

Fast or slow: Unveiling the speed of market leverage adjustment in China

Yujun Lian, Jun Wang, Manqi Huang



PII: S0927-538X(24)00174-4

DOI: <https://doi.org/10.1016/j.pacfin.2024.102423>

Reference: PACFIN 102423

To appear in: *Pacific-Basin Finance Journal*

Received date: 19 November 2023

Revised date: 7 April 2024

Accepted date: 2 June 2024

Please cite this article as: Y. Lian, J. Wang and M. Huang, Fast or slow: Unveiling the speed of market leverage adjustment in China, *Pacific-Basin Finance Journal* (2023), <https://doi.org/10.1016/j.pacfin.2024.102423>

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

# **Fast or Slow: Unveiling the Speed of Market Leverage Adjustment in China**

Yujun Lian<sup>1</sup>, Jun Wang<sup>1</sup>, Manqi Huang<sup>2</sup>

<sup>1</sup>Lingnan College, Sun Yat-sen University, No. 135, Xingang Xi Road, Guangzhou,  
Guangdong 510275, P. R. China

<sup>2</sup> Research Department, China International Capital Corporation Limited, No. 5033,  
Yitian Road, Futian District, Shenzhen, 518048, P. R. China

Corresponding Author: Jun Wang, Email: wangj676@mail2.sysu.edu.cn

Declaration of Conflicts of Interest:

The authors declare no conflicts of interest.

# Fast or Slow: Unveiling the Speed of Market Leverage Adjustment in China

**Abstract:** In the capital structure literature, the practice of using market leverage to estimate the speed of adjustment (SOA) to target capital structures is debated. We empirically examine the capital structure adjustment behavior of Chinese firms using the SOA decomposition model proposed in Yin and Ritter (2020). Our findings suggest an overestimation of SOA towards the target market capital structure in Chinese firms, with a pre-correction speed of around 19.6% and a post-decomposition active adjustment speed of merely 7.4%. This overestimation is attributed to significant price fluctuations in the stock market. We further explore the cross-sectional differences and time-series variation in SOA to confirm our findings, advising caution in the use of market leverage for robustness tests. Our results imply that the trade-off and pecking order theories have limited explanatory power for the capital structure decisions of Chinese firms, while market timing theory appears to be more applicable.

**Keywords:** Speed of Adjustment, Market Leverage, Market Timing Theory

## 1. Introduction

In capital structure literature that examines the speed of adjustment (SOA), both book leverage and market leverage are frequently used as dependent variables (Flannery and Rangan, 2006; Öztekin and Flannery, 2012). It is notable that market SOA estimates tend to exceed those of book SOA.<sup>1</sup> However, survey evidence indicates that, in real-world practices, firms rarely modify their capital structure to counteract the influence of stock price changes (Graham and Harvey, 2001). A significant cause of fluctuations in market leverage can be attributed to changes in stock prices (Welch, 2004). He and Kyaw (2023) found that the market SOA is significantly higher during periods of intense stock market volatility compared to stable periods. Therefore, we speculate that if the factor of stock return volatility is excluded, the estimated values of market SOA may not significantly surpass those of book SOA. This perspective contrasts with empirical results from prior studies (Hovakimian and Li, 2011; Huang and Ritter, 2009).

This raises questions about whether market SOA is overestimated due to stock return volatility and whether this still supports the trade-off theory. Yin and Ritter (2020) addressed this by developing a model that decomposes the estimated SOA into passive and positive components. Using the SOA decomposition model, they corrected for the bias caused by stock return volatility and found that the adjusted market SOA was around 10%, in contrast to the raw market SOA, which stood at approximately 26%. This suggests that the upward bias in market SOA primarily stems from fluctuations in stock prices rather than corporate financial decisions.

The issue of market SOA overestimation due to stock return volatility is particularly relevant when examining the financial dynamics in different markets. We observe that the gap between the estimated values of market SOA and book SOA in China is larger than in the United States.<sup>2</sup> This

<sup>1</sup> For example, using long-difference estimation, Huang and Ritter (2009) found that, between 1963-2001, the book SOA for firms was 17%, compared to 23% for market SOA. Through employing various estimation methods, Hovakimian and Li (2011) substantiated that market SOA consistently exceeded book SOA. Mukherjee and Wang (2013), Drobetz et al. (2015) and Vo et al. (2022) also found similar results.

<sup>2</sup> For example, Li et al. (2017) found that Chinese firms had a book SOA of 8.8% and a market SOA of

difference may stem from the lesser maturity of the Chinese stock market, which experiences more significant stock price fluctuations (Liao et al., 2014). Therefore, we aim to explore the adjusted market SOA for Chinese listed firms when accounting for stock price fluctuations, and assess the trade-off theory's applicability in China, thereby offering insights for developing markets.

In this paper, we employ the SOA decomposition model proposed by Yin and Ritter (2020) to estimate the SOA of Chinese firms. The results indicate that the book SOA is about 11%, whereas the raw market SOA is much higher, at around 19.6%. However, after controlling for the influence of stock price fluctuations, the adjusted market SOA significantly decreases to only about 7.4%. This suggests that the observed upward bias in market SOA can be primarily attributed to the influence of stock price fluctuations.

To further validate these findings, we examine the cross-sectional differences by grouping the data based on stock return volatility and estimating both the raw and adjusted market SOA. We define the bias as the gap between the raw market SOA and adjusted market SOA. We observe that the group with the highest stock return volatility demonstrates the highest proportion of the bias in the market SOA, accounting for approximately 74.8%. This suggests that stock return volatility significantly contributes to the upward bias of market SOA.

We also explore the time-series variation of market SOA and bias using a rolling regression method. The results show that, from 2006 to 2012, the bias increased sharply, accounting for over 80% of the market SOA. Concurrently, the adjusted market SOA demonstrated a modest upward trend since 2006. These changes are attributed to the effects of the Split-share Structure Reform initiated in 2005, which aimed to eliminate institutional discrepancies in share transfers, converting approximately two-thirds of non-tradable shares into tradable ones. This reform led to pronounced fluctuations in the capital market and reduced adjustment costs for firms. From a time-series perspective, our results confirm the significant impact of stock return volatility on the estimation of market SOA.

To provide broader insights applicable to emerging markets, we conduct an in-depth analysis of the impact of institutional reforms in China's capital market, namely the Split-share Structure Reform, Margin Trading Reform, and the HK Connect Program, on stock return volatility and SOA estimates. The Split-share Structure Reform had a profound impact, leading to increased stock price volatility in the short term. We observed a sharp rise in bias in SOA estimates following this reform, consistent with time-series analysis results. In contrast, the Margin Trading Reform conducted pilot programs for short selling and margin buying, and the HK Connect Program introduced international investors to A-share market, thus strengthening the capital market's price discovery efficiency and reducing stock price volatility. Consequently, following the implementation of these two reforms, the bias demonstrated a decline. These findings highlight the diverse effects of institutional reforms in capital markets, offering valuable insights for similar initiatives in developing markets.

In our final analysis, we evaluate the applicability of the three predominant capital structure theories in the Chinese market: the trade-off theory, the pecking order theory, and the market timing theory. The results diminish the prominence of both the trade-off and pecking order theories in shaping the capital structures of Chinese firms. We find the market timing theory to be

---

15.6%, a difference of nearly 7%. In contrast, Elsas and Florysiak (2015) reported that U.S. firms had a book SOA of 27.3% and a market SOA of 26.3%, with a gap of only 1%.

highly relevant and applicable in the Chinese context.

The contributions of this paper are summarized as follows. Firstly, we show that the adjusted market SOA attributed to firms' active financing decisions is only 7.4%, implying that it would take approximately 13.5 years to bring the leverage closer to the target level. This finding differs from the conclusions drawn by He and Kyaw (2018) and Li et al. (2017), who suggest that Chinese firms exhibit a higher market SOA compared to book SOA. The significance of this finding for future research on Chinese firms' capital structure is that the SOA calculated based on the market leverage lacks guidance, as a substantial portion of it is influenced by noise generated from stock price fluctuations rather than firms' active financing behavior. Therefore, it is suggested to exercise caution when using market leverage as a substitute in robustness tests.

Secondly, our findings highlight the relevance of the market timing theory in the Chinese stock market. This supports the research by Huang et al. (2016), who argue that Chinese managers are capable of timing the market despite strict regulations, and Zhao et al. (2020), who demonstrate the long-term impact of market timing on firms' financing decisions. This differs from earlier studies, for example, Tong and Green (2005) and Nguyen et al. (2020) have shown a preference for the pecking order theory in the Chinese stock market. We further find that the prevalence of market timing behavior in China might be shaped by the relative ease of issuing additional equity under existing regulatory policies. Thus, this paper contributes to the literature by augmenting the understanding of the relevance of various mainstream capital structure theories in the Chinese market.

Thirdly, our study has implications for other developing markets. Existing literature on capital structure primarily focuses on developed markets (Elsas and Florysiak, 2015; Yin and Ritter, 2020), with relatively limited research on developing markets. Existing studies about the SOA estimates and capital structure theory applicability in developing markets are also inconsistent (Getzmann et al., 2014; Abdeljawad and Mat Nor, 2017; Wojewodzki et al., 2018). The Chinese A-share market, often seen as a typical developing market with high volatility and a large proportion of retail investors (Gu et al., 2018), may provide valuable perspectives for other developing markets. On one hand, from an academic perspective, we find that stock return volatility significantly influences market SOA estimates, highlighting the need for research on developing markets to take this factor into account. On the other hand, from a practical standpoint, China's institutional reforms such as the Margin Trading Reform and the HK Connect Program provide insights for these developing markets to enhance price discovery in capital markets, reduce volatility, and promote healthy market development.

