Earnings Management and Price Informativeness*

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Abstract

We investigate the relationship between stock prices and future earnings in the Chinese A-share market. Firms with higher market valuations tend to achieve higher earnings in the subsequent one to five years, suggesting that stock prices reflect future earnings. However, we also observe earnings reversal, where higher stock prices predict negative earnings growth in 3-5 years, indicative of short-term earnings management driven by stock price pressures, which partially reverses over time. Additionally, we provide evidence of earnings management through non-recurring gains and losses (NRGLs) and utilize the 2020 delisting rule reform as a natural experiment to explore this dynamic.

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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.[1] Carpenter, Lu, and Whitelaw (2021) apply this approach to the Chinese A-share market and find that Chinese stock prices are as informative as those in the U.S. This result aligns with China's successful marketization reforms and the rapid development of its capital markets, as reviewed by Carpenter and Whitelaw (2017). However, it is surprising given the high volatility and speculative nature of the Chinese stock market, as documented by 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) relies on a key assumption that earnings reliably reflect firm fundamentals. However, this assumption may not hold in emerging markets like the Chinese A-share market. Notably, extensive evidence points to widespread earnings management and manipulation, suggesting low financial reporting quality (see, e.g., Piotroski and Wong (2012) for a comprehensive review). Additionally, 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 solely price informativeness or are also influenced by earnings management. To reconcile the observed empirical patterns, we propose a "manipulate-to-cater" mechanism, in which firm managers—under pressure from elevated share prices—manipulate reported earnings to meet investor expectations. Extending the framework of Hirshleifer and Teoh (2003), we develop a simple model, in which a subset of inattentive investors accept reported earnings at face value, leading to stock overvaluation relative to underlying

[1] Bond, Edmans, and Goldstein (2012) survey a broad set of stock-price informativeness measures that reflect different facets of the information environment, such as the returnfuture-earnings relation, firm-specific return variation, analyst-based proxies, and microstructure-based measures, and discuss how information impounded in stock prices can feed back into corporate decisions. Dávila and Parlatore (2025) measure price informativeness as an equilibrium signal-to-noise object—how much observing the price reduces uncertainty about fundamentalsidentified separately from non-informational trading; in contrast, Bai, Philippon, and Savov (2016) proxy informativeness using the extent to which prices/returns predict future fundamentals.

fundamentals. In response, market valuation pressures motivate managers to adjust earnings to align with these inflated expectations.

This "manipulate-to-cater" mechanism generates several testable predictions that contrast 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, since managed earnings are inherently unsustainable, they should eventually reverse over the long run. Third, the managed component in earnings should be associated with lower future stock returns, as investors gradually recognize the earnings management. This paper empirically tests these predictions and finds supportive evidence, as summarized below.

We begin by following Bai et al. (2016) to estimate cross-sectional regressions of 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), also scaled by A_t. Our sample includes all Chinese A-share firms from 1995 to 2024. For comparison, we replicate this analysis for U.S. firms using a sample of S&P 500 constituents from 1960 to 2024, adopting the methodology of Carpenter et al. (2021).

We find that the main result of Carpenter et al. (2021) remains generally robust when the sample is extended through 2024. While the magnitude of predictability is smaller, the informativeness of the valuation of Chinese A-share stocks remains comparable to that of U.S. S&P 500 stocks in predicting future earnings. However, several new and more nuanced patterns emerge.

First, unlike the U.S. S&P samplewhere earnings predictability increases monotonically with the forecast horizonearnings predictability in China is stronger at the medium-term (three-year) horizon than at the one-year horizon, and it declines modestly at longer horizons (by year $t+5$). This decline suggests a potential long-horizon reversal that is not observed in the U.S. market. Second, we find that earnings predictability is concentrated primarily among firms in the bottom decile by total assets. Because total assets serve as the scaling variable for both earnings and market valuations, extremely low asset values can introduce substantial measurement noise into the key regression variables. For this reason, we exclude the bottom decile of firms ranked by total assets in our subsequent analyses.

Next, we replace future earnings with future total payouts ($D_{t+1}, \ldots, D_{t+5}$), including both cash dividends and share repurchases, as the dependent variable. The results show that higher reported earnings do not translate into greater future payouts. This pattern supports our hypothesis that reported earnings by Chinese firms may, at least in part, reflect earnings management rather than genuine firm fundamental or future shareholder payouts. In contrast, the market value of U.S. S&P 500 stocks exhibits strong predictive power for future payouts, comparable to its ability to predict future earnings.

A key prediction of our "manipulate-to-cater" hypothesis is earnings reversal: a high market value (M_t) should be associated with stronger earnings growth in the short run, followed by a sharper decline in the long run. This prediction highlights the time-series properties of reported earnings, complementing the cross-sectional focus emphasized in the analysis of Carpenter et al. (2021).

To test long-run reversal, we examine changes in earnings from year t to $t+1$, $t+1$ to $t+3$, and $t+3$ to $t+5$. Our findings support this hypothesis. In a panel regression, a higher M_t/A_t is associated with higher $(E_{t+1} - E_t)/A_t$, insignificant $(E_{t+3} - E_{t+1})/A_t$, and lower $(E_{t+5} - E_{t+3})/A_t$. In contrast, this reversal pattern is absent in the U.S. S&P 500 sample. The observed earnings reversal suggests that firms in the Chinese A-share market may have inflated reported earnings to align with market expectations.

The earnings reversal pattern becomes more pronounced when controlling for firm 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 of Carpenter et al. (2021). This suggests that our "manipulate-to-cater" hypothesis and their price-informativeness view are not mutually exclusive; instead, both contribute to explaining the strong correlation between firm valuations and future reported earnings in our sample of Chinese firms.

We decompose reported earnings into operating cash flows (OCF), accruals, and non-recurring gains and losses (NRGLs). Operating cash flows are generally less susceptible to managerial manipulation, whereas accruals and NRGLs often serve as primary channels for earnings management in the U.S. and China, respectively. Under China's accounting rules, NRGLs—which include non-operating and one-time items such as government subsidies, asset sales, and donations—were included in total earnings reported in firms' financial statements until the 2020 delisting reform. To curb inflated earnings among financially weak firms seeking to avoid delisting, the reform excluded NRGLs from the earnings measure.[2]

We examine which components of reported earnings are most predictable by market valuation. In the U.S. sample, operating cash flows exhibit the strongest and most robust predictability by market valuation, whereas the predictability for accruals is significant only over short horizons of one year. For non-recurring gains and losses (NRGLs), the predictability is occasionally significant but economically small. In contrast, in the Chinese sample, the predictability of market valuation for cash flows is insignificant—and even negative—when $k < 3$, and becomes positive but remains economically small as k increases. The predictability for accruals is positive and significant over short horizons (up to three years), while NRGLs show the most robust relationship: positive and significant across all horizons from one to five years.

We further investigate whether investors fully account for managed earnings. Under the efficient market hypothesis of Stein (1989), if investors recognize that better-than-expected reported earnings driven by high NRGLs are unlikely to persist, they should discount such earnings, resulting in no return predictability by NRGLs. However, if investors fail to fully recognize earnings inflation, as suggested by Hirshleifer and Teoh (2003), NRGLs should negatively predict future stock returns. Our findings support the latter: the level of NRGLs predicts lower stock returns. Specifically, a two standard deviation increase in NRGLs is associated with a 3.99% lower return in the subsequent year.

To further strengthen identification, we leverage 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 idea that NRGLs was used to inflate earnings, we find that after the reform, firms with higher valuation ratios experienced greater reductions in reported NRGLs. Additionally, the correlation between market value (M_t) and reported future earnings (E_{t+k}) weakens after 2020. Notably, this pattern is absent in the U.S. data. This shift in China's A-share market, likely driven by the 2020 policy reform, helps explain why the estimated price informativeness in our sample (which includes 2017-2024) is lower than that reported by Carpenter et al. (2021) (whose sample period ends in 2016).

[2]Other methods of earnings management include 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.

Overall, our findings strongly support the 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. Such earnings inflation, however, is inherently unsustainable and leads to subsequent earnings reversals, thereby shaping the long-term predictability of market valuation. Our analysis extends the perspective of Carpenter et al. (2021) by highlighting that, beyond the market's information discovery, firms' efforts to cater to market valuation through earnings manipulation constitute an important force driving this predictability.

Literature Review. We use the world's second-largest equity market as a laboratory to deepen the understanding of the relationship between stock prices and future earnings. While the cross-sectional predictability of current stock prices for future earnings, as proposed by Bai, Philippon, and Savov (2016), may reflect the informativeness of stock prices for firm fundamentals, it could also indicate future earnings management driven by market valuation pressures. To address this possibility, our analysis extends the approach of Bai, Philippon, and Savov (2016) by incorporating time-series analysis to identify potential earnings reversals. By combining cross-sectional and time-series perspectives, we provide a more comprehensive test of price informativeness.

