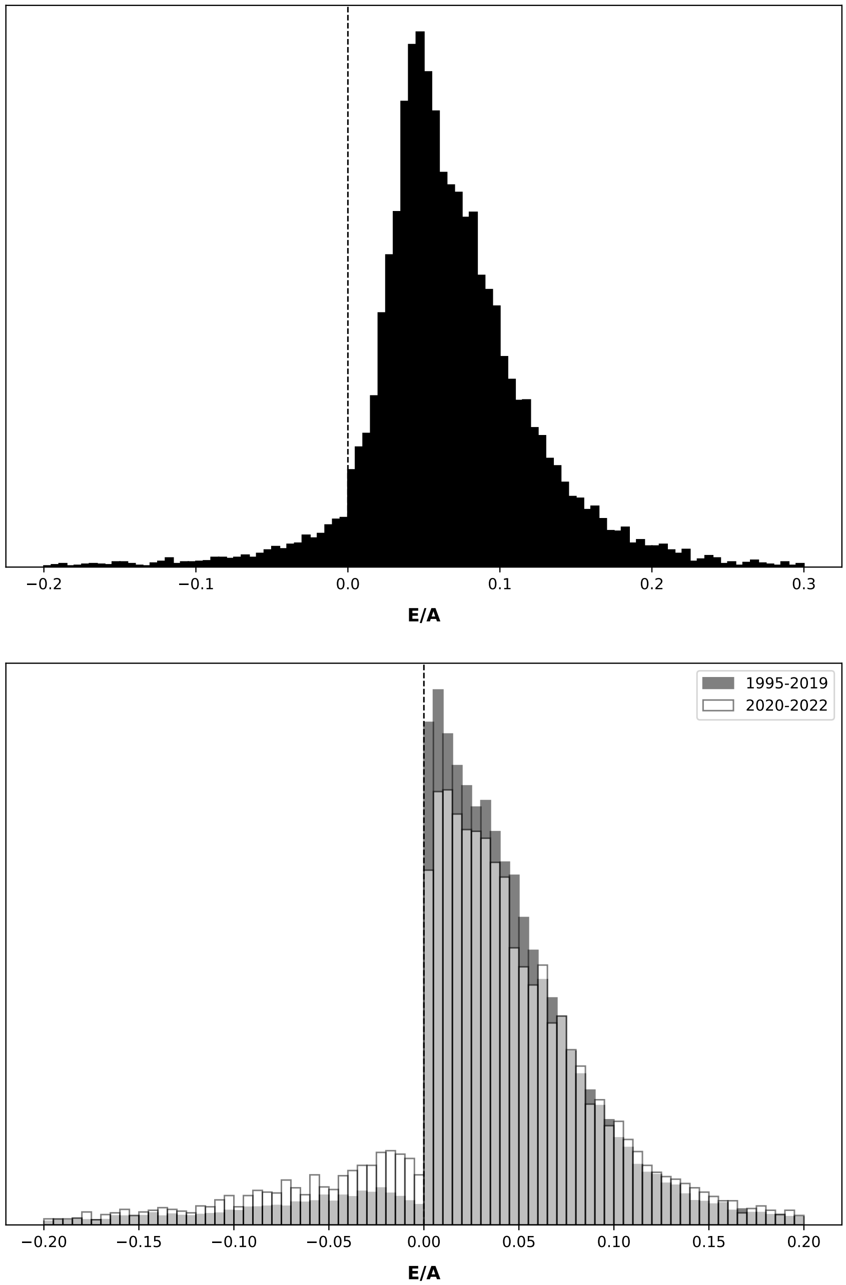

Figure III. Earnings Distribution of US S&P 500 Firms and Chinese A-share Firms

This figure presents the earnings-to-assets ratio (ROA) for US S&P 500 (upper panel) and Chinese A-share firms (lower panel). For Chinese A-share firms, the distribution of ROA between the period of 1995-2019 (in black) and the period of 2020-2022 (in gray) are plot separately.