The rest of the paper is organized as follows: Section 2 outlines the methodology used for decomposing and estimating the SOA. Section 3 provides an overview of the descriptive statistical characteristics of the data and sample used in this study. Section 4 analyzes the empirical results, including SOA estimates, the cross-sectional and time-series differences of the SOA upward bias. Section 5 discusses the impact of institutional reforms in China on stock return volatility and SOA estimates, including the Split-share Structure Reform, Margin Trading Reform, and the HK Connect Program. Section 6 discusses the applicability of capital structure theories in the Chinese market. Section 7 presents the robustness tests conducted. Finally, Section 8 summarizes the main findings of the paper.

## 2. Decomposition and Estimation of SOA

### 2.1 Decomposition of SOA

We begin with the widely used partial adjustment model (Flannery and Rangan, 2006).

$$LEV_{it} = (1 - \lambda)LEV_{i,t-1} + \lambda LEV_{it}^* + \varepsilon_{it} \quad \#(1)$$

where  $LEV_{it}$  is the firm's current leverage and  $LEV_{it}^*$  is the target leverage. The coefficient  $\lambda$  denotes the SOA towards the target leverage, which varies between 0 and 1. Specifically,  $\lambda = 0$  implies no adjustment, while  $\lambda = 1$  signifies an instantaneous adjustment.

A commonly accepted definition of leverage is the proportion of debt to total assets. Using this definition, the leverage at time  $t$  can be calculated based on debt and total assets at both time  $t$  and time  $t - 1$ . It can be written as:

$$LEV_{it} = \frac{D_{it}}{A_{it}} = \frac{D_{i,t-1} + \Delta D_{it}}{A_{i,t-1} + \Delta A_{it}} = \frac{D_{i,t-1}/A_{i,t-1} + \Delta D_{it}/A_{i,t-1}}{1 + \Delta A_{it}/A_{i,t-1}} \quad \#(2)$$

where  $D_{it}$  and  $A_{it}$  denote the amount of debt and total assets at time  $t$ , respectively.  $\Delta D_{it}$  and  $\Delta A_{it}$  represent the change of debt and total assets from time  $t - 1$  to time  $t$ , respectively. To align more closely with equation (1), we can restructure equation (2) into a dynamic form wherein the leverage at time  $t$  is viewed as a weighted average of the leverage at time  $t - 1$  and the ratio  $d_{it}/g_{it}$ .

$$LEV_{it} = \left(1 - \frac{g_{it}}{1 + g_{it}}\right) LEV_{i,t-1} + \frac{g_{it}}{1 + g_{it}} \times \frac{d_{it}}{g_{it}} \quad \#(3)$$

In equation (3),  $d_{it} = \Delta D_{it}/A_{i,t-1}$  is the net debt change relative to lagged total assets, and  $g_{it} = \Delta A_{it}/A_{i,t-1}$  measures the firm value growth rate.  $d_{it}/g_{it} = \Delta D_{it}/\Delta A_{it}$  is the ratio of net debt change to change of total assets. The weight  $g_{it}/(1 + g_{it}) = \Delta A_{it}/A_{it}$  represents the ratio of change in total assets relative to the current total assets.

To illustrate the decomposition approach, we assume a constant value for  $g$ .<sup>3</sup> This can provide us some insight into the determination of  $\lambda$ . By solving equations (1) and (3) simultaneously under this assumption, we can derive the following expression:

$$\lambda = \frac{g}{1 + g} (1 - \beta) \quad \#(4)$$

where  $\beta = \text{Cov}(d_{it}/g, LEV_{i,t-1})/\sigma_L^2$  and  $\sigma_L^2 = \text{Var}(LEV_{i,t-1})$ . It can be observed that  $\beta$  serves as the coefficient within the regression equation  $d_{it}/g = \omega + \beta LEV_{i,t-1} + \omega_{it}$ .

Equation (4) is pivotal for comprehending the SOA decomposition model as it reveals that the SOA is influenced by two factors: the active factor denoted by  $\beta$ , which represents the sensitivity of the net debt issuance to lagged leverage, and the passive factor denoted by  $g$ , which quantifies the firm value growth rate and is equivalent to the proportion of asset change to lagged assets. This aligns with the perspective presented by DeAngelo et al. (2011), asserting that the dynamic shifts in leverage represent not just an intent to align with target leverage, but also mirror investment opportunities.

A higher value of  $\beta$  suggests a stronger correlation between net debt issuance and lagged leverage, indicating a slower adjustment rate  $\lambda$ . Furthermore, there is a positive correlation between  $\lambda$  and the magnitude of  $g$ , suggesting that firms with greater firm value growth volatility tend to have a larger SOA.

<sup>3</sup> In section 2.2, we relax the assumption of constant  $g$  and allow  $g_{it}$  to change endogeneously in response to lagged leverage.

## 2.2 Estimation of SOA

In this subsection, we relax the assumption of constant value for  $g$  and allow  $g_{it}$  to change endogeneously in response to lagged leverage. Given that the SOA estimates depend on the direction of firm value growth, we assume that  $d_{it}/g_{it}$  and  $g_{it}/1 + g_{it}$  follow equations (5) and (6) by adding the direction of firm value growth rate  $N_{it}^-$  and its interaction with lagged leverage.

$$\frac{d_{it}}{g_{it}} = \omega_1 + \omega_2 N_{it}^- + \beta_1 LEV_{i,t-1} + \beta_2 LEV_{i,t-1} N_{it}^- + \omega_{it} \#(5)$$

$$\frac{g_{it}}{1 + g_{it}} = z_1 + z_2 N_{it}^- + \delta_1 LEV_{i,t-1} + \delta_2 LEV_{i,t-1} N_{it}^- + z_{it} \#(6)$$

where  $N_{it}^-$  is an indicator variable that equals 1 if  $g_{it}$  is less than 0, and equals 0 otherwise. And  $\omega_{it}$  and  $z_{it}$  are zero-mean error terms. By assuming that  $Cov(\omega_{it}, LEV_{i,t-1}) = Cov(z_{it}, LEV_{i,t-1}) = 0$ , and  $Cov(\omega_{it}, N_{it}^-) = Cov(z_{it}, N_{it}^-) = 0$ , equations (3), (5), and (6) enable us to obtain the covariance of leverage and lagged leverage:

$$Cov(LEV_{it}, LEV_{i,t-1}) = aCov(N_{it}^-, LEV_{i,t-1}) + bCov(LEV_{i,t-1} N_{it}^-, LEV_{i,t-1}) + cCov(LEV_{i,t-1}^2 N_{it}^-, LEV_{i,t-1}) + df(LEV_{i,t-1}) + e\sigma_L^2 \#(7)$$

where  $a = z_1\omega_2 + z_2\omega_1 + z_2\omega_2$ ,  $b = (z_1 + z_2)\beta_2 - z_2(1 - \beta_1) + \omega_1\delta_2 + (\delta_1 + \delta_2)\omega_2$ ,  $c = \delta_2(\beta_1 - 1) + (\delta_1 + \delta_2)\beta_2$ ,  $d = \delta_1(\beta_1 - 1)$ ,  $e = 1 - z_1(1 - \beta_1) + \omega_1\delta_1$  and  $f(LEV_{i,t-1}) = E(LEV_{i,t-1}^3) - E(LEV_{i,t-1}^2)E(LEV_{i,t-1})$ .

Moreover, taking into account the impact of firm-specific operating variables and time-invariant firm-specific effects (such as CEO's management style, corporate culture, etc.) on the target capital structure of a firm, we incorporate the firm-fixed effect into the equation determining  $LEV_{it}^*$ .

$$LEV_{it}^* = \theta_0 X_{i,t-1} + \gamma_{i0} \#(8)$$

where  $X_{i,t-1}$  is a vector of lagged firm control variables and  $\gamma_{i0}$  is firm-fixed effect.

Substituting equation (8) into equation (1) and setting  $\theta = \lambda\theta_0$  and  $\gamma_i = \lambda\gamma_{i0}$ , we have:

$$LEV_{it} = (1 - \lambda)LEV_{i,t-1} + \theta X_{i,t-1} + \gamma_i + \varepsilon_{it} \#(9)$$

Assuming  $Cov(\varepsilon_{it}, LEV_{i,t-1}) = 0$ , and derived from equation (9).

$$Cov(LEV_{it}, LEV_{i,t-1}) = (1 - \lambda)\sigma_L^2 + Cov(\theta X_{i,t-1} + \gamma_i, LEV_{i,t-1}) \#(10)$$

Building on the framework of Yin and Ritter (2020), we relax the assumptions of  $Cov(LEV_{it}^*, LEV_{i,t-1}) = 0$ , which means that the target leverage can be correlated with the lagged leverage. By simultaneously solving equations (7) and (10), we obtain:

$$\lambda = \frac{-\frac{aCov(N_{it}^-, LEV_{i,t-1})}{\sigma_L^2} - \frac{bCov(LEV_{i,t-1} N_{it}^-, LEV_{i,t-1})}{\sigma_L^2}}{-\frac{cCov(LEV_{i,t-1}^2 N_{it}^-, LEV_{i,t-1})}{\sigma_L^2} - \frac{df(LEV_{i,t-1})}{\sigma_L^2} + 1 - e + h} \#(11)$$

where the expression from  $a$  to  $e$  and  $f(LEV_{i,t-1})$  is the same as equation (7) and  $h = Cov(\theta X_{i,t-1} + \gamma_i, LEV_{i,t-1})/\sigma_L^2$ .<sup>4</sup> The detailed derivation process can be found in the appendix.

<sup>4</sup> The difference in  $\lambda$  derived in this paper compared to Yin and Ritter (2020) is the addition of  $h = Cov(\theta X_{i,t-1} + \gamma_i, LEV_{i,t-1})/\sigma_L^2$ . This is because we relaxed the assumption that target leverage and lagged leverage are not correlated.



