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 manipulate their reported earnings to align with optimism-driven stock valuations. We show that higher-valued stocks report higher earnings over next three years, but this does not increase shareholders payouts or operating cash flows; and earnings eventually reverse. Additionally, we provide evidence of earnings management through non-recurring gains and losses (NRGLs), 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 assess stock market price informativeness by estimating cross-sectional regressions of firms' future earnings on current stock market valuations. The predictive power of market valuations reflects the extent to which stock prices incorporate information about future firm performance. 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 high volatility and speculative characteristics of the Chinese stock market (e.g., Song and Xiong, 2018; Hu, Pan, and Wang, 2021; and Bian, Da, He, Lou, Shue, and Zhou, 2024).

It is important to recognize that the price informativeness measure proposed by Bai, Philippon, and Savov (2016) rests on a key assumption that earnings reliably reflect firm fundamentals. However, this assumption may not hold in the context of the Chinese A-share market. Notably, there is extensive evidence of widespread earnings management and manipulation, indicating low financial reporting quality (see, e.g., Piotroski and Wong (2012) for a comprehensive review). Moreover, prior studies highlight significant governance challenges 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 are instead driven by earnings management. To reconcile the observed empirical patterns, we propose a "manipulate-to-cater" mechanism, in which firm managers—motivated by the desire to sustain elevated share prices—manipulate reported earnings to meet investor expectations. Building on the framework of Hirshleifer and Teoh (2003), we build a simple model in Section 2 and posit that a subset of investors are inattentive and take reported earnings at face value, resulting in stock overvaluation relative to underlying fundamentals. In response, market valuation pressures incentivize firm managers to adjust earnings to conform to these inflated expectations.

This "manipulate-to-cater" mechanism generates several testable predictions that stand in contrast to the price-informativeness view. First, while high market valuations may predict higher reported earnings, they need not be associated with greater shareholder payouts or stronger operating cash flows. Second, because managed earnings are inherently unsustainable, they should eventually reverse in the long run. Third, the component of earnings driven by manipulation should be associated with lower future stock returns, as investors gradually come to recognize the manipulation. This paper empirically tests these predictions and finds supportive evidence, as summarized below.

We first follow Bai et al. (2016) to estimate cross-sectional regressions of Chinese firms' future reported earnings over the next one to five years ($E_{t+1}, \ldots, E_{t+5}$), scaled by current firm assets (A_t), on the log of current market valuation (M_t) similarly scaled by A_t. Our sample includes all Chinese A-share firms from 1995 to 2022. For comparison, we conduct the same analysis on U.S. firms using a sample of S&P 500 constituents from 1960 to 2021, following the approach of Carpenter et al. (2021).

Our analysis builds on Carpenter et al. (2021), with one important modifications. We conduct the analysis 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 helps mitigate the influence of outliers and extreme values on coefficient estimates, as adopted in prior research including Lakonishok et al. (1994); Fama and French (1995); Chen (2017).[1]

We find that the main result of Carpenter et al. (2021) remains generally robust when the sample is extended to include more recent years through 2022 and the analysis is conducted at the portfolio level: though the magnitude of predictability is a bit smaller, 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, in China, earnings predictability is stronger at the medium-term horizon (3-year) than at the 1-year horizon, but it declines at longer horizon at year $t+5$, revealing a reversal pattern that is not observed in the U.S. market. Second, in recent years, the earnings predictability of Chinese stocks has weakened—a trend not present during the original sample period of 1995-2016 analyzed by Carpenter et al. (2021). As we discuss later, this decline may be partially attributed to the 2020 delisting rule reform in China's

[1]These studies construct stock portfolios based on firm characteristics such as book-to-market ratio, size, and sales growth, and examine the portfolio-level growth rates in earnings and dividends. Notably, Chen (2017) discusses in Section III.B how firm-level regression results can be heavily influenced by a small number of extreme observations, often involving small firms. In contrast, portfolio-level analysis tends to yield more robust and reliable results. We observe a similar pattern in our analysis.

A-share market.

Next, we replace future earnings with future total payouts ($D_{t+1}, \ldots, D_{t+5}$), which include both cash dividends and share repurchases, as the dependent variable, and find that higher reported earnings do not lead to greater future payouts. In addition, we examine whether higher reported earnings are driven by future stronger underlying fundamentals by using future operating cash flow ($OCF_{t+1}, \ldots, OCF_{t+5}$) as the dependent variable. The analysis reveals a weak and statistically insignificant relationship between valuation and subsequent cash flows, further casting doubt on the fundamental basis of future reported earnings.

These patterns support our hypothesis that reported earnings among Chinese firms may, at least partly, reflect earnings manipulation/inflation rather than genuine operational cash flow or future shareholder payouts. In sharp contrast, the market value of U.S. S&P 500 stocks exhibits strong predictive power for both future payouts and operating cash flows, comparable to its ability to forecast future earnings.

A key prediction of our "manipulate-to-cater" hypothesis is earnings reversal. More specifically, a high market value (M_t) should be associated with elevated reported earnings in the short run, followed by a decline in the long run. This prediction concerns the time-series property of reported earnings, in contrast to the cross-sectional property emphasized in the analysis of Carpenter et al. (2021). To test the long-run reversal, we examine 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 greater M_t/A_t is associated with higher values of $(E_{t+1} - E_t)/A_t$, insignificant values of $(E_{t+3} - E_{t+1})/A_t$, and lower 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 may have inflated reported earnings to meet market expectations.

The earnings reversal pattern strengthens when controlling for portfolio fixed effects (i.e., in time-series regressions), but weakens—and even becomes insignificant—when controlling for time fixed effects, as in the cross-sectional approach used by Carpenter et al. (2021). This suggests that our "manipulate-to-cater" view and their price-informativeness view are not mutually exclusive; rather, both help explain the strong correlation between firm valuations and future reported earnings in our sample of Chinese firms.

We also examine 89 Chinese non-financial firms that are dual-listed in both the A-share and Hong Kong markets. Consistent with Carpenter et al. (2021), we find that AH dual-listed stocks exhibit weaker correlations between market valuations and future earnings compared to A-share-only stocks. While Carpenter et al. (2021) attribute this lower earnings predictability to noise arising from Hong Kong investors discount rate shocks, this explanation appears inconsistent with our additional finding: the A-share valuations of these dual-listed firms show no significant predictive power for future earnings, whereas H-share valuations do—without evidence of earnings reversals. This finding is consistent with the fact that Hong Kong investors are primarily sophisticated institutions, in contrast to the retail-driven nature of the A-share market. Taken together, our cater-to-manipulate explanation naturally accounts for both of these observations.

We also provide direct evidence of earnings inflation through Non-Recurring Gains and Losses (NRGLs). Under China's accounting rules, NRGLs, which comprises 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 modification that excludes NRGLs from earnings calculations. This policy change underscores the importance of NRGLs and motivates our focus on its role in reported earnings inflation. Consistent with our hypothesis, we show that firms with higher market valuations tend to report elevated NRGLs during our full sample period (but weakened after 2020, as explained shortly).[2]

We further examine whether investors can fully see through these managed earnings. If investors recognize that the better-than-expected reported earnings driven by a high NRGLs component are unlikely to persist, they should rationally discount such news, resulting in no return predictability by NRGLs, 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), NRGLs would negatively predict subsequent stock returns. Our findings suggest that investors do not fully account for earnings inflation. Both the level of quarterly NRGLs and changes in NRGLs predict lower stock returns over the next one to four quarters. Specifically, a one standard deviation increase

[2] 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.

in NRGLs (or change of NRGLs) 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 NRGLs was used to inflate earnings, we find that after the reform, firms with higher valuation ratios experienced greater reductions in reported NRGLs. In addition, the correlation between the market value (M_t) and the reported future earnings (E_{t+k}) weakens after 2020, while the correlation between market value and future payouts (D_{t+k}) and cash flows (OCF_{t+k}) strengthens. Notably, this pattern is absent in the U.S. data. This shift in China's A-share market, presumably driven by the policy reform in 2020, helps explain why the estimated price informativeness in our sample (which includes the period 2017-2022) is lower than that reported by Carpenter et al. (2021) (whose sample period ends at 2016).

Overall, our findings strongly support our proposed "manipulate-to-cater" mechanism. Firms with higher valuations in the Chinese A-share market are more likely to report inflated earnings, partly through NRGLs. However, this earnings inflation is unsustainable, resulting in an eventual reversal of earnings and affecting the long-term predictability of market valuation. While our findings do not contradict those reported by Carpenter et al. (2021), our analysis extends their perspective on the earnings predictability of market valuation in the Chinese A-share market. Rather than solely reflecting the market's information discovery, we demonstrate that firms' efforts to cater to market valuation through earnings inflation also play a significant role in shaping earnings predictability.

Literature Review. Our paper seeks to refine the 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 fully establish the true informativeness of Chinese stock prices. Our findings highlight the importance 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. We identify NRGLs as an additional and significant 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 NRGLs, echoing similar observations of investors overlooking accruals in the U.S. market (e.g., Sloan, 1996; Hirshleifer et al., 2012). More importantly, our findings underscore market valuation as a critical mechanism driving firms to inflate earnings.

By highlighting investors' tendency to overlook earnings inflation, our study also adds an important dimension to the literature on investor behavior in the Chinese stock market. Prior research has shown that A-share stock prices often deviate from fundamentals, as evidenced by their significantly higher valuations compared to B-share prices issued by the same firms to foreign investors. This disparity is largely attributed to speculative trading by A-share investors (e.g., Mei et al. (2009)). Furthermore, extensive studies have documented various behavioral biases among Chinese investors, including overconfidence, gambling preferences, extrapolative expectations, and attention constraints (e.g., Liu et al. (2022), Liao et al. (2022), Chen et al. (2023), and Bian et al. (2024)).

2 A Simple Model and Hypotheses Development

In this section, we present a simple model to illustrate the "manipulate-to-cater" mechanism and to derive several empirical hypotheses for our analysis. The model integrates two related mechanisms: the pressure arising from the signal-jamming mechanism of Stein (1989), in which rational investors fully account for earnings inflation, and the investor inattention mechanism proposed by Hirshleifer and Teoh (2003).

2.1 Model Setting

We consider a three-period model with dates $t = 0, 1, 2$. The firm has a fixed stock supply, normalized to one share.

Agents. The firm is run by a risk-neutral manager. Stock market investors are risk-averse with constant absolute risk aversion (CARA), characterized by risk tolerance ρ. For simplicity, we ignore time discounting.

Firm earnings. At $t = 2$, the firm is liquidated, generating a final value v, drawn from a normal distribution:

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

where μ is the mean and h_v is the precision of the distribution.

At $t = 0$, investors share a common belief about v, represented by:

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

where $\hat{\mu}$ and $\hat{h}_v$ reflect the markets perceived mean and precision. This belief captures the market's information discovery or sentiment at $t = 0$ and is treated as given in our analysis.

When $\hat{\mu} > \mu$, the market price—driven by $\hat{\mu}$—reflects optimism relative to the unconditional mean μ, which we proxy using the firm's market value in our empirical analysis. Our model investigates how such optimism $\hat{\mu}$ creates pressure for the firm to manage its earnings report at $t = 1$, prior to liquidation at $t = 2$.

At $t = 1$, the firm's manager privately observes an interim signal about the final liquidation value 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 then issues a public earnings report, which can be inflated by an amount b, resulting in reported earnings:

$$e = e^n + b. \tag{1}$$

Earnings inflation imposes a non-pecuniary cost of $\frac{\kappa}{2}b^2$ with $\kappa > 0$ on the manager, interpreted as a reputational penalty for using aggressive accounting tactics such as accrual adjustments and non-recurring gains/losses (NRGLs) that shift cash flows forward.[3] Let b_* denote the equilibrium level of inflation.

It is also useful to note that our setting is isomorphic to a regulatory change that affects

[3] An alternative specification is to model the cost of inflation as pecuniary, directly reducing the firms liquidation value. While this would lead to even stronger earnings reversals in the long run, it also introduces more complex expressions for the firms market valuation by requiring adjustments for the impact of earnings inflation. For tractability, we adopt the simpler setting in which the inflation cost is non-pecuniary.

the easiness that earnings can be inflated.[4] In the context of China we will consider a policy that bans certain ways through which A-share firms can influence their reported earnings; this policy shock corresponds to a higher κ.

