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EARNINGS MANAGEMENT AND PRICE INFORMATIVENESS

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ABSTRACT

We investigate the relationship between stock prices and future earnings in China's A-share market. In the cross-section, firms with higher market valuations report higher earnings over the subsequent one to five years, suggesting that stock prices contain information about future fundamentals. In the time series, however, we find evidence of earnings reversal: higher stock prices predict weaker earnings growth three to five years ahead, consistent with short-term earnings management induced by stock-price pressures. We further document such earnings management through non-recurring gains and losses (NRGLs) and use the 2020 delisting rule reform as a natural experiment to examine these mechanisms.

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1 Introduction

Economists often view the stock market as a "crystal ball." Known as "price informativeness," this hypothesis says that today's stock prices are excellent predictors of a company's future health—that is, when a stock price is high today, this is because the market anticipates that the company will be more profitable tomorrow. Bai, Philippon, and Savov (2016) formally 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]

A recent study by Carpenter, Lu, and Whitelaw (2021) has applied this approach to China and found something surprising: despite China's stock market being known for wild volatility and speculation (Song and Xiong, 2018; Hu et al., 2021; Allen et al., 2024), its prices appeared to be just as informative as those in the United States. On the surface, it seemed that Chinese stock prices were predicting future corporate earnings with impressive accuracy.

However, there is a catch. The "crystal ball" view assumes that the future earnings reported by companies are real and honest. While this assumption generally holds water in developed markets like the U.S., it demands much closer scrutiny in emerging economies, including China. Although China has rapidly grown into the world's second-largest equity market, its financial infrastructure—specifically the accounting rules and corporate governance systems that keep public companies in check—is still under construction. Extensive evidence points to widespread "earnings management" and manipulation in Chinese stock market, suggesting that the financial reports on which investors rely may have been of low quality, particularly during earlier years (Piotroski and Wong, 2012). Furthermore, recent studies highlight significant governance challenges within Chinese listed firms, where checks and balances are often weaker than in mature markets (e.g., Allen, Qian, Shan, and Zhu, 2024).

This paper investigates a different explanation for why Chinese stock prices seem to predict earnings so well. We propose a mechanism that we call "manipulate-to-cater." Imagine a scenario where "the tail wags the dog." Instead of the stock price reflecting the company's true future performance, the reverse happens: a high stock price puts pressure on the company's managers. To justify that high valuation and satisfy investor expectations, managers manipulate their accounting to produce the earnings that the market expects. In this scenario, the stock

[1] Dávila and Parlatore (2025) propose an alternative measure of price informativeness based on an equilibrium signal-to-noise ratio—defined as the reduction in uncertainty about earnings gained from observing the price—which is identified separately from non-informational trading. In contrast, Bai, Philippon, and Savov (2016) proxy informativeness using the extent to which prices predict future earnings.

market is not a crystal ball predicting the future; it is a source of pressure forcing managers to manufacture a specific future.

To formulate the mechanism of "manipulate-to-cater" formally, we build a simple dynamic model based on the framework of Hirshleifer and Teoh (2003). In the model, a subset of inattentive investors takes reported earnings at face value, leading to stock prices that exceed fundamentals. Elevated valuations, in turn, create pressure on managers to inflate reported earnings to meet market expectations.

These two-way interactions between market valuation and earnings manipulation generate a set of testable predictions that contrast with the crystal-ball view. First, high stock prices might predict higher reported earnings, but they will not necessarily translate into real benefits for shareholders, like cash dividends or strong operating cash flows. It is profit on paper, not in the bank. Second, because these "managed" earnings are artificial, they are inherently unsustainable. Like a sugar rush, we expect a short-term spike in earnings followed by a long-term reversal as reality sets in. Third, as investors gradually realize that the earnings were manufactured, the stock price should suffer; that is, the "managed" part of earnings predicts lower future returns for the stock.

To empirically test these predictions, we follow the methodology of 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 1995–2024, excluding the bottom 5% by A_t to limit China-specific non-fundamental effects and scaling-induced outliers. 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 first show 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.

Nevertheless, two distinct patterns emerge in our China sample, which challenge the crystal-ball interpretation in Carpenter et al. (2021). First, unlike in the U.S. S&P sample, where market value strongly predicts future total payouts, defined as cash dividends plus share repurchases, the higher reported earnings of Chinese listed firms do not translate into greater future payouts.

Second, and more importantly, consistent with a key prediction of our "manipulate-to-cater" hypothesis, we find evidence of earnings reversal: in panel regressions, higher M_t/A_t

is associated with significantly higher earnings growth over the subsequent year, insignificant growth over years 1–3, and significantly lower growth over years 1–5. In contrast, this reversal pattern is absent in the U.S. S&P 500 sample. The earnings reversal in China suggests that firms in the A-share market may inflate reported earnings to meet market expectations, only for those earnings to revert later.

We emphasize that this earnings reversal is inherently a within-firm, time-series phenomenon. By contrast, the analysis in Carpenter et al. (2021) is primarily cross-sectional: firms with higher market valuations subsequently report higher earnings. Consistent with this distinction, our panel regressions show that the earnings-reversal pattern becomes stronger when we control for firm fixed effects, thereby exploiting within-firm variation over time, but weakens, and in some specifications becomes insignificant, when we control for time fixed effects, which moves the analysis closer to the cross-sectional framework in Carpenter et al. (2021). These findings suggest that our "manipulate-to-cater" mechanism and their "crystal-ball" view are not mutually exclusive. Rather, both mechanisms likely contribute to the observed correlation between firm valuations and future reported earnings in our sample of Chinese firms.

To pinpoint the sources of earnings predictability and potential earnings management, we decompose reported earnings into three distinct components: operating cash flows (OCF), accruals, and non-recurring gains and losses (NRGLs). Operating cash flows are generally less susceptible to managerial manipulation and better reflect the core health of the business; whereas accruals and NRGLs often serve as channels for earnings management.[2] Under China's accounting rules, NRGLs consist of non-operating and one-off items, such as government subsidies, asset disposals, and donations. These items were included in reported earnings until the 2020 delisting reform, which excluded NRGLs from the relevant earnings metric.

We examine which of these three components is most strongly predicted by current market valuation. The results reveal a sharp contrast between the United States and China. In the U.S. sample, market valuation primarily forecasts operating cash flows, for which the relationship is strongest and most robust. Predictability for accruals is limited to short horizons, mainly one year, while predictability for NRGLs is only sporadically significant and economically small.

In the Chinese sample, the pattern differs markedly. Market valuation has little, and sometimes even negative, predictive power for operating cash flows at horizons shorter than three years. It becomes positive only at longer horizons, with a modest magnitude. Instead, pre-

[2] In the literature, accrual-based manipulation is identified as the predominant form of earnings management in the U.S. market. In contrast, Chinese firms more commonly rely on non-recurring items—such as asset sales, one-time government subsidies, and major asset restructurings—to boost reported earnings and avoid delisting (see Lee et al., 2023, for details). Other channels of earnings management, including related-party transactions (RPTs), also exist. However, many RPTs lack clear directional implications for profit tunneling (Allen et al., 2024; Fisman and Wang, 2010). Therefore, our analysis focuses on NRGLs and accruals.

dictability is driven by more manipulable components. Accruals are positively and significantly predicted at short horizons, but this effect attenuates over time. By contrast, NRGLs exhibit the most robust relationship, remaining 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), rational investors should recognize that better-than-expected reported earnings driven by high NRGLs are unlikely to persist. They should therefore price in earnings inflation, leaving no return predictability from NRGLs. However, if investors fail to fully recognize earnings inflation, as suggested by Hirshleifer and Teoh (2003) and our model, NRGLs should negatively predict future stock returns. The data support this prediction. Specifically, a two-standard-deviation increase in NRGLs is associated with a 3.99% lower return over the subsequent year. This finding indicates that participants in the Chinese market, who are predominantly unsophisticated retail investors (An et al., 2022), do not fully see through earnings management, allowing such manipulation to temporarily inflate stock prices before fundamentals reassert themselves.

To further strengthen identification, we exploit the 2020 reform of delisting rules as a natural experiment. As the new rules took effect for the 2020 fiscal year, we designate 2020 and onward as the post-event period. We first document that NRGLs were widely used to inflate earnings prior to 2020, whereas after the reform, firms with higher valuation ratios exhibit significantly larger reductions in reported NRGLs. We then show that the correlation between market value and reported future earnings weakens after 2020; notably, no comparable structural break is observed in the U.S. data. This shift, likely driven by the 2020 policy reform in China, helps explain why the estimated price informativeness in our extended sample (which spans 2017–2024) is lower than that reported by Carpenter et al. (2021), whose sample ends in 2016.

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, primarily through NRGLs. Such earnings inflation, however, is inherently unsustainable and leads to subsequent earnings reversals, thereby shaping the long-term predictability of market valuation.

Literature Review. Our study leverages the world's second-largest equity market to deepen the understanding of the relationship between stock prices and future earnings. While Bai, Philippon, and Savov (2016) interpret the cross-sectional predictability of stock prices for future earnings as evidence of price informativeness, we propose that this relationship may also reflect managerial catering to market valuation pressures. To distinguish between these two channels, we extend the cross-sectional approach of Bai, Philippon, and Savov (2016) by incorporating a time-series analysis of earnings reversals. By combining these perspectives, we provide a more comprehensive test of price informativeness that accounts for the temporal dynamics of reported earnings.