Our empirical evidence also contributes to the extensive finance literature on the feedback effects of stock prices on firm behavior and the real economy, as reviewed by Bond, Edmans, and Goldstein (2012). Stock prices not only provide valuable information that guides firms investment decisions but also exert pressure on managers to adopt short-term strategies aimed at boosting earnings, consistent with the insight of Stein (1989).

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, significant channel through which Chinese firms manage reported earnings. Moreover, our analysis provides strong evidence that A-share investors fail to fully recognize earnings inflation via NRGLs, aligning with similar findings of investors overlooking accruals in the U.S. market (e.g., Sloan, 1996; Bergstresser and Philippon, 2006; Hirshleifer et al., 2012). More importantly, our results emphasize market valuation as a key driver motivating 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 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

[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.

[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.

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. These demands are given by:

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

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

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 $\Phi(\cdot) \in (0, 1)$, 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,

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

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_*:

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

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 stock's future dividend payouts and cash flows. Finally, we analyze a set of dually listed firms in both China's 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 2024. 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), operating cash flow (OCF), and accruals ($Accruals$). More specifically, D includes both annual cash dividends and net share repurchases, and OCF equals EBITDA minus change in working capital and income taxes. To ensure that market participants have access to the accounting variables, we use stock trading data that leads the fiscal year end by six months. All variables are adjusted for inflation using the GDP deflator, with the deflator data obtained from CSMAR. We fill zeros to missing earnings and payout 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 annual financial statements since 1999, making NRGL data available only from that year onward.

For the U.S. data, we obtain annual accounting information from the Compustat database. Following Bai et al. (2016), we focus on S&P500 non-financial firms over the period from 1960 to 2024. We also present results using a recent sample from 1995 to 2024. All variables are adjusted for inflation using the GDP deflator from the World Bank. We do not fill in missing earnings data. NRGLs refer to the extraordinary items in the U.S. 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 2.78% with the 25th and 75th percentiles of 1.12% and 6.08%, respectively. The average D/A ratio equals 1.31% with the 25th and 75th percentiles of 0.00% and 1.82%, respectively. The average ratio of NRGL scaled by total assets is relatively modest, 1.01% with a standard deviation of 2.24%.

Panel B presents the summary statistics for U.S. S&P500 firms. The average E/A ratio is 6.02%, while the average D/A ratio is 4.03%. The 25th and 75th percentiles for E/A are 3.28% and 8.99%, respectively, and for D/A, they are 0.31% and 4.9%, 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.

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

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

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. Firms that are delisted over the five-year window relative to year t are filled with zero earnings.

We first use the sample of all A-share stocks and report the regression results in Panel A of 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 2024, along with the average coefficient over two periods: 1995–2016 (the sample period in Carpenter et al. (2021)) and 1995–2024. During the 1995–2016 period, the predicted variation is 0.019 (t-stat = 8.4) for $k = 1$, increasing to 0.032 for $k = 3$ (t-stat = 5.4) and 0.034 for $k = 5$ (t-stat = 3.7).

When moving on to U.S. S&P 500 firms, 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 0.027 (0.032) for $k = 1$, 0.036 (0.039) for $k = 3$, and 0.043 (0.047) for $k = 5$ in the 1960–2024 (1995–2024) 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.

Another notable pattern in Table II Panel A is that price informativeness in China, based on the 1995–2024 sample, is generally lower than that estimated using the 1995–2016 sample from Carpenter et al. (2021), across all $k = 1, ..., 5$. This piece of evidence points to a declining price informativeness on reported earnings in recent years in China's A-share market. As we discuss later in Section 4.4, this decline is plausibly linked to China's delisting rule reform in 2020.

Based on the estimates of β_k, Figure I visualizes the predicted variation of $\log(M_{i,t}/A_{i,t})$ for $k \in \{1, 2, ..., 5\}$ from 1995 to 2024 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 increases when $k < 3$ but becomes flattened and even revered as $k \geq 3$. This suggests that the predictability of future earnings initially rises but later reverses. This reversal pattern differs from the findings of Carpenter et al. (2021), who show that earnings predictability increases with k using the sample of 1995 to 2016.

Bottom decile of A_t vs. others. In addition, we find that the predictability of M_t for future earnings is driven primarily by firms with very low total assets (A_t). In Panel B of Table II, we divide the sample each year into two groups based on total assets, the bottom decile and all remaining firms, and re-estimate Equation 10 within these subsamples. The results show that the predicted variation in $\log(M_t/A_t)$ is substantially larger for bottomdecile firms than for the rest of the sample, particularly for $k \geq 3$. For example, over 1995-2016, the predicted variation is 0.051 (0.023) for $k = 3$ and 0.060 (0.020) for $k = 5$ for the bottomdecile (remaining) firms. This pattern likely reflects the fact that A_t is the scaling variable in Equation 10, making the ratios for firms with lower A_t more sensitive to measurement error.

To address this issue, we exclude the bottom decile of firms ranked by total assets each year from our subsequent analysis. This approach is consistent with Liu et al. (2019), which excludes the bottom 30% of stocks sorted by size when constructing return factors for the Chinese stock market.

Summary. Overall, Table II Panel A 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 through two distinct channels. One possibility is a "genuine" channel, where market valuations reflect underlying fundamentals, consistent with the interpretation of Carpenter et al. (2021). Alternatively, the predictability may be "artificial," driven by managerial efforts to inflate earnings in response to market overoptimism, as proposed in our model in Section 2.

Our new finding—an emerging reversal in earnings over the extended sample period—indicates a weakening long-run relationship between market valuation and reported earnings. This result supports Hypothesis 1 in Section 2.3 and marks a meaningful departure from the conclusions of Carpenter et al. (2021). While both channels—price informativeness in the sense of Carpenter et al. (2021) and earnings inflation as documented in our study—may operate simultaneously in China's A-share market, our analysis focuses on validating the latter manipulate-to-cater mechanism by directly testing the reversal effect in Section 3.4.

3.3 Predicting Payouts

The possibility that firms actively manage earnings makes earnings an unreliable measure of firm fundamentals. In this section, we examine whether market valuation can predict firm payouts, a measure of firms' real cash distribution that is less prone to manipulation.

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:

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

Here we additionally control for current payouts, and 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 1995–2024 period, the predicted variation of $\log(M_{i,t}/A_{i,t})$ remains close to zero at short horizons, equaling 0.002 for $k = 1$ (t-stat $= 7.75$). It increases slightly to 0.004 for $k = 3$ (t-stat $= 5.20$) and 0.004 for $k = 5$ (t-stat $= 3.79$). 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 0.014 (0.008) to 0.040 (0.025) as k increases from 1 to 5 over the 1995–2024 (1960–2024) 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.

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:

$$\frac{E_{j,t+1} - E_{j,t}}{A_{j,t}} = \alpha + \beta^{0\to1} \log(\frac{M_{j,t}}{A_{j,t}}) + \gamma \frac{E_{j,t}}{A_{j,t}} + \lambda \frac{D_{j,t}}{A_{j,t}} + v_t + u_j + \epsilon_{j,t}, \tag{12}$$

$$\frac{E_{j,t+3} - E_{j,t+1}}{A_{j,t}} = \alpha + \beta^{1\to3} \log(\frac{M_{j,t}}{A_{j,t}}) + \gamma \frac{E_{j,t}}{A_{j,t}} + \lambda \frac{D_{j,t}}{A_{j,t}} + v_t + u_j + \epsilon_{j,t}, \tag{13}$$

$$\frac{E_{j,t+5} - E_{j,t+3}}{A_{j,t}} = \alpha + \beta^{3\to5} \log(\frac{M_{j,t}}{A_{j,t}}) + \gamma \frac{E_{j,t}}{A_{j,t}} + \lambda \frac{D_{j,t}}{A_{j,t}} + v_t + u_j + \epsilon_{j,t}, \tag{14}$$

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 $\beta^{1\to3}$ and $\beta^{3\to5}$, where negative values indicate long-run earnings reversal predicted by current stock valuation.

Based on regression equations in (12) to (14), we present evidence of earnings reversal in China's A-share market by progressively introducing different fixed effects. We begin by estimating these regressions with only time fixed effect, which capture cross-sectional variation. We then examine the time-series dimension by adding only firm fixed effects, and finally estimate the full panel regression that includes both time and firm fixed effects, v_t and u_j. Driscoll–Kraay standard errors with a lag of 1 are reported to account for both cross-sectional and temporal dependencies.