Inattentive investors. Following Hirshleifer and Teoh (2003), we assume that a fraction θ of investors are inattentative and fail to recognize that thereported earnings may be inflated. As a result, they interpret the reported earnings e as the true signal e^n. In contrast, the remaining $1-\theta$ fraction are fully rational and account for the possibility of inflation. Although these rational investors cannot observe the inflated component b directly, they form rational expectations and correctly anticipate the equilibrium level of inflation $b = b_*$. As shown by Stein (1989), even when all investors are rational, the signal jamming mechanism can still lead the manager to inflate reported earnings.

2.2 The Equilibrium

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

$$p_0 = \hat{\mu} - \frac{1}{\rho \hat{h}_v}. \tag{2}$$

Date-1 price. Let p_1 denote the stock price at $t = 1$. We first solve for the equilibrium price p_1 as a function of both the actual earnings inflation b and the rational investors' conjectured equilibrium inflation b_*. This will allow us to determine the manager's optimal inflation choice in the next step.

Due to differences in how the two investor groups perceive earnings inflation, their stock demands at $t = 1$ differ. Specifically, both inattentive and attentive investors base their demand on the expected excess (dollar) return, divided by the return variance.

[4]To see this formally, suppose that the inflation activity $\hat{b}$, which involves a cost of $\frac{1}{2}\hat{b}^2$, affects the firm's reported earnings e by $e = e^n + \hat{b}/\sqrt{\kappa}$. The higher κ, the more difficult it is for the firm to generate the same reported earnings. This setting with $\hat{b} \equiv \sqrt{\kappa} b$ is exactly the same as in our main model.

These demands are given by:

$$\rho\frac{E^{ir}\left(v\left|e\right.\right)-p_1}{Var(v|e)}=\rho(\hat{h}_v+h_\epsilon)[(1-\alpha)\,\hat{\mu}+\alpha e-p_1], \tag{3}$$

$$\rho\frac{E^{r}\left(v\left|e\right.\right)-p_1}{Var(v|e)}=\rho(\hat{h}_v+h_\epsilon)[(1-\alpha)\,\hat{\mu}+\alpha\left(e-b_*\right)-p_1], \tag{4}$$

where $\mathbb{E}^{ir}$ and $\mathbb{E}^{r}$ denote the expectation of inattentive and rational investors, respectively. The coefficient

$$\alpha\equiv\frac{h_\epsilon}{\hat{h}_v+h_\epsilon}$$

captures the weight investors place on updating their beliefs about the final dividend v upon observing the reported earnings e.

Inattentive investors fail to adjust for the anticipated inflation b_* and thus take reported earnings at face value in (3). In contrast, rational investors correctly deduct the expected inflation from e in (4).

Given the fixed share supply of one, the market-clearing condition requires that the sum of the demands in (4) and (3) equals one. Solving this condition yields the equilibrium price at $t=1$:

$$p_1=(1-\alpha)\,\hat{\mu}+\alpha e^n+\underbrace{\alpha[b-(1-\theta)b_*]}_{\text{due to earnings inflation}}-\frac{1}{\rho(\hat{h}_v+h_\epsilon)}. \tag{5}$$

Because of risk aversion, rational investors cannot completely arbitrage away the price distortion caused by inattentive investors. As a result, the manager's earnings inflation b affects the equilibrium price through the term $\alpha[b-(1-\theta)b^*]$.

In equilibrium, $b=b^*$, and this term simplifies to $\alpha\theta b_*$. Intuitively, the price impact of earnings inflation increases with both α, the weight investors place on earnings when updating beliefs about v, and θ, the fraction of inattentive investors in the market.

Managerial incentives. To capture stock market pressure on the manager, we assume she faces the risk of being fired at $t=1$. Her probability of retaining the position until $t=2$ is given by an increasing and concave function $\Phi(p_1-p_0)$, where p_1-p_0 reflects the firm's stock market performance under her management.[5] We assume that $\Phi(\cdot)\in(0,1)$,

[5]There are many other channels through which managers would like to inflate their earnings to influence the current stock prices. For instance, managers or major shareholders care about current market prices because they need to sell some of their holdings after their shares are unlocked (Titman

with $\Phi'(0) > 0$ and $\Phi'(\infty) = 0$. These properties imply that the hazard rate function $\phi(x) \equiv \frac{\Phi'(x)}{\Phi(x)}$ is strictly decreasing.

If the manager remains in office until $t = 2$, her compensation is proportional to the firm's final dividend. If fired, she receives a fixed severance pay, normalized to zero for simplicity. At $t = 1$, the manager forms an expectation of her continuation payoff, conditional on her private signal e^n, as follows: $\mathbb{E}\left(v - \frac{\kappa}{2}b^2 \middle| e^n\right) = e^n - \frac{\kappa}{2}b^2$, where we assume the manager begins with an improper prior and updates her belief fully based on the observed signal.

Therefore, the manager chooses b to maximize her expected payoff:

$$\max_{b} \quad \Phi(p_1(b, b_*) - p_0)\left(e^n - \frac{\kappa}{2}b^2\right). \tag{6}$$

In problem (6) we write $p_1(b, b_*)$ to highlight the dependence of date-1 price p_1 on the manager's inflation choice b and the rational investors' conjecture of the equilibrium inflation b_*.

Equilibrium earnings inflation. Recall the expressions for the date-0 and date-1 prices from (2) and (5). Their difference is given by:

$$p_1(b, b_*) - p_0 = \alpha[b - (1-\theta)b^* + e^n - \hat{\mu}] + \frac{1}{\rho\hat{h}_v} - \frac{1}{\rho(\hat{h}_v + h_\epsilon)}. \tag{7}$$

This difference increases with b, indicating that the manager can improve perceived stock performance by inflating reported earnings.

The manager's optimal inflation choice b is characterized by the first order condition of problem (6), evaluated at the equilibrium level $b = b_*$:

$$\phi'(p_1(b = b_*, b_*) - p_0) = \frac{\kappa b_*}{\alpha(e^n - \frac{\kappa}{2}b_*^2)}. \tag{8}$$

Substituting (7) into (8) and imposing $b = b_*$ yields the equilibrium condition that determines b_*:

$$\phi'\left(\alpha(\theta b_* + e^n - \hat{\mu}) + \frac{1}{\rho\hat{h}_v} - \frac{1}{\rho(\hat{h}_v + h_\epsilon)}\right) = \frac{\kappa b_*}{\alpha(e^n - \frac{\kappa}{2}b_*^2)}. \tag{9}$$

et al., 2022), or take out share pleading loans from securities firms (He et al., 2022).

Since $\phi(x) = \frac{\Phi'(x)}{\Phi(x)}$ is strictly decreasing, the left-hand side of equation (9) decreases with b_*, while the right-hand side increases with b_*. At $b_* = 0$, the left-hand side is strictly positive, while the right-hand side is zero. Thus, there exists a unique $b_* > 0$ that satisfies the first-order condition, implying a unique equilibrium in which the manager inflates reported earnings.

Treating equation (9) as an implicit function for b_*, we can derive the following comparative statics:

Proposition 1. *There exists a unique equilibrium, in which the equilibrium earnings inflation $b_* > 0$ even when $\theta = 0$. All else equal, b_* decreases with θ.*

This result highlights that even when all investors are rational ($\theta = 0$), the manager still inflates earnings in equilibrium ($b_* > 0$). This outcome is driven by the signal-jamming mechanism suggested by Stein (1989): When rational investors anticipate inflation of b_*, the manager must match that expectation; otherwise, investors will discount reported earnings by b_*, resulting in a lower stock price.

The second part of the proposition—that equilibrium inflation b_* decreases with θ—may initially seem counterintuitive. Intuitively, one might expect more inattentive investors to encourage greater inflation. However, when θ increases, a given level of earnings inflation has a stronger positive impact on the stock price (since more naive investors take reported earnings at face value or less rational ones debias the earnings inflation). As a result, the manager can achieve the desired price impact with a smaller amount of inflation.

Equation (9) also yields comparative statics on how the equilibrium earnings inflation b_* responds to changes in market expectations and the cost of inflation:

Proposition 2. *All else equal, the equilibrium earnings inflation b_* increases with the market expectation $\hat{\mu}$ and decreases with the cost of earnings inflation κ.*

2.3 Hypothesis Development

We now map the predictions of the model to our empirical setting. The model provides direct implications for how the market's expectation $\hat{\mu}$—reflected in the stock price p_0—affects the dynamics of reported earnings at $t = 1$ and the final liquidation value at $t = 2$.

In our empirical analysis, we proxy p_0 with the current stock valuation M_t and examine how M_t predicts future earnings E_{t+k} at various horizons $k > 0$.

In our model, the current stock valuation p_0 in (2) moves one to one with the market expectation $\hat{\mu}$. Therefore, by regressing short-term reported earnings $e = e^n + b$ on the market expectation $\hat{\mu}$, the resulting coefficient is:

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

where the inequality follows from Proposition 2, which implies $Cov(b_*, \hat{\mu}) > 0$. The final equality follows from the fact that $e^n = v + \epsilon$, where ϵ is independent of $\hat{\mu}$.

The term $\frac{Cov(e^n+b_*,\hat{\mu})}{Var(\hat{\mu})}$ represents the regression coefficient when using market valuation to predict short-term earnings, whereas $\frac{Cov(v,\hat{\mu})}{Var(\hat{\mu})}$ represents the coefficient when predicting long-term fundamentals. Therefore, the model implies the following empirical hypothesis:

Hypothesis 1. *In the presence of earnings inflation, the predictability of current stock valuation (M_t) for future short-term reported earnings (E_{t+k} with small k) is greater than its predictability for long-term earnings (E_{t+k} with large k).*

In our empirical analysis, we use non-recurring gains and losses (NRGLs) to proxy for the managed component of reported earnings (b_*). Combining the insights from Propositions 1 and 2 yields the following hypothesis:

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

The first part of Hypothesis 2 follows from Proposition 2, which shows that earnings inflation increases with market expectations. The second part follows from Proposition 1 in settings where the fraction of inattentive investors is positive. In such cases, earnings inflation contributes to temporary overvaluation, which eventually corrects, leading to lower future stock returns.

We also investigate a policy change that increases the cost of earnings inflation via NRGLs. Proposition 2 directly implies the following hypothesis; intuitively, without earnings management ($\kappa = \infty$) there should be zero correlation between earnings management and market valuations.

Hypothesis 3. *Following a positive shock to the cost of earnings inflation (κ), 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} for small k).*

3 Market Valuation and Future Earnings

After briefly describing the data we used in this article, 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 and cash flows. Finally, we analyze a set of dually listed firms in both Chinas A-share market and the Hong Kong stock market; there, we explore how stock valuations in these two segmented markets relate to future earnings.

3.1 Data

Our sample period starts in 1995 following Carpenter et al. (2021) and ends in 2022. 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 non-financial A-share 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), total market capitalization (M), dividend payouts (D), and operating cash flow (OCF). More specifically, D includes both annual cash dividends and net share repurchases, and OCF equals EBITDA minus change in working capital and income taxes. All variables are adjusted for inflation using the GDP deflator, with the deflator data obtained from CSMAR. We do not fill in missing earnings data.

One of the important accounting variables that we use, which captures earnings management by Chinese firms, is non-recurring gains and losses (NRGL). 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 U.S. data, we obtain annual accounting information from the Compustat database. Following Bai et al. (2016), we focuses on S&P500 non-financial firms over the 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. Panel B reports the variables, mainly for accounting information, at the quarterly frequency. The average ratio of NRGL scaled by previous total assets is relatively modest, 1.2% with a standard deviation of 2.7%.

Panel C presents the summary statistics for U.S. 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 could be driven by the simple fact that our sample consists of high-quality S&P500 firms in US whereas all listed firms in China regardless of quality.[6]

3.2 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. 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).

[6]This particular US-China sample difference is also in Carpenter et al. (2021), as we largely follow their sample construction for a sharper comparison.

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.

This portfolio approach follows the spirit of Fama and French (1995); we essentially aggregate all firms within one portfolio and treat the portfolio as one single but combined firm (and then carry out the analysis as in Carpenter et al. (2021)). Compared to the stock-level analysis as in Carpenter et al. (2021), portfolio aggregation helps smooth out firm-level outliers and reduces estimation noises (as discussed extensively in Chen (2017)). Moreover, when predicting payouts (D), the portfolio approach mitigates the issue of excessive observations with a value of zero.