### 2.3 Adjusted Market SOA

Given the frequent fluctuations in stock prices, it is observed that market SOA in Chinese firms is often higher than book SOA (Mai et al., 2017; Li et al., 2017). This suggests a possible hypothesis that stock price volatility contributes to an increase in the speed of adjustment (SOA) for the firm. Moreover, we can assume the following relationship between market value growth rate ( $g_{it}^M$ ) and book value growth rate ( $g_{it}^B$ ), as proposed by Yin and Ritter (2020).

$$g_{it}^M = m(g_{it}^B + \mu_{it}), \mu_{it} \sim N(0, \eta) \quad \#(12)$$

Equation (12) reveals two mechanisms that contribute to the higher SOA. The first mechanism, known as the multiplier effect  $m$ , occurs when the absolute value of  $g_{it}^M$  exceeds the absolute value of  $g_{it}^B$ , leading to an elevated market SOA. The second mechanism, known as the variance effect  $\eta$ , arises when the random fluctuations in  $g_{it}^M$  are stronger, resulting in greater fluctuations in  $d_{it}/g_{it}^M$ . Consequently, the correlation between  $d_{it}/g_{it}^M$  and  $LEV_{i,t-1}$  weakens, causing  $\beta$  to deviate further from one and amplifying the market SOA.

To properly estimate the market SOA, we can eliminate the passive adjustment factor arising from the market value's volatility surpassing the book value by setting  $g_{it}^M = g_{it}^B$  in the expression for  $\lambda$ . This adjustment allows us to obtain the actively adjusted market SOA, which reflects the firm's inclination to rebalance towards the target market capital structure.

## 3. Data

### 3.1 Data and Variables

Our sample is the firms listed on China's Shanghai and Shenzhen markets from 1998 to 2018, using data obtained from the CSMAR database. Following the approach of Fama and French (2002) and Niu et al. (2023), we processed the data as follows: (1) excluding ST, PT, and delisted firms; (2) excluding firms that also issue shares in B or H shares outside the A-share market; (3) excluding firms in the financial industry; (4) excluding firms with less than 4 consecutive years; (5) excluding firms with negative market value of book debt and equity; (6) excluding firms with missing variables required for empirical analysis. As a result, we obtained a dataset of 27,751 firm-year panel observations. To mitigate the influence of outliers, all continuous variables were winsorized at the 1st and 99th percentiles.

Referring to previous research (Fama and French, 2002; Flannery and Rangan, 2006), we define the variables as follows: The dependent variable, capital structure, is measured in two ways: book capital structure ( $LEV_B = \text{book debt}/\text{total book assets}$ ) and market capital structure ( $LEV_M = \text{book debt}/(\text{book debt} + \text{equity market value})$ ). The firm characteristics variables include firm size ( $\text{LnTA} = \text{natural logarithm of total book assets}$ ), growth capacity ( $\text{TOBINQ} = (\text{book debt} + \text{equity market value})/\text{total book assets}$ ), profitability ( $\text{EBIT/TA} = \text{EBIT}/\text{total book assets}$ ), collateral capacity ( $\text{NET\_PPE} = \text{net fixed assets}/\text{total book assets}$ ), R&D capacity ( $\text{RD/TA} = \text{R\&D expenses}/\text{total book assets}$ ), depreciation and amortization ( $\text{DEP/TA} = \text{depreciation and amortization}/\text{total book assets}$ ), a dummy variable indicating whether R&D expenses are disclosed ( $\text{RD\_DUMMY}$ ), and industry characteristics ( $\text{IND\_LEV}_B$  and  $\text{IND\_LEV}_M$ , industry median of the capital structure).



### 3.2 Descriptive Statistics

Table 1 presents descriptive statistics of the main variables (Panel A) and a comparison of the mean asset growth rate (Panel B). In Panel A, the average book leverage (LEVB) for Chinese listed companies is 45.4%, with a standard deviation of 0.202. The average market leverage (LEVM) is 30.6%, with a standard deviation of 0.196. Although the standard deviations of the two variables are similar, the mean of market leverage is much lower.

In Panel B, we present a comparison of the mean difference between the growth rates of book firm value ( $g^B$ ) and market firm value ( $g^M$ ). Notably, the mean of  $g^M$  is 0.249, substantially exceeding the mean of  $g^B$ , which stands at 0.177. This results in a mean difference of 0.072 between the two growth rates. Furthermore, the standard deviation of  $g^M$  is greater than that of  $g^B$ , with values of 0.539 and 0.348, respectively. These findings indicate distinct characteristics between Chinese listed firms and U.S. firms, as presented by Yin and Ritter (2020). Specifically, Chinese listed firms demonstrate a higher market value growth rate (the mean value of  $g^M$  for U.S. firms is only 1.48%), as well as greater volatility (the standard deviation of  $g^M$  for U.S. firms is only 0.218). These differences not only validate the existence of mechanisms  $m$  and  $\eta$  mentioned earlier, but also further support our hypothesis, suggesting that the SOA for Chinese listed firms may exhibit a more pronounced passive adjustment bias.

[Insert Table 1 about here]

## 4. Empirical Results

In this section, we begin by calculating the book SOA and raw market SOA. We then adjust the SOA for market leverage by assuming that the growth rate of market value is equal to the growth rate of book value. To investigate whether the difference between the raw and adjusted market SOA stems from stock return volatility, we conduct our analysis from both cross-sectional and time-series perspectives. In the cross-sectional analysis, we divide the sample based on the extent of stock return volatility and calculate both the raw and adjusted market SOA for each category, thus quantifying the bias induced by stock return volatility. In the time-series analysis, we use rolling regression to calculate the annual raw market SOA, adjusted market SOA, and the bias, enabling us to assess the annual impact of stock return volatility.

### 4.1 SOA Estimates

We initially performed Ordinary Least Squares (OLS) regression analysis on the full sample using equations (5) and (6) to obtain the coefficients necessary for calculating  $\lambda$  in equation (11). The regression results are presented in Panel A (Table 2). Specifically, columns (1) and (2) show the regression results using book leverage, columns (3) and (4) present the regression results using market leverage, and columns (5) and (6) display the regression results after excluding the passive adjustment component (by setting  $g_{it}^M = g_{it}^B$ ).

In Panel A of Table 2, we observe several coefficients related to active adjustment factors: the coefficient  $\beta_1^B$  for  $LEVB_{it}$  in column (1) is 0.403, in column (3) the coefficient  $\beta_1^M$  for  $LEVM_{it}$  is 0.569, and in column (5), the coefficient  $\beta_1^{MB}$  for  $LEVM_{it}$  is 0.840. After excluding the passive adjustment component, the coefficient  $\beta_1^M$  is underestimated by 0.271 ( $0.271 = 0.840 - 0.569$ ) compared to  $\beta_1^{MB}$ , which confirms the existence of multiplier effect  $m$  and variance effect  $\eta$ , i.e., the higher mean and standard deviation of  $g^M$  result in an underestimation

of  $\beta_1$  and its estimate deviates more from one, which may lead to an upward bias of SOA estimates.<sup>5</sup> Additionally, the adjusted  $\beta_1^{MB}$  is closer to one, indicating that the financing decision of the firm is very sticky to the previous period's market leverage, and the decomposition may show a very low speed of active adjustment of the market capital structure.

In Panel B of Table 2, we calculate the influence of firm-fixed effects. For our econometric analysis, we applied the fractional dependent variable (DPF) methodology as elaborated by Elsas and Florysiak (2015), chosen for its particular appropriateness in handling our dependent variable: the firm's leverage, which is constrained to values between 0 and 1. For firms that make financing decisions in a seemingly random manner, the DPF approach is capable of pinpointing an SOA value of 0, while alternative techniques like GMM might yield upwardly biased estimates.

Equation (13) presents the expression for  $\gamma_i$ , where  $LEV_{i0}$  represents the actual capital structure of firm  $i$  in the initial period. According to Lemmon et al. (2008), a significant portion of the variation in capital structure across firms can be attributed to the initial capital structure established at the time of the initial public offering (IPO). In line with Lemmon et al. (2008), we consider the capital structure of the firm in the first non-missing period of the sample as its initial value.  $\bar{X}_i$  denotes the within-group mean of  $X_{i,t-1}$ , and  $\alpha_i$  represents the disturbance term, which follows a normal distribution with mean 0 and variance  $\sigma_\alpha^2$ .

$$\gamma_i = \alpha_0 + \alpha_1 LEV_{i0} + \alpha_2 \bar{X}_i + \alpha_i \#(13)$$

In Equation (11), the expression for  $\lambda$  includes the term determined by  $\gamma_i$ , which is  $h = \text{Cov}(\theta X_{i,t-1} + \gamma_i, LEV_{i,t-1}) / \sigma_L^2$  in the section 2.2. Recall that target leverage is exactly  $\theta X_{i,t-1} + \gamma_i$ , then we regress target leverage on lagged leverage to obtain the influence of the firm-fixed effect. By substituting this calculated result into Equation (11), we can obtain the SOA estimates with firm-fixed effects.

In Panel C of Table 2, we report the estimates of book SOA, raw market SOA and adjusted market SOA. The book SOA for Chinese listed firms is 11.0%, while the raw market SOA is higher at 19.6%. These values are close to the estimates provided by Li et al. (2017). However, they are lower compared to the book SOA of 16.1% and market SOA of 25.7% for U.S. firms, as reported by Yin and Ritter (2020).

[Insert Table 2 about here]

After decomposition, we find that the adjusted market SOA for Chinese firms stands at a mere 7.4%. This figure is notably less than the 10.5% estimated for U.S. firms. Insights from Öztekin and Flannery (2012) shed light on this discrepancy. The institutional environment is pivotal in shaping the SOA. Relative to the U.S. market, China is characterized by reduced financing efficiency, more pronounced financial constraints, elevated bankruptcy costs, and less rigorous legislative regulation. These factors, taken together, contribute to increased adjustment costs and reduced adjustment benefits.

The findings detailed above emphasize an upward bias in the market SOA of Chinese listed firms. This bias is primarily attributed to the passive adjustment factor, which, driven by the volatility of firms' market valuations, contributes a bias of 12.2% (equals to 19.6% – 7.4%). When accounting for this factor, the adjusted market SOA for Chinese firms is lower than the book SOA.

---

<sup>5</sup> From the equation  $\lambda = \frac{g}{1+g}(1 - \beta)$ , it's easy to show that lower  $\beta$  results in higher  $\lambda$ , implying a higher SOA.

