Earnings Management and Price Informativeness*

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Abstract

We address the puzzling finding by Carpenter, Lu, and Whitelaw (2021) that Chinese A-share stock prices are as informative about future earnings as those in the U.S. market. Due to prevalent earnings management and less sophisticated investors in the Chinese A-share market, firms may align reported earnings with stock valuations. We show that higher-valued stocks report higher earnings over next three years, but this does not increase shareholder payouts, and earnings eventually reverse. Additionally, we provide evidence of earnings management through non-recurring gains and losses (NRGL), and leverage the 2020 delisting rule reform as a natural experiment.

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1 Introduction

Bai, Philippon, and Savov (2016) develop a method to measure stock market price informativeness by running cross-sectional regressions of firms' future earnings on current stock market valuation. The predictive power of market valuation reflects the extent to which stock prices incorporate information about future profits. Carpenter, Lu, and Whitelaw (2021) apply this method to the Chinese A-share market and find that Chinese stock prices are as informative as those in the U.S. This finding is surprising, given the Chinese stock market's high volatility and speculative nature (e.g., Song and Xiong, 2018; Hu, Pan, and Wang, 2021).

It is important to recognize that the price informativeness measure of Bai, Philippon, and Savov (2016) relies on the assumption that earnings are truthfully reported and reflect firm fundamentals. However, this assumption may not hold in the Chinese A-share market. Notably, there is extensive evidence of earnings management and manipulation, indicating low financial reporting quality (see, e.g., Piotroski and Wong (2012) for a review). Additionally, previous studies highlight severe governance issues among Chinese A-share listed firms (e.g., Allen, Qian, Shan, and Zhu, 2024).

This paper examines whether the findings of Carpenter, Lu, and Whitelaw (2021) reflect genuine price informativeness or earnings management. To reconcile the observed empirical patterns, we propose a "manipulate-to-cater" mechanism, in which firm managers, seeking to sustain high share prices, manipulate reported earnings to align with investor expectations. Specifically, following Hirshleifer and Teoh (2003), we posit that a fraction of investors are inattentive and blindly trust reported earnings, leading to stock overvaluation relative to firm fundamentals. In turn, market valuation pressures firm managers to adjust reported earnings to conform to these inflated expectations.

This "manipulate-to-cater" mechanism generates several distinct predictions that contrast with the price-informativeness view. First, while high market valuation should predict higher reported earnings, it may not translate into greater shareholder payouts. Second, since managed earnings are unsustainable, they should eventually reverse in the long term. Third, the managed earnings component should correlate with lower future stock returns as investors gradually recognize the manipulation. This paper empirically tests these predictions and finds supportive evidence, as summarized below.

To test these predictions, we run cross-sectional regressions of Chinese firms' future reported earnings over the next one to seven years ($E_{t+1}, \ldots, E_{t+7}$), scaled by current firm assets (A_t), on the log of market valuation (M_t) scaled by A_t. Our sample includes all Chinese A-share stocks from 1995 to 2022. For comparison, we analyze U.S. data using a sample of S&P 500 constituent stocks from 1960 to 2021, following Carpenter et al. (2021) and Bai et al. (2016).

Our analysis follows Carpenter et al. (2021) with two key modifications. First, to explore the long-term predictability of market prices, we extend our analysis to include earnings at longer horizons, specifically E_{t+6} and E_{t+7}. Second, we conduct regressions at the portfolio level rather than the individual stock level. At the end of each year, we form 50 stock portfolios by independently sorting stocks into deciles based on market capitalization and quintiles based on the book-to-market ratio. Within each portfolio, we aggregate earnings, payouts, market capitalization, and total assets for empirical analysis. This portfolio-based approach, following Fama and French (1995), mitigates the impact of extreme values on coefficient estimation.

We find that the main result of Carpenter et al. (2021) remains robust over the extended sample period at the portfolio level: the valuation of Chinese A-share stocks is as informative as that of U.S. S&P 500 stocks in predicting future earnings. However, several new patterns emerge. First, predictability is stronger for medium-term earnings (3 to 5 years) than for short-term earnings (1 year) but declines for earnings at 6 and 7 years in China–an "reversal" pattern absent in the U.S. market. Second, in recent years, earnings predictability in China has weakened, a trend not observed in Carpenter et al., 2021's original sample period. As we discuss later, this decline may be linked to the 2020 delisting rule reform in the A-share market.

Next, we replace future earnings with future total payouts ($D_{t+1}, \ldots, D_{t+7}$) as the dependent variable to assess whether higher reported earnings translate into actual shareholder payoffs. We find that higher reported earnings do not result in greater payouts, which include cash dividends and share repurchases. Our analysis controls for current earnings and payouts. In addition, we examine whether higher reported earnings stem from increased operating cash flow by using future operating cash flow ($OCF_{t+1}, \ldots, OCF_{t+7}$) as the dependent variable. We find a weak and insignificant correlation between valuation and subsequent cash flow.

These patterns support our hypothesis that reported earnings in Chinese firms may reflect earnings management or manipulation rather than genuine operational cash flow or future payouts. In contrast, the market value of S&P 500 stocks in the U.S. exhibits strong predictive power for future payouts and operating cash flow, comparable to its ability to predict future earnings.

A key prediction of our "manipulate-to-cater" hypothesis is earnings reversal—specifically, a high market value (M_t) should be associated with elevated reported earnings in the short term, followed by a decline in the long term. To formally test this reversal pattern, we modify the specification of Carpenter et al. (2021) by examining the change in earnings from year t to $t+1$, from $t+1$ to $t+3$, and from $t+3$ to $t+5$.

Our findings support this hypothesis. 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 $(E_{t+3} - E_{t+1})/A_t$, and low values of $(E_{t+5} - E_{t+3})/A_t$. In contrast, this reversal pattern is absent in the sample of U.S. S&P 500 firms. The observed earnings reversal suggests that firms in the Chinese A-share market might have inflated reported earnings to meet market expectations.

Our "manipulate-to-cater" mechanism primarily explains the time-series patterns in firms' reported earnings, whereas the price informativeness view of Carpenter et al. (2021) focuses on cross-sectional patterns across firms. Notably, the earnings reversal pattern becomes more pronounced when controlling for portfolio fixed effects but weakensand even turns insignificantwhen controlling for time fixed effects, a specification similar to that used by Carpenter et al. (2021). This suggests that the two economic forces are not mutually exclusive; rather, both contribute to the observed strong correlation between firm valuations and future reported earnings in our sample of Chinese firms.

Additionally, we leverage a sample of 89 Chinese non-financial firms that are simultaneously listed in both the A-share market and the Hong Kong stock market. Although the shares issued in these two markets carry the same rights, restrictions on cross-market transfers prevent arbitrage trading, leading to valuation differences between A and H shares of the same firms. When using A-share and H-share valuations to predict future earnings for these dually listed firms, we find that H-share market valuation significantly predicts future earnings, whereas A-share valuation becomes insignificant. More importantly, there is no earnings reversal associated with H-share valuations. These findings align with the predominance of institutional investors in the Hong Kong market, which enhances the informativeness of H-share prices.

We also provide direct evidence of earnings inflation through Non-Recurring Gain and Loss (NRGL). Under Chinas accounting rules, NRGL—comprising non-operating and one-time items such as government subsidies, asset sales, and donations—was included in total earnings calculations for regulatory delisting decisions until the 2020 reform. This reform, designed to prevent weak firms from artificially inflating earnings to avoid delisting, introduced a key rule excluding NRGL from earnings calculations. This policy change underscores the importance of NRGL and motivates our focus on its role in reported earnings inflation. Consistent with our hypothesis, we find that firms with higher market valuations tend to report elevated NRGL.[1]

We further examine whether investors can fully see through these managed earnings. If investors recognize that reported earnings driven by a high NRGL component are unlikely to persist, they should rationally discount such earnings, resulting in no return predictability by NRGL, as suggested by the efficient market hypothesis of Stein (1989). However, if investors fail to fully recognize earnings inflation, as argued by Hirshleifer and Teoh (2003), NRGL would negatively predict subsequent stock returns. Our findings suggest that investors do not fully account for earnings inflation. Both the level of quarterly NRGL and changes in NRGL predict lower stock returns over the next one to four quarters. Specifically, a one standard deviation increase in NRGL (or its change) is associated with a 0.68% (0.91%) lower return in the following quarter.

To further strengthen identification, we exploit the 2020 reform of delisting rules as a natural experiment. With the new rules taking effect for the 2020 fiscal year, we designate 2020 and onward as the post-event window. Consistent with the notion that NRGL was used to inflate earnings, we find that after the reform, firms with higher valuation ratios experienced greater reductions in reported NRGL.

More interestingly, the correlation between market value (M_t) and future reported earnings (E_{t+k}) weakened after 2020, while the correlation between market value and future payouts (D_{t+k}) strengthened. This shift helps explain why the estimated price informativeness in our sample (which includes recent years, 2017-2022) is lower than that reported by Carpenter et al. (2021). Notably, this pattern is absent in the U.S. data.

Overall, our findings strongly support our proposed "manipulate-to-cater" mechanism.

[1]Other methods of earnings management include accruals and related party transactions (RPTs). However, accrual anomalies are relatively insignificant in China (Chen et al. (2010); Liu et al. (2019)), and RPTs lack information on the direction in which profits are tunneled, making it challenging to design tests for their impact.

Firms with higher valuations in the Chinese A-share market are more likely to report inflated earnings, partly through NRGL. However, this earnings inflation is unsustainable, leading to earnings reversal in the long-term predictability of market valuation.

These results refine our understanding of price informativeness in the world's second-largest equity market (e.g., Carpenter et al. (2021)). While market prices strongly predict future earnings, this predictability alone may not be sufficient to establish the true informativeness of Chinese stock prices. Our findings also underscore the necessity of accounting for earnings management when evaluating stock price informativeness (e.g., Bai et al. (2016)).

Our findings also contribute to the literature on earnings management in China. Prior studies (e.g., Piotroski and Wong, 2012; Allen et al., 2024) document widespread earnings manipulation among A-share firms through related-party transactions, accruals, and other practices. Our analysis identifies NRGL as an additional and important channel through which Chinese firms manage reported earnings. Furthermore, our analysis provides compelling evidence that A-share investors fail to fully recognize earnings inflation through NRGL, reinforcing similar observations of investors overlooking accruals in the U.S. market (e.g., Sloan, 1996; Hirshleifer et al., 2012).

The rest of the paper is organized as follows. Section **??** provides the institutional background, while Section 2 outlines the empirical hypotheses. Section 3 describes the data and variable construction for empirical tests. Section 4 presents the main results, and Section 6 concludes.

2 Hypothesis Development

In this section, we present a simple model to illustrate the "manipulate-to-cater" mechanism and derive several empirical hypotheses for our analysis. The model integrates the pressure created by the signal-jamming mechanism of Stein (1989) with rational investors who fully account for earnings inflation, while also incorporating the investor inattention mechanism proposed by Hirshleifer and Teoh (2003).

The model consists of three dates: $t = 0, 1, 2$. At $t = 2$, the firm generates an uncertain dividend v, which follows a normal distribution:

$$v \sim \mathcal{N}\left(\mu, \frac{1}{h_v}\right),$$

where μ and h_v represent the mean and precision of the prior distribution, respectively.