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

$$\frac{E_{i,t+k}}{A_{i,t}} = \alpha + \beta_k \log(\frac{M_{i,t}}{A_{i,t}}) + \gamma \frac{E_{i,t}}{A_{i,t}} + \lambda \frac{D_{i,t}}{A_{i,t}} + \epsilon_{i,t}, \text{where } k \in \{1, 2, ..., 5\}. \tag{10}$$

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). Firms that do not have five 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 predicted variation 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 predicted variation is 0.010 (t-stat = 5.0) for $k = 1$ and increases to 0.015 for $k = 3$ (t-stat = 4.2).

When moving on to U.S. S&P 500 firms, similarly we first form 50 size by book-to-market portfolios and conduct the same regressions at the portfolio level. The estimations yield predicative variations that are larger but with 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). The stronger predictability of $\log(M_{i,t}/A_{i,t})$ in more recent sample years echoes the main finding of Bai et al. (2016) that the U.S. stock market has become more informative.

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 0.015 for $k = 3$ (t-stat = 4.23) to 0.013 for $k = 5$ (t-stat = 1.98). In contrast, in the U.S. market from 1960 to 2021 (1995 to 2021), the estimate continues to increase with k, reaching 0.032 (0.037) for $k = 5$ and remaining statistically significant.

Based on the estimates of β_k, Figure I visualizes the predicted variation of $\log(M_{i,t}/A_{i,t})$ for $k \in \{1, 2, ..., 5\}$ 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.[7] This reversal pattern differs from the findings of Carpenter et al. (2021), who show that earnings predictability increases with k.

Comparison to Carpenter et al. (2021). A key econometric difference likely explains the discrepancy: we employ a portfolio-based approach, whereas Carpenter et al. (2021) estimate β_k at the individual stock level. We report the corresponding results using individual stocks in Section A.3 of the Online Appendix, Table A.1. At the individual stock level, the reversal in the predictability of M_t is less pronounced compared to that reflected by the portfolio-level regression. As mentioned earlier, smaller firms are more prone to measurement error issues. Portfolio aggregation, by essentially value-weighting our sample observations, helps mitigate estimation noises (Chen, 2017).[8]

[7] In unreported results, we find that β_k becomes statistically insignificant when $k = 7$. We decided to keep the predictive horizon of 5-year to have a closer comparison to Carpenter et al. (2021).

[8] We provide more details on the individual stock level regressions in Appendix A.3. There, Table A.4 shows that the distribution of E_{t+k}/A_t appears to have higher standard deviation for high M_t stocks and to be positively skewed; and Figure A.4 shows that regression coefficients from OLS regression is even larger than that from the 75^{th} percentile quantile regression, suggesting the effect in Carpenter et al. (2021) is likely driven by right-skewed outliers. Regarding corporate payouts and cash flows (to be discussed in the next section), at the individual stock level, we find the predictability of A-share market value is an order of magnitude smaller than that of U.S. S&P500 stocks (see Table A.2 and A.3). This is consistent with the premise that the Chinese stock market is less effective at reflecting firm fundamentals compared to its U.S. counterpart.

The regression results in Table A.1 also suggest somewhat weaker predictability results compared to Carpenter et al. (2021). For instance, during the sample period ending in 2016, the predictability in China begins to flatten from $k = 4$ to $k = 5$, a pattern not observed in the U.S. These findings align with our premise that price informativeness in the U.S. market is stronger than in the Chinese market.

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 $k = 1, ..., 5$. Furthermore, in the sample period ending at 2022, at the individual stock level regression (shown in Table A.1) the comparison between China and U.S. is even more pronounced. Both pieces of evidence point to a declining price informativeness on reported earnings in recent years in China's A-share market. As we discuss in later in Section 4.4, this decline is plausibly linked to China's delisting rule reform in 2020.

Summary. Overall, Table II and Figure I confirm the main findings of Carpenter et al. (2021): in the Chinese A-share market, stocks with higher market valuations tend to exhibit higher future earnings. However, this predictability may arise from two distinct channels. First, it may be "genuine," reflecting market valuations based on underlying fundamentals—the interpretation offered by Carpenter et al. (2021). Alternatively, the predictability may be "artificial," driven by managerial manipulation of earnings to cater to market overoptimism, as posited by our model in Section 2.

Our new finding—an eventual reversal in earnings—indicates a weakening relationship between market valuation and reported earnings over the long term. This provides supporting evidence for Hypothesis 1 in Section 2.3 and marks a significant departure from the conclusions of Carpenter et al. (2021). While both channels—price informativeness as described by Carpenter et al. (2021) and earnings inflation as analyzed in our study—may both operate in China's A-share market, our analysis centers on validating the latter manipulate-to-cater mechanism by directly testing the reversal effect in Section 3.4.

3.3 Predicting Payouts and Cash Flows

The possibility that firms actively manage earnings makes earnings an unreliable measure of firm fundamentals. In this section we study whether market valuation can predict firm payouts and operating cashflows, two measures of firm fundamental that are less prone to manipulation.

Payouts. We adopt the regression specified in Equation 10, replacing earnings with total payouts denoted by $D_{t+1}, ..., D_{t+5}$. As explained, total firm payouts include both cash dividends and share repurchases. 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.

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

$$\frac{D_{i,t+k}}{A_{i,t}} = \alpha + \beta_k \log(\frac{M_{i,t}}{A_{i,t}}) + \gamma \frac{E_{i,t}}{A_{i,t}} + \lambda \frac{D_{i,t}}{A_{i,t}} + \epsilon_{i,t}, \text{where } k \in \{1, 2, ..., 5\}. \tag{11}$$

As before, we multiply the coefficient of $\log(M_{i,t}/A_{i,t})$ by its 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 China. 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) and 0.004 for $k = 5$ (t-stat = 2.5). 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 of the S&P 500 firms in U.S. The predicted variation of $\log(M_{i,t}/A_{i,t})$ ranges from 0.012 (0.006) to 0.035 (0.021) as k increases from 1 to 5 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.

Figure II summarizes our result by plotting the predicted variation of $\log(M_{i,t}/A_{i,t})$ with 95% confidence intervals for $k \in \{1, 2, ..., 5\}$ in both markets. The sharp contrast in the predictability of payouts between the Chinese and U.S. markets reinforces concerns that earnings in the Chinese market may be actively managed and, therefore, may not fully reflect firm fundamentals.

Operating cashflows. That market valuation has low predictive power in China market admits an alternative explanation: 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.

To address this, we also examine the predictability of stock valuation for operating cash flows. Relative 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: EBITDA – Change in Working Capital – Income Taxes.[9] We then replace payouts (D) in (11) with OCF and rerun the regression, whose results are reported in Table IV. One observes 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. It equals -0.011 for $k = 1$ (t-stat $= 5.2$), increases slightly to -0.002 for $k = 3$ (t-stat $= 0.7$), and 0.001 for $k = 5$ (t-stat $= 0.2$). 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 sample 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 0.037 (0.023) as k increases from 1 to 5 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 $k \in \{1, 2, ..., 5\}$ in both markets.

In summary, we find that market valuation has weak predictive power for future payouts and cash flows 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

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

consistently predicts earnings, dividends, and cash flow, yielding more coherent results across all measures.

3.4 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 book-to-market ratio portfolios:

$$\frac{E_{j,t+1}-E_{j,t}}{A_{j,t}} = \alpha + \beta^{0\to 1}\log(\frac{M_{j,t}}{A_{j,t}}) + \gamma\frac{E_{j,t}}{A_{j,t}} + \lambda\frac{D_{j,t}}{A_{j,t}} + v_t + u_j + \epsilon_{j,t}, \tag{12}$$

$$\frac{E_{j,t+3}-E_{j,t+1}}{A_{j,t}} = \alpha + \beta^{1\to 3}\log(\frac{M_{j,t}}{A_{j,t}}) + \gamma\frac{E_{j,t}}{A_{j,t}} + \lambda\frac{D_{j,t}}{A_{j,t}} + v_t + u_j + \epsilon_{j,t}, \tag{13}$$

$$\frac{E_{j,t+5}-E_{j,t+3}}{A_{j,t}} = \alpha + \beta^{3\to 5}\log(\frac{M_{j,t}}{A_{j,t}}) + \gamma\frac{E_{j,t}}{A_{j,t}} + \lambda\frac{D_{j,t}}{A_{j,t}} + v_t + u_j + \epsilon_{j,t}, \tag{14}$$

Unlike Equation (10), 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.

Based on regression equations in (14), we present evidence for earnings reversal in China's A-share market by adding various fixed effects in a progressive way. We first estimate these regressions with only time fixed effect which focuses on cross-sectional variation. We then examine the time-series effects by only adding portfolio fixed effects, and then finally run the panel regression including both time and portfolio fixed effects, v_t and u_j, respectively. 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. In Panel A, we first include time fixed effects; it is worth emphasizing that this approach is similar to Carpenter et al. (2021). We observe that the coefficients $\beta^{0\to 1}$ and $\beta^{1\to 3}$ are both positive, with t-statistics of 5.4 and 1.3, respectively. The coefficient $\beta^{3\to5}$, however, is negative but statistically insignificant. That the earnings change from year 3 to year 5 is flattened is consistent with Table II where we show similar magnitudes of β_3, β_4 and β_5 for regression (10).

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; Panel B with portfolio fixed effects only, the coefficients $\beta^{1\to3}$ and $\beta^{3\to5}$ are both significantly negative, with t-statistics of 2.4 and 2.6, respectively, providing strong evidence of long-run earnings reversal.

In Panel C, we report the results with including both time and portfolio fixed effects. The coefficient $\beta^{0\to1}$ remains significant and positive, with a t-statistic of 4.7. The point estimates of $\beta^{1\to3}$ and $\beta^{3\to5}$ are both negative, but statistically insignificant. That adding time series fixed effects weakens the earnings reversal in Panel C, compared to Panel B with portfolio fixed effects only, suggests the potential presence of earnings reversal at the aggregate level in China's A-share market.

Finally, in all panels A, 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 U.S. market underscores a fundamental difference between the U.S. and Chinese markets, which is crucial for interpreting the results of Carpenter et al. (2021).

3.5 Price Informativeness of Dually Listed A-H Shares

To provide further evidence that supports our hypothesis, we now further exploit a small sample of firms that are dually listed on both the Chinese A-share and the Hong Kong markets. Interestingly, while our empirical findings align with those of Carpenter et al. (2021), our interpretation points in the opposite direction, offering an explanation that better aligns with the well-established institutional differences between Chinas A-share and Hong Kongs H-share markets.

Dual-listed A-H stocks vs. sole-listed A stocks. We obtain the list of A-H dual-listed firms from CSMAR. The sample includes 89 unique non-financial firms that simultaneously issue A-shares in the mainland market and H-shares in the Hong Kong market. These firms must comply with regulations in both jurisdictions; and given that the Hong Kong stock market may impose more stringent disclosure requirements, the reporting quality of dual-listed firms should be higher compared to those sole-listed in A-share market. From this angle, one way to map this dual-market setting into our simple model discussed in Section 2 is that A-H dual-listed firms are subject to a higher manipulation cost κ for earnings management than solely A-share listed stocks.

Following the intuition of Proposition 2 and Hypothesis 3 regarding κ,[10] we conjecture that the correlation between M_t and subsequent reported earnings E_{t+k} for the dual listed stocks should be weaker than other A-share firms. To verify this conjecture, we extend the cross-sectional regression specified in (10) by adding an interaction dummy of A-H share and market valuations. Due to the relatively small number of A-H dual-listed firms, we estimate the regression at the individual stock level. Specifically, for each year t between 1995 and 2022, we run the cross-sectional regressions:

$$\frac{E_{i,t+k}}{A_{i,t}} = \alpha + \beta_k \log(\frac{M_{i,t}}{A_{i,t}}) + \theta_k AH_i \times \log(\frac{M_{i,t}}{A_{i,t}}) + AH_i + \gamma\frac{E_{i,t}}{A_{i,t}} + \lambda\frac{D_{i,t}}{A_{i,t}} + \epsilon_{i,t}, \qquad (15)$$

with $k \in \{1, 2, ..., 5\}$, where AH refers to a dummy variable that equals one if the stock i is dual-listed in A and H markets and the market valuation is based on A-share prices even for the dual-listed stocks.

Panel A of Table VI reports the estimated regression coefficients of β and θ. The coefficients $\{\beta_k\}$ of $\log(\frac{M_{i,t}}{A_{i,t}})$, are significantly positive for all k, is consistent with the findings shown in Table II. The coefficients $\{\theta_k\}$ of the interaction term $AH_i \times \log(\frac{M_{i,t}}{A_{i,t}})$, are all negative and statistically significant for $k \geq 2$. Such patterns are consistent with our "cater-to-manipulate" mechanism.