Our evidence contributes to the extensive literature on the feedback effects of stock prices on the real economy, as reviewed by Bond, Edmans, and Goldstein (2012). In this framework, stock prices do not merely reflect fundamentals but actively shape firm behavior. Our findings show that this feedback effect manifests through firms' earnings management, supporting the "managerial myopia" channel highlighted by Stein (1989), where pressure from current stock prices induces managers to adopt strategies aimed at boosting short-term earnings at the expense of long-term value. Consistent with this view, Bergstresser and Philippon (2006) and Kedia and Philippon (2009) offer empirical evidence that stock-based managerial compensation leads to earnings manipulations.

We also extend the literature on earnings management in China. While prior studies document widespread manipulation through related-party transactions and accruals (e.g., Piotroski and Wong, 2012; Allen et al., 2024), we identify Non-Recurring Gains and Losses (NRGLs) as a distinct and critical channel for earnings management. Furthermore, our results parallel the U.S. "accrual anomaly" (Sloan, 1996; Hirshleifer, Hou, and Teoh, 2012) by demonstrating that A-share investors fail to fully recognize the low persistence of earnings inflated via NRGLs. Crucially, we add to this literature by identifying high market valuation as a key factor driving this specific form of manipulation.

Finally, our findings align with the literature on investor behavior and inefficiencies in the Chinese stock market. The fact that investors fail to discount inflated earnings is consistent with the view that A-share prices are driven largely by speculative trading rather than fundamentals—a phenomenon exemplified by the persistent premium of A-shares over B-shares (Mei, Scheinkman, and Xiong, 2009). Our results suggest that the behavioral biases documented in this market, including overconfidence, gambling preferences, and extrapolative expectations (Liu et al., 2022; Liao et al., 2022; Chen et al., 2023; Bian et al., 2024) create an environment where "manipulate-to-cater" strategies can successfully temporarily boost stock prices.

2 A Simple Model and Hypotheses Development

We build a simple model to illustrate the "manipulate-to-cater" mechanism and to derive several testable empirical hypotheses. The model integrates two perspectives on how earnings inflation affects stock prices: the signal-jamming framework of Stein (1989), where rational investors fully anticipate and discount earnings inflation, and the limited-attention framework of Hirshleifer and Teoh (2003), where investors fail to fully recognize it. By incorporating both channels, we show that earnings management incentives persist even when investors are not fooled, while whether inflated reports predict subsequent negative returns depends on the degree of limited attention.

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 fundamental value, market value, and earnings. The firm's fundamental value at $t = 2$ is a random variable v. At $t = 0$, investors share a common belief about v, captured by a normal distribution:

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

Here, $\hat{\mu}$ and $\hat{h}_v$ represent the markets perceived mean and precision, respectively. The belief $\hat{\mu}$ captures the market's sentiment at $t = 0$, which we treat as given in our analysis. More specifically, we investigate how market optimism—which may pushes $\hat{\mu}$ up—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:

$$e^n = v + \epsilon, \quad \text{where} \quad v \perp \epsilon \sim \mathcal{N}\left(0, \frac{1}{h_\epsilon}\right).$$

The manager then issues a public earnings report that can be inflated by an amount b, resulting in reported earnings of:

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

This earnings inflation imposes a non-pecuniary cost of $\frac{\kappa}{2}b^2$ on the manager, where $\kappa > 0$ is an exogenous parameter. This cost captures the reputational penalty associated with 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.

This setting also allows us to analyze regulatory changes that affect the ease of inflating earnings. In the Chinese context, we consider a policy that restricts specific methods through which A-share firms can influence reported earnings. In the model, such a policy shock corresponds to an increase in κ.

Inattentive investors. Following Hirshleifer and Teoh (2003), we assume that a fraction θ of investors are inattentative and fail to recognize that reported earnings may be inflated. As a result, they interpret reported earnings e as the true signal e^n. In contrast, the remaining fraction, $1-\theta$, are fully rational: although they cannot directly observe the inflated component b, they form rational expectations and correctly anticipate the equilibrium level of inflation, $b = b_*$.

When $\theta = 0$, all investors are rational. Even in this benchmark case, the signal-jamming mechanism in Stein (1989) leads the manager to inflate reported earnings.

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 the initial price 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_*; we then invoke the the equilibrium condition $b_* = b$ to determine the manager's equilibrium inflation.

Due to differences in how the two investor groups perceive earnings inflation, their stock demands at $t = 1$ differ. Specifically, denote by $\mathbb{E}^{ir}$ and $\mathbb{E}^{r}$ the expectations of inattentive and

[3] An alternative specification would model the cost of inflation as pecuniary, directly reducing the firms liquidation value. While this approach would generate even stronger long-run earnings reversals, it would also complicate the expression for the firm's market valuation by requiring adjustments for the value effect of earnings inflation. For tractability, we adopt the simpler setting in which the inflation cost is non-pecuniary, without sacrificing any core insights.

rational investors, respectively, their demands are:

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

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

Here, inattentive investors fail to filter out 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). Note that 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.

To solve for the equilibrium price at $t = 1$, we impose the market-clearing condition that the sum of the demands in (3) and (4) equals one. This yields

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

Because investors are risk averse, rational investors cannot fully arbitrage away the price distortion induced 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, $b = b_*$, so this term simplifies to $\alpha\theta b_*$. Intuitively, the price impact of earnings inflation increases with both α, the weight investors place on reported earnings when updating beliefs about v, and θ, the fraction of inattentive investors in the market.

Managerial incentives. In practice, firm managers face strong pressure and incentives to maintain high stock prices. Managers are often compensated with stock and stock options (Bergstresser and Philippon, 2006); initial founders may need to sell holdings after lock-up periods expire (Titman et al., 2022); controlling shareholders may pledge shares as collateral for loans from securities firms (He et al., 2022); and, perhaps most importantly, share prices are a key factor in managerial performance evaluations.

To capture stock market pressure on the manager, we assume she faces the risk of being fired at $t = 1$. Her probability of retaining her position until $t = 2$ is given by an increasing function $\Phi(p_1 - p_0)$, where $p_1 - p_0$ reflects the firm's stock market performance under her management. For $\Phi(x) \in (0, 1)$, we assume that the associated hazard-rate function, $\phi(x) \equiv \frac{\Phi'(x)}{\Phi(x)}$, is finite, strictly positive, and decreasing.[4]

If the manager remains in office until $t = 2$, her compensation is proportional to the firm's

[4]Here, $\Phi(x)$ denotes the manager's survival probability. A set of sufficient conditions for the desired properties of the hazard-rate function is that $\Phi(x)$ is increasing and concave, and that $\frac{\Phi'(0)}{\Phi(0)}$ is finite.

final dividend. If fired, she receives a fixed severance pay, normalized to zero for simplicity. At $t = 1$, the manager forms an expectation of her continuation payoff, conditional on her private signal e^n. Assuming she begins with an improper prior, her expected payoff conditional on survival is $\mathbb{E}\left(v - \frac{\kappa}{2}b^2 \middle| e^n\right) = e^n - \frac{\kappa}{2}b^2$. So the manager at $t = 1$ chooses b to maximize:

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

In (6), $p_1(b, b_*)$ highlights 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_*, as in (5).

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_*:

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

The left-hand side of equation (9) is finite and decreasing in b_*, given the assumed property of $\phi(x)$. The right-hand side is increasing in b_*, equals to zero at $b_* = 0$, and diverges to infinity as $b_* \to \sqrt{2e^n/\kappa}$. We therefore obtain the following proposition:

Proposition 1. *For any $\theta \geq 0$, there exists a unique equilibrium in which the equilibrium level of earnings inflation satisfies $b_* \in \left(0, \sqrt{2e^n/\kappa}\right)$.*

Consistent with the signal-jamming mechanism in Stein (1989),[5] the manager inflates earnings in equilibrium even when all investors are rational, that is, when $\theta = 0$.

[5] When rational investors anticipate inflation of b_*, the manager must match this expectation. Otherwise, investors subtract b_* from reported earnings, leading to a lower stock price.

Equation (9) also delivers comparative statics on how equilibrium earnings inflation b_* responds to market expectations and the cost of inflation, as summarized in the next proposition:

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

2.2 Hypothesis Development

Our model offers direct implications for how the market 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 the model, the current stock valuation p_0 in (2) moves one-to-one with $\hat{\mu}$. Therefore, regressing short-term reported earnings, $e = e^n + b_*$, on $\hat{\mu}$ yields the coefficient

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

The inequality follows from Proposition 2, which implies $Cov(b_*, \hat{\mu}) > 0$. The final equality follows because $e^n = v + \epsilon$, with ϵ independent of $\hat{\mu}$. Thus, $\frac{Cov(e^n + b_*, \hat{\mu})}{Var(\hat{\mu})}$ is the regression coefficient from using market valuation to predict short-term reported earnings, whereas $\frac{Cov(v, \hat{\mu})}{Var(\hat{\mu})}$ is the corresponding coefficient for predicting long-term fundamentals.