## 4.2 Cross-sectional Differences of Market SOA

In acknowledgment of the significant role stock return volatility plays in influencing the difference between firms' market values and their book values, we undertake a cross-sectional analysis. This analysis involves dividing the entire sample according to the degree of stock return volatility. To achieve this categorization, we compute the standard deviation of monthly stock returns for each firm, spanning the preceding 36-month period (i.e., the previous three years). Subsequently, we categorize firms into three classifications—low, medium, and high stock return volatility—utilizing the annual 33rd and 66th percentiles as thresholds.

Table 3 reports the SOA decomposition estimation results for the grouped categories. First, the raw market SOA for the group with the lowest stock return volatility is only 12.8%, whereas for the groups with medium and high volatility, the raw market SOA is 21.2% and 21.0%, respectively. Second, we define the passive adjustment bias as the difference between the raw market SOA and adjusted market SOA. The magnitude of the passive adjustment bias is more pronounced in groups with higher stock return volatility. Specifically, across the groups with low, medium, and high stock return volatility, the upward bias in firms' market SOA is 6.2%, 14.0%, and 15.7%, respectively. In terms of proportions, the passive adjustment bias accounts for 48.2%, 66.0%, and 74.8% (calculated as the ratio of bias to the raw market SOA). Third, when comparing the decomposed actively adjusted market SOA, the differences among the three groups are not significant. The actively adjusted market SOA for the low, medium, and high stock return volatility groups is 6.6%, 7.2%, and 5.3%, respectively. These findings suggest that the variations in market SOA among firms with different stock return volatility primarily arise from differences in passive adjustment factors rather than differences in firms' proactive behavior towards rebalancing against the market capital structure.

[Insert Table 3 about here]

## 4.3 Time-series Variation of Market SOA

Over the past two decades, China's financial market has experienced profound evolution. Factors, including market liquidity and transaction costs, have undergone substantial changes (Liao et al., 2014; Li et al., 2018; Xu et al., 2020), affecting firms' business decisions and financing preferences over time. To explore the potential variations in the SOA and its upward deviation in firms' market capital structure across different periods, we first conduct an analysis of time-based differences. Figure 1 illustrates the annual distribution of the gap between market value growth rate and book value growth rate for firms, defined as  $gap_{it} = g_{it}^M - g_{it}^B$ .

[Insert Figure 1 about here]

Before 2005, the gap's mean was relatively small. However, after 2005, there was a significant increase in this gap. Moreover, the variation of the gap after 2005 also increased significantly. This may imply there exists a substantial variation in the time-series of SOA.

To further examine the time-series variation of leverage SOA, we consider using the rolling regression method to estimate the market SOA on an annual basis. This involves using six years of historical data for each estimation. For example, to calculate the SOA for the year 2003, we use data from 1998 to 2003. This method allows us to derive annual market SOA estimates from 2003 to 2018, which includes the raw market SOA, the adjusted market SOA, and the bias—defined as the difference between the raw and adjusted market SOA.

Figure 2 presents the annual estimates of market SOA. Before 2005, the bias was small, indicating minimal volatility in stock returns. However, starting from 2006 to 2012, this bias began to widen significantly, accounting for over 80% of the raw market SOA. We attribute the change to the Split-share Structure Reform, which greatly increased market liquidity and had a profound effect on the capital market (Guo et al., 2016). Over the long term, particularly after 2012, the raw market SOA decreased to approximately 18%, with the bias also decreasing to less than 40% of the raw market SOA. This decline suggests that while the Split-share Structure Reform's impact on market liquidity remains, it has lessened from its peak following the reform, yet still surpasses pre-reform levels. This trend corresponds with the trend of stock return volatility in Figure 1, underscoring the persistent, though moderated, influence of the Split-share Structure Reform on market dynamics beyond the immediate effects on liquidity.

[Insert Figure 2 about here]

## 5. The Role of Institutional Environments

In this section, we aim to investigate the impact of specific institutional reforms in China on the market SOA and the bias, including the Split-share Structure Reform, the Margin Trading Reform and the HK Connect Program. As discussed in section 4.2 regarding the time-series variation of market SOA, the Split-share Structure Reform unleashed a significant amount of liquidity into the capital market, leading to significant fluctuations in stock prices (Liao et al., 2014), and may cause an upward bias in raw market SOA. In contrast, the Margin Trading Reform and the HK Connect Program have enhanced the capital market's efficiency in price discovery (Li et al., 2018; Xu et al., 2020), contributing to a reduction in stock return volatility and potentially decreasing the bias. By analyzing these reforms, we can further confirm the impact of stock return volatility on the bias and offer insights relevant to developing markets.

### 5.1 Split-share Structure Reform

In Figure 2, the significant increase of bias can be attributed to the Split-share Structure Reform implemented in 2005. Prior to this reform, only a fraction of a listed firm's shares were tradable, with the majority, approximately two-thirds, being non-tradable state-owned shares. This hindered the normal functioning of the capital market. Therefore, the objective of the Split-share Structure Reform was to eliminate institutional differences in share transfers within the A-share market. It allowed shareholders of non-tradable shares to convert their shares into tradable ones by providing specified compensation to tradable shareholders. This reform released a significant amount of liquidity into the market and also led to the prevalence of speculative trading (Liao et al., 2014).

To explore the impact of the Split-share Structure Reform, we divide the sample into three periods: pre-2005, 2006 to 2012, and 2013 to 2018. The period from 2006 to 2012 should capture the direct effects of the Split-share Structure Reform on the capital market. Post-2012, there should be a diminished impact of the reform on market volatility.

Table 4 presents the SOA estimates based on the Split-share Structure Reform. We find a prominent shift in the upward bias of market SOA after the reform. Between 1998 and 2005, the raw market SOA was 7.9%, the adjusted market SOA was 5.9%, and the bias was only 2%, accounting for 25.2% of the raw market SOA. After the implementation of the Split-share

Structure Reform, between 2006 and 2012, the raw market SOA sharply increased to 30.3%, while the adjusted market SOA was 5.1%, resulting in the bias proportion reaching 83.2%. After 2012, the impact of the Split-share Structure Reform on market volatility diminished, with the raw market SOA decreasing to 21.3%, and the adjusted market SOA increasing to 14.3%, thereby reducing the bias.

Our results reveal two critical insights: First, the Split-share Structure Reform significantly impacted stock return volatility (Gu et al., 2018). After adjusting for stock return volatility, the raw market SOA surged from 7.9% to 30.3%, indicating a significant increase of bias. Therefore, it's important to note that the raw market SOA may not be reliable, as it includes the effects of stock return volatility. Secondly, the adjusted market SOA increased from 5.9% before the reform to 14.3% afterwards, illustrating a significant rise. Better institutional environment reduces capital adjustment costs (Jiang et al., 2021; Cook and Tang, 2010), facilitating faster SOA (Öztekin and Flannery, 2012). This suggests that the Split-share Structure Reform improved the market's institutional environment and reduced the adjustment costs for firms (Liao et al., 2014; Zhang et al., 2016; He and Wang, 2020).

[Insert Table 4 about here]

## 5.2 Margin Trading Reform

To enhance market efficiency, the China Securities Regulatory Commission (CSRC) launched a pilot program on March 31, 2010, that allowed investors to short sell or margin buy the securities of selected firms. Initially, the program included 90 firms, and it expanded five times between 2011 and 2018. Despite existing research presenting mixed conclusions on the impact of margin trading on capital markets (Hong and Stein, 2003; Boehmer and Wu, 2013), the consensus on China's Margin Trading Reform is that margin traders possess informational advantages, leading to reduced stock return volatility and improved market price discovery (Chang et al., 2014; Li et al., 2018). Therefore, we can expect that the Margin Trading Reform has reduced the stock return volatility of the pilot firms, reflecting a decrease in the bias proportion.

Panel A in Table 5 displays the market SOA estimates exclusively for pilot firms, with the sample divided into two phases relative to the Margin Trading Reform: before the reform and after the reform. This division enables a direct comparison of the pilot firms' SOA estimates across these periods. To avoid the influence of the Split-share Structure Reform, we have only included observations of pilot firms from 2013 onwards. Before the reform, the raw market SOA was approximately 12.1%. After adjusting for stock return volatility, it decreased to 7.3%. The bias represented 39.7% of the raw market SOA, suggesting that the SOA estimates before the reform was overestimated due to stock return volatility. Post-reform, the raw market SOA was around 11.6%, and after adjusting for stock return volatility, it slightly reduced to 11.2%. The effect of stock return volatility was much smaller, at only 3.4% of the raw market SOA, indicating that the Margin Trading Reform effectively enhanced price discovery and reduced stock price volatility.

## 5.3 HK Connect Program

The HK Connect program, launched on November 17, 2014, aimed to globalize and enhance the efficiency of the capital market. It enabled Hong Kong and international investors to access the Shanghai Stock Exchange, while mainland Chinese investors could trade on the Hong Kong stock

market. In December 2016, the program extended to include the HK-Shenzhen Connect, further linking Hong Kong investors with the Shenzhen Stock Exchange. Xu et al. (2020) analyzed the HK-SSE Connect's impact and discovered that the introduction of international investors increased market liquidity and competition, leading to faster information absorption and more efficient price discovery. Thus, the HK Connect Program is likely to reduce the bias of SOA estimates by improving information absorption and decreasing market volatility.

Panel B in Table 5 presents the market SOA estimates for pilot firms participated in the HK Connect Program. We divided the sample into two groups based on their enrollment in the program: pre the program and after the program. To avoid the impact of the Split-share Structural Reform, we limited our samples to those from 2013 onwards. The first column of panel B shows the SOA estimates before the HK Connect Program, with the raw market SOA is 15.7%. After adjusting for stock return volatility, it decreased to 8.2%. The bias was approximately 7.5%, indicating that stock return volatility accounted for about 47.7% of the raw market SOA. However, following the implementation of the HK Connect Program, the raw market SOA at 12.4% closely aligns with the adjusted value of 12.0%. This significant reduction in bias underscores the effectiveness of the HK Connect Program in lowering stock return volatility, confirming our expectation that the program would significantly enhance price discovery and market stability.