Comparison to the literature. Carpenter et al. (2021) also document a similar empirical pattern in their Table 3 that the prices of A-H dual-listed stocks are less correlated with the firms' future earnings compared to that of A-listed only stocks. However, because Carpenter et al. (2021) view the correlation to reflect genuine price informativeness,

[10] We will further test this hypothesis later by taking advantage of a policy shock in Section 4.4.

their interpretation of A-H stocks having lower predictability on future earnings is drastically different from ours. On page 690, they argue that "*because investors trading Hong Kong H shares price Chinese firms so differently than Chinese investors trading mainland A shares, dual listing reduces stock price informativeness by introducing noise into the A-share prices associated with Hong Kong investors discount rate shocks.*"

This argument is inconsistent with the well-documented distinction between the investor compositions of the Hong Kong and Chinese A-share markets. The Hong Kong stock market is predominantly composed of sophisticated institutional investors, many of whom are foreign. In contrast, the A-share market is largely driven by relatively inexperienced retail investors. For instance, according to the website of Hong Kong Exchange, "institutional investors from Hong Kong and overseas account for about 65 per cent of total turnover." By comparison, the number is 11.7% in the A-share market, and retail investors contribute to 86.6% of trading volume (An et al., 2022).

A direct implication of this disparity in investor sophistication is that, for AH dual-listed stocks, H-share prices should be more informative than A-share prices. These firms are listed on two segmented markets and traded by two distinct investor bases, and prior research has documented a persistent valuation wedge between A and H shares (e.g., Jia et al., 2017). Given the difference in investor composition, we hypothesize that H-share prices will display greater predictive power for future firm fundamentals than A-share prices. In the context of our model in Section 2, this corresponds to investors in the H-share market having a more accurate initial belief $\hat{\mu}$ than their A-share counterparts.[11]

To test this hypothesis, we apply the cross-sectional regression specified in Equation (10), for these A-H dual listed stocks but using valuations based on both A-share and H-share prices. Specifically, for each year t, we estimate the following cross-sectional regression:

$$\frac{E_{i,t+k}}{A_{i,t}} = \alpha + \beta_k^A \log(\frac{M_{i,t}^A}{A_{i,t}}) + \beta_k^H \log(\frac{M_{i,t}^H}{A_{i,t}}) + \gamma\frac{E_{i,t}}{A_{i,t}} + \lambda\frac{D_{i,t}}{A_{i,t}} + \epsilon_{i,t}, k \in \{1, 2, ..., 5\}. \quad (16)$$

Here, M^H and M^A denote the firms total market capitalization based on A-share and H-

[11] One could also consider a fully dynamic setting with the presence of inattentive investors and earnings inflation, recognizing that earnings in each period may comprise both a natural component and a managed component. In such a setting, we expect the more sophisticated investors in the H-share market to better anticipate future earnings, encompassing both natural and managed components. This necessarily extends beyond our model which assumes a final liquidation date at $t = 2$ for the firm to settle its obligations, and we await future research to investigate this interesting case.

share prices, respectively, calculated by multiplying the price with the total outstanding shares (of the dual-listed firm).

In Panel B of Table VI, we report that for these dual-listed stocks, the predictability power of H-market-valuation is significantly positive while that of A-market-valuation is rather weak. That is, the predicted variation of $\log(M_{i,t}^H/A_{i,t})$ increases with the forecast horizon k, ranging from 0.009 to 0.017 as k increases from 1 to 5, with all t-statistics exceeding 3.5. In contrast, the predicted variation of $\log(M_{i,t}^A/A_{i,t})$ is statistically insignificant across all horizons and even turns negative for $k \geq 4$. This stark contrast provides valuable evidence that A-share prices may be less informative than H-share prices in reflecting future earnings.

4 Direct Tests of Manipulate-to-Cater Mechanism

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.

We start with a brief overview of the practice of earnings management in China in Section 4.1, where we introduce non-recurring gains and losses (NRGLs) as one of the important earnings management tools by Chinese listed firms. We then analyze the relationship between NRGLs and market valuations in Subsection 4.2 and examine whether NRGLs predict subsequent stock returns in Subsection 4.3. Together, these analyses serve as tests for Hypothesis 2. Subsection 4.4 tests Hypothesis 3 by leveraging the 2020 delisting rule reform as a natural experiment.

4.1 Earnings Management in China

Revisit Piotroski and Wong (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 the upper panel depicting S&P 500 firms in the U.S. market and the lower panel showing Chinese A-share firms.

In the upper panel, 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.

The lower panel 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 the upper panel, the lower panel 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 (which we will study shortly) but remains substantial.

These patterns are consistent with the findings of Piotroski and Wong (2012) for earlier years. There were strong incentives for firms to avoid reporting losses, which triggers the prevalence of earnings management in the Chinese A-share markets. For instance, before 2020 firms reporting negative net profits for two consecutive years were labeled as ST (special treatment) firms, and continued negative earnings could lead to delisting from the exchange. Beyond regulatory concerns, firms also manage earnings to meet investor expectations, as posited by our hypotheses.

Earnings management: U.S. versus China. 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).

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.[12] Highlighting tunneling activities and other governance issues, several studies (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.

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.[13]

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. In 2020 a new regulation was introduced to exclude NRGLs in the net profit calculation for delisting purposes, a policy shock that we will study in detail later. This underscores the practical significance of NRGLs in China, motivating us to use NRGLs as our primary measure of earnings management.

[12] 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.

[13] 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.

4.2 Market Valuation and NRGLs

The earnings reversal evidence presented in Section 3.4 supports Hypothesis 1 we developed in Section 2.3, indicating the possibility of firm managers inflating earnings in response to market pressure. We now test Hypothesis 2 which says that firms with higher market valuation ratios tend to use more NRGLs in the near future. Following the discussion in the previous section, 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 $NRGL_{i,t+1}$ on $\log(M_{i,t}/A_{i,})$ and other control variables at time t. In the second and third columns we regress $NRGL_{i,t+2}$ and $NRGL_{i,t+3}$, respectively, 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) to control for the company's expected shell probability (ESP). Due to the strict quota on IPOs in China, underperforming firms have strong incentives to retain their listed status by maintaining positive earnings, as this allows them to capture their shell value through reverse mergers by private firms (who seek listing). We calculate ESP_t based on firm characteristics at year t, including firm size, profitability, ST status, and the ownership concentration among the top ten shareholders (see details in Online Appendix Section A.1).

Table VII shows that $\log(M_{i,t}/A_{i,t})$ can predict $NRGL_{i,t+1}$ in a positive way, with a t-stat $= 11.5$. Such correlations remain positive but decrease in magnitude in year $t+2$ and $t+3$. 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 NRGLs, consistent with the findings in previous studies on the relationship between delisting risk and earnings management in China (e.g., Piotroski and Wong (2012); Lee et al. (2023)) Also, coefficients for firms' past NRGLs are all negative, indicating that earnings management tends to be mean-reverting.

4.3 Return Predictability of Managed Earnings

We now examine how firms' NRGLs can predict the subsequent stock returns. This analysis helps assess whether investors fully recognize the managed component of reported earnings, that is, whether θ, which is the fraction of rational investors in our model in Section 2, is less than 1. If investors understand that high earnings deu to large NRGLs are unlikely to persist, current stock prices should reflect this information, resulting in no subsequent underperformance as predicted 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 quarterly stock returns and NRGLs 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. We lag one quarter for NRGL variables to ensure tradability.

As shown in Table VIII, our results support the notion that investors do not fully see through earnings management via NRGLs; that is, $\theta < 1$ in our model in Section 2 so not all investors are fully rational in the China stock market. Both the quarterly level $NRGL_{i,q}$ 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 U.S. 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 NRGLs use in reported earnings.

4.4 The 2020 Reforms of Delisting Rules

To further strengthen the identification of our tests, we exploit the 2020 reforms of delisting rules—an important policy change in the Chinese A-share market. This also serves a test for our Hypothesis 3.

Institutional background. 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.

One of the key changes from the reform is that firms were no longer allowed to include NRGLs in their earnings calculations for regulatory compliance, effectively removing a key tool for earnings management. 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 Online 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, there were only less than 10 delisting cases, and the number of delisted firms was even lower between 2008 and 2018, a period when reverse mergers were prevalent.

Policy shock on NRGLs and market valuations. 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. Figure VI shows that firms that reported high NRGLs in the pre-reform period significantly reduced their use of NRGLs starting in 2020, 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 subsequent 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 4) for NRGLs in all three subsequent years. In terms of economic magnitude, in Column (1) for predicting NRGLs in year $t+1$, 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 2022—the first three fiscal years under the new rule—exhibits fewer irregularities around zero compared to the pre-reform period, indicating a reduction in earnings management.

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

To test this hypothesis, we modify Equation (10) 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:

$$\frac{E_{i,t+k}}{A_{i,t}} = \alpha + \beta_k \log(\frac{M_{i,t}}{A_{i,t}}) + \theta_k \log(\frac{M_{i,t}}{A_{i,t}}) \times POST_t + \gamma \frac{E_{i,t}}{A_{i,t}} + \lambda \frac{D_{i,t}}{A_{i,t}} + \upsilon_t + \epsilon_{i,t}, \qquad (17)$$

for $k \in \{1, 2, 3\}$; we set $k \leq 3$ because our sample ends in 2022 while the policy year is 2020. Here, 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.

We also run the same test using the sample of U.S. S&P 500 firms. This can help rule out the possibility that the weaker predictability of market valuation on earnings is due to the disruption of the COVID-19 pandemic. 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 run regression based on (17) but replacing the dependent variable with payouts and cash flows 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. We also observe similar patterns for predicting operating cash flows. The coefficients on the interaction term for all three forecasting horizons are all positive and significant. The increased predictability after 2020 rules out the potential contaminating effect from COVID-19 but supports our hypothesis that the 2020 delisting rule reform improves price informativeness 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 relationship between market valuation and subsequent earnings weakened.

5 Conclusion

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

	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
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
$\log(M_t/A_t)$	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: Quarterly variables of Chinese A-share stocks

	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: Annual variables of U.S. S&P500 stocks

	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
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
$\log(M_t/A_t)$	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) 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 $k \in \{1, ..., 5\}$, to conduct regressions. The table shows predicted variation $\hat{\beta}_k \sigma(log(M_t/A_t))$ and White-heteroscedasticity-consistent t-statistics from the following portfolio-level cross-sectional regressions using the sample of Chinese A-share stocks:

$$\frac{E_{t+k}}{A_t} = \alpha + \beta_k \log(\frac{M_t}{A_t}) + \gamma\frac{E_t}{A_t} + \lambda\frac{D_t}{A_t} + \epsilon_t. \text{where } k \in \{1, 2, ..., 5\}$$

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 U.S. S&P500 stocks are also reported. Variable definitions are in Appendix A.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Year	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$	
	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
1996	0.018	4.191	0.028	2.726	0.026	3.027	0.031	3.388	0.017	1.031
1997	0.020	3.201	0.019	1.831	0.025	2.701	0.012	0.774	0.002	0.137
1998	0.009	3.844	0.008	1.597	0.011	1.859	-0.004	-0.428	-0.004	-0.497
1999	0.016	3.983	0.012	2.419	0.003	0.672	-0.001	-0.140	-0.015	-1.938
2000	-0.003	-0.879	-0.004	-1.355	-0.008	-1.869	-0.019	-3.702	-0.018	-3.463
2001	0.000	-0.151	-0.003	-1.150	-0.005	-0.830	-0.011	-2.280	-0.008	-2.400
2002	0.002	0.761	-0.004	-0.773	-0.001	-0.235	-0.002	-0.509	0.003	0.600
2003	0.003	0.879	0.003	1.272	0.002	1.209	0.012	3.281	0.018	3.420
2004	0.004	1.780	0.005	2.085	0.014	3.067	0.019	2.542	0.019	3.527
2005	0.007	2.465	0.014	2.771	0.021	3.076	0.020	5.883	0.021	6.146
2006	0.014	3.258	0.022	4.886	0.028	3.726	0.029	4.329	0.034	6.050
2007	0.011	3.231	0.010	2.544	0.012	3.207	0.010	1.441	0.020	4.140
2008	0.010	3.250	0.017	5.165	0.024	5.010	0.024	6.596	0.028	5.646
2009	0.013	3.791	0.023	3.566	0.026	6.915	0.026	5.566	0.016	3.665
2010	0.009	2.732	0.021	2.917	0.026	2.346	0.014	4.668	0.019	3.344
2011	0.013	4.747	0.020	3.343	0.011	1.872	0.024	3.775	0.040	4.153
2012	0.016	1.936	0.010	2.614	0.019	4.626	0.030	4.384	0.026	2.651
2013	0.014	3.274	0.017	9.505	0.027	6.836	0.019	2.488	-0.030	-3.657
2014	0.014	7.322	0.022	7.731	0.017	2.943	-0.013	-2.106	-0.013	-1.649
2015	0.013	6.016	0.010	3.509	-0.011	-2.102	-0.012	-1.492	-0.002	-0.337
2016	-0.002	-1.160	-0.002	-1.024	-0.001	-0.323	0.000	-0.132	-0.002	-0.547
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	
	(5.032)		(4.816)		(4.233)		(2.653)		(1.981)	
1995 to 2022-k	0.008		0.011		0.013		0.010		0.009	
	(6.026)		(4.827)		(4.392)		(2.989)		(2.587)	
Averages US S&P500										
1960 to 2021-k	0.021		0.029		0.030		0.032		0.032	
	(12.994)		(18.940)		(17.033)		(18.410)		(19.168)	
1995 to 2021-k	0.028		0.033		0.033		0.037		0.037	
	(10.898)		(14.626)		(14.913)		(22.678)		(17.104)	