At $t = 0$, stock market investors have already formed a common belief about v, represented as

$$v \sim \mathcal{N}\left(\hat{\mu}, \frac{1}{\hat{h}_v}\right).$$

This belief captures the market's information discovery or market sentiment at $t = 0$ and is taken as given in our analysis. If $\hat{\mu} > \mu$, the market price—driven by $\hat{\mu}$—is more optimistic than the unconditional mean reflected by μ, which we proxy by the firm's asset value in our empirical analysis. Our model examines how this optimism $\hat{\mu}$ pressures the firm to manage its earnings announcement at $t = 1$ before final liquidation at $t = 2$.

At $t = 1$, the firm manager privately observes an interim signal about the final dividend v, reflecting the firm's operating conditions:

$$e^n = v + \epsilon,$$

where $\epsilon \sim \mathcal{N}\left(0, \frac{1}{h_\epsilon}\right)$ is noise, independent of v. The manager must then issue an earnings report to the public.

The reported earnings can be inflated by an amount b, such that:

$$e = e^n + b,$$

Earnings inflation incurs a cost of $\frac{\rho}{2}b^2$ with $\rho > 0$, which arises from activities such as accrual adjustments and non-recurring gains/losses (NRGLs) that shift cash flows forward. This cost is deducted from the firm's liquidating dividend at $t = 2$, reducing the final dividend to $v - \frac{\rho}{2}b^2$.

Following Hirshleifer and Teoh (2003), a fraction θ of investors are inattentative and fail to recognize that the reported earnings may be inflated by the manager. Consequently, they interpret e as simply e^n. In contrast, the remaining $1 - \theta$ fraction of investors are rational and account for the possibility of earnings inflation. Although these rational investors cannot directly observe the inflated component b, they form rational expectations, assuming the expected earnings inflation is $b^* = b$. As suggested by Stein (1989), even when all investors are rational, the signal jamming mechanism may still lead the manager to inflate reported earnings.

Let p_1 denote the stock price at $t = 1$. Investors are risk averse, with risk tolerance denoted by τ. The differing recognition of earnings inflation leads to different stock demand between the two investor groups at $t = 1$. Specifically, each group's demand is given by its expected excess return from investing in the stock, divided by the return variance:

$$d^{ir}(p_1) = \tau \frac{E^{ir}(v|e) - p_1}{Var(v|e)} = \tau(\hat{h}_v + h_\epsilon)[(1-\alpha)\hat{\mu} + \alpha e - p_1]$$
$$d^{r}(p_1) = \tau \frac{E^{r}(v|e) - p_1}{Var(v|e)} = \tau(\hat{h}_v + h_\epsilon)[(1-\alpha)\hat{\mu} + \alpha(e - b^*) - p_1]$$

where $\alpha = \frac{h_\epsilon}{\hat{h}_v + h_\epsilon}$ represents the weight investors place on updating their beliefs about the final dividend v upon observing the reported earnings e. The intattentive group fails to adjust for the anticipated earnings inflation b^* in their expectations, whereas the rational group correctly deducts it.

Assuming the stock supply is fixed at one unit, the market-clearing condition is given by:

$$\theta\tau(\hat{h}_v + h_\epsilon)[(1-\alpha)\hat{\mu} + \alpha e - p_1] + (1-\theta)\tau(\hat{h}_v + h_\epsilon)[(1-\alpha)\hat{\mu} + \alpha(e - b^*) - p_1] = 1.$$

Solving for p_1, the equilibrium price at $t = 1$ is:

$$p_1 = (1-\alpha)\hat{\mu} + \alpha e_n + \alpha\underbrace{[b - (1-\theta)b^*]}_{\text{manipulation}} - \frac{1}{\tau(\hat{h}_v + h_\epsilon)}. \quad (1)$$

Due to risk aversion, rational investors cannot fully arbitrage away the price impact induced by inattentative investors. Consequently, the firm's earnings management b affects the equilibrium price by $\alpha[b - (1-\theta)b^*]$. Given that $b = b^*$ in equilibrium, this simplifies to $\alpha\theta b$.

Let p_0 denote the stock price at $t = 0$. For simplicity, we assume that each investor determines her demand for the stock based on the expected excess return from p_0 to the final dividend v, ignoring the possible re-trading opportunity at $t = 1$. Since all investors share the same belief that $v \sim \mathcal{N}\left(\hat{\mu}, \frac{1}{\hat{h}_v}\right)$, the equilibrium price is given by:

$$p_0 = \hat{\mu} - \frac{1}{\tau \hat{h}_v}.$$

To capture the pressure from the stock market on the manager, we assume that the manager faces a risk of being fired at $t = 1$. The probability of retaining the position until $t = 2$ is given by an increasing and concave function $h(p_1 - p_0)$, where $h(p_1 - p_0) \in (0, 1)$, with $h'(0) > 0$ and $h'(\infty) = 0$. If the manager remains in position at $t = 2$, her compensation is proportional to the firm's final dividend. If fired, she receive a fixed severance pay, which is normalized to zero.

Thus, at $t = 1$, the manager chooses b to maximize:

$$M = h(p_1 - p_0)E\left(v - \frac{\rho}{2}b^2 \middle| e^n\right) = h(p_1 - p_0)\left(e_n - \frac{\rho}{2}b^2\right).$$

Note that

$$p_1 - p_0 = \alpha[b - (1 - \theta)b^* + e_n - \hat{\mu}] + \frac{1}{\tau \hat{h}_v} - \frac{1}{\tau(\hat{h}_v + h_\epsilon)},$$

which increases with b. Thus, the first order condition $\frac{dM}{db} = 0$ yields

$$l'(p_1 - p_0) = \frac{\rho b}{\alpha(e_n - \frac{\rho}{2}b^2)}, \tag{2}$$

where $l(x) = \frac{h'(x)}{h(x)}$ is a decreasing function.

The left-hand side of this equation decreases with b, while the right-hand side increases with b. At $b = 0$, the left-hand side is positive, while the right-hand side is zero. Thus, a unique $b > 0$ satisfies the first-order condition, implying a unique optimal choice for the manager.

Using the equilibrium condition for b, we can derive the following comparative statics.

Proposition 1. The manager's optimal choice of b is independent of θ (the fraction of inattentive investors), while the stock price p_1 increases with θ.

This result shows that even when $\theta = 0$ (i.e., all investors are rational), the equilibrium still yields $b > 0$. This arises from the signal jamming mechanism suggested by Stein (1989). When rational investors anticipate earnings inflation of b^*, the manager must inflate by that amount; otherwise, rational investors would discount the reported earnings by b^*, leading to a lower stock price.

Although the fraction of inattentive investors does not affect the manager's earnings inflation, it does impact the equilibrium price, amplifying price overvaluation. As a result, earnings inflation predicts lower stock return from $t = 1$ to $t = 2$, providing a key criterion for distinguishing between different mechanisms of earnings manipulation.

Proposition 2. Given the private signal e^n observed by the manager at $t = 1$, the earnings inflation b increases with the market's expectation $\hat{\mu}$ and decreases with the cost of earnings inflation ρ.

This result implies that a higher market expectation, as reflected by $\hat{\mu}$, induces greater earnings inflation b.

We now map this simple model to our empirical setting. The model provides direct implications for the predictability of $\hat{\mu}$ in relation to reported earnings at $t = 1$, e, and final earnings at $t = 2$, $v - \frac{\rho}{2}b^2$. In our empirical analysis, we proxy $\hat{\mu}$ with the current stock valuation M_t and use M_t to predict future earnings E_{t+k} at different horizons $k > 0$.

From the model, if we regress short-term reported earnings $e = e^n + b$ on the market expectation $\hat{\mu}$, the regression coefficient is:

$$\frac{Cov(e^n + b, \hat{\mu})}{Var(\hat{\mu})} = \frac{Cov(e^n, \hat{\mu}) + Cov(b, \hat{\mu})}{Var(\hat{\mu})} > \frac{Cov(e^n, \hat{\mu})}{Var(\hat{\mu})},$$

where $\frac{Cov(e^n, \hat{\mu})}{Var(\hat{\mu})}$ represents the predictability in the absence of earnings inflation. This term also reflects the informativeness of market expectation regarding the firm's fundamentals. The inequality follows from $Cov(b, \hat{\mu}) > 0$, as implied by Proposition 2.

Similarly, if we regress the long-term earnings $v - \frac{\rho}{2}b^2$ on the market valuation $\hat{\mu}$, the regression coefficient is:

$$\frac{Cov(v - \frac{\rho}{2}b^2, \hat{\mu})}{Var(\hat{\mu})} = \frac{Cov(v, \hat{\mu}) - Cov(\frac{\rho}{2}b^2, \hat{\mu})}{Var(\hat{\mu})} < \frac{Cov(v, \hat{\mu})}{Var(\hat{\mu})}.$$

This inequality follows from $Cov(\frac{\rho}{2}b^2, \hat{\mu}) > 0$, as also implied by Proposition 2.

Together, these results lead to the following hypothesis on the predictability of stock valuation for future earnings across different horizons:

Hypothesis 1. The presence of earnings inflation increases the predictability of current stock valuation (M_t) for future short-term reported earnings (E_{t+k}, i.e., small k), but weakens its predictability for future long-term earnings (E_{t+k}, i.e., large k).

In our empirical analysis, we use non-recurring gains and losses (NRGLs) to measure the managed component of reported earnings. Combining Propositions 1 and 2 leads to the following hypothesis:

Hypothesis 2. The managed component of reported earnings is positively correlated with current stock share valuation (M_t) but negatively correlated with subsequent stock returns.

The first part of Hypothesis 2 follows from Proposition 2, which establishes that earnings inflation increases with market expectations. The second part follows from Proposition 1 in cases where the fraction of inattentive investors is nonzero, as their presence contributes to price overvaluation, leading to lower future stock returns.

We also examine a policy change that increases the cost of earnings inflation through NRGLs. Proposition 2 directly implies the following:

Hypothesis 3. Following a positive shock to the cost of earnings management, the level of earnings management should decline. Consequently, the correlation between earnings management and market valuation should weaken, as should the correlation between current stock valuation (M_t) and future short-term reported earnings (E_{t+k}, i.e., small k).

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), operating cash flow (OCF) and total market capitalization (M). D includes cumulative annual cash dividends and net share repurchases. OCF equals EBITDA minus change in working capital and income taxes. We retain the consolidated financial statements and exclude the parent company's financial statements. E, D, A, OCF, 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. Details on variable construction are provided in Section A.1 of the Online Appendix.

Table I shows summary statistics of main variables at the stock level. The average E/A ratio for the A-share stocks is 5.4% with the 25th and 75th percentiles of 0.96% and 6.5%, respectively. The average D/A ratio equals 1.4% with the 25th and 75th percentiles of 0.0% and 1.8%, respectively. The mean of NRGL ratio is relatively modest, 1.2% with a standard deviation of 2.7%.