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 different horizons $k > 0$. The model therefore implies the following empirical hypothesis:

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

In the 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 states that earnings inflation increases with market expectations, as shown in Proposition 2. This implication holds for any $\theta \in [0, 1]$, regardless of whether investors are rational or inattentive to earnings inflation. The second part arises only when $\theta > 0$, so that a positive fraction of investors is inattentive. In that case, earnings inflation contributes to temporary overvaluation that eventually corrects, leading to lower subsequent stock returns.

We also examine a policy change that increases the cost of earnings inflation through NRGLs. Proposition 2 implies that such a policy should reduce the level of earnings management. Intuitively, as earnings management becomes sufficiently costly, its equilibrium level should decline, weakening the correlation between market valuation and earnings management.

Hypothesis 3. *Following a positive shock to the cost of earnings inflation, κ, the level of earnings management should decline. Consequently, the correlation between current stock valuation, M_t, and short-term reported earnings, E_{t+k} for small k, should weaken.*

Before turning to the empirical analysis, it is useful to contrast the implications of our model with the crystal-ball view considered by Carpenter et al. (2021). Their analysis focuses on the cross-section of firms and treats cross-sectional heterogeneity in current market valuation as information about the firms final payoff, v. Under this view, firms with higher current valuations should exhibit higher future earnings across all horizons. Our model does not rule out this information channel, but it adds an important complication: the same positive relation between current valuation and future reported earnings may also arise from earnings inflation. Specifically, our model predicts stronger reported earnings in the short run, followed by earnings reversal in the long run. This divergence motivates us to examine the predictability of current firm valuation for future earnings growth not only in the cross-section of firms, but, more importantly, within firms across periods.

Our analysis focuses on the pressure created by elevated market valuations by taking $\hat{\mu}$ as given. In a more general model with periods preceding $t = 0$, however, $\hat{\mu}$ may arise endogenously from investors' misinterpretation of earnings manipulation in earlier periods. In this case, firm heterogeneity can stem from κ, the cost of earnings inflation: managers facing lower costs may choose to report higher short-term earnings. If investors do not fully anticipate this behavior, such firms may command higher valuations, which in turn create pressure for further earnings inflation in subsequent periods to meet market expectations.

This extended setting gives rise to two-way interactions between market valuation and earnings manipulation, reinforcing each other and jointly generating the "manipulate-to-cater" mechanism. Empirically, disentangling the direction of this feedback is difficult and not central to our analysis. In either case, the presence of earnings manipulation alters the interpretation of the predictability of market valuation for future earnings in ways that differ fundamentally from the crystal-ball view.

3 Market Valuation and Future Earnings

In this section, we first describe the data used in our analysis and then examine the relationship between stock valuation and future earnings. We measure stock valuation by the ratio of a firms market cap to its asset book value, that is, M_t/A_t. We begin with the cross-sectional predictability of M_t/A_t for future earnings. The core idea is to assess whether firms with higher equity valuations subsequently generate higher earnings than firms with lower valuations. We then turn to a complementary time-series perspective, asking whether a firms unusually high valuation in the current year predicts its own future earnings growth. Our results reveal important differences between these two perspectives, shedding light on the manipulate-to-cater mechanism proposed in this paper.

3.1 Data

Following Carpenter et al. (2021), our sample period begins in 1995 and extends through 2024, incorporating the most recent data. We obtain financial information and stock returns of publicly listed Chinese firms from the China Stock Market and Accounting Research (CSMAR) database. The sample includes only non-financial A-share firms, including those listed on the STAR and ChiNext boards. Unless otherwise specified, our main analysis excludes the bottom 5% of stocks ranked by total assets.[6]

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 ($Accruals$). Dividend payouts include both annual cash dividends and net share repurchases. Operating cash flow is defined as EBITDA minus the change in working capital and income taxes. To ensure that market participants have access to the accounting information, we match accounting variables to stock trading data six months after the fiscal year end. Firms that are delisted over the five-year window relative to year t are assigned zero earnings. All variables are adjusted for inflation using the GDP deflator obtained from CSMAR. Missing values for earnings and payouts are set to zero.

An important accounting variable in our analysis, capturing earnings management by Chinese firms, is non-recurring gains and losses (NRGLs). The China Securities Regulatory Commission (CSRC) has required public companies to disclose NRGLs in their annual financial

[6]We exclude firms with extremely small assets for two reasons. First, doing so helps mitigate potential contamination from non-fundamental pricing factors unique in China, such as the shell-value effects discussed in Lee et al. (2023) and Liu et al. (2019). Second, very small values of total assets A_t, which serve as the scaling variable, may generate extreme ratios and hence poorly behaved observations. For reference, Bai et al. (2016) avoid this issue by restricting their sample to S&P 500 firms. Importantly, our main results remain robust when all stocks are included.

statements since 1999, making these data available only after 1999.

For the U.S. comparison sample, we obtain annual accounting information from the Compustat. Following Bai et al. (2016), we focus on non-financial S&P500 firms over the period from 1960-2024 and also report results for the more recent period 1995-2024. All variables are adjusted for inflation using the World Bank GDP deflator. We do not fill missing earnings data. In the U.S. data, NRGL corresponds to extraordinary items. Details on variable construction are provided in Section A.1 of the Online Appendix. For both the China and U.S. samples, all ratio variables are winsorized at the 1st and 99th percentiles for each year.

Table I reports summary statistics of the main variables at the stock level. For Chinese A-share firms, the average E/A ratio is 3.19%, with the 25th and 75th percentiles equal to 1.21% and 6.20%, respectively. The average D/A ratio is 1.33%, with the 25^{th} and 75^{th} percentiles equal to 0.00% and 1.85%. The average NRGLs-to-asset ratio is 0.85%, with a standard deviation of 1.56%.

Panel B presents summary statistics for U.S. S&P 500 firms, with average E/A ratio being 6.02% and average D/A ratio being 4.03%. These values are higher than those observed for A-share firms, likely reflecting the fact that our U.S. sample consists of large, high-quality S&P500 firms, whereas the Chinese sample includes all listed firms regardless of quality.[7]

3.2 Carpenter, Lu, and Whitelaw (2021) Revisited

We begin by replicating the main result of Carpenter et al. (2021). Specifically, we conduct cross-sectional regressions of firms' future earnings over 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).

Main results. 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 follow Carpenter et al. (2021) to report its value multiplied by the standard deviation $\sigma(\log(M_{i,t}/A_{i,t}))$, which represents the predicted variation in future earnings associated with a one standard deviation change in valuation. We also report the average coefficient across sample years.

[7]This difference in sample composition is also present in Carpenter et al. (2021), whose sample construction we largely follow to facilitate comparison.

The regression results, reported in Table II, remain consistent with Carpenter et al. (2021). 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 coefficients for two periods: 1995–2016 (the sample period used in Carpenter et al. (2021)) and 1995–2024. During 1995–2016, the predicted variation equals 0.017 (t-stat $= 7.9$) for $k = 1$, increasing to 0.025 for $k = 3$ (t-stat $= 6.1$) and 0.023 for $k = 5$ (t-stat $= 3.7$).[8]

For the U.S. sample of S&P 500 firms, the estimates yield larger but broadly comparable predicative magnitudes. The predicted variation of $\log(M_{i,t}/A_{i,t})$ equals 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 closely aligns with the findings of Carpenter et al. (2021). The stronger predictability of $\log(M_{i,t}/A_{i,t})$ in more recent years is also consistent with Bai et al. (2016), who document increasing price informativeness in the U.S. stock market.

One notable pattern in Table II is that price informativeness in China, based on the recent 1995–2024 sample, is lower than that from the 1995–2016 sample in Carpenter et al. (2021). Pointing to a decline in price informativeness for reported earnings in recent years in China's A-share market, we associate this decline to China's 2020 reform of delisting rules (see later in Section 4.4).

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. While the magnitude generally increases with k in the U.S. market, price informativeness in China increases when $k < 3$ but flattens—and even reveres—when $k \geq 3$. This suggests that the predictability of future earnings initially rises but later weakens. This reversal pattern differs from the findings of Carpenter et al. (2021), who show that earnings predictability increases with k over the 1995–2016 sample.

Summary. Overall, Panel A of Table II and Figure I confirm the main finding of Carpenter et al. (2021): in China's 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, in which market valuations reflect underlying fundamentals, consistent with the crystal-ball 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.

[8]Results based on the sample of *all* A-share non-financial firms (including those in the bottom 5% by total assets) are slightly larger in magnitude and more comparable to those reported in Carpenter et al. (2021); see Online Appendix Table A.1. For the reasons discussed in footnote 6, we consider the sample excluding the bottom 5% to better represent a setting for testing between the information-based theory in Bai et al. (2016) and our proposed mechanism.

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 2.2 and represents a meaningful departure from the conclusions of Carpenter et al. (2021). While both channels—the "crystal ball" effect and the "manipulate-to-cater" effect—may operate simultaneously in China's A-share market, we focus on validating the latter by directly testing for the predicted reversal effect in Section 3.4.

3.3 Predicting Payouts

The possibility that firms actively manage earnings makes reported earnings an imperfect 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 susceptible to manipulation.

We adopt the regression specified in (10), replacing earnings with total payouts denoted by $D_{t+1}, ..., D_{t+5}$. Total payouts include both cash dividends and share repurchases. If higher firm earnings ultimately translate into greater payouts to investors, stock valuation should exhibit similar predictive power for payouts as it does for earnings.