The regression results, presented in Table IV, 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 $\beta^{0\to1}$ and $\beta^{1\to3}$ are both positive, with t-statistics of 9.22 and 1.10, 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 current stock valuations, earnings reversal should be more pronounced in the time-series dynamics of individual firms. This corresponds to specifications that include firm fixed effects. Consistent with this prediction, Panel B—which includes only firm fixed effects—shows that the coefficients $\beta^{1\to3}$ and $\beta^{3\to5}$ are both negative, with t-statistics of 0.60 and 1.57, respectively.

Panel C reports results including both time and firm fixed effects. The coefficient $\beta^{0\to1}$ remains significantly positive, with a t-statistic of 21.6. The point estimates of $\beta^{1\to3}$ is close to zero. The coefficient $\beta^{3\to5}$ is significantly negative, with a t-statistic of 2.25, indicating the presence of long-run earnings reversal.

Across Panels A, B, and C, S&P 500 sample consistently shows no long-run earnings reversal. Short-term earnings growth predictability for $(E_{j,t+1} - E_{j,t})$ remains significantly positive, while predictability at 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 highlights a key contrast with the Chinese Ashare market, where longrun reversal is present.

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.

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 117 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 because the Hong Kong stock market generally imposes more stringent disclosure requirements, the reporting quality of dual-listed firms should be higher than that of firms listed solely in the A-share market. From this perspective, one way to map the dual-market setting into our simple model in Section 2 is to treat A-H dual-listed firms as facing a higher manipulation cost κ for earnings management than firms listed only in the A-share market.

Following the intuition of Proposition 2 and Hypothesis 3 regarding κ,[7] we conjecture that the correlation between M_t and subsequent reported earnings E_{t+k} should be weaker for duallisted firms than for other Ashare firms. To test this conjecture, we extend the cross-sectional regression specified in (10) by adding an interaction between the A-H dummy and market valuation. Specifically, for each year t from 1995 to 2024, we run the cross-sectional regression:

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

for $k \in \{1, 2, ..., 5\}$, where AH_i is a dummy equal to one if stock i is dual-listed and market valuation is always based on A-share prices, even for dual-listed firms.

Panel A of Table V reports the estimated coefficients β_k and θ_k. The coefficients $\{\beta_k\}$ on $\log(\frac{M_{i,t}}{A_{i,t}})$ are significantly positive for all k, consistent with the results in Table II. The interaction coefficients $\{\theta_k\}$ are negative and statistically significant for $k \geq 2$. This pattern aligns with our "cater-to-manipulate" mechanism.

Comparison to the literature. Carpenter et al. (2021) also document a similar empirical pattern in their Table 3: the prices of A-H dual-listed stocks are less correlated with firms' future earnings compared with A-share-only stocks. However, because Carpenter et al. (2021) interpret this correlation as reflecting genuine price informativeness, their explanation for the lower predictability of duallisted stocks differs fundamentally from ours. They argue that dual listing makes Ashare prices less informative because differences in how Hong Kong investors value the firms introduce extra noisedriven by their discountrate shocksinto Ashare prices.

This interpretation appears difficult to reconcile with the well-documented differences in investor composition between the Hong Kong and Chinese A-share markets. The Hong Kong market contains a higher proportion of sophisticated institutional investors, including many from overseas, whereas the Ashare market is dominated by relatively

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

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." In contrast, the corresponding figure in the A-share market is 11.7%, with retail investors responsible for 86.6% of trading volume (An et al., 2022).

A natural implication of this disparity in investor sophistication is that, for AH dual-listed stocks, H-share prices may be more informative than A-share prices. These firms trade simultaneously in two segmented markets with 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 differences in investor composition, we hypothesize that H-share prices should exhibit 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 possessing a more accurate initial belief $\hat{\mu}$ than their A-share counterparts.[8]

To test this hypothesis, we apply the cross-sectional regression in Equation (10) to the sample of A-H dual-listed firms, using market valuations based on both A-share and H-share prices. We require at least 20 dual-listed firms in a given year, resulting in a sample period from 2002 to 2024. 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 H-share and A-share prices, respectively, calculated by multiplying each price by the firm's total outstanding shares.

Panel B of Table V reports the corresponding regression estimates. For these dual-listed firms, the predictive power of H-share market valuation is consistently significant, whereas that of A-share valuation is comparatively weak. The predicted variation associated with $\log(M_{i,t}^H/A_{i,t})$ increases with the forecast horizon k, ranging from 0.005 to 0.018 as k increases from 1 to 5, with all t-statistics exceeding 2.28. By contrast, the predicted variation for $\log(M_{i,t}^A/A_{i,t})$ is statistically insignificant across all horizons and

[8] One could also consider a fully dynamic setting with inattentive investors and earnings inflation, where reported earnings each period contain both natural and managed components. In such a setting, it is reasonable to expect the more sophisticated Hshare investors to better anticipate future earningsboth natural and managed. This scenario goes beyond our model, which assumes a final liquidation date at $t = 2$ for the firm to settle its obligations, and we leave it to future research to explore this interesting extension.

turns negative for $k \geq 2$. This contrast provides direct evidence that Ashare prices may contain less information about firms future earnings than Hshare prices.

4 Earnings Management

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 begin with a brief overview of earnings management practices in China in Section 4.1, introducing non-recurring gains and losses (NRGLs) as a key tool used by Chinese listed firms. In Subsection 4.2, we decompose reported earnings into three componentscash flows, accruals, and NRGLsand compare the predictability of market valuation for each. Subsection 4.3 examines whether NRGLs predict subsequent stock returns. Together, these analyses serve as tests of Hypothesis 2. Finally, Subsection 4.4 tests Hypothesis 3 by exploiting the 2020 delisting rule reform as a natural experiment.

4.1 Institutional Background

In the U.S., firms commonly use accrual accounting, under 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 components such as depreciation, amortization, bad-debt provisions, and warranty liabilities. As highlighted in prior research, these accounting accruals have often been used as a channel for earnings management among U.S. firms, e.g., Sloan (1996), Bergstresser and Philippon (2006), Hirshleifer et al. (2012).

While earnings management is widely recognized as prevalent among firms listed in the Chinese A-share market (e.g., Piotroski and Wong, 2012), accruals are not the primary tool used in China (e.g., Chen et al. (2010); Liu et al. (2019)). Instead, Chinese-listed firms tend to rely more heavily on related party transactions (RPTs) and non-recurring gains and losses (NRGLs).

RPTs—transactions between entities with shared ownership or control, often within state-owned enterprises—provide a flexible mechanism for shifting profits, smoothing earnings, and navigating regulatory constraints. Firms can inflate revenues by selling goods or services at abovemarket prices to related entities, or dampen earnings in strong years by selling at artificially low prices, creating reserves for future downturns. These practices effectively allow firms to manage reported performance across periods.[9] Highlighting tunneling behavior and governance concerns, prior studies (Fisman and Wang, 2010; Jiang et al., 2010; Li et al., 2020; Allen et al., 2024) have analyzed RPTs as an important channel of earnings management among Chineselisted firms. Although information on RPTs is available, disclosures generally do not specify the direction of profit flows, making it difficult to construct tests that capture their overall impact on firm earnings.[10]

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 one-time, irregular, or extraordinary in nature. Before 2020, regulatory authorities relied primarily on net profitwhich includes both operating earnings and NRGLsfor key regulatory decisions, including IPO qualification and delisting criteria. Consequently, firms frequently used NRGLs as a tool for earnings management, employing strategies such as asset sales or oneoff government subsidies from affiliated local governments to meet regulatory thresholds and avoid delisting. In 2020, a new regulation was introduced to exclude NRGLs from the netprofit calculation used for regulatory purposesa policy shock that we will study in detail later. This underscores the practical importance of NRGLs in the Chinese market and motivates our use of NRGLs as the primary measure of earnings management.

[9] Starting in 1997, the China Securities Regulatory Commission (CSRC) introduced a series of regulations aimed at improving oversight of RPTs. These rules emphasize accurate identification and management of related parties, with goals that include enhancing earnings quality, strengthening corporate governance, and protecting minority shareholders. Firms must disclose the nature, pricing, and financial impact of RPTs, and transactions above certain thresholds require approval from independent directors and, in some cases, shareholders.

[10] To address this challenge, Fisman and Wang (2010) and Allen et al. (2024) focus on loanbased RPTs and measure tunneling by tracking money outflows from the listed firm. However, loanbased RPTstypically in the form of loan guaranteesrepresent only a small share of all RPT activity.

4.2 Decomposition of Reported Earnings

Following the discussion above, we decompose firms' reported earnings (E) into three components: operating cash flows (OCF), accruals, and non-recurring gains and losses ($NRGL$). In both the U.S. and China, operating cash flows are generally more difficult to manipulate through accounting or auditing processes than earnings. Moreover, because regulators and investors typically do not rely on cash flows as the primary metric for evaluating firm performance, they are less likely to be targeted for managerial manipulation. By contrast, accruals and NRGLs constitute the main channels through which firms manage reported earnings in the U.S. and China, respectively.