Table III. Stock Price Informativeness about Future Payouts

For each year t, stocks are sorted independently 10×5 portfolios based on size (M) 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 $k \in \{1, ..., 5\}$, to conduct regressions. The table shows predicted variation $\hat{\beta}_k \sigma(log(M_t/A_t))$ and White-heteroscedasticity-consistent t-statistics from the following portfolio-level cross-sectional regressions using the sample of Chinese A-share stocks,

$$\frac{D_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 5\}$$

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)
Year	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$	
	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
1996	-0.002	-1.266	0.001	0.477	0.001	0.862	0.008	3.319	0.003	1.450
1997	-0.001	-0.593	-0.001	-0.489	0.002	1.139	0.003	0.999	-0.001	-0.419
1998	0.000	-0.491	0.003	2.434	0.002	1.866	0.002	1.701	-0.002	-1.010
1999	0.002	2.681	0.002	2.548	0.002	1.720	0.000	-0.253	0.000	-0.139
2000	0.000	-0.836	-0.002	-2.549	-0.002	-2.019	-0.003	-1.899	-0.004	-2.490
2001	0.000	0.362	-0.001	-1.148	-0.001	-1.745	-0.002	-2.496	-0.002	-1.868
2002	0.000	0.090	0.000	-0.350	0.000	-0.317	-0.001	-0.776	0.000	0.289
2003	0.001	1.741	0.000	0.767	0.000	0.722	0.001	1.119	0.003	3.227
2004	0.001	1.406	0.001	1.544	0.001	0.994	0.003	3.380	0.004	2.094
2005	0.000	0.736	0.001	1.001	0.003	3.903	0.004	3.089	0.005	4.600
2006	0.000	1.205	0.002	3.523	0.003	2.613	0.003	3.101	0.005	3.533
2007	0.001	2.825	0.002	2.485	0.002	2.105	0.002	1.970	0.005	3.351
2008	0.000	-0.599	0.000	-0.305	0.003	2.209	0.003	2.826	0.003	2.937
2009	0.001	1.263	0.005	2.481	0.006	3.041	0.003	2.375	0.004	3.083
2010	0.002	2.073	0.002	3.104	0.002	1.790	0.002	2.711	0.004	4.039
2011	0.001	3.710	0.001	1.746	0.002	2.947	0.004	3.291	0.006	4.401
2012	0.000	0.777	0.001	2.729	0.003	3.794	0.005	3.371	0.007	3.425
2013	0.000	0.934	0.001	2.076	0.003	2.987	0.006	3.621	0.010	4.409
2014	0.002	3.726	0.005	3.054	0.005	4.994	0.008	4.304	0.012	2.516
2015	0.001	2.038	0.002	2.307	0.004	3.540	0.015	2.608	0.007	2.618
2016	0.000	-0.120	0.002	1.553	0.003	1.822	0.001	0.478	0.002	1.012
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	
	(2.648)		(3.670)		(4.600)		(3.539)		(3.445)	
1995 to 2022-k	0.001		0.001		0.002		0.003		0.004	
	(1.626)		(2.502)		(3.269)		(2.838)		(2.494)	
Averages US S&P500										
1960 to 2021-k	0.006		0.014		0.017		0.019		0.021	
	(3.458)		(7.964)		(9.089)		(8.470)		(7.986)	
1995 to 2021-k	0.012		0.024		0.027		0.030		0.035	
	(7.563)		(16.818)		(15.363)		(11.362)		(10.025)	

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) 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 $k \in \{1, ..., 5\}$, to conduct regressions. The table shows predicted variation $\hat{\beta}_k \sigma(log(M_t/A_t))$ and White-heteroscedasticity-consistent t-statistics from the following portfolio-level cross-sectional regressions using the sample of Chinese A-share stocks,

$$\frac{OCF_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \delta \frac{OCF_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 5\}$$

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)
Year	$k = 1$		$k = 2$		$k = 3$		$k = 4$		$k = 5$	
	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
1999	-0.014	-3.873	-0.015	-3.377	-0.021	-6.335	0.005	1.255	-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
2001	-0.011	-4.563	-0.006	-1.540	-0.010	-3.417	0.002	0.457	-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
2003	-0.006	-1.814	-0.002	-0.838	-0.003	-0.585	0.004	1.044	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
2005	-0.009	-2.000	-0.009	-0.892	0.001	0.273	0.016	1.639	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
2007	-0.009	-0.873	-0.002	-0.226	0.004	1.282	0.017	3.058	-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
2009	-0.006	-0.633	-0.028	-2.060	0.028	3.611	-0.025	-2.343	-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
2011	0.010	0.580	-0.001	-0.148	0.008	2.273	0.005	0.724	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
2013	-0.029	-2.577	-0.022	-1.388	-0.026	-4.230	0.033	1.281	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
2015	-0.036	-4.145	0.007	0.971	0.013	2.041	0.019	1.132	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
2017	-0.007	-1.433	-0.007	-1.715	0.004	0.538	-0.007	-1.255	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										
1998 to 2016-k	-0.012		-0.013		-0.005		0.000		-0.005	
	(-4.844)		(-3.720)		(-1.457)		(0.042)		(-0.980)	
1998 to 2022-k	-0.011		-0.009		-0.002		0.006		0.001	
	(-5.245)		(-3.418)		(-0.676)		(1.139)		(0.200)	
Averages US S&P500										
1960 to 2021-k	0.007		0.015		0.017		0.019		0.023	
	(6.306)		(7.892)		(8.224)		(8.202)		(8.502)	
1995 to 2021-k	0.014		0.025		0.028		0.031		0.037	
	(12.286)		(14.925)		(11.777)		(9.777)		(9.049)	

Table V. Earnings Reversal

For each year t, stocks are sorted independently 10×5 portfolios based on size (M) 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 $k \in \{1, ..., 5\}$, 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 time fixed effect

	China (1995-2022)			US SP500 (1960-2021)		
	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$
$\log(M_t/A_t)$	0.020	0.009	-0.009	0.032	0.005	0.006
	(5.35)	(1.30)	(-1.28)	(10.67)	(1.70)	(2.09)
D_t/A_t	1.657	-0.688	0.180	0.175	0.057	0.013
	(4.33)	(-1.79)	(0.41)	(3.06)	(1.07)	(0.24)
E_t/A_t	-0.752	-0.096	-0.123	-0.664	-0.177	-0.079
	(-9.12)	(-1.44)	(-1.88)	(-13.51)	(-3.93)	(-1.89)
Portfolio FE	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1050	1050	1050	2621	2621	2621

Panel B: With portfolio fixed effect

	China (1995-2022)			US SP500 (1960-2021)		
Variable	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$
$\log(M_t/A_t)$	0.003	-0.021	-0.019	0.020	0.008	0.001
	(0.31)	(-2.42)	(-2.59)	(5.56)	(2.07)	(0.18)
D_t/A_t	0.652	-0.258	0.687	0.053	0.032	0.034
	(2.39)	(-0.54)	(1.74)	(0.88)	(0.55)	(0.62)
E_t/A_t	-0.663	0.060	-0.254	-0.574	-0.234	-0.062
	(-7.13)	(0.77)	(-3.20)	(-10.38)	(-5.08)	(-1.49)
Portfolio FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
N	1050	1050	1050	2621	2621	2621

Panel C: With group and time fixed effect

	China (1995-2022)			US SP500 (1960-2021)		
	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$
$\log(M_t/A_t)$	0.042	-0.021	-0.001	0.030	0.009	0.005
	(4.71)	(-1.22)	(-0.06)	(9.64)	(2.65)	(1.48)
D_t/A_t	0.978	-0.022	0.277	0.172	0.048	-0.002
	(3.95)	(-0.06)	(0.68)	(3.03)	(0.92)	(-0.04)
E_t/A_t	-0.784	0.090	-0.157	-0.677	-0.168	-0.070
	(-9.07)	(1.12)	(-2.13)	(-13.72)	(-3.75)	(-1.66)
Portfolio FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1050	1050	1050	2621	2621	2621

Table VI. Stock Price Informativeness about Future Earnings: A-H Dual-list Shares

Panel A presents the time-series point estimates of β and θ from the following stock-level cross-sectional regressions from 1995 to 2022$-k$:

$$\frac{E_{i,t+k}}{A_{i,t}} = \alpha + \beta_k \log(\frac{M_{i,t}}{A_{i,t}}) + \theta_k AH \times \log(\frac{M_{i,t}}{A_{i,t}}) + AH + \gamma\frac{E_{i,t}}{A_{i,t}} + \lambda\frac{D_{i,t}}{A_{i,t}} + \epsilon_{i,t}, \text{where } k \in \{1,2,...,5\},$$

where AH refers to a dummy variable that equals one if the stock is dual-listed. t-statistics based on Newey-West standard errors lag of one year in parentheses. Panel B 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 dual-list shares from 1995 to 2022$-k$,

$$\frac{E_{t+k}}{A_t} = \alpha + \beta_k^H log(\frac{M_t^H}{A_t}) + \beta_k^A log(\frac{M_t^A}{A_t}) + \gamma\frac{E_t}{A_t} + \lambda\frac{D_t}{A_t} + \epsilon_t, \text{where } k \in \{1,2,...,5\}.$$

M^H and M^A refer to market capitalization based on H-share and A-share prices, respectively. 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.

Panel A: AH dual-listed vs solely-listed A shares

	(1)	(2)	(3)	(4)	(5)
	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$
$log(M_t/A_t)$	0.0174	0.0267	0.0355	0.0379	0.0397
	(6.13)	(5.62)	(4.79)	(3.93)	(3.47)
$AH \times log(M_t/A_t)$	-0.00155	-0.00973	-0.0168	-0.0196	-0.0274
	(-0.38)	(-1.89)	(-2.50)	(-2.37)	(-2.44)

Panel B: M^H vs M^A

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

Table VII. Market Valuation and NRGL

This table presents the estimated coefficients from firm-level regressions that examine the impact of market valuation 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), expected shell probability (ESP), 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.