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

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

Here we additionally control for current payouts;[9] and as before, we multiply the coefficient on $\log(M_{i,t}/A_{i,t})$ by its standard deviation $\sigma(\log(M_{i,t}/A_{i,t}))$ and report the average over our sample period.

The regression results, reported in Table III, show that stock valuation has little predictive power for future payouts in China. Over 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 $= 9.77$). It increases only slightly to 0.004 for $k = 3$ (t-stat $= 7.21$) and remains at 0.004 for $k = 5$ (t-stat $= 5.69$). Overall, the predictive power of stock valuation for payouts is much smaller in magnitude than its predictability for earnings, as shown in Table II.

In contrast, for U.S. S&P 500 firms, market valuation continues to hold strong predictive power for future payouts. As shown in the bottom panel of Table III, 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 these results by plotting the predicted variation of $\log(M_{i,t}/A_{i,t})$ with

[9] Our results are almost the same qualitatively if we do control for current payouts.

95% confidence intervals for $k \in \{1, \ldots, 5\}$ in both markets. The stark contrast in payout predictability between China and the U.S. suggests that reported earnings in China may be actively managed and do not fully reflect fundamentals.

3.4 Earnings Reversal

The cross-sectional evidence based on Fama-MacBeth regressions on earnings predictability points to long-run earnings reversal among Chinese firms, consistent with potential earnings management. To further investigate, we adopt a time-series approach, testing whether firms with higher valuations subsequently exhibit stronger earnings reversals over longer horizons relative to their own medium-term earnings.

Specifically, we run panel regressions for each equation below:

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

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

$$\frac{E_{j,t+5} - E_{j,t+1}}{A_{j,t}} = \alpha + \beta^{1\to5} \log\left(\frac{M_{j,t}}{A_{j,t}}\right) + \gamma\frac{E_{j,t}}{A_{j,t}} + \lambda\frac{D_{j,t}}{A_{j,t}} + v_t + u_j + \epsilon_{j,t}. \tag{14}$$

Unlike (10), the dependent variable in these regressions is the change in earnings over different horizons, scaled by current assets: (12) from year t to $t + 1$, (13) from year $t + 1$ to $t + 3$, and finally (14) from $t+1$ to $t+5$. The coefficients of interest are $\beta^{1\to3}$ and $\beta^{1\to5}$; negative estimates indicate long-run earnings reversal predicted by current stock valuation.[10]

To illustrate the difference between cross-section and time-series, we progressively introduce different fixed effects. We begin by estimating these regressions with only time fixed effect, which capture cross-sectional variation; note this is matches closely with the specification of Carpenter et al. (2021), which is essentially a Fama-MacBeth regression. We then include only firm fixed effects u_j's to examine the time-series dynamics within firms, and finally we estimate the full panel specification including both time and firm fixed effects, v_t's and u_j's. Driscoll–Kraay standard errors with one lag are reported to account for both cross-sectional and temporal dependence.

The regression results, reported in Table IV, support the presence of earnings reversal in the Chinese market. In Panel A, which includes time fixed effects only so corresponds to cross-sectional analysis, the coefficients $\beta^{0\to1}$ and $\beta^{1\to3}$ are both positive, with t-statistics of 10.8 and 1.33, respectively. The coefficient $\beta^{1\to5}$ is negative but statistically insignificant. The flattening

[10] Recall that firms that are delisted over the three- or five-year window relative to year t are assigned zero earnings in the regression, so our analysis is free of survivor-ship bias.

of earnings changes between year 1 and year 5 is consistent with Table II, where we show similar magnitudes of β_3, β_4 and β_5 in regression (10).

If firms manage earnings to align with market expectations embedded in current valuations, earnings reversal should appear more clearly in the time-series dynamics of individual firms. This corresponds to specifications in Panel B which includes firm fixed effects only. Consistent with this prediction, we observe that $\beta^{1\to3}$ is negative (with a t-statistic of 0.47) and $\beta^{1\to5}$ is significantly negative (with a t-statistic of 2.86).

Panel C reports the full specification including both time and firm fixed effects. The coefficient $\beta^{0\to1}$ remains significantly positive, with a t-statistic of 22.6. The estimate of $\beta^{1\to3}$ is close to zero, while $\beta^{1\to5}$ is significantly negative, with a t-statistic of 2.15, indicating the presence of long-run earnings reversal.

Turing to the U.S. S&P 500 sample, across all Panels A–C we observe no evidence of long-run earnings reversal. Short-term earnings growth predictability ($\beta^{0\to1}$) remains significantly positive, while predictability at longer horizons ($\beta^{1\to3}$ and $\beta^{1\to5}$) is either positive or statistically insignificant. The absence of reversal in the U.S. market highlights an important contrast with the Chinese A-share market.

3.5 Price Informativeness of Dually Listed A-H Shares

To provide further evidence supporting our hypothesis, we exploit a sample of firms that are dually listed in both the Chinese A-share market and the Hong Kong market. We obtain the list of A-H dual-listed firms from the CSMAR database, which 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. Because the Hong Kong stock market generally imposes more stringent disclosure requirements, the reporting quality of dual-listed firms is likely higher than that of firms listed solely in the A-share market. In the context of our model in Section 2, this institutional difference can be interpreted as dual-listed firms 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, we conjecture that the correlation between M_t and subsequent reported earnings E_{t+k} should be weaker for dual-listed firms than for other A-share 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 estimate the following cross-sectional regression:

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

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 measured using A-share prices.[11]

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 well with our Hypothesis 3.

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 than those of A-share-only stocks. However, since Carpenter et al. (2021) interpret this correlation as genuine price informativeness, their explanation for the lower predictability of dual-listed stocks differs fundamentally from ours. They argue that dual listing makes A-share prices less informative because differences in how Hong Kong investors value firms introduce additional noises into A-share 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 A-share market is dominated by relatively inexperienced retail investors (An et al., 2022).[12]

A natural implication of this disparity in investor sophistication is that, for A-H 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 documents a persistent valuation wedge between A and H shares (e.g., Jia et al., 2017). Given these 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 forming a more accurate belief

[11]We choose the A-share market valuation because we are testing Hypothesis 3 regarding κ in Section 2.2, with the presumption that the market price with the presence of irrational investors is subject to manipulation. H-share market valuation is less appropriate in this test because, as explained shortly, H-share market price reflects the fundamental better.

[12]For example, according to the website of the Hong Kong Exchange, "institutional investors from Hong Kong and overseas account for about 65% of total turnover." In contrast, the corresponding numbers in the A-share market is only 11.7%, with retail investors accounting for 86.6% of trading volume, as documented in (An et al., 2022).

about the firm's fundamentals than their A-share counterparts.[13]

To test this hypothesis, we calculate market valuations based on A-share and H-share prices respectively, and apply the cross-sectional regression in Equation (10) to the our dual-listed sample but include both market valuations as regressors.[14] Specifically, for each year t, we estimate the following cross-sectional regression:

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

Here, M^H and M^A denote the firm's 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 that the predictive power of H-share market valuation is consistently significant, whereas that of A-share valuation is relatively 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 turns negative for $k \geq 2$. This contrast provides direct evidence that A-share prices contain less information about firms future earnings than H-share prices.

4 Earnings Management

Accounting rules often grant firm managers a degree of discretion in reporting earnings, balancing the need for accurate financial representation with the flexibility required to reflect complex business realities. Because firms operate across diverse industries and economic environments, rigid standardization of every transaction is impractical. Such discretion allows managers to exercise judgment in areas such as asset valuation, revenue recognition, and provisions for future losses. While this flexibility can make financial reporting more informative about a firm's future prospects, it also creates opportunities for manipulation.

In this section, we first provide a brief overview of earnings management practices in China, introducing non-recurring gains and losses (NRGLs) as an important tool used by Chinese listed firms. We then test Hypothesis 2 by decomposing reported earnings into three components (cash flows, accruals, and NRGLs), and examining how market valuation predicts each component

[13] 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 framework, it is plausible that the more sophisticated H-share investors would better anticipate future earnings—both natural and managed. This scenario goes beyond our model, which assumes a final liquidation date at $t = 2$, and we leave it to future research to explore this extension.

[14] We require at least 20 dual-listed firms in a given year, resulting in a sample period from 2002 to 2024.

in the future. Finally, we test 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 served 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 China (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 enterprise groups—provide a flexible mechanism for shifting profits, smoothing earnings, and navigating regulatory constraints. Firms can inflate revenues by selling goods or services at above-market prices to related entities or reduce earnings in strong years by selling at artificially low prices, thereby creating reserves for future downturns. These practices allow firms to manage reported performance across periods.[15] Highlighting tunneling behavior and governance concerns, prior studies (Fisman and Wang, 2010; Jiang et al., 2010; Li et al., 2020; Allen et al., 2024) analyze RPTs as an important channel of earnings management among Chinese listed firms. Although information on RPTs is available, disclosures generally do not specify the direction of profit flows, making it difficult to construct empirical measures that capture their overall impact on firm earnings.[16]

Non-recurring gains and losses (NRGLs) refer to income and expenses that are not directly related to a company's core business operations and are typically onetime, irregular, or extraordinary in nature. Before 2020, regulatory authorities relied primarily on net profit—which includes both operating earnings and NRGLs—for key regulatory decisions, including IPO eligibility and delisting criteria. As a result, firms frequently used NRGLs as a tool for earnings

[15] 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 monitoring of related parties and are intended to enhance earnings quality, strengthen corporate governance, and protect 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.