Panel C presents the summary statistics for US S&P500 firms. The average E/A ratio is 7.2%, while the average D/A ratio is 4.3%. The 25th and 75th percentiles for E/A are 3.9% and 10.1%, respectively, and for D/A, they are 0.79% and 5.1%, respectively. These values are higher than those observed for A-share stocks. This difference is expected, as the sample consists of high-quality S&P500 firms, whereas the Chinese stock sample includes all listed firms, regardless of quality.

4 Market Valuation and Future Earnings

In this section, we examine the relationship between stock valuation, measured by the ratio of a stocks market value to asset value (M_t/A_t), and future earnings. We begin by analyzing the cross-sectional predictability of M_t/A_t for a stock's future earnings, following the approach of Carpenter et al. (2021). The core idea is to assess whether stocks with higher valuations tend to generate larger earnings in subsequent years compared to those with lower valuations.

Building on this approach, we also explore an alternative time-series perspective, investigating whether a firm with a high valuation in one year is more likely to report higher earnings in subsequent years. Additionally, we examine the predictability of M_t/A_t for a stocks future dividend payouts. Finally, we analyze a set of dually listed firms in both Chinas A-share market and the Hong Kong stock market, allowing us to explore how stock valuations in these two segmented markets relate to future earnings.

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 assets (A_t), on the log of market capitalization (M_t) scaled by A_t. Our sample includes all Chinese A-share stocks from 1995 to 2022, excluding financial firms. For comparison, we also analyze a sample of S&P 500 stocks, following the analysis of Carpenter et al. (2021) and Bai et al. (2016).

We follow the procedure of Carpenter et al. (2021) with one key difference: instead of conducting regressions at the individual stock level, we perform them at the portfolio 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 aggregate 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. To account for inflation, we adjust all variables using the GDP deflator. Additionally, we scale by total assets at year t (A_t) to control for size effects.

This portfolio approach follows the spirit of Fama and French (1995). Compared to an individual stock-level analysis, portfolio aggregation helps smooth out firm-level outliers and reduces estimation noises. Moreover, when predicting payouts (D), the portfolio approach mitigates the issue of excessive observations with a value of zero.

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

$$\frac{E_{i,t+k}}{A_{i,t}} = \alpha + \beta_k \log(\frac{M_{i,t}}{A_{i,t}}) + \gamma \frac{E_{i,t}}{A_{i,t}} + \lambda \frac{D_{i,t}}{A_{i,t}} + \epsilon_{i,t}, \text{where } k \in \{1, 2, ..., 7\}. \quad (3)$$

To facilitate interpretation of the main coefficient β_k on $\log(M_{i,t}/A_{i,t})$, we report its value multiplied by the standard deviation $\sigma(\log(M_{i,t}/A_{i,t}))$, representing the predicted variation. We also report the average coefficient over the sample years. Unlike Carpenter et al. (2021), we include and control for $D_{i,t}/A_{i,t}$ (which is relevant to our later analysis) and extend the predictive horizon beyond 5 years to examine $k = 6, 7$. Firms that do not have seven years of earnings data at year t are excluded from the analysis.

We report the regression results in Table II. For the Chinese market, the table shows the scaled coefficient of $\log(M_{i,t}/A_{i,t})$ for each year from 1995 to 2021, along with the average coefficient over two periods: 1995-2016 (the sample period in Carpenter et al. (2021)) and 1995-2022. During the 1995-2016 period, the scaled coefficient is 0.010 (t-stat = 5.0) for $k = 1$ and increases to 0.015 for $k = 3$ (t-stat = 4.2).

In comparison, the U.S. S&P 500 sample exhibits a larger but comparable magnitude over the same prediction horizon. The predicted variation of $\log(M_{i,t}/A_{i,t})$ is 0.021 (0.028) for $k = 1$ and 0.030 (0.033) for $k = 3$ in the 1960–2021 (1995–2021) sample, with all estimates highly significant. This pattern aligns closely with the main findings of Carpenter et al. (2021).

However, when we extend the prediction horizon, notable differences emerge. In the Chinese market, during the 1995–2016 period, the predicted variation of $\log(M_{i,t}/A_{i,t})$ declines from 0.013 for $k = 5$ (t-stat = 1.98) to 0.009 for $k = 7$ (t-stat = 1.24). In contrast, in the U.S. market, the estimate continues to increase with k, reaching 0.032 (0.037) for $k = 5$ and 0.037 (0.047) for $k = 7$, while remaining statistically significant.

In Figure I, we visualize the predicted variation of $\log(M_{i,t}/A_{i,t})$ (based on the estimates of β_k) for $k \in \{1, 2, ..., 7\}$ in both markets, along with 95% confidence intervals. In the U.S. market, the magnitude generally increases with k, consistent with Bai et al. (2016). In contrast, in the Chinese market, price informativeness exhibits an inverted-U pattern as k increases. This suggests that the predictability of future earnings initially rises but later reverses, becoming insignificant over the long term. This reversal pattern differs from the findings of Carpenter et al. (2021), who show that earnings predictability increases with k.

A key methodological difference likely explains this discrepancy: we employ a portfolio-based approach, whereas they estimate β_k at the individual stock level (we report the corresponding results using individual stocks in Section A.3 of the Appendix).

Another notable pattern in Table II is that price informativeness, based on the 1995–2022 sample, is generally lower than that estimated using the 1995–2016 sample from Carpenter et al. (2021), across all $k = 1, ..., 7$. This suggests that the magnitude of price informativeness has declined in recent years. As we discuss in later sections, this decline is plausibly linked to China's delisting rule reform in 2020.

Overall, Table II and Figure I confirm the main findings of Carpenter et al. (2021): in the Chinese A-share market, stocks with higher valuations tend to exhibit higher future earnings. However, unlike Carpenter et al. (2021), we find that this predictability weakens over horizons beyond five years, showing signs of earnings reversal, as posited by Hypothesis 1. In Section 4.3, we will directly test this reversal using time-series regressions.

4.2 Predicting payouts and operating cashflow

The possibility that firms actively manage earnings makes earnings an unreliable measure of firm fundamentals. In contrast, firm payouts to investors are less prone to this concern. In this subsection, we examine the predictability of stock valuation for subsequent payouts.

We adopt the regression specified in Equation 3, replacing earnings with total payouts $(D_{t+1}, ..., D_{t+7})$. If higher firm earnings bring greater payouts to investors, we should find that stock valuation exhibits similar predictive power for payouts as it does for earnings.

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

$$\frac{D_{i,t+k}}{A_{i,t}} = \alpha + \beta_k log(\frac{M_{i,t}}{A_{i,t}}) + \gamma \frac{E_{i,t}}{A_{i,t}} + \lambda \frac{D_{i,t}}{A_{i,t}} + \epsilon_{i,t}, \text{where } k \in \{1, 2, ..., 7\}. \quad (4)$$

As before, we multiply the coefficient of $\log(M_{i,t}/A_{i,t})$ by the standard deviation $\sigma(\log(M_{i,t}/A_{i,t}))$ and report the average over our sample period.

The regression results, presented in Table III, indicate that stock valuation has little predictive power for future payouts in the Chinese market. In the 1995–2022 period, the predicted variation of $\log(M_{i,t}/A_{i,t})$ remains close to zero at short horizons, equaling 0.001 for $k = 1$ (t-stat $= 1.6$). It 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 of stock valuation for payouts is much weaker than its predictability for earnings, as shown in Table II.

By comparison, as shown at the bottom of Table III, market valuation has significant predictive power for future payouts in the S&P 500. The predicted variation of $\log(M_{i,t}/A_{i,t})$ ranges from 0.012 (0.006) to 0.040 (0.023) as k increases from 1 to 7 over the 1995–2021 (1960–2021) sample period, with all estimates statistically significant. Notably, these magnitudes are closely aligned with the predictive power of market valuation for earnings.

In Figure II, we visualize the predicted variation of $\log(M_{i,t}/A_{i,t})$ with 95% confidence intervals for $k \in \{1, 2, ..., 7\}$ in both markets.

The sharp contrast in the predictability of payouts between the Chinese and US markets reinforces concerns that earnings in the Chinese market may be actively managed and, therefore, may not fully reflect firm fundamentals. That said, an alternative explanation is also plausible: Chinese firms may follow different payout policies than their U.S. counterparts, making payouts less sensitive to firm fundamentals. In other words, Chinese firms may retain a larger share of their cash flows rather than distributing them to shareholders. If this is the case, the weak predictability of stock valuation for payouts cannot be taken as definitive evidence of earnings management.

We also examine the predictability of stock valuation for firms' operating cash flow. Compared to earnings, cash flow is more difficult to manipulate in accounting and auditing practices. Additionally, since regulators and investors do not typically use cash flow as a primary metric for evaluating firm performance, it is less likely to be subject to managerial manipulation.

Following Allen et al. (2024), we define operating cash flow (OCF) as:[2]

$$\text{OCF} = \text{EBITDA} - \text{Change in Working Capital} - \text{Income Taxes}.$$

We then replace payouts (D) in Equation (5) with OCF and rerun the regression.

The regression results, presented in Table IV, show that in the Chinese market (1995-2022), the predicted variation of $\log(M_{i,t}/A_{i,t})$ is weak and even negative at short horizons.

[2]The results remain virtually unchanged when using net cash flow, which subtracts capital expenditures from operating cash flow.

It equals -0.011 for $k = 1$ (t-stat $= 5.2$), increases slightly to -0.002 for $k = 3$ (t-stat $= 0.7$), 0.001 for $k = 5$ (t-stat $= 0.2$), and 0.019 for $k = 7$ (t-stat $= 1.4$). The results are similar to—or even weaker than—those for predicting payouts.

By contrast, as shown at the bottom of Table IV, market valuation in the S&P 500 remains significant in predicting future cash flows. The predicted variation of $\log(M_{i,t}/A_{i,t})$ ranges from 0.014 (0.007) to 0.049 (0.031) as k increases from 1 to 7 over the 1995–2021 (1960–2021) sample period, with all estimates statistically significant. Notably, these magnitudes closely align with the predictive power of stock valuation for earnings and dividends.

In Figure III, we visualize the predicted variation of $\log(M_{i,t}/A_{i,t})$ with 95% confidence intervals for $k \in \{1, 2, ..., 7\}$ in both markets.

In summary, we find that market valuation has weak predictive power for future payouts and cash flow in the Chinese market, in contrast to its strong predictive power for reported earnings. By comparison, in the U.S. S&P 500 sample, market valuation consistently predicts earnings, dividends, and cash flow, yielding more coherent results across all measures.

4.3 Earnings reversal

The cross-sectional analysis of earnings predictability suggests the presence of long-run earnings reversal among Chinese firms. This reversal provides a mechanism to assess earnings management, as posited by Hypothesis 1. To further investigate this, we now adopt a time-series approach to directly test whether firms with higher stock valuations exhibit stronger earnings reversals over the long run.