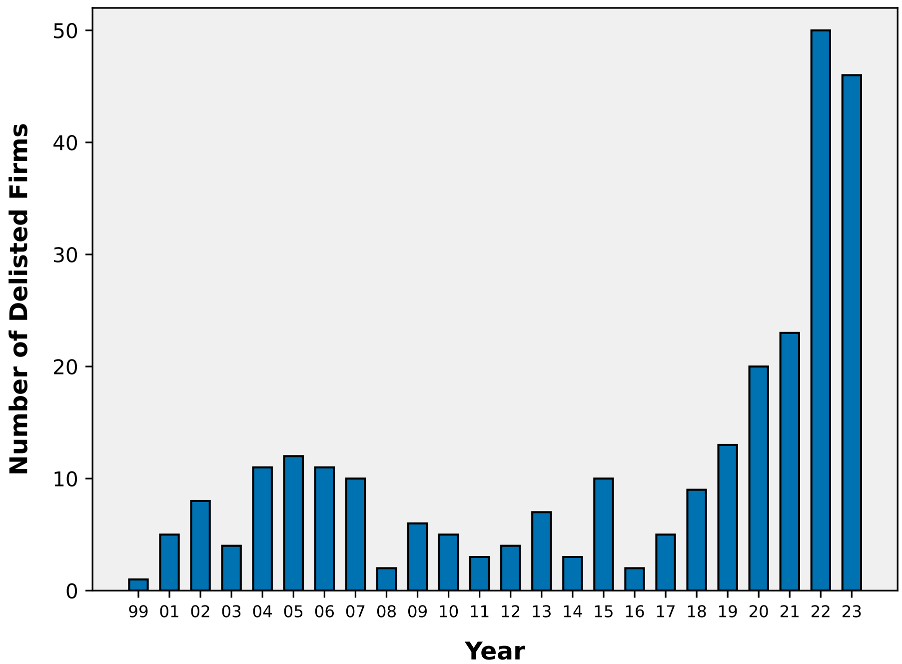

Figure IV. Number of Delisted Firms by Year in the Chinese A-share Market

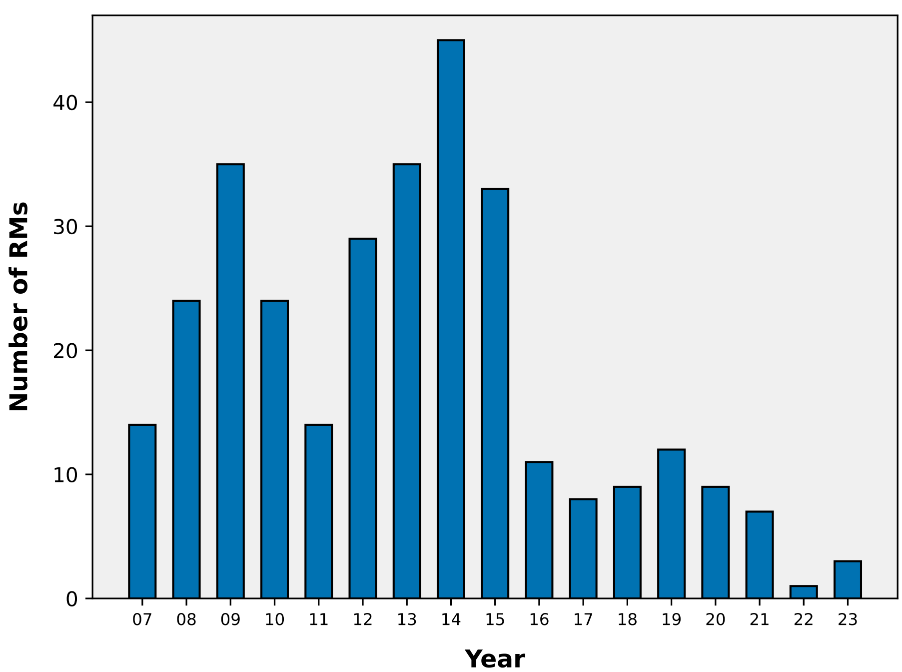

Figure V. Number of Successful Reverse Mergers by Year

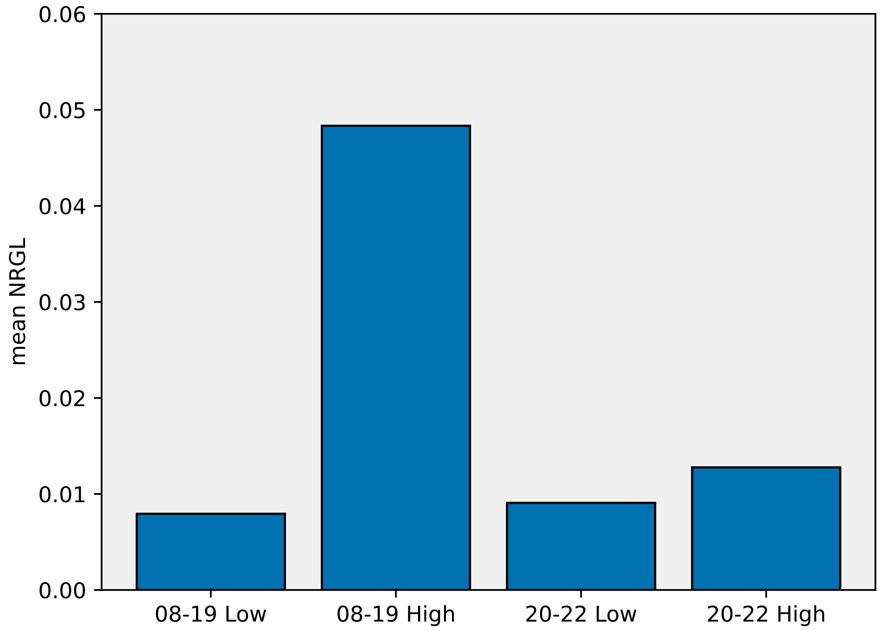

Figure VI. Level of NRGL Before and After the 2020 Delisting Rule

Chinese A-share firms are sorted into high (top 5%) and low (bottom 95%) groups based on their average NRGL between 2008 to 2019. The figure plots each group's average NRGL between 2008 to 2019 and 2020 to 2022. NRGL refers to a firm's annual non-recurring gain and loss scaled by total assets in the previous year.

A Online Appendix

A.1 Variable definitions

A_t: This represents the total assets at year t. It is sourced from the CSMAR Balance Sheets data the field labeled as `a001000000`. For the US, total assets are defined using the variable `at` from the Compustat database.

E_{t+k}/A_t: The ratio E_{t+k}/A_t measures the net profit in year $t+k$ relative to the total assets at year t. E is calculated using data from the CSMAR Income Statements the variable labeled as `b002000000`. For US data, net profit is sourced from the Compustat Income Statements data, where it is labeled as `ni`. Note that to be consistent with specification of the analysis on the Chinese market, we do not exclude extraordinary items from total profit as the literature does.

D_{t+k}/A_t: This ratio represents the total dividend payouts in year $t+k$ normalized by the total assets at year t. The total dividend payouts include the sum of cash dividends paid according to the implementation stage of distribution plans and net repurchase activities. We follow Fama and French (2001) for repurchase calculation.

We use dividend payout data from the CSMAR Dividend Distribution Document/CD_Dividend data table, focusing specifically on implemented dividend distributions. Initially, we focus on dividend payout amount (`numdiv`). We keep only those records where the dividend payout has been implemented and where an actual dividend payout amount is reported. Next, we aggregate the dividend payout amounts for each company per year.

We use stock repurchase data from the CSMAR Detailed Table of Actual Share Repurchase Implementation/SR_IMPLEMENT data table, focusing on transactions by A-share holders. We focus on cumulative total payment (`cumulateTotal`) variable. Initially, the data is imported and filtered to include only records for A-share holders. We address potential issues with data completeness by deriving the year from either the repurchase end date or start date depending on availability. Specifically, if the year derived from the end date is missing, we use the year from the start date. After ensuring all records have a valid year and cumulative total payment, we sum these payments for each company per year. Duplicate records are removed to maintain data integrity.