[16] To address this challenge, Fisman and Wang (2010) and Allen et al. (2024) focus on loan-based RPTs and measure tunneling by tracking money outflows from the listed firm. However, loan-based RPTs—typically in the form of loan guarantees—represent only a small share of total RPT activity.

management, employing strategies such as asset sales or one-off government subsidies from affiliated local governments to meet regulatory thresholds and avoid delisting. In 2020, a regulatory reform, which we will study shortly, excluded NRGLs from the net profit measure used for these regulatory purposes. This reform underscores the practical importance of NRGLs in the Chinese market and motivates our use of NRGLs as the primary measure of earnings management.

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 NRGLs. In both U.S. and China, operating cash flows are generally more difficult to manipulate than earnings.[17] By contrast, accruals and NRGLs represent 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 subtracting the sum of Change in Working Capital and Income Taxes.[18] Accrual is calculated as earnings (E) minus OCF and NRGLs. NRGLs for Chinese firms are disclosed in notes to financial statements. For U.S. firms, NRGLs correspond to extraordinary items, defined as the difference between net income (`ni`) and net income before extraordinary items (`ib`) in Compustat.

We re-estimate the baseline regression in (10) using each of the three earnings components as the dependent variable, while retaining controls for current earnings and payouts. Specifically, for $k \in \{1, 2, \ldots, 5\}$, we estimate:

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

where y can be OCF, Accruals, and NGFLs. Data on NRGLs are available for Chinese firms beginning in 1999. For earlier years, we use non-operating profit as a proxy for NRGLs.

Regression results are reported in Table VI. As shown on the right side of Panel A which concerns OCF, market valuation in the S&P 500 sample remains a significant predictor of future cash flows. The predictive variation associated with $\log(M_{i,t}/A_{i,t})$ ranges from 0.0274 (0.0224) to 0.0603 (0.0555) as k increases from 1 to 5 over the 1995–2024 (1960–2024) sample periods, with all estimates statistically significant. These magnitudes are comparable to the predictive power of valuation for future earnings and dividends, indicating that valuation consistently predicts earnings, dividends, and cash flows in the U.S. market.

[17]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.

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

In contrast, for the Chinese firm sample (1995-2016), the predictive coefficient on $\log(M_{i,t}/A_{i,t})$ is weak and even negative at short horizons: -0.009 for $k = 1$ (t-stat $= 3.19$), rising slightly to 0.002 for $k = 3$ (t-stat $= 0.69$) and 0.006 for $k = 5$ (t-stat $= 1.40$). These results are similar to—or even statistically weaker than—those for predicting payouts in (11). This finding rules out an alternative explanation for the weak predictability of M for payouts in China, namely that Chinese firms follow payout policies fundamentally different from those of U.S. firms. In other words, the evidence does not support the view that Chinese firms simply retain a larger share of their operating cash flows rather than distributing them to shareholders.

Panel B reports the result when we take accruals as the dependent variable. For China, market valuation shows a significant positive correlation with future accruals, although the magnitude declines as the horizon extends to $k = 5$. In the U.S. sample, the correlation is positive only for $k = 1$ and becomes significantly negative at longer horizons.

Finally, we report the results on NRGLs in Panel C. As a benchmark, in the U.S. sample the predictability of market valuation for NRGLs is economically small. For China, $\log(M_{i,t}/A_{i,t})$ positively predicts $NRGL_{i,t+1}$, with t-statistics above 4.7. This positive relationship persists and strengthens as the forecast horizon extends from $k = 2$ to $k = 5$. These findings support Hypothesis 2, in that highly valued firms are more likely to engage in earnings management to align reported earnings with market expectations embedded in 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 appears to stem primarily from NRGLs.

4.3 Return Predictability of Managed Earnings

To assess whether investors fully recognize the managed component of reported earnings, we now examine whether firms' NRGLs predict subsequent stock returns. If investors understand that high earnings driven by large NRGLs are unlikely to persist, stock prices should reflect this information, implying no subsequent under-performance (Stein, 1989). Conversely, if investors fail to fully account for the transitory nature of managed earnings, firms with large NRGLs may become overvalued, leading to lower subsequent returns, as predicted by Hypothesis 2.

In Chinese A-share market NRGLs disclosed in firms' annual reports, which are typically released in April–May. We then 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 earnings (E) and its three components (OCF, Accruals, and NRGLs). We also control for a set of commonly used stock characteristics and include industry fixed effects.

Table VII reports the results. Column (1) includes only E/A into the regression and find no significant return predictability. In column (2), we add OCF/A, whose coefficient is negative but insignificant. Column (3) includes $Accruals/A$, which displays a positive coefficient with a t-stat of 2.15. This finding contrasts with the accrual literature based the U.S. data, which typically documents negative return predictability of accruals (e.g., Sloan, 1996).

Finally, as shown in columns (4), $NRGL_t$ significantly predict lower stock returns in the following year (with a t-statistic of 5.6). In terms of economic magnitude, a two-standard deviation increase in NRGL is associated with a 3.03% ($= 2 \times 0.01565 \times 0.97$) decline in returns over the subsequent year. In column (5), we replace E/A with its three components, the negative predictability of NRGLs remains statistically significant.

Taken together, the findings from Tables VI and VII confirm Hypothesis 2: market pressure, reflected in high stock valuations, induces firms to rely more heavily on NRGLs. And, because Chinese investors do not fully see through earnings management via NRGLs, these inflated earnings in turn help sustain market overvaluation, as investors fail to fully recognize the extent to which NRGLs contribute to reported earnings.

4.4 The 2020 Reforms of Delisting Rules

To further strengthen identification in our tests, we exploit the 2020 reform of the delisting rules, which 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 reform process began in March 2019, when new delisting standards were introduced for the STAR board on the Shanghai Stock Exchange as a pilot program. In March 2020, the National Peoples Congress passed the new Securities Law, and in December 2020 the revised delisting rules were formally implemented for all mainboard firms on all Chinese 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 channel of earnings management. The first fiscal year affected by the new rule was 2020, implying that earnings reported from 2020 onward should be less susceptible to manipulation through NRGLs. In our event study, we therefore define 2020 and subsequent years as the postevent period. Additional details on the reform timeline are provided in Online Appendix A.2.

Policy shock on NRGLs. Linking this reform to the simple theoretical framework in Section 2, the revised delisting rules effectively increased the cost of earnings management, creating a natural experiment to test Hypothesis 3. We first examine the impact of the reform on the use of NRGLs. Figure III shows that firms reporting high NRGLs in the pre-reform period significantly reduced their use of NRGLs beginning in 2020. This pattern reflects the regulatory change that NRGLs could no longer be included in reported earnings for compliance purposes in the post-reform period, confirming the effectiveness of the 2020 delisting rule reform.

Policy shock on market value and future earnings. Given that the managed component of reported earnings—namely NRGLs—declined for some firms after the 2020 rule change, we expect the correlation between firms' market value ($M_{i,t}$) and future reported earnings ($E_{i,t+k}$) to weaken in the post-2020 period, as suggested by Hypothesis 3.

We therefore 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:

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

for $k \in \{1, 2, 3\}$. We restrict $k \leq 3$ because our sample ends in 2024 while the policy year is 2020. 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 reports the results. The coefficient on the interaction term is significantly negative and equals -0.005 (t-stat $= 9.62$) for $E_{i,t+1}$, which is sizable relative 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 $= 10.6$) and -0.008 (t-stat $= 8.01$), respectively, while the coefficients on $\log(\frac{M_{i,t}}{A_{i,t}})$ are 0.024 and 0.026.

We also run the same test using the sample of U.S. S&P 500 firms, and find positive coefficients on the interaction term. This exercise helps rule out the possibility that the weaker predictability of market valuation for earnings in China reflects a global time trend, reinforcing the China-specific nature of the effect associated with the policy shock.[19]

To complement the analysis reported in Table VI, Panel B further examines the decomposition of earnings by replacing the dependent variable with cash flows, accruals, and NRGLs for Chinese firms but in the specification of (18). The coefficient on the interaction term is

[19]This policy shock coincided with the onset of the Covid pandemic, which affected China and the United States with different timing and intensity. Nevertheless, we see no clear reason to attribute the post-2020 change in the predictability of market valuation for future earnings to the pandemic.

significantly positive, at 0.003 (t-stat = 2.08) for OCF_{t+1}, which is substantial relative to the coefficient on $\log(\frac{M_{i,t}}{A_{i,t}})$. This result, al beit preliminary, suggests that post-reform the market value has become more informative about firms' underlying fundamentals.

Finally, Hypothesis 3 implies that the correlation between market valuation and subsequent NRGLs should weaken significantly after the reform. This is indeed the case. As shown in Columns (7)–(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), the coefficient on the interaction term when predicting $t+3$ NRGLs is -0.001, compared with 0.005 for the coefficient on $\log(M_{i,t}/A_{i,t})$. Interestingly, the correlation between market valuation and accruals also appears to weaken after the reform, as shown in Columns (4)–(6).