Specifically, we estimate the following panel regressions using the 50 size-by-market-to-asset ratio portfolios:

$$\frac{E_{j,t+1} - E_{j,t}}{A_{j,t}} = \alpha + \beta^{0\to 1}\log(\frac{M_{j,t}}{A_{j,t}}) + \gamma\frac{E_{j,t}}{A_{j,t}} + \lambda\frac{D_{j,t}}{A_{j,t}} + \epsilon_{j,t}, \tag{5}$$

$$\frac{E_{j,t+3} - E_{j,t+1}}{A_{j,t}} = \alpha + \beta^{1\to 3}\log(\frac{M_{j,t}}{A_{j,t}}) + \gamma\frac{E_{j,t}}{A_{j,t}} + \lambda\frac{D_{j,t}}{A_{j,t}} + \epsilon_{j,t}, \tag{6}$$

$$\frac{E_{j,t+5} - E_{j,t+3}}{A_{j,t}} = \alpha + \beta^{3\to 5}\log(\frac{M_{j,t}}{A_{j,t}}) + \gamma\frac{E_{j,t}}{A_{j,t}} + \lambda\frac{D_{j,t}}{A_{j,t}} + \epsilon_{j,t}, \tag{7}$$

Unlike Equation (3), the dependent variable in these regressions is the change in earnings over different horizons, normalized by current assets: from year t to $t+1$, from year $t+1$ to $t+3$, and from $t+3$ to $t+5$. The key coefficients of interest are $\beta^{1\to 3}$ and $\beta^{3\to 5}$, where negative values indicate long-run earnings reversal predicted by current stock valuation.

We first estimate these regressions without any fixed effects, then with portfolio fixed effects (essentially time-series regressions), and finally with time fixed effects (essentially cross-sectional regressions). Driscoll–Kraay standard errors with lag of 1 are reported to account for cross-sectional and temporal dependencies.

The regression results, presented in Table V, support the presence of earnings reversal in the Chinese market. Panel A reports results without fixed effects. Consistent with previous findings, stock valuation ($\log(M_{j,t}/A_{j,t})$) is associated with higher short-term earnings growth ($E_{j,t+1} - E_{j,t}$), with a coefficient of 0.013 (t-stat $= 2.5$). However, when examining earnings changes from year 1 to year 3 ($E_{j,t+3} - E_{j,t+1}$), the coefficient $\beta^{1\to 3}$ is small and insignificant, suggesting that earnings remain at similar levels between $t+1$ and $t+3$. In contrast, from year 3 to year 5, we observe a significant reversal: the coefficient $\beta^{3\to 5}$ is -0.013 (t-stat $= 3.0$). Comparing the magnitude of these coefficients suggests that by year 5, earnings have roughly reverted to their initial level at t.

By comparison, columns (4) to (6) show no evidence of earnings reversal in the U.S. market. Firms with higher market valuations tend to report higher earnings at $t+1$ and these earnings remain at similar levels in $t+3$ and $t+5$, indicating no reversal. This contrast between China and the U.S. highlights fundamental differences in earnings dynamics across the two markets.

If firms manage earnings to align with market expectations reflected in the current stock valuations, we would expect earnings reversal to be more pronounced in the time-series dynamics of individual firms. This corresponds to including portfolio fixed effects in our panel regressions.

Indeed, this is what we observe. In Panel B, where we include portfolio fixed effects, the coefficients $\beta^{1\to 3}$ and $\beta^{3\to 5}$ are both significantly negative, with t-statistics of 2.1 and 2.4, respectively, providing strong evidence of long-run earnings reversal.

In Panel C, we instead include time fixed effects, following an approach similar to Carpenter et al. (2021), which focuses on cross-sectional variation. Here, the coefficients $\beta^{0\to 1}$ and $\beta^{1\to 3}$ are both significantly positive, with t-statistics of 5.4 and 2.1, respectively. The coefficient $\beta^{3\to 5}$, however, is negative but statistically insignificant, indicating only weak evidence of earnings reversal in the cross section.

Finally, in both panels B and C, the sample of S&P 500 firms exhibits a consistent and robust pattern of no long-run earnings reversal. Specifically, the predictability of short-term earnings growth ($E_{j,t+1} - E_{j,t}$) remains significantly positive, while the predictability for longer horizons ($E_{j,t+3} - E_{j,t+1}$) and ($E_{j,t+5} - E_{j,t+3}$) is either positive or statistically insignificant. This absence of reversal in the US market underscores a fundamental difference between the US and Chinese markets, which is crucial for interpreting the results of Carpenter et al. (2021).

4.4 Comparing informativeness of dually listed A-share and H-share prices

In this subsection, we further leverage a sample of firms that are dually listed in both the Chinese A-share market and the Hong Kong stock market. Since these dual-listed shares are segmented and trade at different prices, this setting allows us to compare which market provides more informative prices for predicting future earnings.

This sample consists of 89 unique non-financial firms that issue both A-shares in the mainland stock market and H-shares in the Hong Kong stock market. Although these shares confer the same rights, they often trade at different prices due to strict regulations that prevent arbitrageurs from transferring shares between the two markets. This restriction effectively rules out arbitrage trading on price differentials between A-shares and H-shares of the same firm. As a result, A-share and H-share prices reflect the distinct valuations assigned by investors in these two markets.

The Hong Kong stock market is dominated by foreign institutional investors, whereas the Chinese A-share market is primarily driven by retail investors. Jia et al. (2017) leveraged this market segmentation to compare how investors in these two markets respond to analyst recommendations. Given this difference in investor composition, we expect H-share prices to be more informative about firms' future earnings than A-share prices.

To test this conjecture, we extend the cross-sectional regression specified in Equation (3) by incorporating market valuations reflected by both A-share and H-share prices. Given the relatively small sample size of A-H firms, we perform this regression at the individual stock level. Specifically, we estimate the following cross-sectional regression for each year t:

$$\frac{E_{i,t+k}}{A_{i,t}} = \alpha + \beta_k^A log(\frac{M_{i,t}^A}{A_{i,t}}) + \beta_k^H log(\frac{M_{i,t}^H}{A_{i,t}}) + \gamma\frac{E_{i,t}}{A_{i,t}} + \lambda\frac{D_{i,t}}{A_{i,t}} + \epsilon_{i,t}, \text{where } k \in \{1, 2, ..., 7\}. \quad (8)$$

Here, M^H and M^A represent the firm's total capitalization, calculated by valuing all outstanding shares using its H-share and A-share prices, respectively.

Since both classes of shares confer the same claims on a firm, investors in the two markets observe the same reported earnings. While the extent to which each markets prices influence managerial decisions is an intricate issue beyond the scope of our analysis, it does not affect our core premise. By publicly observing current and past reported earnings, as well as the market prices of both A-shares and H-shares, investors in both markets form valuations that reflect expectations of future firm fundamentals and potential earnings inflation by managersregardless of which class of shares exerts greater pressure on corporate decision-making.

Table VI shows that the predicted variation of $\frac{M_{i,t}^A}{A_{i,t}}$ and $\frac{M_{i,t}^H}{A_{i,t}}$, along with the time-series t-statistics. The results align with our conjecture. The predicted variation of $\log(M_{i,t}^H/A_{i,t})$ ranges from 0.009 to 0.022 as k increases from 1 to 7, with all t-statistics exceeding 3.4. In contrast, the predicted variation of $\log(M_{i,t}^A/A_{i,t})$ is insignificant across all forecast horizons and even turns negative for $k \geq 4$.

This stark contrast suggests that A-share prices are less informative about future earnings than H-share prices. While this does not provide a direct comparison between the informativeness of stock prices in the Chinese A-share market and the U.S. market, it nonetheless offers a valuable indication that A-share prices may be less informative than those in another highly relevant market outside mainland China.

5 Earnings Management

The earnings reversal discussed in the previous section supports Hypothesis 1, indicating the possibility of firm managers inflating earnings in response to market pressure. In this section, we directly investigate earnings management to test Hypotheses 2 and 3.

Accounting rules often grant firm managers a degree of discretion in reporting earnings to balance the need for accurate financial representation with the flexibility required to reflect complex business realities. Given that businesses operate across diverse industries and economic conditions, rigid standardization of every transaction is impractical. Discretion enables managers to exercise judgment in areas such as asset valuation, revenue recognition, and provisions for future losses. While such flexibility can make financial reporting more informative about a firm's future prospects, it also introduces risks of manipulation.

In the U.S., it is common practice for firms to use accrual accounting, in which revenues and expenses are recognized when they are earned or incurred, rather than when cash is received or paid. This system requires managers to estimate key financial elements such as depreciation, amortization, bad debt provisions, and warranty liabilities. As highlighted in the literature, accounting accruals have frequently served as a tool for earnings management among U.S. firms, e.g., Sloan (1996); Hirshleifer et al. (2012).

Earnings management is widely recognized as prevalent among firms listed in the Chinese A-share market. To visually illustrate this, we follow Piotroski and Wong (2012) and Burgstahler and Dichev (1997) by plotting the distribution of reported earnings in China and the U.S. Specifically, Figure IV presents the distribution of firms' return on assets (ROA), with Panel A depicting S&P 500 firms in the U.S. market and Panel B showing Chinese A-share firms.

In Panel A, the distribution approximates a normal distribution curve with a modest spike around zero, suggesting that some S&P 500 firms may have engaged in earnings management to avoid reporting negative figures. This pattern indicates that firms may have slightly inflated their earnings to cross the zero threshold.

Panel B separately displays the ROA distribution for Chinese A-share firms from 1995 to 2019 (dark bars) and 2020 to 2022 (light bars). In stark contrast to Panel A, Panel B reveals a sharp spike at zero, particularly during the 1995–2019 period, where the distribution abruptly jumps from near zero to a peak, resembling a truncated normal distribution centered around zero earnings. The spike moderates somewhat in recent years following a rule change in 2020 but 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 important to note that, before 2020, firms reporting negative net profits for two consecutive years were labeled as ST (special treatment) firms. Additionally, continued negative earnings could lead to delisting from the exchange, creating strong incentives for firms to avoid reporting losses. Beyond regulatory concerns, firms also manage earnings to meet investor expectations, as posited by our hypotheses.

Interestingly, accruals are not the primary tool for earnings management in China (e.g., Chen et al. (2010); Liu et al. (2019)). Instead, Chinese-listed firms tend to use related party transactions (RPTs) and non-recurring gains and losses (NRGL).

RPTs, which occur between entities with shared ownership or control—often in state-owned enterprises—serve as a flexible mechanism for shifting profits, managing earnings volatility, and circumventing regulatory constraints. Firms can inflate revenues by selling goods or services at artificially high prices to related entities. Conversely, they can suppress earnings in strong years by selling at artificially low prices, effectively creating reserves for future downturns—a form of income smoothing.[3] Several studies, e.g., Fisman and Wang (2010); Jiang et al. (2010); Li et al. (2020); Allen et al. (2024), have analyzed RPTs as a measure of earnings management of firms listed in China, highlight tunneling activities and other governance issues.

While it is possible to collect information on a firm's RPTs, the available disclosures lack details on the direction of profit transfers, making it challenging to design tests that accurately assess their total impact on firm earnings.[4]

Non-recurring gains and losses (NRGLs) refer to income and expenses that are not directly related to a company's core business operations. These items are typically classified as extraordinary, one-time, or irregular and are excluded from the companys normal operating performance to provide a clearer picture of sustainable earnings.

Before 2020, regulatory authorities primarily relied on net profit—which includes both operating earnings and NRGLs—for determining IPO qualification and delisting criteria. As a result, firms frequently used NRGLs as a tool for earnings management, employing methods such as asset sales or one-off government subsidies from affiliated local governments to meet regulatory thresholds and avoid delisting.