Following Allen et al. (2024), we define operating cash flow (OCF) as: EBITDA – Change in Working Capital – Income Taxes.[11] Accrual is calculated as earnings (E) minus OCF and NRGLs. NRGLs for Chinese firms are reported in notes to financial statement. For the U.S. firms, NRGLs refer to extraordinary items, which equals the difference between net income (`ni`) and net income before extraordinary items (`ib`) in Compustat.

We re-estimate the baseline regression in Equation (10) using each of the three earnings components as the dependent variable and replace the control variable E_t with its corresponding components. Specifically, for $k \in 1, 2, \ldots, 5$, we estimate:

$$\frac{OCF_{i,t+k}}{A_{i,t}} = \alpha + \beta_k \log(\frac{M_{i,t}}{A_{i,t}}) + \gamma \frac{E_{i,t}}{A_{i,t}} + \lambda \frac{D_{i,t}}{A_{i,t}} + \epsilon_{i,t}, \tag{17}$$

$$\frac{Accrual_{i,t+k}}{A_{i,t}} = \alpha + \beta_k \log(\frac{M_{i,t}}{A_{i,t}}) + \gamma \frac{E_{i,t}}{A_{i,t}} + \lambda \frac{D_{i,t}}{A_{i,t}} + \epsilon_{i,t}, \tag{18}$$

$$\frac{NRGL_{i,t+k}}{A_{i,t}} = \alpha + \beta_k \log(\frac{M_{i,t}}{A_{i,t}}) + \gamma \frac{E_{i,t}}{A_{i,t}} + \lambda \frac{D_{i,t}}{A_{i,t}} + \epsilon_{i,t}. \tag{19}$$

Data on NRGLs are available for Chinese firms beginning in 1999, and before 1999 we use non-operating profit to proxy for NRGLs.

Regression results are reported in Table VI. In Panel A, the dependent variable is operating cash flow (OCF). As shown on the right side of the panel, market valuation in the S&P 500 sample remains a significant predictor of future cash flows. The predictive coefficient on $\log(M_{i,t}/A_{i,t})$ ranges from 0.0274 (0.0224) to 0.0603 (0.0555) as k increases

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

from 1 to 5 over the 1995-2024 (1960-2024) sample periods, with all estimates statistically significant. Notably, these magnitudes are comparable to the predictive power of stock valuation for future earnings and dividends.

In contrast, for the Chinese firm sample (1995-2016), the predictive coefficient of $\log(M_{i,t}/A_{i,t})$ is weak and even negative at short horizons: -0.083 for $k = 1$ (t-stat $=$ 3.15), rising slightly to 0.0037 for $k = 3$ (t-stat $= 1.45$) and 0.0079 for $k = 5$ (t-stat $=$ 2.24). These results are similar to—or even weaker than—those for predicting payouts. This finding rules out an alternative explanation for the weak predictability of M for payouts in China, namely that Chinese firms simply follow different payout policies than U.S. firms, making payouts less sensitive to fundamentals. In other words, the evidence does not support the idea that Chinese firms merely retain a larger share of their operating cash flows rather than distributing them to shareholders.

Taken together, these results show that market valuation has limited predictive power for future payouts and cash flows in the Chinese market, in sharp contrast to its strong predictive power for reported earnings. By comparison, in the U.S. S&P 500 sample, market valuation consistently predicts earnings, dividends, and cash flows, yielding a more coherent pattern across all measures.

In Panel B, the dependent variable is accruals. For both China and the U.S., market valuation shows a significant positive correlation with future accruals over short horizons ($k \leq 3$). As the horizon extends to $k = 5$, however, the correlation becomes insignificant in China and turns negative in the U.S.

In Panel C, the dependent variable is NRGLs. As a benchmark, in the U.S. sample, the predictability of market valuation for NRGLs is very weak and economically small. In contrast, on the left, we find that in the Chinese sample, $\log(M_{i,t}/A_{i,t})$ positively predicts $NRGL_{i,t+1}$, with t-statistics above 4. This positive relationship not only persists but also strengthens as the forecast horizon extends from $k = 2$ to $k = 5$. These findings support Hypothesis 2, suggesting that highly valued firms are more likely to engage in earnings management to align reported earnings with market expectations reflected in their stock valuations.

In sum, the results suggest that the strong predictability of M_t for future reported earnings among Chinese firms is largely driven by the managed components—accruals and NRGLs. Moreover, the long-term predictability primarily stems from NRGLs.

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 annual stock returns and NRGLs disclosed in firms' annual reports (which are typically released in April–May). We estimate Fama-MacBeth regressions of annual stock returns from July of year $t+1$ to June of year $t+2$ on firms' fiscal year t's E, as well as the three components (OCF, Accruals, and NRGLs). We control for a set of commonly used stock characteristics, and industry fixed effects.

As shown in Table VII, 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. In column (1), we only include E/A into the regression, and it does not exhibit any return predictability. In column (2), we add OCF/A, and the coefficient is negative but insignificant. Column (3) includes $Accruals/A$, and the coefficient appears to be positive with a t-stat of 2.19. This is surprising given that the accrual literature using the U.S. data shows negative return predictability of accruals (e.g., Sloan, 1996).

Finally, as shown in columns (4), $NRGL_t$ predict significantly lower stock returns in the subsequent year (t-stat of 5.7). In terms of economic magnitude, a two standard deviation increase in NRGL is associated with a 3.99% ($= 2 \times 0.02245 \times 0.89$) decline in returns over the following year. In column (5), we replace E/A with its three components, the negative predictability of NRGLs remain significant.

Taken together, the findings from Tables VI and VII 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 the delisting rules—an important policy change in the Chinese A-share market. This reform also provides a natural setting to test Hypothesis 3.

Institutional background. Historically, the A-share market had an extremely low delisting rate (Lee et al., 2023), driven largely by the high shell value created by IPO restrictions and by the ease with which firms could use earnings management to avoid breaching delisting criteria.

The reforms began in March 2019 with new delisting standards introduced for the STAR board on the Shanghai Stock Exchange as a pilot program. In March 2020, the National Peoples Congress passed a new Securities Law, and in December 2020 the revised delisting rules were officially implemented for all mainboard firms on the Shanghai and Shenzhen Stock Exchanges.

A key element of the reform was the exclusion of NRGLs from earnings used for regulatory compliance. This change effectively removed an important tool of earnings management. The first fiscal year under the new rule was 2020, meaning earnings reported for 2020 and onward should be less susceptible to manipulation via NRGLs. In our event study, we therefore define 2020 and subsequent years as the postevent window. Additional details on the reform timeline are provided in Online Appendix A.2.

Policy shock on NRGLs. 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 III 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. The finding confirms that the 2020 delisting rule reform effectively constrained the use of NRGLs for earnings management in the post-reform period.

Policy shock on market value and future earnings. Further, 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 our main regression 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:

$$\frac{E_{i,t+k}}{A_{i,t}} = \alpha + \beta_k \log(\frac{M_{i,t}}{A_{i,t}}) + \theta_k \log(\frac{M_{i,t}}{A_{i,t}}) \times POST_t + \gamma \frac{E_{i,t}}{A_{i,t}} + \lambda \frac{D_{i,t}}{A_{i,t}} + \upsilon_t + \epsilon_{i,t}, \tag{20}$$

for $k \in \{1, 2, 3\}$; we set $k \leq 3$ because our sample ends in 2024 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 VIII presents the results. The coefficient on the interaction term is significantly negative and equals -0.006 (t-stat $= 10.1$) for $E_{i,t+1}$, which is sizable compared to the coefficient on $\log(\frac{M_{i,t}}{A_{i,t}})$, which equals 0.020. The interaction term remains significantly negative for $E_{i,t+2}$ and $E_{i,t+3}$, with coefficients of -0.008 (t-stat $= 9.75$) and -0.006 (t-stat $= 5.76$), respectively, while the coefficients on $\log(\frac{M_{i,t}}{A_{i,t}})$ are 0.024.

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 positive coefficients before the interaction term, reinforcing the China-specific effect of the delisting rule reforms.

We further examine the decomposition of earnings. We replacing the dependent variable with cash flows, accruals, and NRGLs for Chinese firms in Panel B. The coefficient on the interaction term is significantly positive, at 0.003 (t-stat $= 1.9$) for OCF_{t+1}, which is substantial relative to the coefficient on $\log(\frac{M_{i,t}}{A_{i,t}})$. This suggests that the market value has become more informative with fundamental.