	$NRGL_{t+1}$	$NRGL_{t+2}$	$NRGL_{t+3}$
log(M/A)	0.009	0.003	0.001
	(11.49)	(4.03)	(1.81)
ESP	0.104	0.099	0.095
	(3.07)	(2.79)	(2.52)
log(A)	-0.005	-0.004	-0.002
	(-7.40)	(-5.61)	(-3.26)
LEVERAGE	0.043	0.025	0.016
	(10.53)	(6.98)	(5.19)
P/B	-0.001	-0.000	-0.000
	(-4.48)	(-2.91)	(-2.31)
ROE	-0.010	-0.007	-0.000
	(-4.62)	(-3.11)	(-0.16)
$NRGL_{(t-2,t)}$	-0.087	-0.109	-0.160
	(-4.00)	(-4.79)	(-7.95)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
R2	0.172	0.123	0.106
N	27884	25050	22092

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 quarters. Controls include log of market value ($\log(M)$), book-to-market ratio (B/M), past quarter and year returns (RET_q and $RET_{(q-12,q-1)}$), turnover rate (TURNOVER), and return on assets (ROA), along with industry dummies. Newey-West standard errors with lag of three quarters are calculated and the corresponding t-statistics are in parentheses below each coefficient. The sample period is from 2008 to 2022. Variable definitions are in Appendix A.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RET_{q+1}	$RET_{(q+1,q+2)}$	$RET_{(q+1,q+3)}$	$RET_{(q+1,q+4)}$	RET_{q+1}	$RET_{(q+1,q+2)}$	$RET_{(q+1,q+3)}$	$RET_{(q+1,q+4)}$
NRGL_q	-0.529	-0.807	-1.100	-1.550				
	(-4.58)	(-3.68)	(-3.61)	(-3.93)				
ΔNRGL_q					-0.484	-0.690	-1.092	-1.417
					(-5.43)	(-4.14)	(-4.99)	(-5.44)
$\log(M)$	-0.0200	-0.0337	-0.0461	-0.0606	-0.0174	-0.0300	-0.0411	-0.0543
	(-3.36)	(-3.31)	(-3.04)	(-2.91)	(-2.84)	(-2.85)	(-2.62)	(-2.51)
B/M	0.00225	0.00806	0.0103	0.0156	0.00206	0.00792	0.00933	0.0126
	(0.24)	(0.48)	(0.42)	(0.50)	(0.23)	(0.48)	(0.38)	(0.40)
RET_q	-0.0293	-0.0132	0.000276	0.00454	-0.0290	-0.0134	-0.00332	0.00491
	(-2.21)	(-0.66)	(0.01)	(0.19)	(-2.19)	(-0.68)	(-0.16)	(0.21)
$RET_{(q-4,q-1)}$	-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: M and NRGL

This table presents the estimated coefficients from firm-level regressions that examine the impact of market valuation (M) 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), expected shell probablity (EPS), 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.

	NRGL_{t+1}	NRGL_{t+2}	NRGL_{t+3}
$\log(M/A) * \text{POST}$	-0.003	-0.002	-0.002
	(-7.28)	(-5.10)	(-4.44)
$\log(M/A)$	0.011	0.004	0.002
	(12.19)	(4.94)	(2.80)
ESP	0.113	0.104	0.097
	(3.36)	(2.95)	(2.59)
$\log(A)$	-0.004	-0.003	-0.002
	(-6.81)	(-5.26)	(-3.09)
LEVERAGE	0.043	0.025	0.016
	(10.63)	(7.04)	(5.18)
P/B	-0.001	-0.000	-0.000
	(-4.69)	(-3.15)	(-2.52)
ROE	-0.010	-0.007	-0.001
	(-4.64)	(-3.17)	(-0.27)
$\text{NRGL}_{(t-2,t)}$	-0.088	-0.110	-0.160
	(-4.09)	(-4.86)	(-8.00)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Adj. R-sq	0.174	0.124	0.107
N	27884	25050	22092

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) 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 and C report the same regressions with replace the dependent variable to D_{t+k}/A_t and OFC_{t+k}/A_t, respectively. 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
$\log(M_t/A_t) * \text{POST}$	-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 and operating cash flow in China

	Payouts			Operating cash flow		
	D_{t+1}/A_t	D_{t+2}/A_t	D_{t+3}/A_t	OCF_{t+1}/A_t	OCF_{t+2}/A_t	OCF_{t+3}/A_t
$\log(M_t/A_t) * \text{POST}$	0.00137	0.00227	0.00206	0.0140	0.0140	0.0136
	(2.38)	(2.08)	(1.23)	(2.76)	(3.05)	(2.31)
$\log(M_t/A_t)$	0.00191	0.00330	0.00494	-0.0243	-0.0183	-0.0112
	(5.37)	(5.84)	(7.73)	(-6.44)	(-3.00)	(-1.77)
D_t/A_t	0.792	0.763	0.816	2.072	2.253	2.285
	(13.44)	(9.57)	(8.51)	(5.71)	(6.41)	(4.54)
E_t/A_t	0.0357	0.0380	0.0257	0.153	0.170	0.202
	(3.96)	(3.11)	(2.68)	(2.68)	(1.38)	(1.78)
OCF_t/A_t				0.0479	0.0236	0.0940
				(1.00)	(0.39)	(1.25)
N	1349	1299	1249	1200	1150	1100
adj. R^2	0.706	0.522	0.525	0.261	0.224	0.168

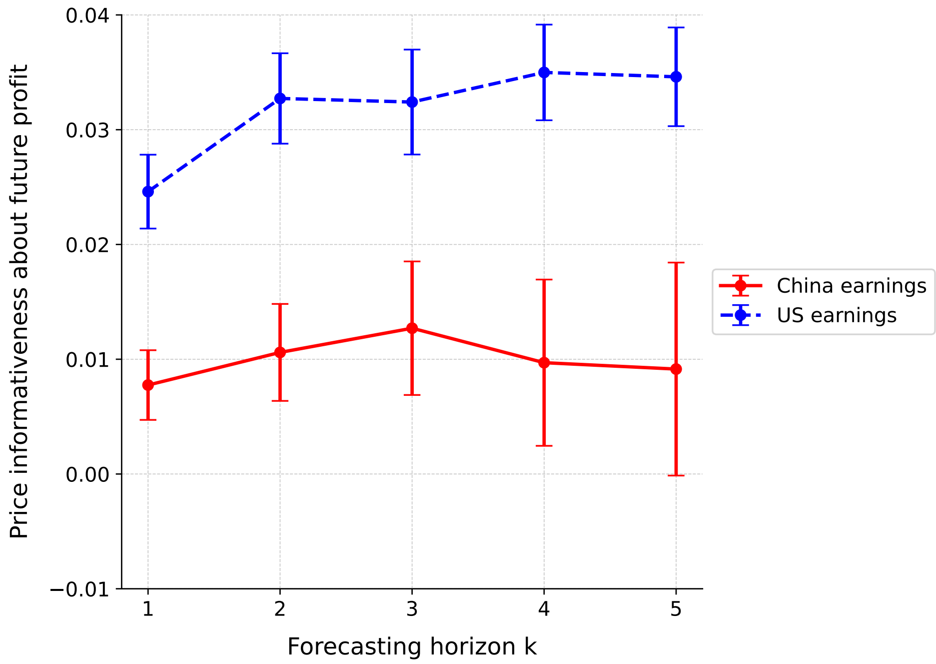

Figure I. Stock Price Informativeness about Future Earnings

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 5. For each year t, stocks are sorted independently 10×5 portfolios based on size (M) 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 $k \in \{0, 1, ..., 5\}$, 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.

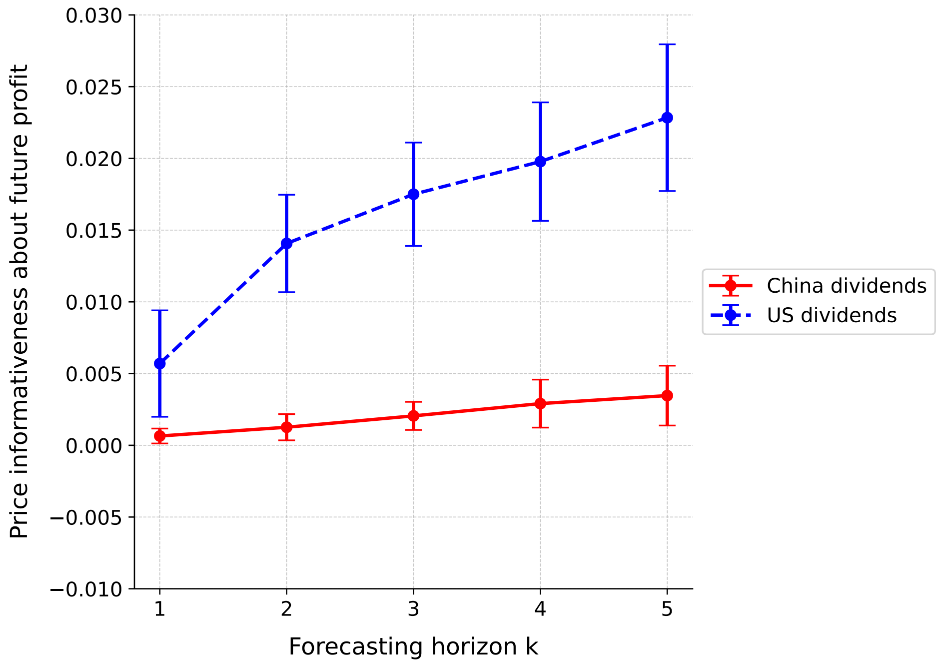

Figure II. Stock Price Informativeness about Future Payouts

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 5. For each year t, stocks are sorted independently 10×5 portfolios based on size (M) 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 $k \in \{0, 1, ..., 5\}$, 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.

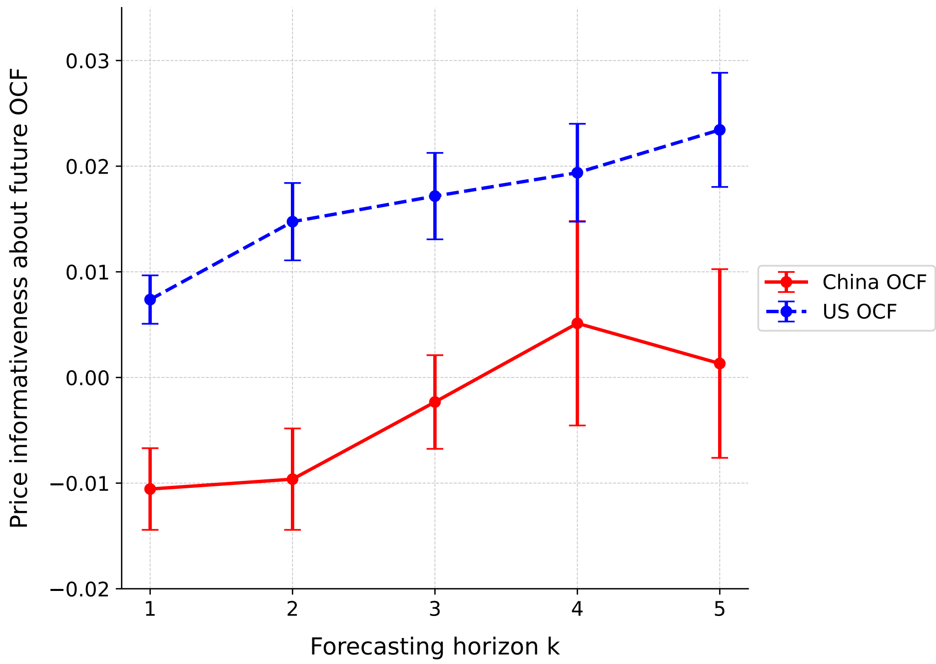

Figure III. Stock Price Informativeness about Future Operating Cash Flows

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:

$$\frac{OCF_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma\frac{E_t}{A_t} + \lambda\frac{D_t}{A_t} + \delta\frac{OCF_t}{A_t} + \epsilon_t,$$

where k ranges from 1 to 5. For each year t, stocks are sorted independently 10×5 portfolios based on size (M) 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 $k \in \{0, 1, ..., 5\}$, 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.