[3]Starting in 1997, the China Securities Regulatory Commission (CSRC) introduced a series of regulations over the past two decades aimed at enhancing oversight of RPTs. These regulations emphasized the accurate identification and effective management of related parties. The goal was not only to limit the impact of RPTs on earnings quality but, more importantly, to strengthen corporate governance and better protect the interests of minority shareholders. Under the current rules, companies must fully disclose the nature, pricing, and financial impact of RPTs in their financial statements. Additionally, transactions exceeding a certain threshold require independent board approval and, in some cases, shareholder approval to ensure transparency and prevent abusive practices.

[4]In an effort to address this issue, Fisman and Wang (2010) and Allen et al. (2024) look at only loan-based RPTs and measure the amount of tunneling profit as the money outflow from the listed firm. But loan-based RPTs, which are typically loan guarantees, consists a small fraction of all RPTs.

In 2020, a new securities law was enacted by the National Peoples Congress, introducing a key change to delisting rules: NRGLs are no longer included in the calculation of net profit for delisting purposes. This change has substantially reduced firms' incentives to use NRGLs for earnings management. By excluding NRGLs from the calculation of net profit, the 2020 delisting rule change underscores the practical significance of NRGLs. This motivates us to use NRGLs as our primary measure of earnings management. Additionally, the 2020 rule change provides a natural experiment to examine how the relationship between firms' earnings and equity valuations evolved in its aftermath.

In this section, we first analyze the relationship between NRGLs and market valuations in Subsection 5.1 and examine whether NRGLs predict subsequent stock returns in Subsection 5.2. Together, these analyses serve as tests for Hypothesis 2. Subsection 5.3 tests Hypothesis 3 by leveraging the 2020 delisting rule reform as a natural experiment.

5.1 Market valuation and NRGLs

We now test the hypothesis that firms with higher market valuation ratios tend to use more NRGLs. We define NRGLs as the ratio of non-recurring gains and losses to total assets from the previous year. Since the disclosure of non-recurring gains and losses became mandatory in 2008, our sample period spans from 2008 to 2022.

Table VII presents the results. In the first column, we regress $NRGL_{i,t}$ on $\log(M_{i,t}/A_{i,})$ and other control variables at time t. In the second column, we regress $NRGL_{i,t+1}$ on these variables to assess the predictive relationship between market valuation and future NRGLs.

To differentiate between firms' incentives to meet investor expectations and their incentives to avoid delisting, we follow Lee et al. (2023) in constructing a measure of whether a firm qualifies as a shell company. Due to the strict quota on IPOs in China, underperforming firms have strong incentives to retain their listed status, as this allows them to realize their shell value through reverse mergers with unlisted firms that are unable to secure an IPO quota through the regular application process. According to Lee et al. (2023), the average shell value was approximately USD 500 million between 2008 and 2018. To avoid delisting, shell companies must maintain positive earnings, and one way to achieve this is by leveraging NRGLs.

Following Lee et al. (2023), we calculate a firm's expected shell probability (ESP), which represents the likelihood of being acquired through a reverse merger by a private company. Specifically, we first estimate a logit regression model using observed firm characteristics—such as firm size, profitability, ST status, and the ownership concentration among the top ten shareholders—to predict reverse merger events. We then use the estimated model and firm characteristics to infer each firm's probability of undergoing a reverse merger. To prevent look-ahead bias, we compute $ESP_{i,t}$ in a rolling manner: for the computation of $ESP_{i,t}$, we only use data from the years 2007 to $t-1$.

Table VII presents the regression results, incorporating $ESP_{i,t}$ as a key control variable. The estimated coefficients show that $\log(M_{i,t}/A_{i,t})$ is positively correlated with contemporaneous $NRGL_{i,t}$ (t-stat = 4.2) and with $NRGL_{i,t+1}$ in the subsequent year (t-stat = 11.5). These findings support Hypothesis 2, indicating that highly valued firms are more likely to engage in earnings management to align reported earnings with market expectations embedded in their stock valuations.

Moreover, we find that firms with a high expected shell probability (ESP) exhibit a significantly positive association with contemporaneous NRGL. This effect persists into the following year, though with a somewhat weaker magnitude compared to its impact on contemporaneous NRGL.

5.2 Return predictability of managed earnings

In this subsection, we examine how firms' NRGLs can predict the subsequent stock returns. This analysis helps assess whether investors fully recognize the managed component of reported earnings. If investors understand that high earnings driven by large NRGLs are unlikely to persist, current stock prices should reflect this information, resulting in no subsequent underperformance—consistent with the rational expectations model for earnings management proposed by Stein (1989). Conversely, if investors do not fully account for the transitory nature of managed earnings, firms with large NRGLs may experience overvaluation in the present, leading to lower subsequent returns, as predicted by Hypothesis 2.

To test this hypothesis, we analyze quaterly stock returns, as NRGLs are disclosed in firms' quarterly reports. We estimate Fama-MacBeth regressions of quarterly stock returns on either $NRGL_{i,q}$ or $\Delta NRGL_{i,q}$, while controlling for return on assets (ROA), a set of commonly used stock characteristics, and industry fixed effects. Here, $\Delta NRGL_{i,q}$

represents the change in NRGL from quarter $q-4$ to quarter q, capturing year-over-year variations in non-recurring gains and losses.

As shown in Table VIII, our results support the notion that investors do not fully see through earnings management via NRGLs. Both the level of quarterly $NRGL_{i,q}$ and $\Delta NRGL_{i,q}$ predict lower stock 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 a 0.68% (0.91%) decline in returns over the following quarter. This pattern is similar to the accruals effect in studies on U.S. stock data, where investors fail to fully recognize and react to the negative implications of high accruals (e.g., Sloan (1996) and Hirshleifer et al. (2012)).

Taken together, the findings from Tables VII and VIII confirm Hypothesis 2: market pressure, as reflected in high stock valuations, drives firm managers to employ larger NRGLs. In turn, these inflated earnings contribute to sustaining market overvaluations, as investors fail to fully recognize the extent of NRGL use in reported earnings.

5.3 The 2020 reforms of delisting rules

To further strengthen the identification of our tests, we exploit the 2020 reforms of delisting rulesan important policy change in the Chinese A-share market. Historically, the A-share market had an extremely low delisting rate (Lee et al., 2023), primarily due to the high shell value associated with IPO restrictions and the ease with which firms could manage earnings to circumvent delisting criteria.

The reforms began in March 2019 with the introduction of new delisting criteria for the Shanghai Stock Exchange's STAR board as a pilot program. In March 2020, a new securities law was passed by the National People's Congress, and in December 2020, the revised delisting rule was formally announced, extending to all main board-listed firms on both the Shanghai and Shenzhen Stock Exchanges.

The reform introduced two key changes. First, firms were no longer allowed to include NRGLs in their earnings calculations for regulatory compliance, effectively removing a key tool for earnings management. Second, the criteria for receiving an ST (special treatment) designation were revised. Under the previous rule, firms were labeled as ST solely based on negative earnings. The new rule, however, required firms to meet both conditions of reporting negative earnings and generating revenue of less than 100 million yuan to receive the ST designation.

The first fiscal year under the new rule was 2020, meaning earnings reported for 2020 and beyond should be less susceptible to manipulation through NRGLs. In our event study, we define 2020 and subsequent years as the post-event window. Additional details on the reform timeline and the specifics of the 2020 delisting rule are provided in Appendix Section A.2.

In Figure V, we plot the number of firms delisted each year. The number began to rise gradually from 2020 onward, reaching approximately 50 in both 2022 and 2023. In contrast, before 2019, the number of delisted firms remained below 10, and it was even lower between 2008 and 2018, a period when reverse mergers were prevalent.

Linking this to our model framework in Section 2, the delisting rule reforms effectively increased the cost of earnings management, creating a natural experiment to test Hypothesis 3.

We first examine the impact of delisting rule reforms on NRGLs. Firms that reported high NRGLs in the pre-reform period significantly reduced their use of NRGLs starting in 2020 (see Figure VI), reflecting the regulatory change that NRGLs could no longer be included in reported earnings for compliance purposes in the post-reform period.

Further, consistent with Hypothesis 3, the correlation between market valuation and NRGLs weakened significantly after the reforms. In Table IX, we re-estimate the regressions from Table VII, adding an interaction term between $\log(M_{i,t}/A_{i,t})$ and $POST_t$, where $POST_t$ is a dummy variable equal to one for fiscal years 2020 and beyond. The coefficients on the interaction term are significantly negative (with t-statistics above 3) for both contemporaneous and future NRGLs. In terms of economic magnitude, in Column (2) for predicting subsequent NRGLs, the coefficient on the interaction term is -0.003, while the coefficient on $\log(M_{i,t}/A_{i,t})$ equals 0.011, implying a 27% reduction in the correlation between market valuation and subsequent NGRLs.

These findings confirm that the 2020 delisting rule reform effectively constrained the use of NRGLs for earnings management in the post-reform period. As shown in the lower panel of Figure IV, the distribution of reported earnings from 2020 to 2022the first three fiscal years under the new ruleexhibits fewer irregularities around zero compared to the pre-reform period, indicating a reduction in earnings management.

Lastly, given that the managed component of reported earnings—NRGLs—diminished for some firms after the 2020 rule change, we expect the correlation between firms market value ($M_{i,t}$) and future reported earnings ($E_{i,t+k}$) to weaken in the post-2020 period, as posted by Hypothesis 3.

To test this hypothesis, we modify Equation (3) by introducing an interaction term between $\log(\frac{M_{i,t}}{A_{i,t}})$ and the dummy variable $POST_t$. To align our approach with the original framework in Carpenter et al. (2021), we include year fixed effects and estimate the following panel regression:

$$\frac{E_{i,t+k}}{A_{i,t}} = \alpha + \beta_k \log(\frac{M_{i,t}}{A_{i,t}}) + \theta_k \log(\frac{M_{i,t}}{A_{i,t}}) * POST_t + \gamma \frac{E_{i,t}}{A_{i,t}} + \lambda \frac{D_{i,t}}{A_{i,t}} + v_t + \epsilon_{i,t}, \text{where } k \in \{1, 2, 3\}, \tag{9}$$

where we expect θ_k to be negative, indicating a reduction in the predictive power of market valuation for future earnings after the reform.

Panel A of Table X presents the results. The coefficient on the interaction term is significantly negative and equals -0.0131 (t-stat $= 3.9$) for $E_{i,t+1}$, which is sizable compared to the coefficient on $\log(\frac{M_{i,t}}{A_{i,t}})$, which equals 0.0175. The interaction term remains significantly negative for $E_{i,t+2}$ and $E_{i,t+3}$, with coefficients of -0.00997 (t-stat $= 3.5$) and -0.0092 (t-stat $= 2.2$), respectively, while the coefficients on $\log(\frac{M_{i,t}}{A_{i,t}})$ are 0.0225 and 0.0254.

In contrast, applying the same regressions to U.S. S&P 500 firms yields insignificant results, reinforcing the China-specific effect of the delisting rule reforms.