Finally, implied from Hypothesis 3, the correlation between market valuation and subsequent NRGLs should be weakened significantly after the reforms. In this indeed the case, as shown in Columns (7) to (9), the coefficients on the interaction term for all three forecasting horizons for NRGLs are all negative. In terms of economic magnitude, in Column (9) for predicting NRGLs in year $t + 3$, the coefficient on the interaction term is

-0.001, while the coefficient on $\log(M_{i,t}/A_{i,t})$ equals 0.005. Interestingly, the correlation between market valuation and accruals also appears to be weakened after the reform.

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 extend the analysis of Carpenter, Lu, and Whitelaw (2021), who argue that stock prices in Chinas A-share market are as informative about future earnings as those in the U.S. market. Complementing their interpretation, we show that Chinese firms may actively manage earnings to align with expectations embedded in their stock valuations. Specifically, firms with higher valuations tend to report higher earnings over the subsequent three years; however, these higher earnings do not translate into greater payouts to shareholders and eventually reverse over the longer horizon. Furthermore, we provide evidence of earnings management through non-recurring gains and losses (NRGLs), exploiting the 2019-2020 delisting rule reform as an exogenous shock to such practices.

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Table I. Summary Statistics

This table presents the summary statistics of the key variables at the stock level in our analysis. The sample period is 1995 to 2024 for Panel A, excluding the bottom decile of stocks ranked on total asset, and 1960 to 2024 for Panel B. Variable definitions are in Appendix A.1.

Panel A: Chinese A-share stocks

	Mean	SD	P10	P25	P50	P75	P90	N
E_t/A_t	0.02785	0.08293	-0.00964	0.01122	0.03280	0.06083	0.09294	41562
E_{t+1}/A_t	0.03512	0.07631	-0.02184	0.00982	0.03282	0.06641	0.10881	41562
E_{t+3}/A_t	0.04816	0.11750	-0.03954	0.00707	0.03273	0.07816	0.14959	41562
E_{t+5}/A_t	0.05383	0.17734	-0.05094	0.00454	0.03177	0.08703	0.18446	41562
D_t/A_t	0.01307	0.01845	0.00000	0.00000	0.00636	0.01824	0.03600	41562
D_{t+1}/A_t	0.01414	0.02104	0.00000	0.00000	0.00631	0.01927	0.03937	41562
D_{t+3}/A_t	0.01744	0.03017	0.00000	0.00000	0.00571	0.02160	0.04909	41562
D_{t+5}/A_t	0.02131	0.04145	0.00000	0.00000	0.00519	0.02415	0.05923	41562
OCF_t/A_t	0.06039	0.11732	-0.06257	0.01635	0.06780	0.12048	0.18390	41562
OCF_{t+1}/A_t	0.05934	0.15026	-0.07912	0.01038	0.06472	0.12831	0.20583	41562
OCF_{t+3}/A_t	0.06923	0.22185	-0.09473	0.00272	0.06257	0.14119	0.25547	41562
OCF_{t+5}/A_t	0.08824	0.31318	-0.09761	0.00000	0.06255	0.15954	0.31596	41562
$Accruals_t/A_t$	-0.04457	0.12071	-0.17434	-0.09877	-0.03840	0.00728	0.07627	41562
$Accruals_{t+1}/A_t$	-0.03778	0.15430	-0.18754	-0.10712	-0.04183	0.01342	0.09787	41562
$Accruals_{t+3}/A_t$	-0.03770	0.22562	-0.21802	-0.11609	-0.04120	0.01668	0.12601	41562
$Accruals_{t+5}/A_t$	-0.05520	0.31620	-0.26706	-0.12995	-0.04300	0.01372	0.13147	41562
$NRGL_t/A_t$	0.01008	0.02245	0.00000	0.00075	0.00382	0.00981	0.02237	41562
$NRGL_{t+1}/A_t$	0.01149	0.02430	0.00000	0.00091	0.00446	0.01135	0.02606	41562
$NRGL_{t+3}/A_t$	0.01419	0.02843	0.00000	0.00115	0.00545	0.01433	0.03390	41562
$NRGL_{t+5}/A_t$	0.01741	0.03868	0.00000	0.00120	0.00606	0.01682	0.04031	41562
$\log(M_t/A_t)$	0.41996	0.85420	-0.69969	-0.14888	0.44203	1.00257	1.49714	41562
$\log(M_t)$	8.51584	0.96450	7.37875	7.84645	8.41920	9.07262	9.81234	41562
B/M	0.41701	0.31460	0.12533	0.20911	0.34874	0.55268	0.81632	41562
RET	0.18048	0.70582	-0.41358	-0.24734	0.00000	0.37122	1.01604	41562
$TURNOVER$	5.96450	5.08711	1.59939	2.63468	4.51211	7.63194	11.93477	41562

Panel B: U.S. S&P500 stocks

	Mean	SD	P10	P25	P50	P75	P90	N
E_t/A_t	0.06024	0.06519	0.00531	0.03279	0.05723	0.08995	0.12985	25956
E_{t+1}/A_t	0.06365	0.06726	0.00000	0.02878	0.05838	0.09645	0.14200	25956
E_{t+3}/A_t	0.06937	0.08243	0.00000	0.00763	0.05849	0.10825	0.16978	25956
E_{t+5}/A_t	0.07412	0.10016	0.00000	0.00000	0.05504	0.11730	0.19668	25956
D_t/A_t	0.04032	0.05776	0.00000	0.00308	0.02248	0.04903	0.10407	25956
D_{t+1}/A_t	0.04125	0.05825	0.00000	0.00000	0.02342	0.05138	0.10769	25956
D_{t+3}/A_t	0.04524	0.06815	0.00000	0.00000	0.02448	0.05689	0.11924	25956
D_{t+5}/A_t	0.05008	0.08190	0.00000	0.00000	0.02370	0.06219	0.13353	25956
OCF_t/A_t	0.11501	0.05540	0.05631	0.08203	0.11069	0.14427	0.18236	25956
OCF_{t+1}/A_t	0.11863	0.06781	0.03495	0.08107	0.11530	0.15505	0.20026	25956
OCF_{t+3}/A_t	0.12782	0.09756	0.00000	0.06619	0.12238	0.18008	0.24568	25956
OCF_{t+5}/A_t	0.13759	0.13045	0.00000	0.00000	0.12585	0.20375	0.29692	25956
$Accruals_t/A_t$	-0.05482	0.05208	-0.10585	-0.07310	-0.05002	-0.03021	-0.00760	25956
$Accruals_{t+1}/A_t$	-0.05527	0.05261	-0.11155	-0.07732	-0.05233	-0.02811	0.00000	25956
$Accruals_{t+3}/A_t$	-0.05861	0.06480	-0.13037	-0.08587	-0.05436	-0.01199	0.00000	25956
$Accruals_{t+5}/A_t$	-0.06374	0.08165	-0.15469	-0.09570	-0.05422	0.00000	0.00000	25956
$NRGL_t/A_t$	0.00000	0.00019	-0.00003	0.00000	0.00000	0.00000	0.00007	25956
$NRGL_{t+1}/A_t$	0.00000	0.00018	-0.00002	0.00000	0.00000	0.00000	0.00006	25956
$NRGL_{t+3}/A_t$	0.00001	0.00019	-0.00001	0.00000	0.00000	0.00000	0.00005	25956
$NRGL_{t+5}/A_t$	0.00000	0.00021	-0.00001	0.00000	0.00000	0.00000	0.00004	25956
$\log(M_t/A_t)$	-0.10749	0.88834	-1.21235	-0.71726	-0.14258	0.49333	1.04049	25956

Table II. 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 all Chinese A-share stocks:

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

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. Panel B reports the results using subsamples: the bottom decile of stocks ranked on total asset and other stocks. Variable definitions are in Appendix A.1.