We use seasonal issue data from the CSMAR Basic Information Document on the Additional Issuance of Shares by Listed Companies/RS_Aibasic data table, specifically focusing on transactions in Chinese Yuan (CNY). We derive the year from the issue closure date (`aiclst`) and, if missing, from the issue start date (`aistdt`). We ensure each record has a valid year and then restrict our data to transactions in CNY, removing any records in other currencies. Additionally, we focus only on entries with a recorded total amount of funds raised (`ptfdrs`) without deduction for issuance expenses. This amount is then aggregated for each company per year.

We use data from the CSMAR Basic Information Document on Rights Issue of Listed Companies/RS_Robasic data table related to company offerings, specifically focusing on those conducted in Chinese Yuan (CNY). The data is filtered to include only records where the ex-rights base day (exddt) is completely provided. We extract the year from the ex-rights base day and confirm that each record has a reported year. The analysis restricts to transactions in CNY, excluding records in other currencies, and to those with recorded amounts of funds raised (ptfdrs) before the deduction of issuance fees. The fund amounts are then aggregated for each company per year. Duplicates are removed for data cleanliness, and the aggregation ensures all figures are included, with missing values set to zero.

We begin with the CSMAR FS_Combas data table, extracting data related specifically to treasury stocks (The treasury stock is from a003102101). We filter this dataset to only include records from 2007 onwards, aligning with the implementation of standardized treasury stock accounting practices. The focus is on entries from the end of each financial year, specifically from consolidated financial statements. For each company, we calculate the annual mean of treasury stock (treasury_stock_avg). This calculation is designed to smooth out fluctuations within the year and adjust for any changes in accounting policies or corporate restructuring. Next, we compute the year-over-year change in treasury stock (net_repu) by subtracting the previous year's average treasury stock from the current year's average.

Upon preparing the treasury stock data, we integrate it with other financial transaction data—specifically repurchases, issues, and offerings—sourced from the corresponding CSMAR datasets. We handle missing data proactively by setting absent issue and offering values to zero. The net repurchase value (net_repu) is then recalculated under the comprehensive formula:

$$\text{net\_repu} = \text{repurchase} - \text{issue} - \text{offering}$$

This formula is applied selectively: for years from 2008 onwards, the calculation is made only when there are no changes in treasury stocks (i.e., treasury_stock and treasury_stock_last_year are zero). For years prior to 2008, where data might be incomplete, net_repu is calculated only when existing data permits. Additionally, any resulting negative values from this formula are reset to zero.