We further test Equation (9) by replacing the dependent variable with payouts in Panel B. The coefficient on the interaction term is significantly positive, at 0.00137 (t-stat $= 2.4$) for $D_{i,t+1}$, which is substantial relative to the coefficient on $\log(\frac{M_{i,t}}{A_{i,t}})$, which equals 0.00191. For $D_{i,t+2}$, the interaction term coefficient increases to 0.00227 (t-stat $=$ 2.1) , while the coefficient on $\log(\frac{M_{i,t}}{A_{i,t}})$ is 0.0033. These patterns suggest an improvement in price informativeness following the 2020 delisting rule reforms. By comparison, the results for S&P 500 firms exhibit the opposite pattern, further highlighting the distinct impact of the reforms in the Chinese A-share market.

Overall, our findings support Hypothesis 3. Following the 2020 delisting rule reforms, firms in the Chinese A-share market significantly reduced their reliance on NRGLs, and the cross-sectional relationship between market valuation and subsequent earnings weakened.

6 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.

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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 $k \in \{0, 1a, ..., 7\}$, 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. Stock Price Informativeness about Future Operating Cash Flows

For each year t, stocks are sorted independently 10×5 portfolios based on size (M_t) and book-to-market ratio (B/M), respectively. Operating cash flows (OCF_t), 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,

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

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.

Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$		$k=6$		$k=7$	
	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat	Pred	t-stat
1998	0.006	2.284	-0.002	-0.392	-0.009	-2.474	0.012	3.012	-0.015	-2.114	-0.019	-3.127	-0.015	-2.114
1999	-0.014	-3.873	-0.015	-3.377	-0.021	-6.335	0.005	1.255	-0.010	-1.515	0.007	0.781	-0.010	-1.515
2000	-0.012	-3.089	-0.019	-3.130	0.002	0.313	0.010	1.751	-0.009	-0.650	-0.017	-2.032	-0.009	-0.650
2001	-0.011	-4.563	-0.006	-1.540	-0.010	-3.417	0.002	0.457	-0.005	-0.354	0.006	0.632	-0.005	-0.354
2002	-0.008	-1.816	-0.006	-1.522	-0.003	-0.840	0.003	0.622	-0.017	-1.089	0.003	0.294	-0.017	-1.089
2003	-0.006	-1.814	-0.002	-0.838	-0.003	-0.585	0.004	1.044	0.004	0.288	0.005	0.889	0.004	0.288
2004	-0.008	-2.996	-0.010	-2.766	0.004	1.452	0.002	0.501	0.014	0.469	0.022	1.986	0.014	0.469
2005	-0.009	-2.000	-0.009	-0.892	0.001	0.273	0.016	1.639	0.059	2.639	0.020	1.354	0.059	2.639
2006	-0.010	-1.325	-0.013	-0.950	-0.003	-0.737	0.003	0.682	0.019	0.727	0.014	0.925	0.019	0.727
2007	-0.009	-0.873	-0.002	-0.226	0.004	1.282	0.017	3.058	-0.032	-0.722	0.013	1.391	-0.032	-0.722
2008	-0.033	-3.169	-0.042	-4.238	-0.045	-7.522	0.023	2.746	0.018	0.384	0.019	1.034	0.018	0.384
2009	-0.006	-0.633	-0.028	-2.060	0.028	3.611	-0.025	-2.343	-0.112	-1.655	0.038	1.842	-0.112	-1.655
2010	-0.030	-2.925	-0.004	-0.426	0.001	0.189	0.003	0.426	0.055	1.489	0.008	0.329	0.055	1.489
2011	0.010	0.580	-0.001	-0.148	0.008	2.273	0.005	0.724	0.124	2.248	0.008	0.443	0.124	2.248
2012	-0.001	-0.096	0.004	0.233	0.001	0.310	0.020	3.316	0.038	1.280	0.011	0.596	0.038	1.280
2013	-0.029	-2.577	-0.022	-1.388	-0.026	-4.230	0.033	1.281	0.101	4.328	0.013	0.856	0.101	4.328
2014	-0.009	-0.641	-0.038	-2.055	0.012	1.768	0.049	1.978	0.066	1.420	0.043	1.510	0.066	1.420
2015	-0.036	-4.145	0.007	0.971	0.013	2.041	0.019	1.132	0.044	1.673	0.014	0.708	0.044	1.673
2016	-0.010	-2.178	-0.003	-0.246	-0.001	-0.161	0.006	1.101	0.006	0.625	0.007	0.707	0.006	0.625
2017	-0.007	-1.433	-0.007	-1.715	0.004	0.538	-0.007	-1.255	0.007	0.888	0.006	0.778	0.007	0.888
2018	-0.002	-0.178	0.005	0.999	0.002	0.368	0.020	4.305						
2019	0.003	0.605	-0.007	-1.079	0.005	0.910								
2020	-0.022	-2.930	0.003	0.610										
2021	-0.004	-0.626												
Averages China														
1995 to 2016-k	-0.012		-0.013		-0.005		0.000		-0.005		0.003		-0.007	
	(-4.844)		(-3.720)		(-1.457)		(0.042)		(-0.980)		(0.511)		(-0.657)	
1995 to 2022-k	-0.011		-0.009		-0.002		0.006		0.001		0.015		0.019	
	(-5.245)		(-3.418)		(-0.676)		(1.139)		(0.200)		(1.939)		(1.390)	
Averages US S&P500														
1960 to 2021-k	0.007		0.015		0.017		0.019		0.023		0.026		0.031	
	(6.306)		(7.892)		(8.224)		(8.202)		(8.502)		(7.516)		(7.063)	
1995 to 2021-k	0.014		0.025		0.028		0.031		0.037		0.042		0.049	
	(12.286)		(14.925)		(11.777)		(9.777)		(9.049)		(6.840)		(5.482)	

Table V. 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,

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

$$\frac{E_{j,t+3} - E_{j,t+1}}{A_{j,t}} = \alpha + \beta^{1\to3} log(\frac{M_{j,t}}{A_{j,t}}) + \gamma\frac{E_{j,t}}{A_{j,t}} + \lambda\frac{D_{j,t}}{A_{j,t}} + \epsilon_{j,t},$$

$$\frac{E_{j,t+5} - E_{j,t+3}}{A_{j,t}} = \alpha + \beta^{3\to5} log(\frac{M_{j,t}}{A_{j,t}}) + \gamma\frac{E_{j,t}}{A_{j,t}} + \lambda\frac{D_{j,t}}{A_{j,t}} + \epsilon_{j,t},$$

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 VI. Stock Price Informativeness about Future Earnings: A-H Twin Shares

The table shows time series averages of predicted variation $\hat{\beta}_k^H \sigma(log(M_t^H/A_t))$ and $\hat{\beta}_k^A \sigma(log(M_t^A/A_t))$ from the following stock-level cross-sectional regressions using the sample of A-H twin shares from 1995 to 2022$-k$,

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

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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$
$\hat{\beta}_k^A \sigma(log(M_t^A/A_t))$	0.006	0.006	0.005	-0.003	-0.008	-0.011	-0.009
	(1.992)	(1.259)	(1.008)	(-0.361)	(-1.046)	(-1.453)	(-1.203)
$\hat{\beta}_k^H \sigma(log(M_t^H/A_t))$	0.009	0.012	0.013	0.015	0.017	0.022	0.022
	(4.744)	(3.502)	(4.001)	(4.679)	(3.921)	(3.431)	(3.975)

Table VII. Market Valuation 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)	(2)
	$NRGL_t$	$NRGL_{t+1}$
log(M/A)	0.00486	0.00914
	(4.20)	(11.51)
ESP	0.241	0.106
	(6.62)	(3.10)
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)
$NRGL_{(t-3,t-1)}$	-0.0573	
	(-2.43)	
$NRGL_{(t-2,t)}$		-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 VIII. 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) RET_{q+1}	(2) $RET_{(q+1,q+2)}$	(3) $RET_{(q+1,q+3)}$	(4) $RET_{(q+1,q+4)}$	(5) RET_{q+1}	(6) $RET_{(q+1,q+2)}$	(7) $RET_{(q+1,q+3)}$	(8) $RET_{(q+1,q+4)}$
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)
$RET_{(q-4,q-1)}$	-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 IX. 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 log(M/A) and POST. 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) NRGL_t	(2) NRGL_{t+1}
$\log(M/A) * \text{POST}$	-0.002	-0.003
	(-3.04)	(-7.28)
$\log(M/A)$	0.005	0.011
	(4.39)	(12.19)
ESP	0.230	0.113
	(6.35)	(3.36)
$\log(A)$	0.001	-0.004
	(1.04)	(-6.81)
LEVERAGE	0.012	0.043
	(2.83)	(10.63)
P/B	0.000	-0.001
	(1.11)	(-4.69)
ROE	0.023	-0.010
	(8.07)	(-4.64)
$\text{NRGL}_{(t-3,t-1)}$	-0.056	
	(-2.37)	
$\text{NRGL}_{(t-2,t)}$		-0.088
		(-4.09)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Firm FE	Yes	Yes
Adj. R-sq	0.118	0.174
N	26392	27884

Table X. 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
$\log(M_t/A_t) * \text{POST}$	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

Panel C: predicting operating CF

	China			US S&P500		
	OCF_{t+1}/A_t	OCF_{t+2}/A_t	OCF_{t+3}/A_t	OCF_{t+1}/A_t	OCF_{t+2}/A_t	OCF_{t+3}/A_t
$\log(M_t/A_t) * \text{POST}$	0.0140	0.0140	0.0136	0.00555	0.0119	0.0130
	(2.76)	(3.05)	(2.31)	(1.32)	(3.29)	(3.27)
$\log(M_t/A_t)$	-0.0243	-0.0183	-0.0112	0.0219	0.0371	0.0340
	(-6.44)	(-3.00)	(-1.77)	(8.62)	(13.22)	(8.67)
$\frac{D_t}{A_t}$	2.072	2.253	2.285	0.0949	0.133	0.0871
	(5.71)	(6.41)	(4.54)	(2.72)	(3.49)	(1.49)
$\frac{E_t}{A_t}$	0.153	0.170	0.202	-0.0477	-0.111	-0.0857
	(2.68)	(1.38)	(1.78)	(-1.53)	(-3.51)	(-2.16)
$\frac{\text{OCF}_t}{A_t}$	0.0479	0.0236	0.0940	0.490	0.214	0.456
	(1.00)	(0.39)	(1.25)	(6.48)	(4.14)	(4.33)
Constant	0.0259	0.0291	0.0309	0.156	0.261	0.231
	(8.62)	(9.37)	(5.99)	(8.35)	(14.57)	(8.84)
N	1200	1150	1100	1283	1217	1157
adj. R^2	0.261	0.224	0.168	0.731	0.683	0.667