Panel A: Full sample

	(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	0.006	2.503	0.019	3.950	0.034	4.460	0.035	4.960	0.045	5.010
1996	0.028	6.192	0.041	5.690	0.048	6.710	0.051	5.900	0.037	3.390
1997	0.034	6.789	0.040	8.680	0.039	7.730	0.032	4.410	0.015	1.910
1998	0.021	8.898	0.024	7.600	0.019	4.140	0.004	0.944	-0.002	-0.359
1999	0.013	5.425	0.015	4.010	0.006	1.800	0.000	-0.067	-0.008	-1.670
2000	0.006	2.221	0.002	0.716	0.000	-0.129	-0.004	-1.200	-0.009	-2.540
2001	0.006	2.619	0.006	2.500	0.006	2.040	0.001	0.301	0.003	1.040
2002	0.008	3.573	0.009	3.310	0.005	1.900	0.007	2.530	0.016	4.170
2003	0.017	7.235	0.015	6.690	0.013	6.010	0.021	6.670	0.023	6.350
2004	0.022	9.666	0.022	10.400	0.032	9.110	0.034	9.200	0.032	7.840
2005	0.018	7.556	0.033	8.050	0.038	8.920	0.035	8.940	0.039	7.030
2006	0.038	9.138	0.038	8.720	0.035	9.320	0.038	8.000	0.059	7.570
2007	0.030	7.350	0.031	8.300	0.035	7.230	0.053	6.950	0.049	8.270
2008	0.024	7.306	0.031	8.100	0.050	7.690	0.060	8.170	0.069	7.530
2009	0.022	9.321	0.039	8.700	0.064	8.070	0.079	7.760	0.063	7.070
2010	0.019	6.310	0.050	6.750	0.062	6.740	0.043	6.680	0.066	7.660
2011	0.024	8.320	0.028	8.680	0.028	7.880	0.052	9.570	0.078	9.110
2012	0.016	7.301	0.021	7.860	0.034	8.670	0.057	9.080	0.053	6.930
2013	0.015	9.857	0.031	10.700	0.052	11.300	0.050	8.700	-0.031	-2.980
2014	0.019	9.261	0.033	9.400	0.032	7.390	-0.033	-4.060	-0.025	-3.330
2015	0.019	10.356	0.020	8.060	0.000	-0.596	-0.004	-0.806	0.001	0.114
2016	0.010	7.663	0.007	3.120	0.009	3.540	0.013	4.810	0.015	4.980
2017	0.009	5.206	0.015	8.640	0.022	10.700	0.023	10.100	0.023	8.650
2018	0.022	14.633	0.026	16.400	0.027	13.700	0.027	12.700	0.019	9.860
2019	0.027	18.071	0.030	16.700	0.029	14.000	0.020	10.600	0.017	8.840
2020	0.025	16.552	0.024	15.000	0.017	11.100	0.015	9.980		
2021	0.014	13.609	0.009	7.930	0.008	6.740				
2022	0.004	4.408	0.005	5.120						
2023	0.007	9.153								
Averages China										
1995 to 2016-k	0.019***		0.026***		0.032***		0.033***		0.034***	
	(8.400)		(7.208)		(5.438)		(4.423)		(3.660)	
1995 to 2024-k	0.018***		0.024***		0.027***		0.027***		0.026***	
	(9.006)		(7.892)		(5.994)		(4.342)		(3.305)	
Averages US S&P500										
1960 to 2024-k	0.027***		0.033***		0.036***		0.039***		0.043***	
	(20.825)		(22.575)		(22.885)		(25.458)		(27.452)	
1995 to 2024-k	0.032***		0.037***		0.039***		0.043***		0.047***	
	(21.169)		(15.697)		(14.671)		(18.565)		(20.272)	

Panel B: Chinese A-share stocks (Bottom decile vs Others)

	(1)	(2)	(3)	(4)	(5)
	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$
Bottom decile					
1995 to 2016-k	0.026***	0.037***	0.051***	0.051***	0.060***
	(5.80)	(3.36)	(2.92)	(3.15)	(3.33)
1995 to 2024-k	0.020***	0.030***	0.041***	0.036**	0.042**
	(4.61)	(3.51)	(3.11)	(2.50)	(2.63)
Others					
1995 to 2016-k	0.017***	0.021***	0.023***	0.022***	0.020***
	(7.84)	(7.28)	(6.04)	(4.64)	(3.50)
1995 to 2024-k	0.016***	0.020***	0.021***	0.019***	0.016***
	(8.92)	(8.44)	(6.73)	(4.79)	(3.49)

Table III. 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 (excluding the bottom decile of stocks ranked on total asset),

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

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	0.481	0.001	0.740	0.003	1.240	0.001	0.252	0.008	3.110
1996	0.005	3.648	0.005	3.310	0.006	3.280	0.013	5.360	0.010	4.160
1997	0.002	1.433	0.003	2.410	0.009	5.730	0.007	5.180	0.006	3.740
1998	0.000	0.200	0.006	5.330	0.005	5.250	0.004	3.380	0.002	1.450
1999	0.004	5.388	0.003	3.560	0.002	2.490	0.000	0.355	0.000	0.246
2000	0.001	1.603	0.000	0.503	-0.001	-1.990	-0.002	-1.840	-0.003	-2.540
2001	0.001	2.116	0.000	-0.362	0.000	-0.423	-0.001	-1.390	-0.002	-1.670
2002	0.001	2.476	0.001	2.010	0.001	0.920	0.000	-0.439	0.000	0.058
2003	0.003	5.936	0.003	4.490	0.002	3.150	0.002	2.450	0.004	4.620
2004	0.004	6.181	0.004	5.850	0.004	5.070	0.005	6.550	0.005	5.790
2005	0.003	5.640	0.003	5.010	0.005	6.910	0.005	6.830	0.006	5.630
2006	0.002	4.228	0.003	6.410	0.004	6.750	0.004	4.850	0.005	4.480
2007	0.005	9.303	0.006	7.530	0.005	6.050	0.006	6.750	0.008	7.380
2008	0.002	5.453	0.002	3.930	0.004	4.530	0.006	6.080	0.006	5.360
2009	0.002	4.580	0.004	5.850	0.006	8.070	0.005	7.010	0.007	5.820
2010	0.002	7.121	0.003	8.550	0.003	5.570	0.004	5.920	0.005	4.950
2011	0.002	6.905	0.003	5.910	0.003	5.950	0.005	6.410	0.006	7.290
2012	0.001	3.587	0.002	5.370	0.003	6.490	0.005	6.430	0.005	5.550
2013	0.002	5.791	0.003	7.300	0.005	7.760	0.005	6.000	0.005	4.210
2014	0.001	3.854	0.003	5.030	0.003	3.530	0.002	1.640	0.003	2.750
2015	0.001	5.020	0.003	5.020	0.002	3.560	0.003	3.980	0.003	3.710
2016	0.001	4.673	0.002	4.210	0.003	4.820	0.003	4.880	0.004	4.350
2017	0.002	5.677	0.003	6.880	0.005	8.330	0.004	6.800	0.006	6.800
2018	0.003	9.552	0.004	10.900	0.005	9.620	0.006	8.700	0.007	11.200
2019	0.004	11.587	0.005	10.300	0.005	9.120	0.007	11.400	0.006	10.600
2020	0.003	9.968	0.004	9.590	0.006	13.000	0.005	11.200		
2021	0.003	10.137	0.005	13.200	0.004	11.600				
2022	0.003	12.799	0.003	11.300						
2023	0.002	9.431								
Averages China										
1995 to 2016-k	0.002***		0.003***		0.004***		0.004***		0.004***	
	(7.751)		(7.449)		(5.200)		(3.918)		(3.789)	
1995 to 2024-k	0.002***		0.003***		0.004***		0.004***		0.004***	
	(9.970)		(9.815)		(7.196)		(5.661)		(5.568)	
Averages US S&P500										
1960 to 2024-k	0.008***		0.014***		0.017***		0.021***		0.025***	
	(6.829)		(7.606)		(7.860)		(7.889)		(8.343)	
1995 to 2024-k	0.014***		0.024***		0.029***		0.035***		0.040***	
	(11.363)		(14.737)		(13.019)		(12.332)		(13.532)	

Table IV. Earnings Reversal

The table shows the results from the following panel regressions from the following firm-level cross-sectional regressions using the sample of Chinese A-share stocks (excluding the bottom decile of stocks ranked on total asset),

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

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

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

This analysis is conducted for both China and the US S&P 500 samples. The data spans from 1995 to 2024 for China and from 1960 to 2024 for the US S&P 500. Panel A shows the result of regressions with year fixed effects, Panel B with firm fixed effects, and Panel C with year and firm 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 (1995-2024)			US SP500 (1960-2024)		
	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$
$\log(M_t/A_t)$	0.018***	0.004	-0.005	0.034***	0.011***	0.012***
	(9.221)	(1.104)	(-0.957)	(16.615)	(4.171)	(6.766)
E_t/A_t	-0.547***	-0.117***	-0.059***	-0.570***	-0.094***	-0.009
	(-9.456)	(-3.304)	(-3.279)	(-15.552)	(-3.586)	(-0.527)
D_t/A_t	0.697***	0.158	0.297**	0.091***	0.026	-0.014
	(6.372)	(1.449)	(2.699)	(6.470)	(1.440)	(-0.932)
Firm FE	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	40545	40545	40545	24382	24382	24382