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

5 Conclusion

This article revisits 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; but these higher earnings do not translate into greater payouts to shareholders and eventually reverse over longer horizons. Furthermore, we provide direct evidence of earnings management through NRGLs, exploiting the 2020 delisting rule reform as an exogenous shock to such practices.

The key economic message of our paper is that the strong link between stock prices and future earnings in Chinese stock market is not solely driven by the markets ability to aggregate and reveal information. Instead, firms' endogenous responses—namely, their incentives to cater to market valuations through earnings manipulation—constitute an equally important force behind this predictability. This distinction carries important implications for both policy and market efficiency; for instance, observed price informativeness in China may be overstated, and policies that tighten accounting rules and delisting criteria can improve the informational content of earnings.

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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 5% 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	0.03195	0.06893	0.00097	0.01216	0.03419	0.06200	0.09326	41646
E_{t+1}/A_t	0.03713	0.06875	-0.01024	0.01019	0.03387	0.06726	0.10867	41646
E_{t+3}/A_t	0.04598	0.10033	-0.03195	0.00675	0.03299	0.07782	0.14513	41646
E_{t+5}/A_t	0.05016	0.14416	-0.04345	0.00411	0.03127	0.08494	0.17471	41646
D_t/A_t	0.01326	0.01871	0.00000	0.00000	0.00641	0.01851	0.03686	41646
D_{t+1}/A_t	0.01429	0.02133	0.00000	0.00000	0.00627	0.01943	0.04015	41646
D_{t+3}/A_t	0.01742	0.02901	0.00000	0.00000	0.00597	0.02212	0.04959	41646
D_{t+5}/A_t	0.02063	0.03788	0.00000	0.00000	0.00535	0.02445	0.05861	41646
OCF_t/A_t	0.06352	0.10967	-0.05626	0.01827	0.06893	0.12117	0.18357	41646
OCF_{t+1}/A_t	0.06374	0.13692	-0.06967	0.01094	0.06575	0.12930	0.20650	41646
OCF_{t+3}/A_t	0.07233	0.19381	-0.08649	0.00160	0.06385	0.14311	0.25678	41646
OCF_{t+5}/A_t	0.08831	0.25473	-0.08521	0.00000	0.06350	0.16045	0.31244	41646
$Accruals_t/A_t$	-0.04127	0.11165	-0.16914	-0.09616	-0.03689	0.00838	0.07716	41646
$Accruals_{t+1}/A_t$	-0.03768	0.14058	-0.18266	-0.10507	-0.04041	0.01383	0.09621	41646
$Accruals_{t+3}/A_t$	-0.03963	0.19775	-0.21680	-0.11541	-0.04020	0.01503	0.12017	41646
$Accruals_{t+5}/A_t$	-0.05529	0.25434	-0.26452	-0.12921	-0.04193	0.01092	0.12076	41646
$NRGL_t/A_t$	0.00847	0.01565	0.00000	0.00063	0.00354	0.00914	0.02012	41646
$NRGL_{t+1}/A_t$	0.00968	0.01751	0.00000	0.00067	0.00403	0.01057	0.02365	41646
$NRGL_{t+3}/A_t$	0.01211	0.02177	0.00000	0.00077	0.00495	0.01329	0.03042	41646
$NRGL_{t+5}/A_t$	0.01476	0.02930	0.00000	0.00077	0.00545	0.01542	0.03641	41646
$\log(M_t/A_t)$	0.36687	0.80726	-0.70370	-0.16530	0.40448	0.93049	1.38363	41646
$\log(M_t)$	8.53241	0.95383	7.41304	7.86777	8.43050	9.08125	9.81549	41646
B/M	0.43160	0.29914	0.14406	0.22327	0.35885	0.55976	0.82164	41646
RET	0.18133	0.69531	-0.40365	-0.23985	0.00000	0.36833	1.00374	41646
$TURNOVER$	5.88712	4.85559	1.62240	2.66930	4.54130	7.57529	11.63099	41646

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 (excluding the bottom 5% of stocks ranked on total asset):

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

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. 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	0.005	1.831	0.017	4.250	0.033	4.300	0.034	4.410	0.039	4.380
1996	0.031	8.149	0.042	5.920	0.047	6.230	0.046	5.230	0.035	3.020
1997	0.033	6.830	0.038	7.550	0.039	7.170	0.031	4.000	0.013	1.470
1998	0.020	7.607	0.024	7.360	0.019	4.500	0.003	0.707	-0.001	-0.201
1999	0.013	5.200	0.018	5.490	0.007	2.250	0.001	0.186	-0.011	-2.240
2000	0.007	2.952	-0.000	-0.097	-0.002	-0.626	-0.009	-2.910	-0.011	-3.140
2001	0.003	1.270	0.005	2.380	0.004	1.520	0.003	1.100	0.004	1.270
2002	0.009	4.596	0.007	2.790	0.007	2.570	0.009	3.460	0.011	3.260
2003	0.016	7.171	0.017	7.470	0.014	7.080	0.017	5.900	0.019	5.480
2004	0.022	10.295	0.023	12.700	0.027	8.680	0.028	8.490	0.026	7.420
2005	0.019	10.265	0.026	9.400	0.030	9.390	0.029	8.340	0.031	6.660
2006	0.025	9.171	0.029	7.290	0.029	9.280	0.030	7.680	0.040	7.550
2007	0.031	7.395	0.030	9.380	0.033	7.200	0.045	7.520	0.044	8.260
2008	0.022	9.149	0.030	9.540	0.036	8.320	0.039	8.860	0.040	7.630
2009	0.020	11.529	0.027	10.900	0.036	9.870	0.038	8.370	0.042	7.950
2010	0.014	7.635	0.020	7.560	0.024	6.160	0.028	7.170	0.034	6.740
2011	0.018	9.743	0.019	8.860	0.022	8.980	0.034	9.980	0.045	10.000
2012	0.011	7.857	0.017	11.400	0.025	9.880	0.037	9.730	0.034	7.280
2013	0.014	10.507	0.026	11.100	0.040	11.000	0.037	8.220	-0.022	-2.540
2014	0.017	10.832	0.026	9.600	0.023	6.590	-0.018	-3.020	-0.020	-3.100
2015	0.017	10.231	0.019	8.250	-0.002	-0.433	-0.002	-0.562	0.000	0.099
2016	0.010	8.250	0.007	3.120	0.009	3.490	0.012	4.410	0.015	5.100
2017	0.009	5.397	0.016	9.040	0.021	10.500	0.023	10.100	0.023	8.730
2018	0.023	16.582	0.026	17.500	0.026	14.900	0.027	13.400	0.020	11.000
2019	0.028	20.239	0.030	17.500	0.029	14.600	0.022	11.900	0.019	9.820
2020	0.024	18.647	0.025	16.300	0.018	11.900	0.015	10.400		
2021	0.015	14.688	0.010	8.570	0.008	6.950				
2022	0.005	5.661	0.005	5.860						
2023	0.007	9.726								
Averages China										
1995 to 2016-k	0.017***		0.022***		0.025***		0.025***		0.023***	
	(7.951)		(7.505)		(6.132)		(4.785)		(3.734)	
1995 to 2024-k	0.017***		0.021***		0.022***		0.022***		0.019***	
	(8.877)		(8.606)		(6.978)		(5.069)		(3.513)	
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)	

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 5% 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	0.409	0.002	1.180	0.002	0.962	0.000	0.188	0.008	3.340
1996	0.005	3.481	0.005	3.130	0.005	2.960	0.013	5.560	0.010	4.240
1997	0.001	1.038	0.002	1.860	0.010	5.290	0.007	5.040	0.005	3.820
1998	-0.000	-0.058	0.006	5.650	0.004	5.160	0.004	4.030	0.002	1.520
1999	0.004	5.165	0.003	3.710	0.002	3.260	0.000	0.554	0.001	0.878
2000	0.001	2.244	0.001	1.420	-0.001	-1.470	-0.001	-1.680	-0.002	-2.390
2001	0.001	2.391	-0.000	-0.523	-0.000	-0.517	-0.001	-0.877	-0.001	-1.590
2002	0.001	1.812	0.001	1.320	0.001	0.891	-0.001	-0.808	-0.000	-0.151
2003	0.003	5.421	0.002	3.930	0.002	2.580	0.002	2.050	0.004	4.550
2004	0.003	6.239	0.004	5.790	0.004	5.000	0.005	6.900	0.005	5.910
2005	0.003	5.658	0.003	4.730	0.005	7.330	0.005	6.970	0.006	5.950
2006	0.002	4.174	0.003	6.440	0.004	7.130	0.004	5.160	0.006	5.290
2007	0.005	8.878	0.005	7.430	0.005	6.140	0.007	7.180	0.010	7.460
2008	0.003	5.902	0.003	4.240	0.005	5.350	0.007	6.380	0.007	5.920
2009	0.002	4.820	0.005	6.520	0.007	8.030	0.006	7.000	0.009	6.000
2010	0.003	6.851	0.004	7.710	0.003	5.650	0.005	5.680	0.006	4.800
2011	0.002	7.378	0.003	6.550	0.004	6.350	0.005	6.650	0.007	7.680
2012	0.001	3.898	0.002	5.350	0.004	6.540	0.005	7.060	0.006	5.990
2013	0.002	5.463	0.003	6.830	0.005	8.020	0.006	6.380	0.005	4.360
2014	0.001	4.576	0.003	5.650	0.003	4.100	0.003	2.710	0.003	3.380
2015	0.002	4.712	0.003	4.830	0.002	3.550	0.003	3.980	0.003	3.760
2016	0.001	4.724	0.002	4.390	0.003	5.150	0.004	5.120	0.004	4.490
2017	0.002	5.558	0.003	6.700	0.004	8.110	0.004	6.590	0.005	6.370
2018	0.003	9.174	0.004	10.400	0.005	9.260	0.005	8.210	0.007	10.600
2019	0.003	11.139	0.005	10.300	0.005	8.730	0.006	11.000	0.006	10.400
2020	0.003	10.001	0.004	9.560	0.006	12.800	0.005	11.500		
2021	0.003	10.260	0.004	12.900	0.004	11.600				
2022	0.003	12.663	0.003	11.400						
2023	0.002	10.120								
Averages China										
1995 to 2016-k	0.002***		0.003***		0.004***		0.004***		0.005***	
	(7.850)		(7.640)		(5.128)		(4.076)		(3.928)	
1995 to 2024-k	0.002***		0.003***		0.004***		0.004***		0.005***	
	(10.100)		(10.100)		(7.190)		(5.960)		(5.755)	
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 5% of stocks ranked on total asset),