After processing and verifying all calculations, we ensure the dataset is clean by removing any records with missing net_repu values.

Lastly, we calculate the total effective dividend for each company by summing the dividend distributions and net repurchase amounts. This calculation is performed using the formula:

$$\text{total\_dividend} = \text{dividend} + \text{net\_repu}$$

For US data, dividends are calculated as the sum of Cash Dividends on Common Stock from Compustat, labeled as cdvc, and Purchase of Common & Preferred Stock from Compustat, labeled as prstkcc. If these values are missing and total assets are not missing, dividends are set to zero. For years before 1971 when cdvc and prstkcc were not available, dividends are taken from total dividends dvt.

M_t/A_t: This ratio, denoted as M_t/A_t, measures the market value of a company's total capitalization relative to its total assets at year t. The numerator, M_t, is from the CSMAR Annual Stock Price Returns dataset and is calculated by aggregating the annual closing market values of all types of shares issued by the company. For US, the market value of equity is calculated using data from the CRSP data and equals the absolute value of the stock price (`prc`) multiplied by the number of shares outstanding (`shrout`).

$NRGL_t$: A firm's annual non-recurring gains and losses at year t, normalized by the previous year's total assets. This variable is derived from non-recurring gains/losses in CNY (datacode `fn_fn00902`) provided by the CSMAR Financial Statement Notes/Profit and Loss Items/Non-recurring Profit and Loss/FN_FN009 data table. We include data only from consolidated financial statements and only in CNY.

$NRGL_q$: A firm's quarterly non-recurring gains and losses over quarter q, normalized by the previous year's total assets. This variable is derived from non-recurring gains/losses in CNY (datacode `f020101`) from the CSMAR disclosed financial indicators/FI_T2 data table.

$\Delta NRGL_q$: Quarterly change of $NRGL_q$, that is, $NRGL_q - NRGL_{q-4}$.

ESP: The ESP variable is calculated following a detailed sequence of steps involving data preparation, cleaning, and merging from iFind, CSMAR, WIND. We follow Lee et al. (2023). Data is combined from multiple data containing information on shell value, industry codes, monthly market cap, earnings, and financial statements. Variables such as size, ownership concentration, profitability, and special treatment (ST) are calculated. The resulting data is used to estimate firm-level probabilities of reverse mergers through logistic regression models, incorporating lagged values of the predictors. To compute ESP, rolling logistic regressions are performed, predicting the likelihood of a reverse merger using historical data up to the previous year.

ROE: It is defined as the ratio of net profit attributable to common shareholders to the average common shareholders' equity, multiplied by 100 to express it as a percentage. The net profit data is sourced from the CSMAR Income Statements, where the original variable is labeled `b002000101`, and the shareholders' equity data is sourced from the CSMAR Balance Sheets, with the original variable labeled `a003100000`. The average equity is computed as mean of the current year's equity and the previous year's equity.

RET_q: Quarterly Return with Dividend Reinvested measures the total return of a stock over a quarter, including the effect of reinvested cash dividends. It is compounded using the monthly return within a quarter and in percentage.The monthly return data is sourced from the CSMAR Monthly Stock Return data, where the original variable is labeled `mretwd`.

$\log(M)$: Natural Logarithm of Market Value represents the natural logarithm of the total market value of a stock at its closing price. This is calculated by dividing the total market value by 1000 and then taking the natural logarithm of the result. The total market value data is sourced from the CSMAR Monthly Stock Return data, where the original variable is labeled `msmvttl`.

B/M**:** Book-to-market ratio for a listed company measures the ratio of the book value of a company's equity to its market value. It is calculated by taking the natural logarithm of the total shareholders' equity divided by the average market value of the stock multiplied by 1000. The total shareholders' equity data is sourced from the CSMAR Balance Sheets, where the original variable is labeled `a003000000`. The average market value is obtained by averaging the monthly market values.

$TURNOVER_q$**:** Turnover ratio for quarter q in a listed company measures the liquidity of a company's stock by indicating how frequently the shares change hands over a quarter. It is calculated by first determining the monthly turnover ratio, which is the ratio of the number of shares traded to the total number of shares outstanding, derived from the market value of tradable shares divided by the monthly closing price and multiplied by 1000. The quarterly turnover ratio is then obtained by summing these monthly turnover ratios for each stock over the quarter. The monthly data is sourced from the CSMAR Monthly Stock Return data, where relevant variables include `msmvosd`, market value of tradable shares, and `mclsprc`, monthly closing price.