Panel B: With firm fixed effect

	China (1995-2024)			US SP500 (1960-2024)		
	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$
$\log(M_t/A_t)$	0.029***	-0.002	-0.010	0.037***	-0.005	0.001
	(7.795)	(-0.604)	(-1.573)	(10.750)	(-1.311)	(0.157)
E_t/A_t	-0.713***	-0.207**	-0.128*	-0.646***	-0.127***	0.000
	(-10.692)	(-2.586)	(-1.979)	(-15.134)	(-4.989)	(-0.005)
D_t/A_t	0.397***	-0.143	0.070	0.020	-0.062**	-0.071**
	(4.258)	(-1.014)	(0.443)	(1.375)	(-2.361)	(-2.736)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
N	40545	40545	40545	24382	24382	24382

Panel C: With firm and time fixed effect

	China (1995-2024)			US SP500 (1960-2024)		
	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+3}$
$\log(M_t/A_t)$	0.040***	0.000	-0.012**	0.047***	-0.005	0.002
	(21.595)	(0.009)	(-2.254)	(17.201)	(-1.627)	(0.642)
E_t/A_t	-0.738***	-0.222**	-0.134**	-0.716***	-0.119***	-0.030
	(-12.954)	(-2.602)	(-2.194)	(-22.666)	(-5.577)	(-1.198)
D_t/A_t	0.378***	-0.166	0.008	0.058***	-0.007	-0.025
	(5.366)	(-1.551)	(0.074)	(4.831)	(-0.358)	(-1.468)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	40545	40545	40545	24382	24382	24382

Table V. 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 2024$-k$:

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

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 2002 to 2024$-k$,

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

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)
	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$
$log(M_t/A_t)$	0.015***	0.024***	0.033***	0.039***	0.041***
	(5.85)	(5.22)	(4.47)	(3.66)	(3.17)
$AH \times log(M_t/A_t)$	-0.004	-0.010**	-0.016**	-0.024**	-0.032**
	(-1.12)	(-2.50)	(-2.42)	(-2.41)	(-2.52)

Panel B: M^H vs M^A

	(1)	(2)	(3)	(4)	(5)
	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$
$\hat{\beta}_k^A \sigma(\log(M_t^A/A_t))$	0.001	-0.002	-0.001	-0.005	-0.008
	(0.311)	(-0.526)	(-0.224)	(-0.609)	(-0.910)
$\hat{\beta}_k^H \sigma(\log(M_t^H/A_t))$	0.005**	0.011***	0.011***	0.014***	0.018***
	(2.283)	(2.827)	(3.004)	(3.453)	(3.764)

Table VI. Earnings Decomposition

The table shows average predicted variation $\hat{\beta}_k \sigma(log(M_t/A_t))$ and White-heteroscedasticity-consistent t-statistics from the following stock-level cross-sectional regressions using the sample of Chinese A-share stocks (excluding the bottom decile of stocks ranked on total asset),

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

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

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

for China. The time series averages are reported, 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.

Panel A: Predict *OCF*

	China						US S&P500				
Averages	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$		$k=1$	$k=2$	$k=3$	$k=4$	$k=5$
1995–2016-k	-0.0083***	-0.0024	0.0037*	0.0063**	0.0079***	1995–2024-k	0.0274***	0.0386***	0.0454***	0.0528***	0.0603***
	(-3.151)	(-1.054)	(1.447)	(1.917)	(2.237)		(17.360)	(22.664)	(27.500)	(25.827)	(21.681)
1995–2024-k	-0.0076***	-0.0008	0.0040**	0.0074***	0.0083***	1960–2024-k	0.0224***	0.0330***	0.0406***	0.0482***	0.0555***
	(-3.845)	(-0.493)	(2.090)	(3.030)	(3.069)		(15.216)	(20.280)	(23.675)	(24.253)	(26.129)

Panel B: Predict *Accruals*

	China						US S&P500				
Averages	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$		$k=1$	$k=2$	$k=3$	$k=4$	$k=5$
1995–2016-k	0.0190***	0.0174***	0.0136***	0.0092***	0.0048	1995–2024-k	0.0021*	-0.0037**	-0.0082***	-0.0115***	-0.0151***
	(6.567)	(5.003)	(3.893)	(2.514)	(0.902)		(1.889)	(-2.029)	(-4.434)	(-7.800)	(-10.053)
1995–2024-k	0.0179***	0.0144***	0.0102***	0.0041	-0.0007	1960–2024-k	0.0035***	-0.0013	-0.0058***	-0.0104***	-0.0141***
	(7.428)	(4.989)	(3.333)	(1.052)	(-0.155)		(3.002)	(-0.985)	(-4.460)	(-8.940)	(-12.672)

Panel C: Predict *NRGL*

	China						US S&P500				
Averages	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$		$k=1$	$k=2$	$k=3$	$k=4$	$k=5$
1995–2016-k	0.0027***	0.0027***	0.0027***	0.0032***	0.0037***	1995–2024-k	0.000025***	0.000010	0.000006	0.000010**	0.000008**
	(4.896)	(5.193)	(4.927)	(4.946)	(5.644)		(5.332)	(2.382)	(1.269)	(2.591)	(2.643)
1995–2024-k	0.0027***	0.0029***	0.0032***	0.0039***	0.0044***	1960–2024-k	0.000021***	0.000012***	0.000008***	0.000011***	0.000010***
	(6.736)	(7.205)	(6.506)	(6.064)	(6.478)		(7.356)	(4.579)	(3.278)	(3.995)	(3.532)

Table VII. Return Predictability of Earnings Decomposition

This table presents the results from Fama-MacBeth stock-level regressions evaluating the predictive power of E, OCF, $Accruals$, and $NRGLs$ on subsequent annual stock returns. Controls include log of market value (log(M)), book-to-market ratio (B/M), past year returns (RET_t), turnover rate (TURNOVER), and industry dummies. Newey-West standard errors with lag of one year are calculated and the corresponding t-statistics are in parentheses below each coefficient. The sample period is from 1995 to 2024, excluding the bottom decile of stocks ranked on total asset. Variable definitions are in Appendix A.1.

	(1) RET_{t+1}	(2) RET_{t+1}	(3) RET_{t+1}	(4) RET_{t+1}	(5) RET_{t+1}
E/A	0.130	0.179**	0.094	0.188*	
	(1.357)	(2.032)	(0.967)	(1.890)	
OCF/A		-0.083			0.110
		(-1.558)			(1.280)
Accruals/A			0.102**		0.189**
			(2.191)		(2.463)
NRGL/A				-0.890***	-0.525***
				(-5.601)	(-3.395)
log(M)	-0.007	-0.007	-0.007	-0.009	-0.005
	(-0.349)	(-0.328)	(-0.346)	(-0.435)	(-0.240)
B/M	0.054**	0.054**	0.054**	0.051**	0.064***
	(2.347)	(2.351)	(2.324)	(2.184)	(2.697)
RET_t	-0.044**	-0.045**	-0.045**	-0.046**	-0.052**
	(-2.067)	(-2.067)	(-2.099)	(-2.138)	(-2.436)
TURNOVER$_y$	-0.004*	-0.004*	-0.004*	-0.004*	0.008
	(-1.629)	(-1.588)	(-1.627)	(-1.628)	(0.934)
Industry FE	Yes	Yes	Yes	Yes	Yes
R2	0.0909	0.0913	0.0913	0.0925	0.0926
N	47111	47111	47111	47052	47052

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

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 individual level with time fixed effects,

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

$POST_t$ is a dummy variable that equals one if E_{t+k} is observed in 2020 or after. Panel B reports the same regressions with replace the dependent variable to OCF_{t+k}/A_t, $NRGL_{t+k}/A_t$ and $Accruals_{t+k}/A_t$, respectively. The A-share stock sample ranges from 1995 to 2024 excluding the bottom decile of stocks ranked on total asset.