[Insert Table 5 about here]

## 6. Beta and Capital Structure Theories

Previous research on capital structure identifies three predominant theories: trade-off theory, pecking order theory, and market timing theory. Despite their prominence, these theories remain subjects of debate in empirical studies. In this section, we aim to investigate which theory applies to the Chinese stock market. The coefficient  $\beta$  captures the relationship between net debt issuance proportion ( $d_{it}/g_{it}^B$ ) and the lagged leverage. It provides deeper insight into the balance between debt and equity, thus serving as an indicator of the relevance and validity of various capital structure theories.

According to the trade-off theory, firms may adjust towards the target capital structure over time. Thus, we would expect firms to reduce their liabilities in the following year (i.e.,  $d_{it} < 0$ ) when their capital structure is higher than the target in the previous year. This indicates a movement towards the target capital structure. Hence, when evaluating the book capital structure, we anticipate a negative value for  $\beta$  in the case of most non-recessionary firms ( $g_{it}^B > 0$ ). The estimated value of  $\beta_1^B$  based on book leverage, presented in Table 2, is 0.403. This result is at odds with the trade-off theory's expectation, which anticipates a negative  $\beta$ .

The pecking order theory suggests that firms prioritize internal financing and prefer debt financing over equity financing. When firms have sufficient internal financing capacity, their financing decisions are not influenced by the book debt ratio from the previous period, resulting in  $\beta$  being close to 0. On the other hand, if firms face a capital shortfall and possess debt capacity, they will opt for debt financing. In this scenario, a higher book debt ratio from the previous period indicates a stronger need for external financing, leading to  $\beta$  being greater than 0. When firms are unable to generate internal financing and already have excessive debt, they are compelled to seek equity financing, resulting in  $\beta$  being negative. Therefore, the pecking order theory might offer varying predictions regarding the coefficient  $\beta$ .

To further examine the applicability of the pecking order theory, we construct the variable



$Def_{it}$  following the approach outlined by Byoun (2008). First, we determine the financial deficit of firms, denoted as  $FD_{it}$ , by aggregating the “dividend payments”, “changes in net working capital”, and “the negative value of operating cash flows after interest and taxes”. The indicator  $Def_{it}$  is set to 1 when internal funds are insufficient, and to 0 otherwise. We estimate the equation (14) to examine the pecking order theory. If the coefficient of  $LEVB_{i,t-1} \times Def_{it}$  is significantly positive, then pecking order theory is applicable.

$$\frac{d_{it}}{g_{it}} = \omega_1 + \omega_2 N_{it}^- + \omega_3 Def_{it} + \beta_1 LEV_{i,t-1} + \beta_2 LEV_{i,t-1} Def_{it} + \beta_3 LEV_{i,t-1} N_{it} + \omega_{it} \quad (14)$$

Table 6 illustrates that firms with adequate internal financing capacity exhibit a coefficient of 0.337 for  $LEVB$ , which is significantly greater than 0. However, the coefficient for the interaction term  $LEVB_{i,t-1} \times Def_{it}$  is economically small and statistically insignificant, indicating that firms lacking internal funds are less inclined to issue debts. These findings offer additional support for the notion that the pecking order theory has limited explanatory power in explaining the capital structure decisions of Chinese firms (Guo et al., 2016).

[Insert Table 6 about here]

The market timing theory posits that firms tend to issue equity financing when they perceive their stock prices to be overvalued by the market (Baker and Wurgler, 2000). This theory suggests that overvalued stock prices correlate with reduced market leverage. Consequently, the issuance of equity is anticipated to lower the ratio of book debt to total assets, implying a reduction in net debt issuance. As a result,  $\beta$  is expected to be significantly positive.

In Table 2, the estimated value of  $\beta_1^{MB}$ , based on market leverage, is 0.840, which is close to 1. This proximity suggests a strong correlation between stock price overvaluation and net debt issuance. Considering the relatively low market SOA of 7.4% for Chinese firms, it is plausible to conclude that the market timing theory may possess greater explanatory power regarding the capital structure decisions of Chinese firms compared to the trade-off theory and pecking order theory.

To undertake a more comprehensive examination of  $\beta$ 's ability to capture the correlation between stock price overvaluation and the equity issuance behavior of Chinese listed firms, annual dummy variables and their interaction terms with the lagged leverage term are incorporated into equation (4) for yearly estimation. This approach allows for a more detailed analysis of the relationship. The estimates of  $\beta_1^{MB}$  for each year are depicted in Figure 3.

Figure 3 illustrates that the  $\beta$  values for China's listed firms predominantly fall within the range of 0.7 to 1 across the majority of years, consistent with the findings of Panel A of Tabel 2 on the full sample. This consistency highlights a robust relationship between the overall stock price overvaluation and the inclination of firms to engage in equity financing. Furthermore, the behavior of firms regarding market timing is influenced by both the market environment and the regulatory control environment for refinancing, as suggested by previous studies (Hu and Xu, 2021; Öztekin, 2015; Frank and Goyal, 2009). During the period of 1999-2018, we identify several noteworthy turning points in  $\beta$ , which align with the shifting patterns in the ease of issuing additional equity within the A-stock market environment. The turning points indicate the relationship between stock price overvaluation and the feasibility of conducting further equity issuances. For instance, the Split-share Structure Reform in 2005 increased the stock price volatility risk for non-tradable shareholders, leading to a decline in financing activities, as reflected by a decrease in  $\beta$ . In early 2008, the Chinese stock market reached its peak during a bull market, resulting in a substantial



rebound in  $\beta$ . The stock market crash in 2015 further reduced  $\beta$ .

[Insert Figure 3 about here]

## 7. Robustness Tests

In this section, we conduct robustness tests to ensure that the observed bias isn't driven by outlier data points. To do this, we: (1) exclude high-growth observations, particularly from information technology firms and those within two years post-IPO; (2) exclude observations where the difference between market and book value growth rates falls within either the top 10% or the bottom 10% decile; (3) remove firms involved in M&As, given that such firms in the A-share market often experience significant valuation hikes. Lastly, we evaluate the impact of operating variables on net debt issuance to mitigate endogeneity concerns.

### 1. Excluding high-growth observations

In the SOA decomposition model, the assumption  $g_{it}^M = g_{it}^B$  is crucial for decomposing raw market SOA. However, high-growth observations in the sample may deviate significantly from this assumption, which can affect the consistency of the estimation results. To address this issue, we exclude two types of observations. First, we exclude information technology firms with industry sector code I, as they exhibit the highest growth characteristics in the sample due to their high-tech attributes. Second, we exclude “firm-year” observations within two years of their IPOs. In the secondary market, Chinese firms frequently witness their stock prices surge well beyond the issue price upon their IPOs. This results in market value fluctuations that significantly exceed book value (Liu et al., 2019; Liu and Chiang, 2022). The estimation results of the SOA decomposition for the sample, after excluding these two types of observations, are presented in Panel A of Table 7.

### 2. Excluding observations with high volatility in market value compared to book value from the total sample

Furthermore, we explore the more general case by grouping observations based on the magnitude of  $\Delta g_{it} = g_{it}^M - g_{it}^B$  for each year. Specifically, we exclude the groups with  $\Delta g_{it}$  in the top 10% and bottom 10% of each year. This exclusion helps eliminate estimation errors caused by extreme deviations of market value from the rate of change of total book assets. The SOA decomposition is then estimated using the processed sample, and the results are presented in Panel B of Table 7.

### 3. Excluding Firms with M&A

Taking into account the possibility that some firms may experience an increase in their valuation through M&A (Tao et al., 2017; Zhang et al., 2023), resulting in a reduction in the market leverage, we exclude such firms from the sample period and conduct the SOA decomposition. This helps prevent an overestimation of the upper bias degree when accounting for the market value change attributed to passive adjustment bias. The results of this analysis are presented in Panel C of Table 7.

### 4. Considering the influence of firm operating variables on the net debt issuance proportion or the firm value growth rate

Some firm-level variables, such as investment opportunities and profitability, may be correlated with both the dependent variables ( $d_{it}/g_{it}$  and  $g_{it}/1 + g_{it}$ ) and the lagged leverage. This can affect the estimated values of  $\beta_1$  and  $\delta_1$ , and consequently, the estimation of  $\lambda$ . Therefore, following the approach of Yin and Ritter (2020), we include  $X_{i,t-1}$  in equations (4)

and (5), estimate the  $\beta_1'$  and  $\delta_1'$ , and re-calculate the SOA. The results are displayed in Panel D of Table 7.

The results of the four robustness tests mentioned above are generally similar to those in Panel C of Table 2, indicating that the SOA decomposition results based on equations (4) and (5) are robust.

[Insert Table 7 about here]

## 8. Conclusions

This paper seeks to determine the speed at which Chinese firms adjust their leverage and identify which capital structure theory is supported. We hypothesize that the market SOA estimates from previous studies appear elevated due to stock market fluctuations. Accounting for stock return volatility, we expect to observe a reduced adjusted market SOA. We apply the SOA decomposition method proposed by Yin and Ritter (2020) to estimate the adjusted market SOA for Chinese firms.

Firstly, we observe that the SOA for Chinese firms is approximately 11% based on book leverage, while the market SOA before adjustment is 19.6%. However, after accounting for the impact of stock return volatility by assuming equal growth rates for book value and market value, the adjusted market SOA is 7.4%, highlighting the limited influence of firms' active financing decisions on the market SOA. These findings yield two main insights: On one hand, the adjusted market SOA is surprisingly lower than the book SOA, challenging the prior studies that the book SOA is typically lower. On the other hand, stock return volatility accounts for a passive adjustment bias estimated at 12.2%. It is suggested for scholars to exercise caution when using market leverage in robustness tests.