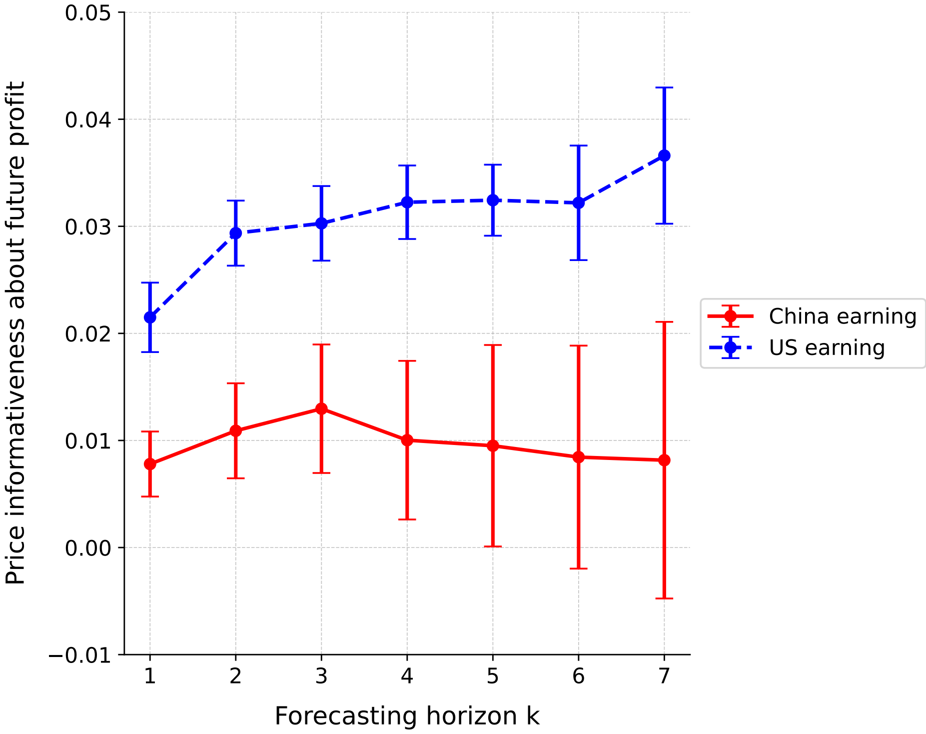

Figure I. Stock Price Informativeness about Future Earnings

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 $2022-k$ 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.

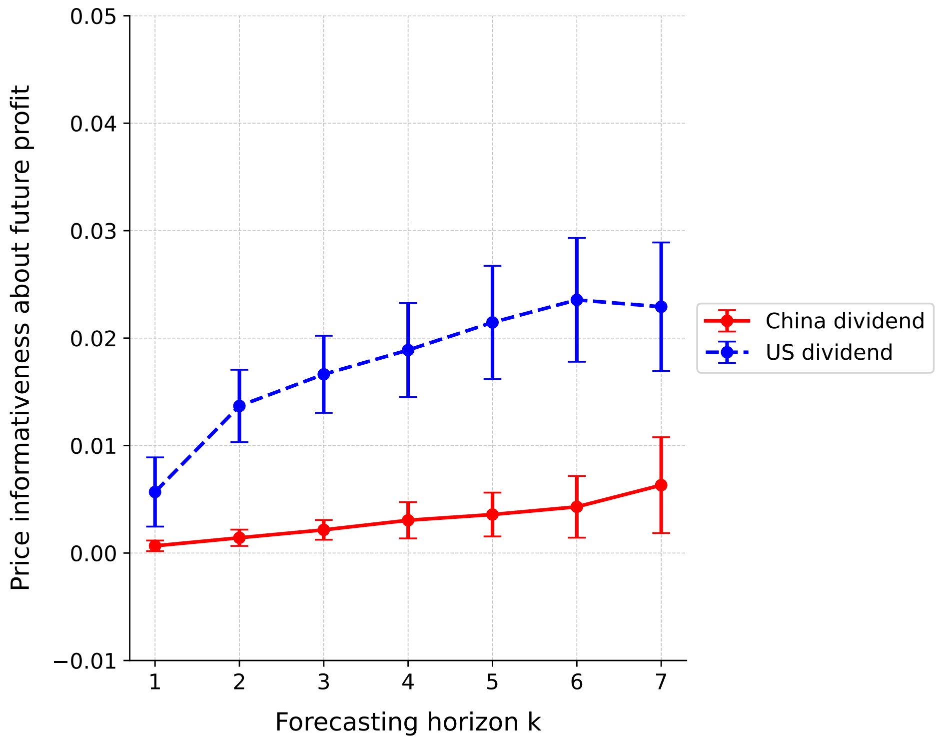

Figure II. Stock Price Informativeness about Future Payouts

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 $2022-k$ 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.

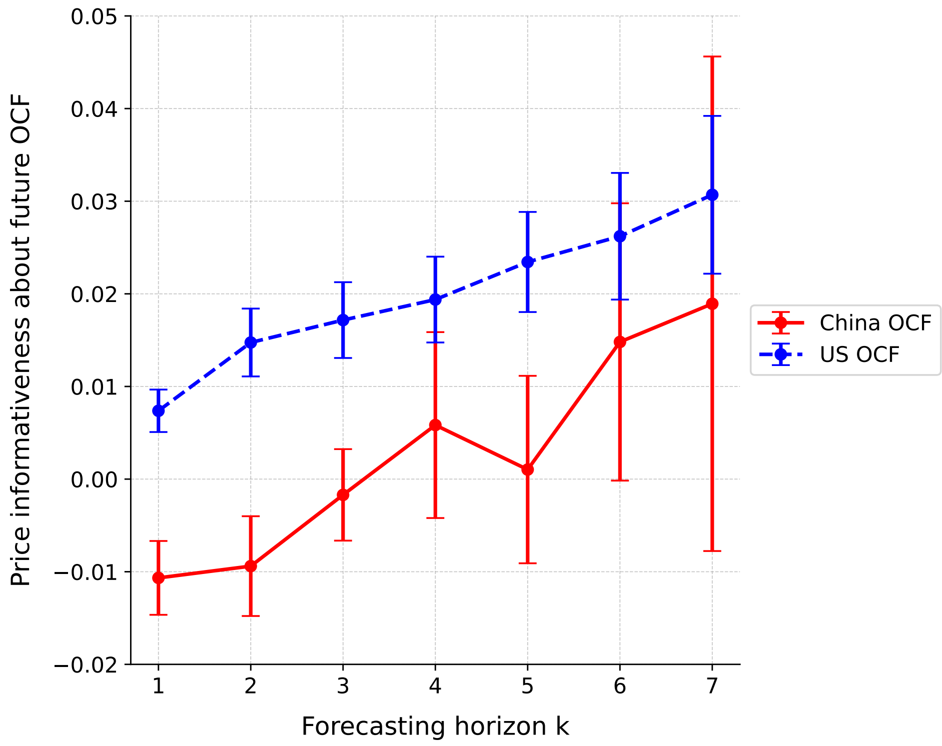

Figure III. Stock Price Informativeness about Future Operating Cash Flows

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:

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

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.

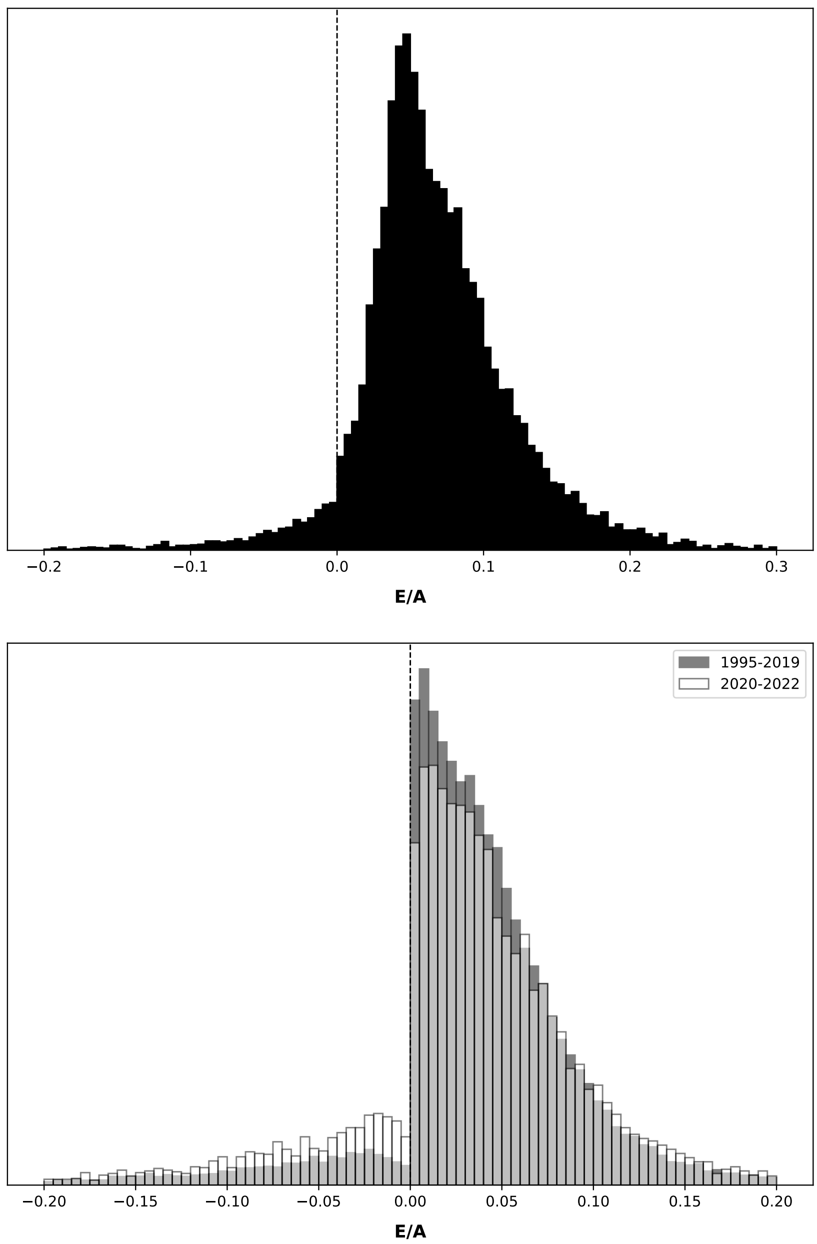

Figure IV. Earnings Distribution of US S&P 500 Firms and Chinese A-share Firms

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.