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

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

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

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)		
	(1)	(2)	(3)	(4)	(5)	(6)
	$E_{t+1}-E_t$	$E_{t+3}-E_{t+1}$	$E_{t+5}-E_{t+1}$	$E_{t+1}-E_t$	$E_{t+3}-E_{t+1}$	$E_{t+5}-E_{t+1}$
$\log(M_t/A_t)$	0.021***	0.005	-0.003	0.042***	0.006	0.023***
	(10.755)	(1.339)	(-0.472)	(18.717)	(0.905)	(7.796)
E_t/A_t	-0.692***	-0.133***	-0.184***	-0.813***	-0.128***	-0.141***
	(-12.707)	(-4.965)	(-4.892)	(-14.544)	(-3.426)	(-3.897)
D_t/A_t	0.808***	0.116	0.368**	0.141***	0.044	-0.021
	(8.017)	(1.205)	(2.352)	(5.516)	(0.900)	(-0.747)
Firm FE	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	42521	42521	42521	24382	24382	24382

Panel B: With firm fixed effect

	China (1995-2024)			US SP500 (1960-2024)		
	(1)	(2)	(3)	(4)	(5)	(6)
	$E_{t+1}-E_t$	$E_{t+3}-E_{t+1}$	$E_{t+5}-E_{t+1}$	$E_{t+1}-E_t$	$E_{t+3}-E_{t+1}$	$E_{t+5}-E_{t+1}$
$\log(M_t/A_t)$	0.033***	-0.002	-0.017***	0.044***	-0.015	-0.004
	(9.240)	(-0.467)	(-2.858)	(11.207)	(-1.327)	(-1.122)
E_t/A_t	-0.842***	-0.202***	-0.302***	-0.869***	-0.161***	-0.139***
	(-14.232)	(-2.910)	(-3.408)	(-14.478)	(-4.298)	(-3.342)
D_t/A_t	0.480***	-0.186	-0.147	0.044*	-0.079**	-0.190***
	(6.052)	(-1.506)	(-0.869)	(1.941)	(-2.042)	(-4.978)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No
N	42521	42521	42521	24382	24382	24382

Panel C: With firm and time fixed effect

	China (1995-2024)			US SP500 (1960-2024)		
	(1)	(2)	(3)	(4)	(5)	(6)
	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+1}$	$E_{t+1} - E_t$	$E_{t+3} - E_{t+1}$	$E_{t+5} - E_{t+1}$
$\log(M_t/A_t)$	0.044***	0.002	-0.016**	0.056***	-0.020	-0.006
	(22.577)	(0.339)	(-2.153)	(18.453)	(-1.471)	(-1.613)
E_t/A_t	-0.860***	-0.213***	-0.321***	-0.960***	-0.145***	-0.168***
	(-16.716)	(-2.882)	(-3.669)	(-19.141)	(-4.679)	(-4.601)
D_t/A_t	0.449***	-0.212**	-0.233*	0.100***	0.003	-0.067**
	(7.226)	(-2.209)	(-1.713)	(4.512)	(0.075)	(-2.410)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	42521	42521	42521	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 5% 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	-0.009***	-0.002	0.002	0.006	0.006	1995–2024-k	0.0274***	0.0386***	0.0454***	0.0528***	0.0603***
	(-3.190)	(-1.036)	(0.693)	(1.408)	(1.400)		(17.360)	(22.664)	(27.500)	(25.827)	(21.681)
1995–2024-k	-0.009***	-0.000	0.003	0.007**	0.007**	1960–2024-k	0.0224***	0.0330***	0.0406***	0.0482***	0.0555***
	(-3.896)	(-0.179)	(1.523)	(2.492)	(2.278)		(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	0.020***	0.018***	0.017***	0.012***	0.010*	1995–2024-k	0.0021*	-0.0037**	-0.0082***	-0.0115***	-0.0151***
	(7.114)	(5.556)	(4.545)	(2.905)	(1.783)		(1.889)	(-2.029)	(-4.434)	(-7.800)	(-10.053)
1995–2024-k	0.019***	0.014***	0.012***	0.006	0.002	1960–2024-k	0.0035***	-0.0013	-0.0058***	-0.0104***	-0.0141***
	(7.932)	(5.315)	(3.878)	(1.548)	(0.486)		(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	0.002***	0.002***	0.002***	0.003***	0.004***	1995–2024-k	0.000025***	0.000010	0.000006	0.000010**	0.000008**
	(4.757)	(4.960)	(4.734)	(4.886)	(5.084)		(5.332)	(2.382)	(1.269)	(2.591)	(2.643)
1995–2024-k	0.003***	0.003***	0.003***	0.004***	0.005***	1960–2024-k	0.000021***	0.000012***	0.000008***	0.000011***	0.000010***
	(6.559)	(6.801)	(5.855)	(5.717)	(5.882)		(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 5% of stocks ranked on total asset. Variable definitions are in Appendix A.1.

	(1)	(2)	(3)	(4)	(5)
	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}	RET_{t+1}
E/A	0.142	0.189*	0.105	0.197*	
	(1.287)	(1.859)	(0.939)	(1.726)	
OCF/A		-0.082			0.111
		(-1.509)			(1.257)
Accruals/A			0.102**		0.193**
			(2.155)		(2.476)
NRGL/A				-0.971***	-0.609***
				(-5.650)	(-3.338)
$\log(M)$	-0.007	-0.007	-0.007	-0.009	-0.005
	(-0.356)	(-0.338)	(-0.353)	(-0.442)	(-0.241)
B/M	0.057**	0.057**	0.056**	0.053**	0.065***
	(2.445)	(2.449)	(2.421)	(2.282)	(2.742)
RET_t	-0.043**	-0.044**	-0.044**	-0.045**	-0.052**
	(-2.107)	(-2.107)	(-2.137)	(-2.169)	(-2.430)
TURNOVER_y	-0.004*	-0.004*	-0.004*	-0.004*	0.008
	(-1.613)	(-1.576)	(-1.611)	(-1.616)	(0.949)
Industry FE	Yes	Yes	Yes	Yes	Yes
R2	0.092	0.092	0.092	0.093	0.093
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 5% of stocks ranked on total asset.

Panel A: Predicting earnings

	China			US S&P500		
	(1)	(2)	(3)	(4)	(5)	(6)
	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
$\log(M_t/A_t) \times POST$	-0.005***	-0.008***	-0.008***	0.003***	0.004***	0.005***
	(-9.619)	(-10.589)	(-8.009)	(3.013)	(2.950)	(2.771)
$\log(M_t/A_t)$	0.020***	0.024***	0.026***	0.035***	0.042***	0.045***
	(49.837)	(45.116)	(35.501)	(77.757)	(74.089)	(67.937)
E_t/A_t	0.342***	0.236***	0.184***	0.354***	0.230***	0.216***
	(92.980)	(48.965)	(28.915)	(61.423)	(31.795)	(25.335)
D_t/A_t	0.804***	0.868***	0.930***	0.116***	0.136***	0.129***
	(60.041)	(48.848)	(39.232)	(18.922)	(17.687)	(14.192)
N	60715	55789	51037	25915	25517	25138
adj. R2	0.378	0.244	0.164	0.559	0.442	0.384

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

	OCF			Accruals			NRGL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
$\log(M_t/A_t) \times POST$	0.003**	-0.000	0.002	-0.006***	-0.006***	-0.006***	-0.000	-0.000*	-0.001***
	(2.077)	(-0.221)	(1.147)	(-4.063)	(-3.606)	(-3.062)	(-1.003)	(-1.846)	(-5.638)
$\log(M/A)$	-0.013***	0.002*	0.003**	0.028***	0.017***	0.015***	0.004***	0.004***	0.005***
	(-14.144)	(1.917)	(2.067)	(28.416)	(14.706)	(10.243)	(32.107)	(28.790)	(31.040)
E_t/A_t	0.200***	0.225***	0.238***	0.222***	0.051***	-0.031**	-0.045***	-0.026***	-0.014***
	(22.598)	(21.771)	(18.461)	(24.096)	(4.811)	(-2.366)	(-41.751)	(-21.136)	(-9.517)
D_t/A_t	0.968***	0.994***	1.004***	-0.188***	-0.098**	-0.035	0.010**	-0.017***	-0.037***
	(30.059)	(26.135)	(20.981)	(-5.614)	(-2.502)	(-0.712)	(2.555)	(-3.705)	(-6.806)
N	60715	55789	51037	60715	55789	51037	60715	55789	51037
adj. R^2	0.056	0.053	0.043	0.063	0.028	0.023	0.070	0.051	0.051