ROA**:** Return on Assets (ROA) measures a company's profitability relative to its total assets. It is calculated by dividing net income by total assets and multiplying the result by 100 to express it as a percentage. The net income data is sourced from the CSMAR Income Statements, and the total assets data is sourced from the CSMAR Balance Sheets, where the original variable for total assets is labeled `a001000000`.

ΔROA**:** Change in Return on Assets (ROA) measures the variation in a company's profitability relative to its total assets from one period to the next. It is calculated by subtracting the ROA of the previous period from the current period's ROA. For quarterly data, this involves comparing the ROA of the current quarter with that of the previous quarter. The net income and total assets data used to calculate ROA are sourced from the CSMAR Income Statements and CSMAR Balance Sheets, respectively.

A.2 Background of the 2019-2020 reform on delisting rules

In October 2014, the China Securities Regulatory Commission (CSRC) issued "Several Opinions on Reforming and Perfecting the Delisting System for Listed Companies and its Strict Implementation." It focused on delisting rules for companies with serious regulatory violations, such as fraudulent issuance and severe illegal disclosure of information.

In July 2018, the China Securities Regulatory Commission (CSRC) released an amendment to the 2014 "Several Opinions on Reforming and Perfecting the Delisting System for Listed Companies and its Strict Implementation." The amendment further clarified the future reforms of the delisting rules and details on the enforcement of the current rule.

In November 2018, both Shanghai and Shenzhen Stock Exchanges issued implementation measures for the mandatory delisting of listed companies that have severe regulatory violations.

In the same month of 2018, the Shanghai Stock Exchange established the Science and Technology Innovation Board (STAR Board) and piloted the registration-based IPO system. Drawing on previous delisting system reforms, the STAR Market has set strict delisting standards, improved delisting criteria, and streamlined delisting procedures.

Specifically, according to the "Stock Listing Rules for the Science and Technology Innovation Board of the Shanghai Stock Exchange" issued in March 2019, the criteria for delisting due to poor financial performance is "a net profit before and after deducting extraordinary gains and losses (including restated amounts) in the most recent audited fiscal year being negative, and with the most recent year's audited operating income (including restated amounts) lower than 100 million yuan." This is different from delisting criteria for main board listed first at that time, which focus on sole-criteria total profit (include non-recurring items) being positive. However, the "Stock Listing Rules for the GEM Board of the Shenzhen Stock Exchange" did not undergo similar amendments in 2019.

On March 1, 2020, the new Securities Law of the People's Republic of China came into effect with the addition of Article 48, which no longer specifies the concrete circumstances for termination listing status. Instead, it delegates this to the listing rules stipulated by the stock exchanges.

On November 2, 2020, the "Implementation Plan for Perfecting the Listed Company Delisting Mechanism" was reviewed and approved by the Central Comprehensively Deepening Reforms Commission of CCP.

In December 2020, the Shanghai and Shenzhen Stock Exchanges released revised delisting rules. Specifically, those are the fourteenth revision by the Shanghai Stock Exchange in December 2020 (for all stocks listed in Main and STAR Boards) and the eleventh revision by the Shenzhen Stock Exchange in December 2020. The main amendments include the new criteria for determining ST stocks. In general, it follows the 2018 pilot rule for stocks listed on the STAR board. That is, the ST status (risk of determination for delisting) is based on a multi-criteria: negative net profit and operating income less than 100 million yuan, where the definition of net profit is clarified as "the lower of the net profit before and after deducting non-recurring gains and losses." Also, the aforementioned "operating income" should exclude the income unrelated to the main business and the income without commercial substance. The 2020 rule is effective for annual financial reports for the fiscal year of 2020.

In April 2024, the Shanghai and Shenzhen Stock Exchanges issued another revision of the delisting rules. One important change is to increase the hurdle for operating income "below 100 million yuan" to "below 300 million yuan" when the firm's net profit is negative.

A.3 Individual firm level results

Table A.1.1. Stock Price Informativeness about Future Earnings

labeltab:carpenter$_{e}arning_{i}nd_{c}hina$
The table shows predicted variation $\hat{\beta}_k\sigma(log(M_t/A_t))$ and White-heteroscedasticity-consistent t-statistics (in parentheses) from the following firm-level cross-sectional regressions using the sample of Chinese A-share stocks,

$$\frac{E_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma\frac{E_t}{A_t} + \lambda\frac{D_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 7\}$$

for China. The time series averages are reported in the bottom rows, with t-statistics based on Newey-West standard errors lag of one year in parentheses. The corresponding statistics from the sample of US S&P500 stocks are also reported. Variable definitions are in Appendix A.1.