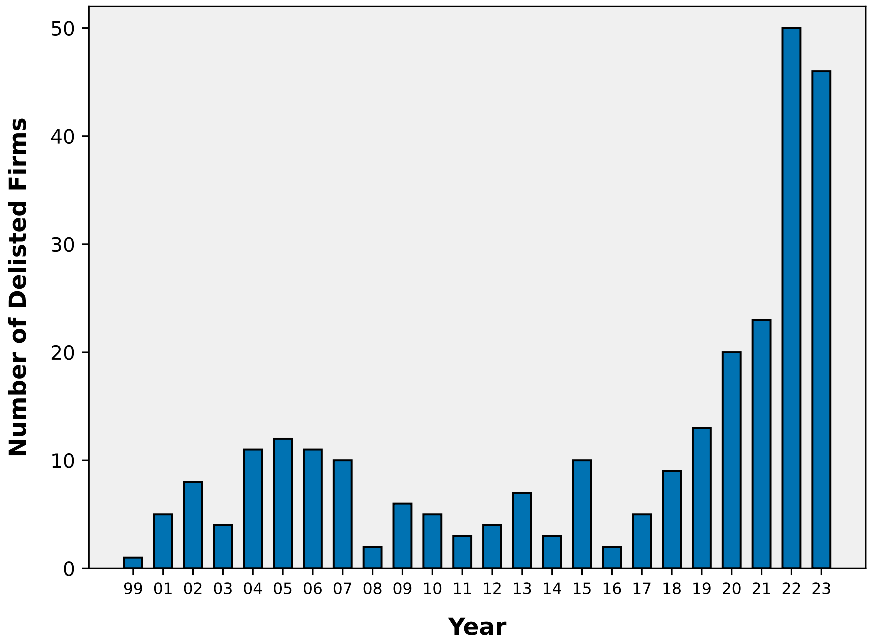

Figure V. Number of Delisted Firms by Year in the Chinese A-share Market

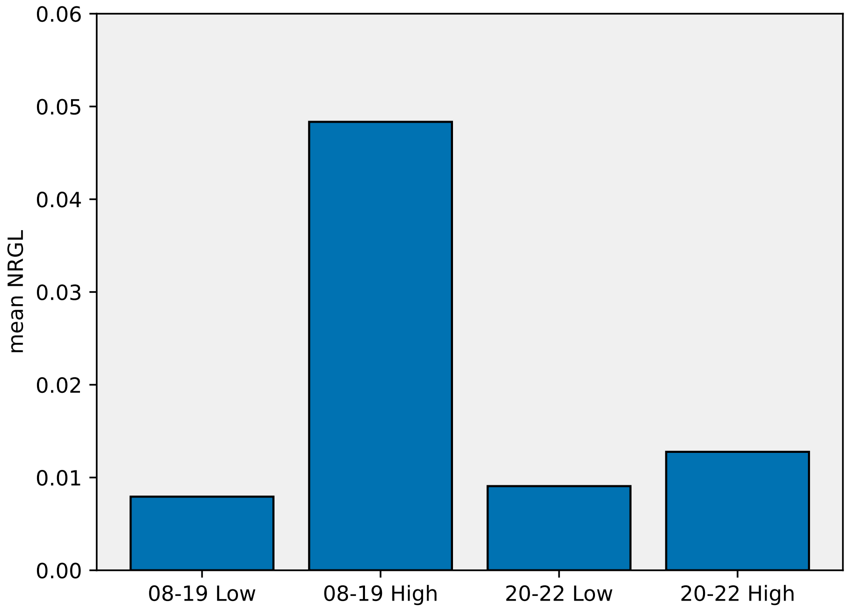

Figure VI. Level of NRGL Before and After the 2020 Delisting Rule

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 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.

OCF: Operating Cash Flows (OCF) measure the cash generated from the core business activities of a company within current period. It is computed by deducting the change in working capital and income taxes from EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization), then dividing by total assets. This calculation uses data sourced from the CSMAR Cash Flow Statements and CSMAR Balance Sheets. We follow **?**.

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

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)	

Table A.1.3. Stock Price Informativeness about Future Operating Cash Flows

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,

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

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
1998	-0.000	-0.013	-0.005	-1.051	-0.001	-0.076	0.010	1.765	0.010	1.445	0.017	2.306	0.009	1.147
1999	-0.003	-0.910	-0.004	-0.868	-0.001	-0.131	0.010	1.859	0.000	0.015	0.004	0.608	0.003	0.424
2000	-0.006	-1.746	-0.006	-2.002	0.002	0.647	-0.007	-2.368	-0.004	-0.869	-0.013	-2.456	-0.020	-2.238
2001	-0.006	-2.376	-0.002	-0.573	-0.009	-2.879	-0.004	-1.119	-0.012	-2.350	-0.020	-2.455	0.001	0.124
2002	-0.004	-1.227	-0.008	-2.817	-0.006	-2.031	-0.010	-2.229	-0.008	-1.218	0.001	0.140	-0.011	-0.986
2003	-0.003	-1.373	0.003	1.064	0.000	0.082	0.003	0.442	0.014	2.078	0.014	1.502	0.006	0.700
2004	0.001	0.332	0.001	0.210	-0.001	-0.172	0.008	1.243	0.013	1.398	0.001	0.146	0.038	2.336
2005	-0.007	-1.818	-0.008	-1.235	0.001	0.119	0.002	0.270	-0.005	-0.553	0.015	0.939	0.039	2.340
2006	-0.007	-1.243	-0.001	-0.166	-0.003	-0.323	-0.004	-0.385	0.019	1.052	0.033	2.204	0.018	0.619
2007	-0.011	-1.512	-0.009	-1.151	-0.012	-1.336	0.023	1.721	0.054	3.198	0.069	2.148	0.012	0.439
2008	-0.010	-1.603	-0.021	-2.757	-0.036	-2.603	0.036	2.423	-0.013	-0.427	0.028	1.152	0.004	0.106
2009	-0.023	-3.689	-0.024	-2.617	0.018	1.847	0.030	1.369	0.036	1.835	0.004	0.148	-0.083	-1.298
2010	-0.029	-4.091	0.016	2.457	0.028	1.710	0.029	2.241	0.025	1.292	0.008	0.224	0.183	4.652
2011	-0.007	-1.661	0.005	0.748	0.017	1.988	-0.006	-0.451	-0.009	-0.368	0.134	4.495	0.121	3.723
2012	-0.016	-2.943	-0.006	-1.196	-0.015	-1.576	-0.021	-1.193	0.075	3.724	0.085	3.662	0.071	2.847
2013	-0.009	-2.311	-0.017	-2.519	-0.026	-2.124	0.035	2.951	0.040	2.749	0.021	1.577	0.061	4.182
2014	-0.022	-3.562	-0.035	-2.956	0.030	2.619	0.009	0.727	0.013	1.104	0.026	2.361	0.031	2.023
2015	-0.044	-6.229	0.021	2.953	0.005	0.817	0.006	0.743	0.012	1.576	0.019	1.708	0.044	4.137
2016	-0.007	-2.093	-0.007	-2.225	-0.007	-1.860	0.006	1.228	0.000	0.023	0.023	3.679		
2017	0.003	1.003	-0.002	-0.711	0.006	1.549	0.011	2.266	0.026	4.737				
2018	0.000	0.088	0.010	2.786	0.015	3.674	0.024	5.903						
2019	0.008	2.649	0.010	2.988	0.020	5.994								
2020	0.000	0.060	0.012	4.039										
2021	0.007	2.621												
Averages China														
1998 to 2016-k	-0.011		-0.007		-0.003		0.006		0.009		0.012		0.001	
	(-3.720)		(-2.319)		(-0.629)		(1.277)		(1.757)		(1.684)		(0.150)	
1998 to 2022-k	-0.008		-0.003		0.001		0.009		0.014		0.025		0.029	
	(-2.876)		(-1.257)		(0.320)		(2.401)		(2.841)		(2.579)		(2.059)	
Averages US S	P500													
1960 to 2021-k	0.011		0.022		0.029		0.036		0.042		0.049		0.057	
	(7.183)		(8.374)		(8.670)		(8.669)		(8.765)		(8.463)		(8.321)	
1998 to 2021-k	0.019		0.037		0.047		0.057		0.068		0.080		0.095	
	(10.500)		(17.225)		(17.398)		(14.682)		(14.153)		(11.494)		(10.781)	

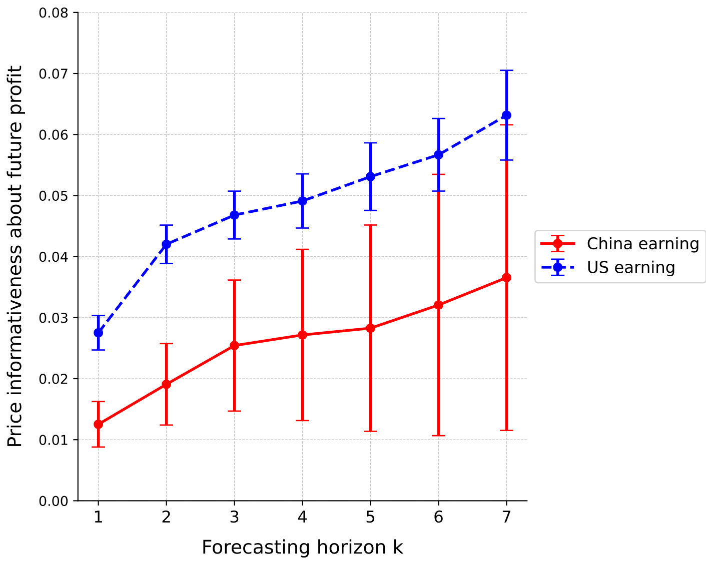

Figure A.1.1. Stock Price Informativeness about Future Earnings.

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.

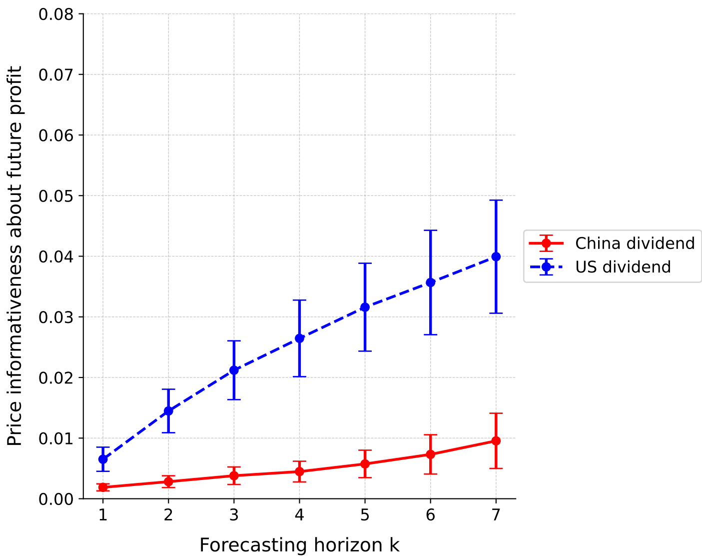

Figure A.1.2. Stock Price Informativeness about Future Payouts.

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.

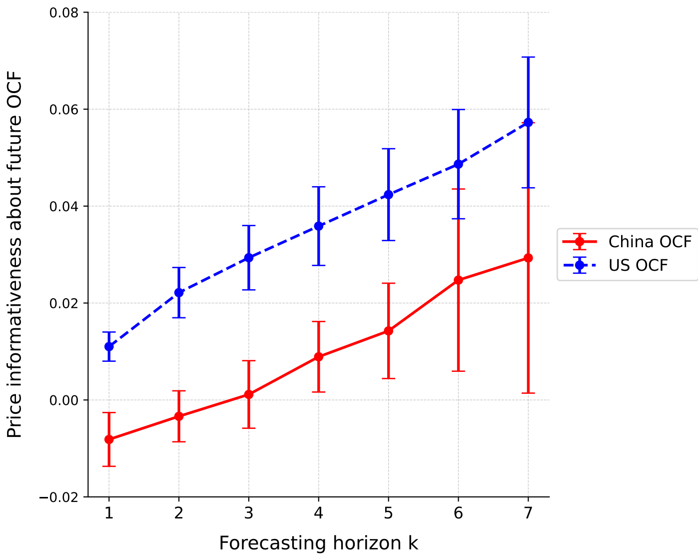

Figure A.1.3. Stock Price Informativeness about Future Operating Cash Flows.

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:

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

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.