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
$\log(M_t/A_t) \times POST$	-0.006***	-0.008***	-0.006***	0.003***	0.004***	0.005***
	(-10.131)	(-9.752)	(-5.767)	(3.013)	(2.950)	(2.771)
$\log(M_t/A_t)$	0.020***	0.024***	0.024***	0.035***	0.042***	0.045***
	(47.245)	(41.855)	(31.123)	(77.757)	(74.089)	(67.937)
E_t/A_t	0.360***	0.229***	0.182***	0.354***	0.230***	0.216***
	(92.266)	(44.607)	(27.148)	(61.423)	(31.795)	(25.335)
D_t/A_t	0.805***	0.919***	0.991***	0.116***	0.136***	0.129***
	(55.882)	(47.714)	(39.071)	(18.922)	(17.687)	(14.192)
N	57848	53181	48667	25915	25517	25138
adj. R2	0.373	0.233	0.157	0.559	0.442	0.384

Panel B: Predicting Operating Cash Flow, Accruals, and NRGL in China

	OCF			Accruals			NRGL		
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
$\log(M_t/A_t) \times POST$	0.003*	-0.000	0.001	-0.005***	-0.006***	-0.003	-0.000	-0.000	-0.001***
	(1.914)	(-0.051)	(0.281)	(-3.748)	(-3.277)	(-1.375)	(-0.471)	(-0.924)	(-3.619)
$\log(M/A)$	-0.012***	0.001	0.005***	0.027***	0.018***	0.012***	0.004***	0.004***	0.005***
	(-12.070)	(1.179)	(3.362)	(25.842)	(14.097)	(7.280)	(28.781)	(25.688)	(26.526)
E_t/A_t	0.235***	0.226***	0.223***	0.216***	0.063***	-0.008	-0.052***	-0.037***	-0.022***
	(26.031)	(21.148)	(16.572)	(23.016)	(5.672)	(-0.561)	(-43.748)	(-26.939)	(-12.871)
D_t/A_t	0.996***	1.018***	1.040***	-0.220***	-0.090**	-0.011	0.017***	-0.009	-0.042***
	(29.967)	(25.483)	(20.440)	(-6.334)	(-2.163)	(-0.211)	(3.855)	(-1.782)	(-6.561)
N	57848	53181	48667	57848	53181	48667	57848	53181	48667
adj. R^2	0.061	0.052	0.040	0.058	0.028	0.020	0.066	0.048	0.042

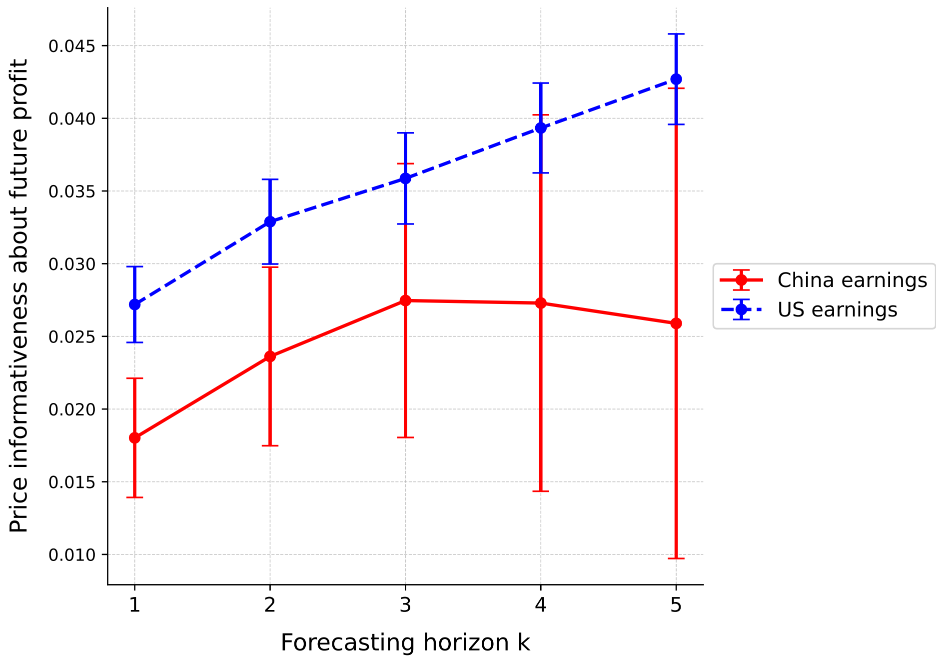

Figure I. Stock Price Informativeness about Future Earnings

The figure presents 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:

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

where k ranges from 1 to 5. This analysis includes all Chinese A-share stocks from 1995 to $2024-k$ and US S&P 500 stocks from 1960 to $2024-k$. Detailed definitions of variables and additional methodological details are delineated in Appendix A.1.

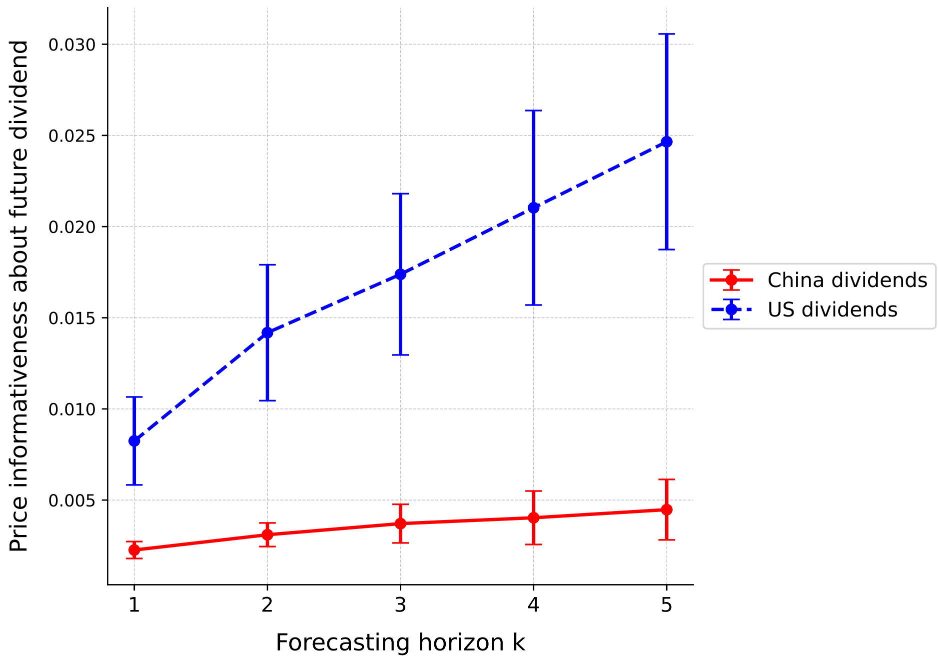

Figure II. Stock Price Informativeness about Future Payouts

This figure presents individual-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. This analysis includes Chinese A-share stocks from 1995 to $2024 - k$ (excluding the bottom decile based on A_t) and US S&P 500 stocks from 1960 to $2024 - k$. Detailed definitions of variables and additional methodological details are delineated in Appendix A.1.

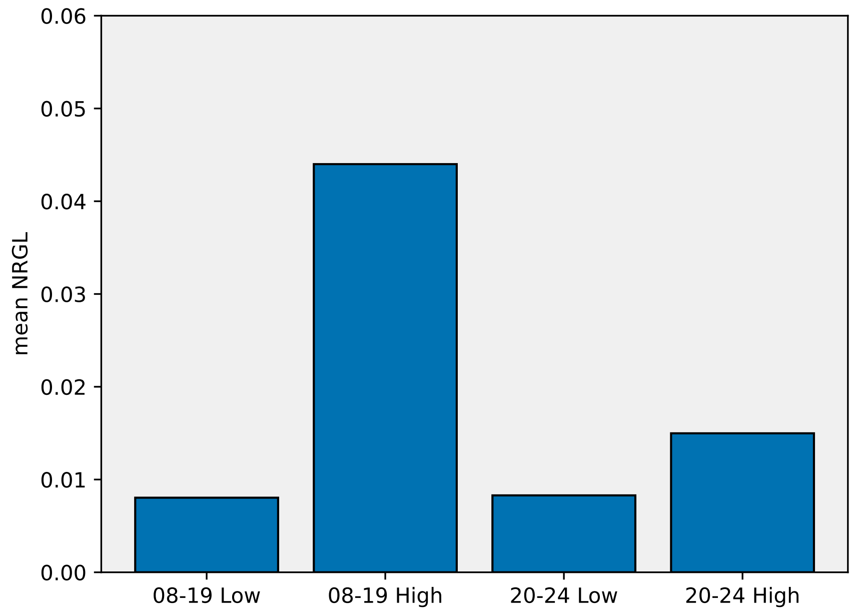

Figure III. Level of NRGL Before and After the 2020 Delisting Rule

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 2024. 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 both `.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`).

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`). 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`).

For US firms, the same calculation method is adopted, which involves deducting the change in working capital (Compustat variable name `wcapch`) and income taxes(`txt`) from EBITDA(`ebitda`).

$NRGL$: 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, in CNY, and `fn_fn00901` $= total$.

For the US firms, NRGLs refer to extraordinary items, which equals the difference between net income (`ni`) and net income before extraordinary items (`ib`) in Compustat.

$Accruals$: $Accrual = E - OCF - NRGL$ for firms in both China and the US.

RET_t: Annually Return with Dividend Reinvested measures the total return of a stock over a year, including the effect of reinvested cash dividends. It is compounded using the monthly return within a year 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.

$TURNOVER_t$: Turnover ratio for year t in a listed company measures the liquidity of a company's stock by indicating how frequently the shares change hands over a year. 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 annually turnover ratio is then obtained by summing these monthly turnover ratios for each stock over the year. 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.

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.