	China (Individual)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Year	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$		$k=6$		$k=7$	
	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat
1995	0.003	1.204	0.013	2.913	0.027	3.869	0.026	4.176	0.039	4.853	0.035	3.296	0.000	-0.002
1996	0.016	4.043	0.026	3.861	0.040	5.625	0.041	4.698	0.035	3.095	0.031	3.279	0.025	2.247
1997	0.028	4.884	0.035	7.717	0.035	6.628	0.032	4.099	0.022	3.015	0.009	1.054	0.003	0.258
1998	0.018	6.959	0.022	6.841	0.020	4.472	0.008	1.710	0.001	0.253	-0.010	-1.575	-0.021	-2.717
1999	0.010	4.420	0.015	3.902	0.005	1.318	-0.001	-0.212	-0.006	-1.270	-0.012	-2.130	-0.000	-0.047
2000	0.005	1.777	0.001	0.288	-0.003	-0.932	-0.006	-2.065	-0.013	-3.207	-0.006	-1.786	-0.002	-0.356
2001	-0.000	-0.078	0.000	0.062	-0.001	-0.192	-0.006	-1.750	-0.002	-0.543	0.005	1.139	0.024	3.781
2002	0.000	0.193	-0.001	-0.360	-0.002	-0.810	0.001	0.511	0.010	2.355	0.019	4.013	0.018	3.421
2003	0.006	2.181	0.006	2.345	0.007	3.023	0.015	4.524	0.020	4.971	0.016	3.806	0.022	4.173
2004	0.007	2.917	0.008	3.481	0.022	5.554	0.026	6.201	0.023	4.764	0.029	4.851	0.049	5.727
2005	0.009	3.944	0.023	5.143	0.031	6.818	0.027	6.164	0.032	5.562	0.060	6.629	0.058	7.418
2006	0.031	6.660	0.035	7.497	0.033	7.865	0.038	7.097	0.069	7.052	0.061	7.685	0.086	7.954
2007	0.022	4.574	0.027	6.148	0.034	5.803	0.071	6.147	0.054	7.249	0.076	6.366	0.053	5.457
2008	0.017	4.856	0.019	5.444	0.052	6.255	0.066	6.974	0.083	6.771	0.071	6.341	0.109	7.154
2009	0.014	5.085	0.034	6.089	0.065	6.510	0.076	6.399	0.048	6.201	0.091	7.506	0.134	7.056
2010	0.017	5.058	0.056	6.203	0.077	5.972	0.046	5.988	0.077	7.050	0.122	6.466	0.142	6.326
2011	0.023	7.067	0.033	7.037	0.031	6.513	0.057	8.312	0.090	7.661	0.096	7.616	0.029	1.761
2012	0.015	4.937	0.017	4.995	0.033	7.044	0.062	7.444	0.064	6.475	0.002	0.181	-0.002	-0.146
2013	0.011	6.018	0.027	8.052	0.045	8.223	0.049	7.049	-0.011	-1.174	-0.016	-1.343	0.003	0.326
2014	0.017	7.500	0.033	7.924	0.037	6.677	-0.015	-1.981	-0.012	-1.434	0.002	0.228	0.011	1.437
2015	0.014	7.320	0.013	4.937	-0.007	-2.038	-0.006	-1.188	-0.000	-0.027	0.011	2.106	0.026	3.733
2016	0.003	2.635	-0.005	-2.439	0.001	0.213	0.005	1.979	0.006	2.092	0.011	2.999		
2017	-0.002	-0.919	0.006	2.897	0.013	5.845	0.014	5.876	0.020	6.000				
2018	0.012	6.563	0.019	9.751	0.020	8.905	0.025	8.890						
2019	0.017	10.691	0.019	10.891	0.022	10.008								
2020	0.016	9.408	0.016	8.911										
2021	0.010	8.734												
Averages China														
1995 to 2016-k	0.013		0.021		0.029		0.032		0.034		0.037		0.037	
	(6.082)		(5.319)		(4.461)		(3.867)		(3.460)		(2.976)		(2.629)	
1995 to 2022-k	0.012		0.019		0.025		0.027		0.028		0.032		0.037	
	(6.592)		(5.605)		(4.643)		(3.796)		(3.279)		(2.936)		(2.863)	
Averages US S&P500														
1960 to 2021-k	0.027		0.042		0.047		0.049		0.053		0.057		0.063	
	(19.152)		(26.237)		(23.412)		(21.712)		(18.814)		(18.675)		(16.845)	
1995 to 2021-k	0.032		0.047		0.051		0.054		0.062		0.066		0.077	
	(16.411)		(22.157)		(15.688)		(15.659)		(15.112)		(14.481)		(13.204)	

Table A.1.2. Stock Price Informativeness about Future Payouts

The table shows predicted variation $\hat{\beta}_k \sigma(log(M_t/A_t))$ and White-heteroscedasticity-consistent t-statistics (in parentheses) from the following firm-level cross-sectional regressions using the sample of Chinese A-share stocks,

$$\frac{D_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 7\}$$

for China. The time series averages are reported in the bottom rows, with t-statistics based on Newey-West standard errors lag of one year in parentheses. The corresponding statistics from the sample of US S&P500 stocks are also reported. Variable definitions are in Appendix A.1.