Secondly, to determine if the bias originates from stock return volatility, we examine the issue from both cross-sectional and time-series perspectives. Cross-sectionally, high stock return volatility leads to a pronounced upward bias in raw market SOA. In the time-series analysis, the notable improvement in market liquidity after China's Split-share Structure Reform results in increased stock return volatility. As a result, post-reform result displays a higher raw market SOA and a more pronounced passive adjustment bias. Additionally, we explore the impact of other institutional reforms such as the Margin Trading Reform and the HK Connect Program. These reforms enhance the capital market's price discovery function, reduce stock return volatility, and ultimately lead to a decrease in bias.

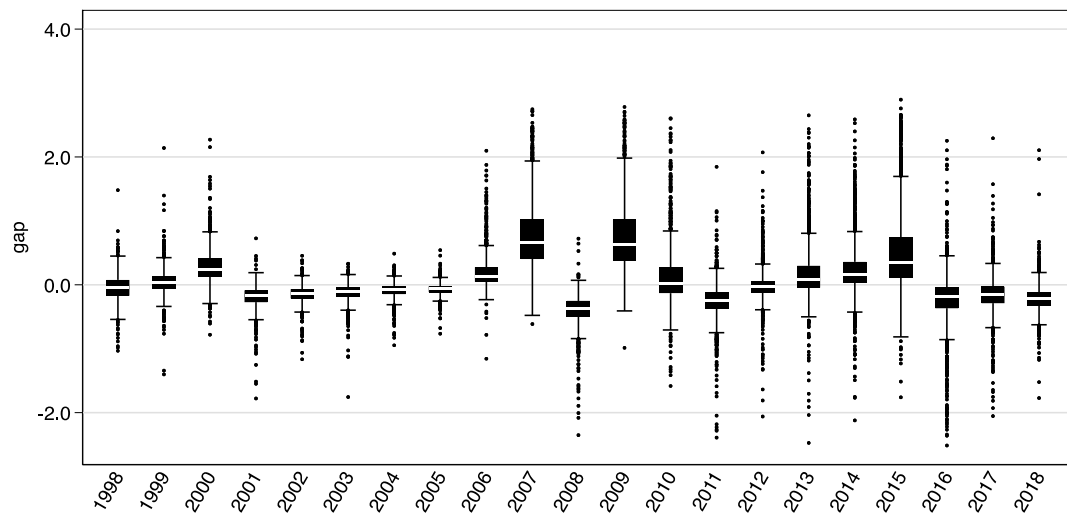
Thirdly, this paper highlights the limited explanatory power of the trade-off theory and pecking order theory in explaining capital structure decisions of Chinese firms. There may be a strong correlation between stock price overvaluation and the decision to issue equity financing, and that market timing theory may be more applicable to explain the capital structure decisions of listed firms in China, although the strength of market timing behavior may also be influenced by the ease of issuing additional equity allotments under regulatory policies.

## Reference

- Abdeljawad, I., Mat Nor, F., 2017. The Capital Structure Dynamics of Malaysian Firms: Timing Behavior Vs Adjustment toward the Target. *International Journal of Managerial Finance*, 13(3): 226-45.
- Baker, M., Wurgler, J., 2000. The Equity Share in New Issues and Aggregate Stock Returns. *The Journal of Finance*, 55(5): 2219-57.
- Boehmer, E., Wu, J., 2013. Short Selling and the Price Discovery Process. *The Review of Financial Studies*, 26(2): 287-322.
- Byoun, S., 2008. How and When Do Firms Adjust Their Capital Structures toward Targets? *The Journal of Finance*, 63(6): 3069-96.
- Chang, E. C., Luo, Y., Ren, J., 2014. Short-Selling, Margin-Trading, and Price Efficiency: Evidence from the Chinese Market. *Journal of Banking & Finance*, 48: 411-24.
- Cook, D. O., Tang, T., 2010. Macroeconomic Conditions and Capital Structure Adjustment Speed. *Journal of Corporate Finance*, 16(1): 73-87.
- DeAngelo, H., DeAngelo, L., Whited, T. M., 2011. Capital Structure Dynamics and Transitory Debt. *Journal of Financial Economics*, 99(2): 235-61.
- Drobtz, W., Schilling, D. C., Schröder, H., 2015. Heterogeneity in the Speed of Capital Structure Adjustment across Countries and over the Business Cycle. *European Financial Management*, 21(5): 936-73.
- Elsas, R., Florysiak, D., 2015. Dynamic Capital Structure Adjustment and the Impact of Fractional Dependent Variables. *Journal of Financial and Quantitative Analysis*, 50(5): 1105-33.
- Fama, E. F., French, K. R., 2002. Testing Trade-Off and Pecking Order Predictions About Dividends and Debt. *Review of Financial Studies*: 1-33.
- Flannery, M. J., Rangan, K. P., 2006. Partial Adjustment toward Target Capital Structures. *Journal of Financial Economics*, 79(3): 469-506.
- Frank, M. Z., Goyal, V. K., 2009. Capital Structure Decisions: Which Factors Are Reliably Important? *Financial Management*, 38(1): 1-37.
- Getzmann, A., Lang, S., Spremann, K., 2014. Target Capital Structure and Adjustment Speed in Asia. *Asia-Pacific Journal of Financial Studies*, 43(1): 1-30.
- Graham, J. R., Harvey, C. R., 2001. The Theory and Practice of Corporate Finance: Evidence from the Field. *Journal of Financial Economics*, 60(2-3): 187-243.
- Gu, L., Wang, Y., Yao, W., Zhang, Y., 2018. Stock Liquidity and Corporate Diversification: Evidence from China's Split Share Structure Reform. *Journal of Empirical Finance*, 49: 57-80.
- Guo, L., Dai, Y., Lien, D., 2016. The Effects of China's Split-Share Reform on Firms' Capital Structure Choice. *Applied Economics*, 48(27): 2530-49.
- He, W., Kyaw, N. A., 2023. Macroeconomic Risks and Capital Structure Adjustment Speed: The Chinese Evidence. *International Journal of Finance & Economics*, 28(3): 2885-99.
- He, W., Kyaw, N. A., 2018. Capital Structure Adjustment Behaviors of Chinese Listed Companies: Evidence from the Split Share Structure Reform in China. *Global Finance Journal*, 36: 14-22.
- He, W., Wang, Q., 2020. The Peer Effect of Corporate Financial Decisions around Split Share Structure Reform in China. *Review of Financial Economics*, 38(3): 474-93.
- Hong, H., Stein, J. C., 2003. Differences of Opinion, Short-Sales Constraints, and Market Crashes. *The Review of Financial Studies*, 16(2): 487-525.
- Hovakimian, A., Li, G., 2011. In Search of Conclusive Evidence: How to Test for Adjustment to Target Capital Structure. *Journal of Corporate Finance*, 17(1): 33-44.
- Hu, Y., Xu, M., 2021. Xi's Anti-Corruption Campaign and the Speed of Capital Structure Adjustment. *Pacific-Basin Finance Journal*, 65: 101483.
- Huang, R., Ritter, J. R., 2009. Testing Theories of Capital Structure and Estimating the Speed of Adjustment. *Journal of Financial and Quantitative Analysis*, 44(2): 237-71.
- Huang, Y., Uchida, K., Zha, D., 2016. Market Timing of Seasoned Equity Offerings with Long Regulatory Process. *Journal of Corporate Finance*, 39: 278-94.
- Jiang, X., Shen, J. H., Lee, C.-C., Chen, C., 2021. Supply-Side Structural Reform and Dynamic