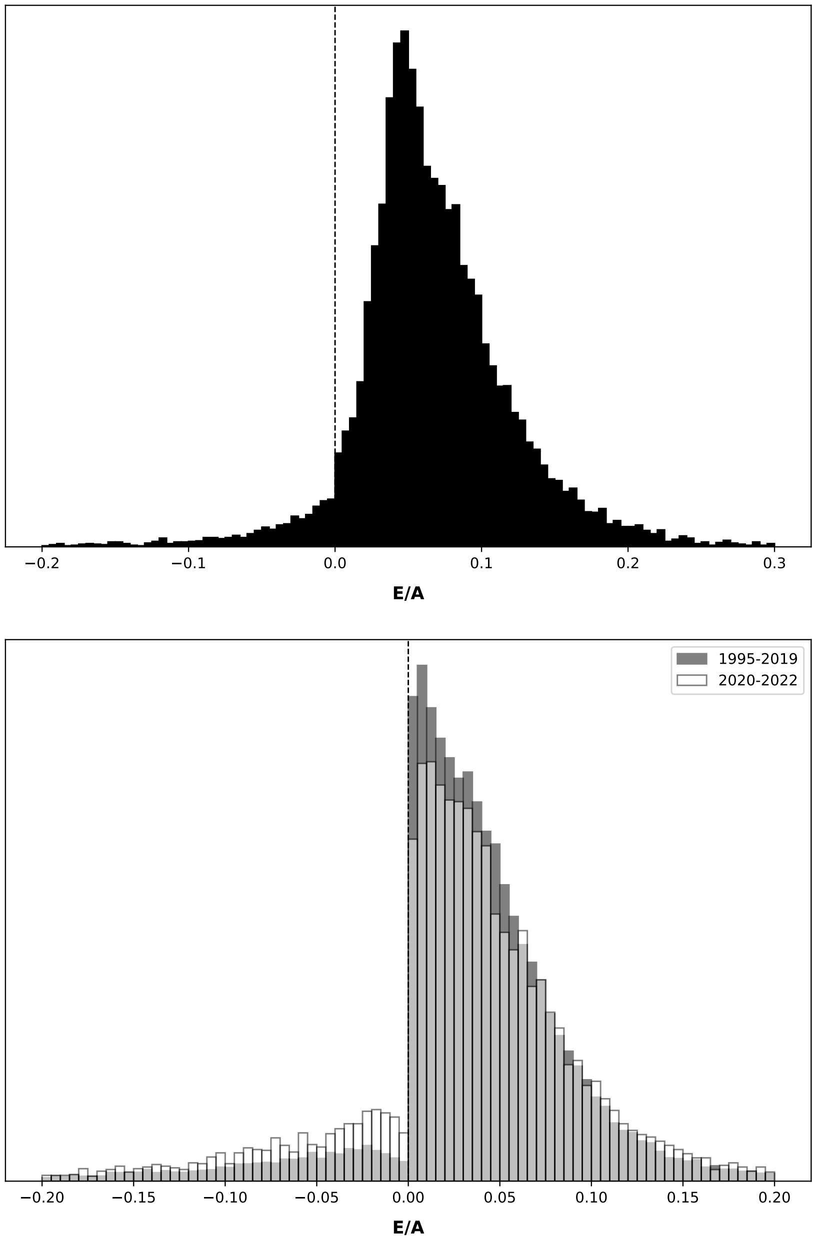

Figure IV. Earnings Distribution of US S&P 500 Firms and Chinese A-share Firms

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.

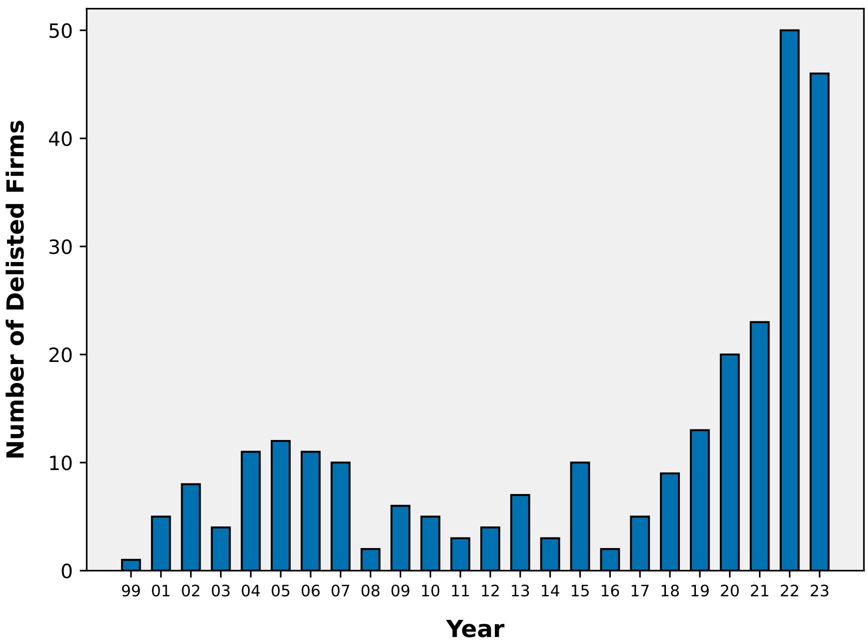

Figure V. Number of Delisted Firms by Year in the Chinese A-share Market

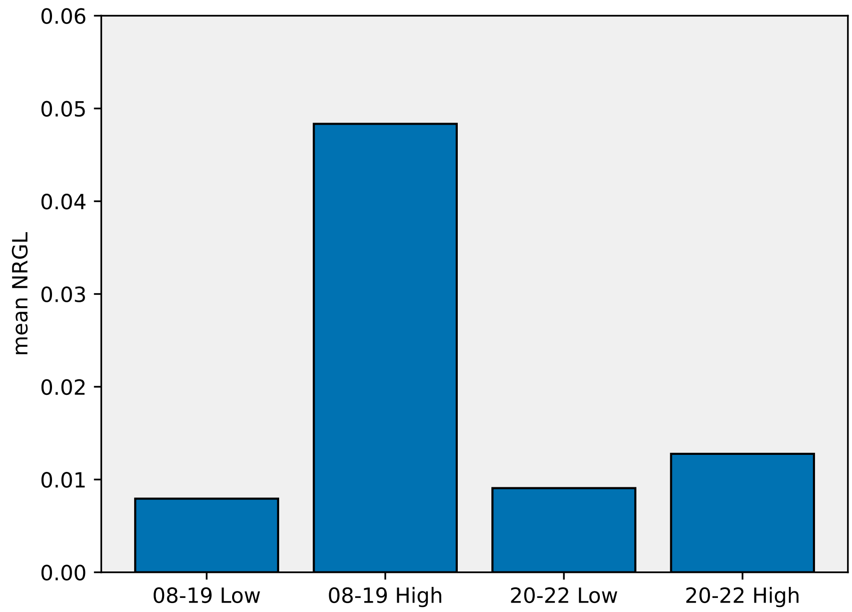

Figure VI. Level of NRGL Before and After the 2020 Delisting Rule

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 `b002000101`. We follow the Rules Governing the Listing of Stocks on Shanghai and Shenzhen Stock Exchanges and use "net profit attributable to parent company shareholders" to measure total earnings. For U.S. 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.

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, CSMAR variable name `f050801B`), then dividing by total assets. This calculation uses data sourced from the CSMAR Cash Flow Statements and CSMAR Balance Sheets. Working capital equals current asset (`a001100000`) minus current liabilities (`a002100000`), and variable income taxes in CSMAR is labeled as (`b002100000`).

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 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 Board 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 firms 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, the formal documents 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

In Table A.1, we report the results of regressions of Equation (10) using individual stocks, following the specification of Carpenter et al. (2021). At the individual stock level, the reversal in the predictability of M_t is less pronounced compared to that reflected by the portfolio-level regression.

In Table A.2 and A.3, we find the predictability of A-share market value on future corporate payouts and cash flows, respectively, is an order of magnitude smaller than that of U.S. S&P500 stocks.

Figures A.1, A.2, and A.3 visualize the predicted variation of $log(M_t/A_t)$ on future earnings, payouts, and operating cash flow, respectively.

Table A.4 presents the distribution of E_{t+k}/A_t of stock groups sort on $log(M_t/A_t)$. As k increases, the standard deviation of E_{t+k}/A_t are larger for the high $log(M_t/A_t)$ group compared to the low $log(M_t/A_t)$ group. Also, the skewness of E_{t+k}/A_t become positive for $k = 3$ and $k = 5$ and increases in $log(M_t/A_t)$.

Such right-skewed distribution of E_{t+5}/A_t, with smaller firms likely to be outliers, suggests that an OLS regression may not be appropriate, as smaller firms are more prone to measurement error issues. This is consistent with the discussion in (Chen, 2017).

To illustrate this, we re-run a pooled panel regressions (with time fixed effect) of Equation (10) but use quantile regressions. We compare the regression coefficient before $log(M_t/A_t)$ in OLS with the 25th, 50th, and 75th percentile quantile regressions in Figure A.4. Note that the figure plots coefficients, which are different from the predicted variations reported in Table A.1. The results show that the coefficients from OLS regressions are even larger in magnitude than those from the 75th percentile quantile regression. This suggests that the point estimates from OLS are largely driven positively skewed outliers. Also, the results from the 50th and 25th percentile quantile regressions show a much weaker predictability of M_t, and the predictability is almost flatten as k increases.

Table A.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 from the following firm-level cross-sectional regressions using the sample of Chinese A-share stocks,

$$\frac{E_{t+k}}{A_t} = \alpha + \beta_k \log(\frac{M_t}{A_t}) + \gamma\frac{E_t}{A_t} + \lambda\frac{D_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 5\}$$

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)
Year	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$	
	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
1996	0.016	4.043	0.026	3.861	0.040	5.625	0.041	4.698	0.035	3.095
1997	0.028	4.884	0.035	7.717	0.035	6.628	0.032	4.099	0.022	3.015
1998	0.018	6.959	0.022	6.841	0.020	4.472	0.008	1.710	0.001	0.253
1999	0.010	4.420	0.015	3.902	0.005	1.318	-0.001	-0.212	-0.006	-1.270
2000	0.005	1.777	0.001	0.288	-0.003	-0.932	-0.006	-2.065	-0.013	-3.207
2001	-0.000	-0.078	0.000	0.062	-0.001	-0.192	-0.006	-1.750	-0.002	-0.543
2002	0.000	0.193	-0.001	-0.360	-0.002	-0.810	0.001	0.511	0.010	2.355
2003	0.006	2.181	0.006	2.345	0.007	3.023	0.015	4.524	0.020	4.971
2004	0.007	2.917	0.008	3.481	0.022	5.554	0.026	6.201	0.023	4.764
2005	0.009	3.944	0.023	5.143	0.031	6.818	0.027	6.164	0.032	5.562
2006	0.031	6.660	0.035	7.497	0.033	7.865	0.038	7.097	0.069	7.052
2007	0.022	4.574	0.027	6.148	0.034	5.803	0.071	6.147	0.054	7.249
2008	0.017	4.856	0.019	5.444	0.052	6.255	0.066	6.974	0.083	6.771
2009	0.014	5.085	0.034	6.089	0.065	6.510	0.076	6.399	0.048	6.201
2010	0.017	5.058	0.056	6.203	0.077	5.972	0.046	5.988	0.077	7.050
2011	0.023	7.067	0.033	7.037	0.031	6.513	0.057	8.312	0.090	7.661
2012	0.015	4.937	0.017	4.995	0.033	7.044	0.062	7.444	0.064	6.475
2013	0.011	6.018	0.027	8.052	0.045	8.223	0.049	7.049	-0.011	-1.174
2014	0.017	7.500	0.033	7.924	0.037	6.677	-0.015	-1.981	-0.012	-1.434
2015	0.014	7.320	0.013	4.937	-0.007	-2.038	-0.006	-1.188	-0.000	-0.027
2016	0.003	2.635	-0.005	-2.439	0.001	0.213	0.005	1.979	0.006	2.092
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	
	(6.082)		(5.319)		(4.461)		(3.867)		(3.460)	
1995 to 2022-k	0.012		0.019		0.025		0.027		0.028	
	(6.592)		(5.605)		(4.643)		(3.796)		(3.279)	
Averages US S&P500										
1960 to 2021-k	0.027		0.042		0.047		0.049		0.053	
	(19.152)		(26.237)		(23.412)		(21.712)		(18.814)	
1995 to 2021-k	0.032		0.047		0.051		0.054		0.062	
	(16.411)		(22.157)		(15.688)		(15.659)		(15.112)	