	China (Individual)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Year	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$		$k=6$		$k=7$	
	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat
1995	-0.001	-0.046	0.001	0.373	-0.001	-0.754	-0.000	-0.110	0.007	3.000	0.007	2.264	0.005	1.898
1996	0.002	1.361	0.004	2.375	0.001	0.857	0.008	4.065	0.007	3.517	0.005	2.666	0.005	2.226
1997	0.003	3.285	0.002	2.320	0.009	5.374	0.008	6.117	0.005	3.490	0.003	2.305	0.005	2.469
1998	0.001	0.933	0.005	5.286	0.005	5.341	0.004	3.829	0.001	1.118	0.003	1.638	0.001	0.293
1999	0.003	4.833	0.003	4.061	0.002	2.685	-0.000	-0.522	0.001	0.695	-0.000	-0.022	0.000	0.114
2000	0.001	1.634	0.000	0.701	-0.001	-1.963	-0.001	-1.772	-0.003	-3.209	-0.002	-2.378	-0.004	-2.909
2001	0.001	1.385	-0.001	-1.892	-0.001	-1.124	-0.002	-2.077	-0.002	-2.114	-0.002	-1.787	0.002	1.979
2002	-0.000	-0.223	-0.000	-0.525	-0.001	-0.813	-0.001	-1.706	-0.001	-0.778	0.003	2.929	0.002	2.493
2003	0.002	4.441	0.001	2.918	0.001	1.726	0.001	1.536	0.004	4.128	0.003	3.267	0.003	3.183
2004	0.002	4.172	0.002	3.028	0.001	2.237	0.004	5.195	0.004	4.478	0.005	3.766	0.009	4.879
2005	0.002	4.039	0.001	2.777	0.004	5.816	0.004	5.527	0.006	4.835	0.010	5.817	0.013	6.025
2006	0.001	2.741	0.004	6.327	0.005	6.791	0.005	5.335	0.010	6.332	0.013	5.895	0.014	6.062
2007	0.003	6.003	0.004	5.838	0.004	4.747	0.007	5.760	0.010	6.159	0.010	5.453	0.010	4.341
2008	0.002	5.267	0.002	3.539	0.006	5.086	0.007	5.327	0.010	5.495	0.012	4.986	0.014	4.506
2009	0.001	2.714	0.004	4.817	0.006	5.416	0.006	5.202	0.009	4.820	0.011	4.944	0.017	5.225
2010	0.003	5.593	0.004	7.077	0.005	5.176	0.007	5.536	0.010	5.370	0.014	5.476	0.023	5.653
2011	0.002	6.054	0.002	5.307	0.004	5.610	0.007	5.966	0.010	6.387	0.016	6.159	0.030	6.086
2012	0.001	2.198	0.002	2.941	0.004	4.269	0.006	4.917	0.010	5.240	0.021	4.338	0.018	4.211
2013	0.001	3.694	0.003	5.122	0.005	5.801	0.007	5.739	0.011	4.626	0.010	4.533	0.009	4.851
2014	0.001	4.575	0.003	5.184	0.005	4.825	0.007	3.964	0.007	4.054	0.007	4.339	0.011	4.236
2015	0.001	3.173	0.002	3.626	0.004	3.804	0.005	3.683	0.005	3.923	0.006	3.047	0.012	4.633
2016	0.001	1.977	0.001	2.776	0.003	3.073	0.003	3.029	0.004	3.069	0.006	3.998		
2017	0.001	2.891	0.003	3.870	0.004	5.542	0.005	4.901	0.008	5.718				
2018	0.004	6.138	0.006	9.166	0.009	8.994	0.011	8.988						
2019	0.005	10.832	0.007	9.693	0.010	9.881								
2020	0.003	6.128	0.007	8.980										
2021	0.005	8.853												
Averages China														
1995 to 2016-k	0.002		0.002		0.003		0.004		0.005		0.006		0.007	
	(7.579)		(5.543)		(3.948)		(3.706)		(3.594)		(3.431)		(3.313)	
1995 to 2022-k	0.002		0.003		0.004		0.004		0.006		0.007		0.010	
	(6.345)		(5.664)		(5.141)		(5.143)		(4.967)		(4.426)		(4.108)	
Averages US SP500														
1960 to 2021-k	0.011		0.024		0.034		0.043		0.051		0.059		0.066	
	(8.000)		(11.450)		(11.693)		(10.362)		(11.119)		(10.202)		(10.933)	
1995 to 2021-k	0.007		0.014		0.021		0.026		0.032		0.036		0.040	
	(6.401)		(7.916)		(8.568)		(8.215)		(8.543)		(8.121)		(8.390)	