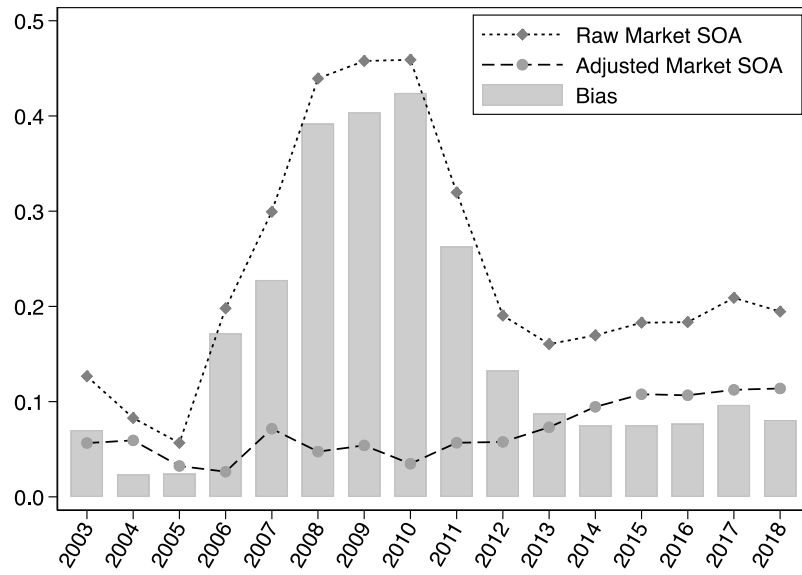
- Capital Structure Adjustment: Evidence from Chinese-Listed Firms. *Pacific-Basin Finance Journal*, 65: 101482.
- Lemmon, M. L., Roberts, M. R., Zender, J. F., 2008. Back to the Beginning: Persistence and the Cross-Section of Corporate Capital Structure. *The Journal of Finance*, 63(4): 1575-608.
- Li, W., Wu, C., Xu, L., Tang, Q., 2017. Bank Connections and the Speed of Leverage Adjustment: Evidence from China's Listed Firms. *Accounting & Finance*, 57(5): 1349-81.
- Li, Z., Lin, B., Zhang, T., Chen, C., 2018. Does Short Selling Improve Stock Price Efficiency and Liquidity? Evidence from a Natural Experiment in China. *The European Journal of Finance*, 24(15): 1350-68.
- Liao, L., Liu, B., Wang, H., 2014. China's Secondary Privatization: Perspectives from the Split-Share Structure Reform. *Journal of Financial Economics*, 113(3): 500-18.
- Liu, H., Chiang, Y.-M., 2022. Confucianism and IPO Underpricing. *Pacific-Basin Finance Journal*, 71: 101701.
- Liu, J., Stambaugh, R. F., Yuan, Y., 2019. Size and Value in China. *Journal of Financial Economics*, 134(1): 48-69.
- Mai, Y., Meng, L., Ye, Z., 2017. Regional Variation in the Capital Structure Adjustment Speed of Listed Firms: Evidence from China. *Economic Modelling*, 64: 288-94.
- Mukherjee, T., Wang, W., 2013. Capital Structure Deviation and Speed of Adjustment. *Financial Review*, 48(4): 597-615.
- Nguyen, H. M., Vuong, T. H. G., Nguyen, T. H., Wu, Y.-C., Wong, W.-K., 2020. Sustainability of Both Pecking Order and Trade-Off Theories in Chinese Manufacturing Firms. *Sustainability*, 12(9): 3883.
- Niu, Y., Wang, S., Wen, W., Li, S., 2023. Does Digital Transformation Speed up Dynamic Capital Structure Adjustment? Evidence from China. *Pacific-Basin Finance Journal*, 79: 102016.
- Öztekin, Ö., 2015. Capital Structure Decisions around the World: Which Factors Are Reliably Important? *Journal of Financial and Quantitative Analysis*, 50(3): 301-23.
- Öztekin, Ö., Flannery, M. J., 2012. Institutional Determinants of Capital Structure Adjustment Speeds. *Journal of Financial Economics*, 103(1): 88-112.
- Tao, F., Liu, X., Gao, L., Xia, E., 2017. Do Cross-Border Mergers and Acquisitions Increase Short-Term Market Performance? The Case of Chinese Firms. *International Business Review*, 26(1): 189-202.
- Tong, G., Green, C. J., 2005. Pecking Order or Trade-Off Hypothesis? Evidence on the Capital Structure of Chinese Companies. *Applied Economics*, 37(19): 2179-89.
- Vo, T. A., Mazur, M., Thai, A., 2022. The Impact of Covid-19 Economic Crisis on the Speed of Adjustment toward Target Leverage Ratio: An International Analysis. *Finance Research Letters*, 45: 102157.
- Welch, I., 2004. Capital Structure and Stock Returns. *Journal of Political Economy*, 112(1): 106-31.
- Wojewodzki, M., Poon, W. P., Shen, J., 2018. The Role of Credit Ratings on Capital Structure and Its Speed of Adjustment: An International Study. *The European Journal of Finance*, 24(9): 735-60.
- Xu, K., Zheng, X., Pan, D., Xing, L., Zhang, X., 2020. Stock Market Openness and Market Quality: Evidence from the Shanghai-Hong Kong Stock Connect Program. *Journal of Financial Research*, 43(2): 373-406.
- Yin, Q. E., Ritter, J. R., 2020. The Speed of Adjustment to the Target Market Value Leverage Is Slower Than You Think. *Journal of Financial and Quantitative Analysis*, 55(6): 1946-77.
- Zhang, H., Gao, S., Yang, F., 2016. Impact of Split Share Structure Reform on Capital Structures: Empirical Evidence from China's Listed Companies. *Applied Economics*, 48(13): 1172-81.
- Zhang, Y., Zhang, Q., Yu, X., Ma, Q., 2023. Equity Overvaluation, Insider Trading Activity, and M&a Premium: Evidence from China. *Pacific-Basin Finance Journal*, 80: 102047.
- Zhao, Y., Lee, C.-F., Yu, M.-T., 2020. Does Equity Market Timing Have a Persistent Impact on Capital Structure? Evidence from China. *The British Accounting Review*, 52(1): 100838.

Figure 1. Evolution of Market and Book Value Growth Rate Differences.

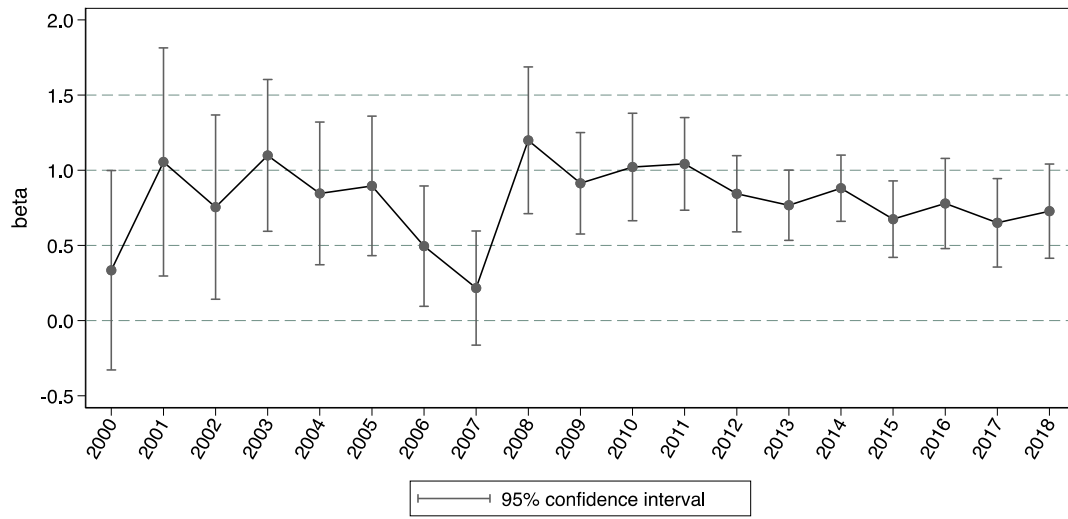


Notes: This figure illustrates the distribution of the gap between the market value growth rate and the book value growth rate for Chinese companies for each year from 1998 to 2018. The gap is calculated as the difference between the market value growth rate ( $g^M$ ) and the book value growth rate ( $g^B$ ).

Figure 2. Annual Market SOA Estimates Derived from Rolling Regression.



Notes: This figure displays the annual estimates of the market SOA from 2003 to 2018, calculated using a rolling regression method with data from the preceding six years. The estimation procedure for raw market SOA and adjusted market SOA is the same as Panel C in Table 2. The bias is defined as the difference between the raw and adjusted market SOA values.

Figure 3. The Annual Estimates of  $\beta_1^{MB}$ 

Notes: This figure presents the estimated values of  $\beta_1^{MB}$  and their corresponding 95% confidence intervals for each year from 2000 to 2018. Specifically, we incorporate annual dummy variables and their interaction terms with lagged leverage into equation (4) for annual estimation.



Table 1. Summary Statistics.

Panel A: Descriptive Statistics						
Variables	N	Mean	S.D.	Min	Median	Max
<i>LEVB</i>	27751	0.454	0.202	0.050	0.456	0.899
<i>LEVM</i>	27751	0.306	0.196	0.016	0.273	0.795
<i>TOBINQ</i>	27751	1.927	1.176	0.903	1.536	7.764
<i>SIZE</i>	27751	21.698	1.193	19.219	21.576	25.145
<i>EBIT/TA</i>	27751	0.051	0.060	-0.195	0.050	0.228
<i>NET_PPE/TA</i>	27751	0.250	0.174	0.002	0.219	0.742
<i>RD/TA</i>	27751	0.004	0.010	0.000	0.000	0.051
<i>DEP/TA</i>	27751	0.025	0.016	0.000	0.022	0.077
<i>RD_Dummy</i>	27751	0.278	0.448	0.000	0.000	1.000
<i>IND_MEDIAN_LEVB</i>	27751	0.442	0.110	0.050	0.427	0.745
<i>IND_MEDIAN_LEVM</i>	27751	0.284	0.131	0.016	0.255	0.742
Panel B: Difference in Means						
Variables	N	Mean	S.D.	Min	Median	Max
$g^B$	27751	0.177	0.348	-0.319	0.099	2.298
$g^M$	27751	0.249	0.539	-0.503	0.109	2.578
<i>Difference_in_means</i>		0.072***				

Notes: This table provides summary statistics for our sample. Among them, Panel A displays the descriptive statistics (mean, standard deviation, minimum value, median, and maximum value) of each variable. Panel B compares the mean of the book value growth rate and the market value growth rate, and employs a T-test to examine the difference in means. *LEVB* represents the ratio of book debt to book assets. *LEVM* is calculated by dividing book debt by the sum of book debt and market capitalization. Ln\_TA stands for the natural logarithm of book assets. *TOBINQ* is defined as the ratio of the sum of book debt and market capitalization to book assets. *EBIT/TA* represents the proportion of EBIT to book assets. *NET\_PPE/TA* indicates the ratio of net fixed assets to book assets. *RD/TA* signifies the proportion of R&D expenses relative to book assets. *DEP/TA* denotes the ratio of depreciation and amortization expenses to book assets. *RD\_DUMMY* is a binary variable assigned a value of 0 if R&D expenses are not disclosed, and 1 otherwise. *IND\_LEVB* is the industry median for *LEVB*, and *IND\_LEVM* is the industry median for *LEVM*.

Table 2. Estimation of SOA.