Table A.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 from the following firm-level cross-sectional regressions using the sample of Chinese A-share stocks,

$$\frac{D_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 5\}$$

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)	
Year	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$	
	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
1996	0.002	1.361	0.004	2.375	0.001	0.857	0.008	4.065	0.007	3.517
1997	0.003	3.285	0.002	2.320	0.009	5.374	0.008	6.117	0.005	3.490
1998	0.001	0.933	0.005	5.286	0.005	5.341	0.004	3.829	0.001	1.118
1999	0.003	4.833	0.003	4.061	0.002	2.685	-0.000	-0.522	0.001	0.695
2000	0.001	1.634	0.000	0.701	-0.001	-1.963	-0.001	-1.772	-0.003	-3.209
2001	0.001	1.385	-0.001	-1.892	-0.001	-1.124	-0.002	-2.077	-0.002	-2.114
2002	-0.000	-0.223	-0.000	-0.525	-0.001	-0.813	-0.001	-1.706	-0.001	-0.778
2003	0.002	4.441	0.001	2.918	0.001	1.726	0.001	1.536	0.004	4.128
2004	0.002	4.172	0.002	3.028	0.001	2.237	0.004	5.195	0.004	4.478
2005	0.002	4.039	0.001	2.777	0.004	5.816	0.004	5.527	0.006	4.835
2006	0.001	2.741	0.004	6.327	0.005	6.791	0.005	5.335	0.010	6.332
2007	0.003	6.003	0.004	5.838	0.004	4.747	0.007	5.760	0.010	6.159
2008	0.002	5.267	0.002	3.539	0.006	5.086	0.007	5.327	0.010	5.495
2009	0.001	2.714	0.004	4.817	0.006	5.416	0.006	5.202	0.009	4.820
2010	0.003	5.593	0.004	7.077	0.005	5.176	0.007	5.536	0.010	5.370
2011	0.002	6.054	0.002	5.307	0.004	5.610	0.007	5.966	0.010	6.387
2012	0.001	2.198	0.002	2.941	0.004	4.269	0.006	4.917	0.010	5.240
2013	0.001	3.694	0.003	5.122	0.005	5.801	0.007	5.739	0.011	4.626
2014	0.001	4.575	0.003	5.184	0.005	4.825	0.007	3.964	0.007	4.054
2015	0.001	3.173	0.002	3.626	0.004	3.804	0.005	3.683	0.005	3.923
2016	0.001	1.977	0.001	2.776	0.003	3.073	0.003	3.029	0.004	3.069
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	
	(7.579)		(5.543)		(3.948)		(3.706)		(3.594)	
1995 to 2022-k	0.002		0.003		0.004		0.004		0.006	
	(6.345)		(5.664)		(5.141)		(5.143)		(4.967)	
Averages US SP500										
1960 to 2021-k	0.011		0.024		0.034		0.043		0.051	
	(8.000)		(11.450)		(11.693)		(10.362)		(11.119)	
1995 to 2021-k	0.007		0.014		0.021		0.026		0.032	
	(6.401)		(7.916)		(8.568)		(8.215)		(8.543)	

Table A.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 from the following firm-level cross-sectional regressions using the sample of Chinese A-share stocks,

$$\frac{OCF_{t+k}}{A_t} = \alpha + \beta_k \log(\frac{M_t}{A_t}) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \delta \frac{OCF_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 5\}$$

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)
Year	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$	
	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
1999	-0.003	-0.910	-0.004	-0.868	-0.001	-0.131	0.010	1.859	0.000	0.015
2000	-0.006	-1.746	-0.006	-2.002	0.002	0.647	-0.007	-2.368	-0.004	-0.869
2001	-0.006	-2.376	-0.002	-0.573	-0.009	-2.879	-0.004	-1.119	-0.012	-2.350
2002	-0.004	-1.227	-0.008	-2.817	-0.006	-2.031	-0.010	-2.229	-0.008	-1.218
2003	-0.003	-1.373	0.003	1.064	0.000	0.082	0.003	0.442	0.014	2.078
2004	0.001	0.332	0.001	0.210	-0.001	-0.172	0.008	1.243	0.013	1.398
2005	-0.007	-1.818	-0.008	-1.235	0.001	0.119	0.002	0.270	-0.005	-0.553
2006	-0.007	-1.243	-0.001	-0.166	-0.003	-0.323	-0.004	-0.385	0.019	1.052
2007	-0.011	-1.512	-0.009	-1.151	-0.012	-1.336	0.023	1.721	0.054	3.198
2008	-0.010	-1.603	-0.021	-2.757	-0.036	-2.603	0.036	2.423	-0.013	-0.427
2009	-0.023	-3.689	-0.024	-2.617	0.018	1.847	0.030	1.369	0.036	1.835
2010	-0.029	-4.091	0.016	2.457	0.028	1.710	0.029	2.241	0.025	1.292
2011	-0.007	-1.661	0.005	0.748	0.017	1.988	-0.006	-0.451	-0.009	-0.368
2012	-0.016	-2.943	-0.006	-1.196	-0.015	-1.576	-0.021	-1.193	0.075	3.724
2013	-0.009	-2.311	-0.017	-2.519	-0.026	-2.124	0.035	2.951	0.040	2.749
2014	-0.022	-3.562	-0.035	-2.956	0.030	2.619	0.009	0.727	0.013	1.104
2015	-0.044	-6.229	0.021	2.953	0.005	0.817	0.006	0.743	0.012	1.576
2016	-0.007	-2.093	-0.007	-2.225	-0.007	-1.860	0.006	1.228	0.000	0.023
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	
	(-3.720)		(-2.319)		(-0.629)		(1.277)		(1.757)	
1998 to 2022-k	-0.008		-0.003		0.001		0.009		0.014	
	(-2.876)		(-1.257)		(0.320)		(2.401)		(2.841)	
Averages US S&P500										
1960 to 2021-k	0.011		0.022		0.029		0.036		0.042	
	(7.183)		(8.374)		(8.670)		(8.669)		(8.765)	
1998 to 2021-k	0.019		0.037		0.047		0.057		0.068	
	(10.500)		(17.225)		(17.398)		(14.682)		(14.153)	

Table A.4. Distribution of E_{t+k}/A_t Group by $log(M_t/A_t)$

The table shows the mean, standard deviation, and skewness of E_{t+k}/A_t for quintiles of stocks sorted on $log(M_t/A_t)$, using the sample of Chinese A-share stocks. Variable definitions are in Appendix A.1.

Sort on $log(M_t/A_t)$	$k = 1$			$k = 3$			$k = 5$		
	Mean	SD	Skewness	Mean	SD	Skewness	Mean	SD	Skewness
1 (lowest)	0.010	0.056	-1.981	0.019	0.072	1.915	0.031	0.089	1.407
2	0.022	0.061	-0.736	0.029	0.080	1.491	0.038	0.109	3.081
3	0.034	0.064	-1.288	0.043	0.101	2.862	0.055	0.142	3.535
4	0.047	0.074	-0.337	0.063	0.117	4.032	0.071	0.165	3.449
5 (highest)	0.071	0.110	0.587	0.110	0.222	4.352	0.136	0.290	3.354

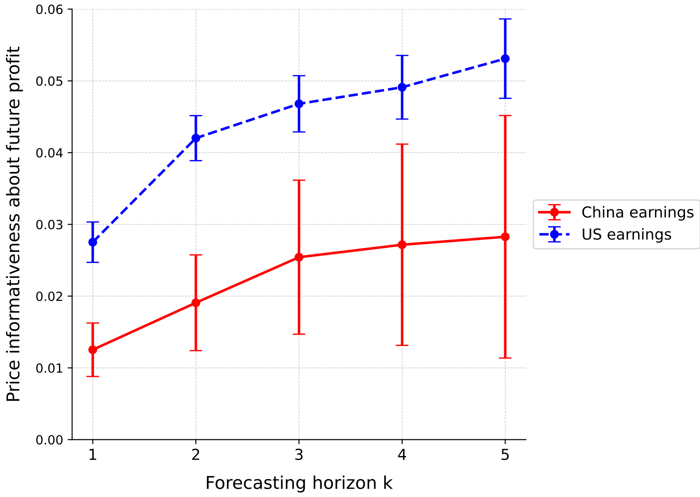

Figure A.1. Stock Price Informativeness about Future Earnings.

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 5. 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 5. 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.

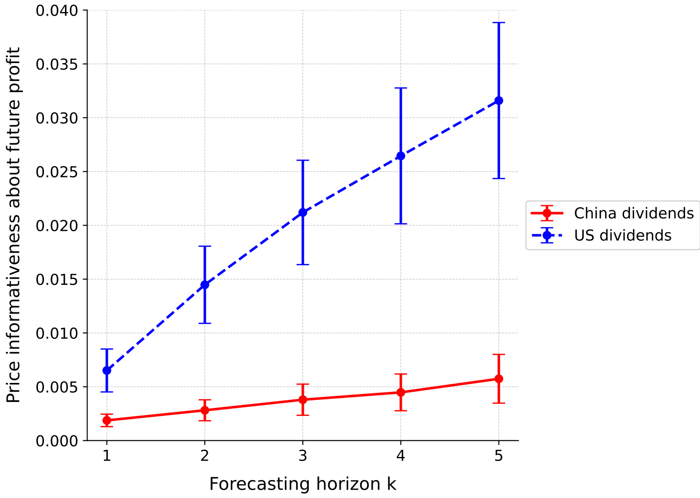

Figure A.2. Stock Price Informativeness about Future Payouts.

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 5. 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 5. 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.

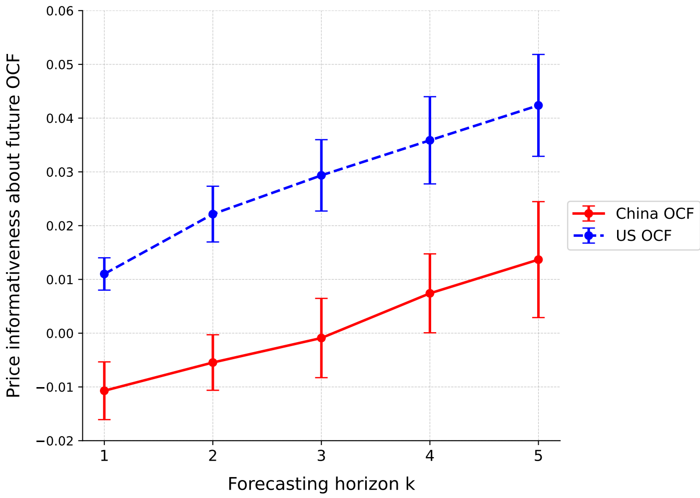

Figure A.3. Stock Price Informativeness about Future Operating Cash Flows.

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 5. 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:

$$\frac{OCF_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \delta \frac{OCF_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 5\}$$

where k ranges from 1 to 5. 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.

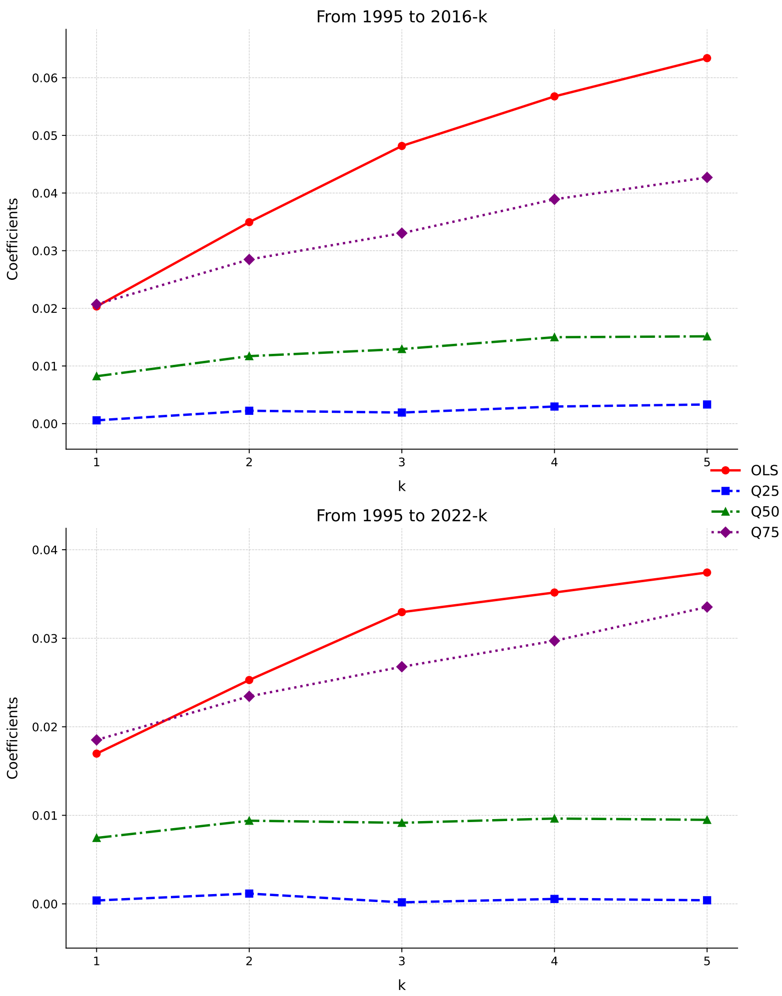

Figure A.4. Coefficients of OLS and Quantile Regression

This figure presents the point estimates of $\hat{\beta_k}$ from the following OLS, the 25th, 50th, and 75th percentile quantile regressions using the sample of Chinese A-share stocks,

$$\frac{E_{t+k}}{A_t} = \alpha + \beta_k log(\frac{M_t}{A_t}) + \gamma \frac{E_t}{A_t} + \lambda \frac{D_t}{A_t} + \epsilon_t, \text{where } k \in \{1, 2, ..., 5\}$$

where year fixed effect is included. The upper panel uses the sample from 1995 to 2016, and the lower panel from 1995 to 2022. Detailed definitions of variables are in Appendix A.1.