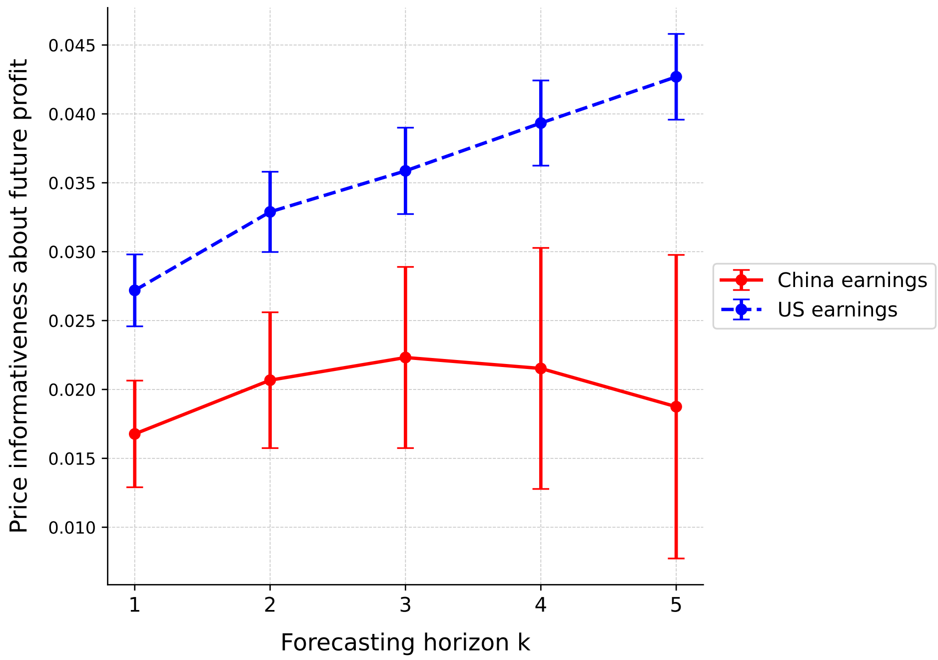

Figure I. Stock Price Informativeness about Future Earnings
The figure presents time-series averages of the predicted variation $\hat{\beta}_k \sigma(\log(M_t/A_t))$ (with 95% confidence intervals) from the annual cross-sectional regressions below:

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

where k ranges from 1 to 5. This analysis includes all Chinese A-share stocks from 1995 to $2024 - k$ (excluding the bottom 5% ranked by total asset) 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.

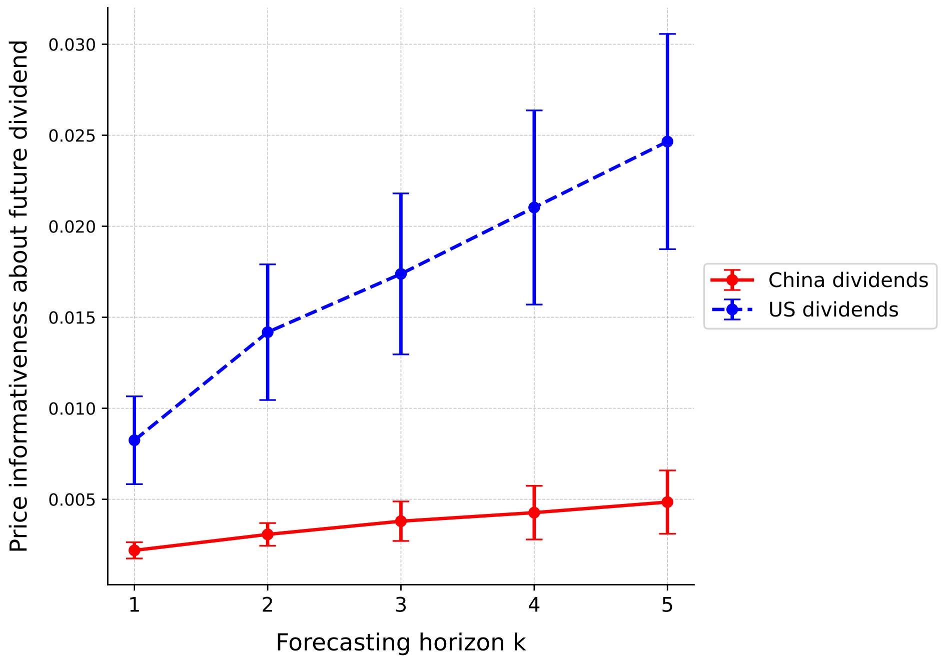

Figure II. Stock Price Informativeness about Future Payouts
This figure presents individual-level time-series averages of the predicted variation $\hat{\beta}_k \sigma(\log(M_t/A_t))$ (with 95% confidence intervals) from the annual cross-sectional regressions below:

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

where k ranges from 1 to 5. This analysis includes Chinese A-share stocks from 1995 to $2024-k$ (excluding the bottom 5% 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.

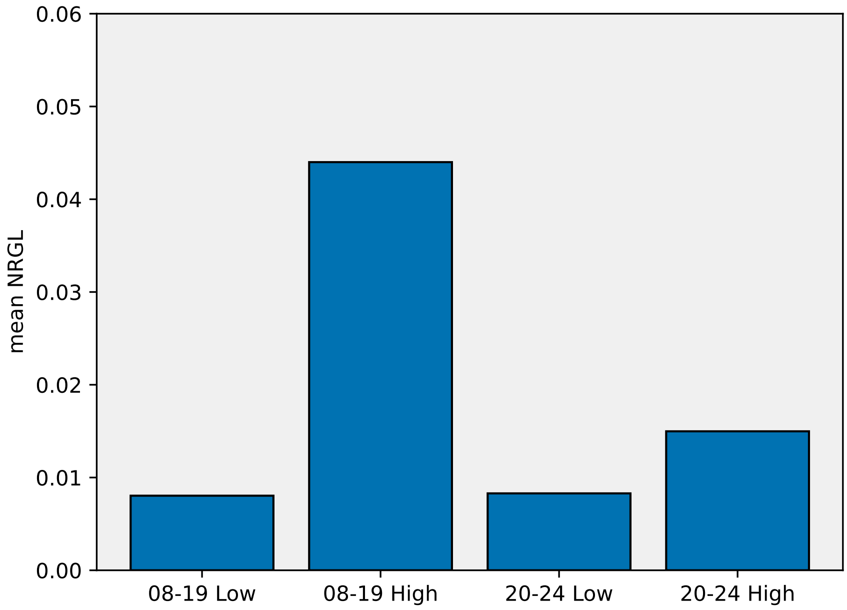

Figure III. Level of NRGL Before and After the 2020 Delisting Rule

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 the document "Several Opinions on Reforming and Perfecting the Delisting System for Listed Companies and its Strict Implementation." This policy focused on strenghening delisting rules for firms 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 direction of future delisting reforms and provided additional details on the enforcement of existing rules.

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

Also in November 2018, the Shanghai Stock Exchange established the Science and Technology Innovation Board (STAR Board) and piloted a registration-based IPO system. Drawing on earlier reforms of the delisting framework, the STAR Board adopted stricter 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, firms are subject to delisting for poor financial performance if "net profit before and after deducting extraordinary gains and losses (including restated amounts) in the most recent audited fiscal year is negative, and audited operating income in the most recent year (including restated amounts) is below 100 million yuan." This criterion differs from the delisting standard applied to main-board firms at that time, which focused primarily on 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 comparable amendments in 2019.

On March 1, 2020, the revised Securities Law of the People's Republic of China came into effect. Article 48 removed the explicit specification of circumstances under which listing status must be terminated, instead delegating this authority to listing rules established 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 the Chinese Communist Party.

In December 2020, the Shanghai and Shenzhen Stock Exchanges released revised delisting rules. These revisions correspond to the fourteenth amendment by the Shanghai Stock Exchange (applying to firms listed on both the Main Board and STAR Board) and the eleventh amendment by the Shenzhen Stock Exchange. The reforms introduced new criteria for determining "ST" status, indicating delisting risk. In general, the new framework follows the 2019 pilot rule implemented on the STAR Board. Under the revised rules, ST status is determined based on multiple criteria: negative net profit and operating income below 100 million yuan, where net profit is defined as "the lower of net profit before and after deducting non-recurring gains and losses." In addition, operating income excludes revenues unrelated to the firm's main business or lacking commercial substance. These revised rules became effective for annual financial reports beginning with fiscal year 2020.

In April 2024, the Shanghai and Shenzhen Stock Exchanges issued another revision of the delisting rules. One notable change was to raise the operating-income threshold from "below 100 million yuan" to "below 300 million yuan" for firms reporting negative net profit.

A.3 Full sample results

Table A.1. Stock Price Informativeness about Future Earnings: All Stocks

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. 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	0.006	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)	