Panel A: OLS Regression Results						
	Book leverage		Market leverage			
	(1)	(2)	(3)	(4)	(5)	(6)
	$\frac{d}{g^B}$	$\frac{g^B}{1+g^B}$	$\frac{d}{g^M}$	$\frac{g^M}{1+g^M}$	$\frac{d}{g^M}$	$\frac{g^M}{1+g^M}$
					(Let $g_{it}^M = g_{it}^B$ )	
$N^-(g < 0)$	0.643*** (10.68)	-0.212*** (-39.87)	-0.682*** (-19.01)	-0.682*** (-137.66)	0.318*** (10.74)	-0.278*** (-68.78)
$LEV_{i,t-1}$	0.403*** (7.13)	0.026*** (5.13)	0.569*** (9.63)	-0.165*** (-20.23)	0.840*** (22.25)	-0.059*** (-11.46)
$LEV_{i,t-1} \times N^-$	-0.295** (-2.55)	-0.133*** (-13.07)	-0.100 (-0.96)	0.555*** (38.55)	-0.059 (-0.76)	0.013 (1.21)
Constant	0.289*** (10.60)	0.154*** (63.97)	0.289*** (12.93)	0.322*** (104.40)	0.074*** (5.56)	0.183*** (100.99)
N	25099	25099	25099	25099	25099	25099
R <sup>2</sup>	0.021	0.422	0.059	0.612	0.043	0.421

Panel B: Estimating the Influence of Firm-fixed Effect with DPF Model		
	Book Leverage	Market Leverage
Influence of Firm-fixed Effect	0.034	0.048

Panel C: SOA Estimates			
	LEVB	LEV <sup>M</sup> (Raw)	LEV <sup>M</sup> (Adjusted) Let $g_{it}^M = g_{it}^B$
$\lambda(SOA)$	0.110	0.196	0.074

Notes: This table provides the OLS regression results using equations (4) and (5) in Panel A, the influence of firm-fixed effect in Panel B, and the estimated book SOA, market SOA and adjusted market SOA in Panel C. In Panel A,  $d/g$  is the proportion of debt change to total asset change, and  $g/1+g$  is the ratio of total asset change to current total assets. The coefficients of all variables shall be employed in the calculation of  $\lambda$ . In Panel B, we estimate the influence of firm-fixed effect on  $\lambda$ . Firstly, we estimate the DPF model as in Elsas and Florysiak (2015). Secondly, we get the estimated  $\gamma_i$  according to equation (13), and add it with  $\theta X_{i,t-1}$  to obtain target leverage. Finally, we regress target leverage on lagged leverage to obtain the influence of the firm-fixed effect, which is  $h = \text{Cov}(\theta X_{i,t-1} + \gamma_i, LEV_{i,t-1})/\sigma_L^2$  in section 2.2. In Panel C, we obtain the SOA estimates using the coefficients from Panel A and taking into account the impact of firm-fixed effects from Panel B. \*\*\* and \*\* represent significance at the 1% and 5% levels, respectively, with t-values shown in parentheses.

Table 3. SOA Estimates Grouping by Stock Return Volatility.

	Group1	Group2	Group3
Stock Return Volatility	Low	Mid	High
$\beta_1^M$	0.601	0.500	0.449
$\delta_1^M$	-0.131	-0.115	-0.197
$\beta_1^{MB}$	0.812	0.910	0.800
$\delta_1^{MB}$	0.025	0.000	-0.093
Raw Market SOA	0.128	0.212	0.210
Adjusted Market SOA	0.066	0.072	0.053
Bias	0.062	0.140	0.157
Bias/Market SOA (%)	48.4%	66.0%	74.8%
Empirical $p$ -value		0.000***	0.000***

Notes: This table presents the regression results for different groups based on stock return volatility. The data is divided into groups by calculating the standard deviation of monthly individual stock returns for each firm over the past three years (i.e., the preceding 36-month period). Firms are then assigned to three groups - low, medium, and high stock return volatility - based on these calculations for each year. The estimation procedure for market SOA and adjusted market SOA is the same as Panel C in Table 2. The bias is the difference between raw market SOA and adjusted market SOA. The empirical  $p$ -values at the bottom row are used to examine the significance of the differences in the ratio of bias to market SOA between Group 2 and Group 1, as well as between Group 3 and Group 1. The empirical  $p$ -values are obtained through 1000 iterations of bootstrap resampling. \*\*\* denotes significance at the 1% level.

Table 4. SOA Estimates Based on the Split-share Structure Reform.

	Before the reform	After the reform	
	(1) $1998 \leq year \leq 2005$	(2) $2005 < year \leq 2012$	(3) $year > 2012$
$\beta_1^M$	1.464	0.305	0.624
$\delta_1^M$	-0.207	-0.057	-0.256
$\beta_1^{MB}$	0.964	0.789	0.798
$\delta_1^{MB}$	-0.103	-0.020	-0.080
Raw Market SOA	0.079	0.303	0.213
Adjusted Market SOA	0.059	0.051	0.143
Bias	0.020	0.252	0.070
Bias/Market SOA (%)	25.2%	83.2%	32.9%
Empirical $p$ -value		0.000***	0.282

Notes: This table presents SOA estimates associated with the Split-share Structure Reform. The sample is divided into three distinct periods, reflecting the timeline of the reform's impact. Column (1) displays SOA estimates for the period before the reform. Columns (2) and (3) show SOA estimates for subsequent periods, demonstrating the reform's direct and diminished impacts, respectively. Specifically, column (2) covers the years 2006 to 2012, while column (3) focuses on 2013 to 2018. The estimation procedure for market SOA and adjusted market SOA is the same as Panel C in Table 2. The bias is the difference between raw market SOA and adjusted market SOA. The empirical  $p$ -values at the bottom row are used to test the significance of the differences in the ratio of bias to market SOA proportion, comparing Column (2) with Column (1) and Column (3) with Column (1). The empirical  $p$ -values are obtained through 1000 iterations of bootstrap resampling. \*\*\* denotes significance at the 1% level.

Table 5. SOA Estimates and Other Institutional Reforms

Panel A: Margin Trading Reform		
	(1) Before the reform	(2) After the reform
$\beta_1^M$	0.526	1.157
$\delta_1^M$	-0.390	-0.184
$\beta_1^{MB}$	0.810	0.899
$\delta_1^{MB}$	-0.223	-0.051
Raw Market SOA	0.121	0.116
Adjusted Market SOA	0.073	0.112
Bias	0.048	0.004
Bias/Market SOA (%)	39.7%	3.4%
Empirical $p$ -value		0.003***
Panel B: HK Connect Program		
	(1) Before the program	(2) After the program
$\beta_1^M$	0.648	1.137
$\delta_1^M$	-0.253	-0.063
$\beta_1^{MB}$	0.891	0.794
$\delta_1^{MB}$	-0.126	0.008
Raw Market SOA	0.157	0.124
Adjusted Market SOA	0.082	0.120
Bias	0.075	0.004
Bias/Market SOA (%)	47.7%	3.2%
Empirical $p$ -value		0.004***

Notes: This table presents the SOA estimates for samples exclusively from pilot firms, starting from 2013. The sample are further divided into two groups based on the Margin Trading Reform and the HK Connect Program. In Panel A, the sample is split into two groups around the Margin Trading Reform. Column (1) shows the SOA estimates for the period before the reform, while column (2) displays the SOA estimates for the period after the reform. In Panel B, the sample is similarly divided around the HK Connect Program. Column (1) shows the SOA estimates before the program, and column (2) displays the estimates after the program. The estimation procedure for market SOA and adjusted market SOA is the same as Panel C in Table 2. The bias is the difference between raw market SOA and adjusted market SOA. The empirical  $p$ -value at the bottom row is used to test the significance of the differences in the ratio of bias to market SOA proportion between Column (2) and Column (1). The empirical  $p$ -value is obtained through 1000 iterations of bootstrap resampling. \*\*\* denotes significance at the 1% level.

Table 6. Pecking Order Theory: Regression Evidence.

	$\frac{d}{g^B}$
$N^-(g < 0)$	0.638*** (10.48)
$LEVB_{i,t-1}$	0.337*** (3.74)
$LEVB_{i,t-1} \times N^-$	-0.276** (-2.36)
$LEVB_{i,t-1} \times Def_{it}$	0.096 (0.93)
$Def_{it}$	-0.028 (-0.55)
<i>Constant</i>	0.309*** (6.95)
$N$	25099
$R^2$	0.022

Notes: This table examines the applicability of pecking order theory in the Chinese capital market. We construct an indicator variable called  $Def_{it}$ , which represents whether a firm lacks sufficient internal financing (assigned a value of 1) or not (assigned a value of 0). Subsequently, we include  $Def_{it}$  and the interaction term  $LEVB_{i,t-1} \times Def_{it}$  in equation (4) for estimation. \*\*\* denotes significance at the 1% level and \*\* denotes significance at the 5% level.

Table 7. Robustness Check.

Panel A: Excluding Observations with High-growth Rate			
	LE VB	LEV <sub>M</sub> (Raw)	LEV <sub>M</sub> (Adjusted) Let $g_{it}^M = g_{it}^B$
$\lambda_0(SOA)$	0.1 10	0.196	0.074
$\lambda(SOA)$	0.0 99	0.201	0.057
Panel B: Excluding Observations with High Market Value Volatility			
$\lambda(SOA)$	0.0 88	0.189	0.067
Panel C: Excluding Firms with M&A			
$\lambda(SOA)$	0.1 09	0.191	0.075
Panel D: Considering the Impact of Firm Operating Variables			
$\lambda(SOA)$	0.1 12	0.245	0.104

Notes: This table presents the results of four robustness tests. The estimation results of  $\lambda_0(SOA)$  in the third row serve as the benchmark and are obtained from Panel C of Table 2. Panel A displays the estimation results after removing observations with high-growth rates. Panel B shows the estimation results after excluding observations with high market value volatility. Panel C presents the estimation results after excluding firms that have undergone M&A. Panel D takes into account the impact of firm operating variables on the net debt issuance proportion and the firm value growth rate, and we re-estimate the model following the approach of Yin and Ritter (2020).



## Author Statement

We declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## CRediT authorship contribution statement

Yujun Lian: Conceptualization, Funding acquisition, Resources, Supervision, Validation, Visualization, Project administration.

Jun Wang: Investigation, Methodology, Writing – original draft, Writing – review & editing.

Manqi Huang: Data curation, Software, Writing – original draft.

**Highlights**

- We employ a speed of adjustment (SOA) decomposition model proposed by Yin and Ritter (2020) to study Chinese firms' market leverage adjustment speed.
- We find an overestimation of the SOA to the target market capital structure in Chinese firms with pre-correction speed at 19.6% and post-decomposition speed at 7.4%.
- Upward bias in SOA is attributed to stock price fluctuations in the stock market.
- Trade-off theory and pecking order theory have limited explanatory power for Chinese firms, while market timing theory is more applicable.