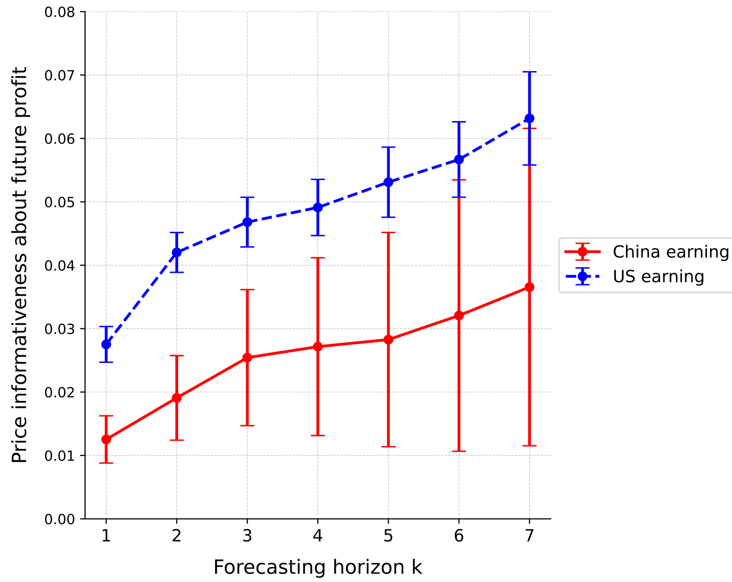

Figure A.1.1. Stock Price Informativeness about Future Earnings.

This figure presents firm-level time-series averages of the predicted variation $\hat{\beta}_k \sigma(\log(M_t/A_t))$ (with 95% confidence intervals) from annual cross-sectional regressions over forecasting horizons $k = 1$ to 7. The regressions evaluate the ratio of future earnings to current assets (E_{t+k}/A_t), modulated by the logarithm of the market-to-assets ratio, historical earnings efficiency, and dividend payout ratio. The regression formula used is:

$$\frac{E_{t+k}}{A_t} = \alpha + \beta_k \log\left(\frac{M_t}{A_t}\right) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \epsilon_t,$$

where k ranges from 1 to 7. This analysis includes Chinese A-share stocks from 1995 to $2022 - k$ and US S&P 500 stocks from 1960 to $2021 - k$. Detailed definitions of variables and additional methodological details are delineated in Appendix A.1.

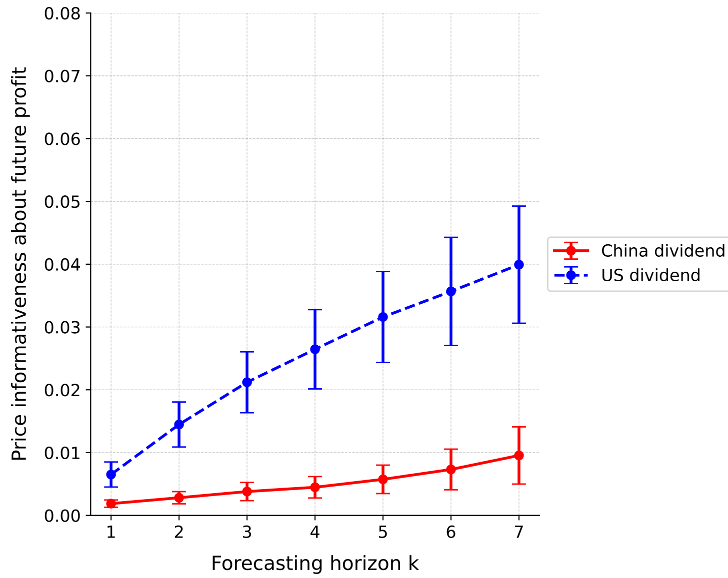

Figure A.1.2. Stock Price Informativeness about Future Payouts.

This figure presents firm-level time-series averages of the predicted variation $\hat{\beta}_k \sigma(\log(M_t/A_t))$ (with 95% confidence intervals) from annual cross-sectional regressions over forecasting horizons $k = 1$ to 7. The regressions evaluate the ratio of future earnings to current assets (E_{t+k}/A_t), modulated by the logarithm of the market-to-assets ratio, historical earnings efficiency, and dividend payout ratio. The regression formula used is:

$$\frac{D_{t+k}}{A_t} = \alpha + \beta_k \log\left(\frac{M_t}{A_t}\right) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \epsilon_t,$$

where k ranges from 1 to 7. This analysis includes Chinese A-share stocks from 1995 to $2022 - k$ and US S&P 500 stocks from 1960 to $2021 - k$. Detailed definitions of variables and additional methodological details are delineated in Appendix A.1.