Discontinuous Managerial Behavior: Seasoned Equity Offering Timing and Financial Disclosure Quality

Abstract

The timing of seasoned equity offerings (SEOs) actively influences managerial concerns regarding earnings fabrication. Theoretically, based on stock price anchoring, this study considers the last-offered equity price as a threshold for evaluating the quality of a firm's financial disclosure. Using the '*price ratio*', a novel instrumental approach for SEO timing, we provide causal estimates at different event times with a regression discontinuity design. We find that when the share price equals or crosses the recent offer price eligible for treatment, it reveals a substantially higher level of poor disclosure quality prior to the SEO. However, this impact is statistically indistinguishable from zero for SEOs and their forward-looking periods. These intertemporal variations in financial disclosure quality are attributable to the notion that, in our context, managers temporarily adjust the accounting numbers upward instead of making frequent fabrications. We also empirically illuminate the theoretical mechanisms by which this relationship is more pronounced. The timing, anchoring, placebo cutoffs, instrumental approach, and heterogeneity theoretically and empirically support the SEO-disclosure nexus. Furthermore, the discontinuous jump at a specific reference point provides a timely warning of the adverse consequences of this point and quantifies the implications for regulatory bodies concerning financial transparency.

JEL Classification: C01, G14, G32, G40, and M41.

Keywords: Corporate misconduct, market timing, regression discontinuity, spillover effects, stock price anchoring

1. Introduction

The time to conduct a seasoned equity offering (SEO) event is arguably a prominent financing decision for publicly listed firms (Hibbert et al., 2020), because the timing of such offerings is affected merely by the share market price. This timing phenomenon is more effectively explained by the conjecture of market timing theory (Baker & Wurgler's, 2002): firms conduct SEOs when the share price is overvalued and treasure them at the lowest price to exploit these interim fluctuations at the cost of issuance to provide a transitory advantage to shareholders.[1] With this conceptualization, firms make decisions regarding raising capital in the best interests of owners (shareholders), even though this is not true in all scenarios, because such decisions are beneficial only to shareholders who strictly monitor managerial practices. Additionally, Chen et al. (2019) and Henderson et al. (2023) report that investor sentiment plays a key role in SEO conduction because it significantly influences market efficiency and mispricing. They claim that high sentiment attracts many uninformed traders, which hurts efficiency and increases the chances of mispricing. In response, they highlighted that under '*ceteris paribus*', high sentiment leads stocks to be overpriced because uninformed investors become more optimistic and bid stock prices up relative to their fair values. Similarly, Lee (2021) reported that managers usually intend to issue shares when they perceive a firm to be overvalued. One possible reason is that by issuing overvalued securities to overly optimistic investors, managers might reap short-term overpricing benefits (Hovakimian & Hu, 2020; Loughran & Ritter, 1995). Survey data have also proven this tight identification of market timing in the context of SEO (Graham & Harvey, 2001).

[1] Previously, the firm SEOs were fairly publicly marketed; since the start of the 21st century, the method of raising capital has drastically changed, and firms have adopted quicker ways to obtain temporary benefits. This can occur because of the prevailing behavioral biases and asymmetric information between owners and managers about the exact situation of the equity market.

The timing functionality of stock prices also significantly affects reported earnings information because investors most likely anticipate aggregate market-wide earnings before firm-specific earnings (Elgers et al., 2008; Piotroski & Roulstone, 2004), and the disclosure of information in financial statements is a key substantive part of corporate communication with stakeholders. The timing element in SEO is also characterized by the dynamics of firms' disclosed information. However, investors are often unable to detect accounting adjustments in firms. In such cases, managers have considerable discretion to artificially increase their income to deceive investors and issue shares deceptively at a price higher than their fundamental value. Similarly, Teoh et al. (1998) reported that firms that issue in the pre-issue period fabricate earnings upward through incremental accounting adjustments. Such offerings probably occur more frequently when the market prices are higher. This can be built to create investor confidence and a favorable market sentiment to benefit from higher issuance prices. By contrast, during the post-issue period, the information disclosure environment changed substantially relative to the pre-issue period. Although there is high skepticism regarding investors' prospects, managers have fewer incentives (Hibbert et al., 2020).[2]

Many measures such as the market-to-book (MB) ratio, Tobin's Q, and post- and pre-issue abnormal returns are common proxies for market timing (DeAngelo et al., 2010; Khan et al., 2012). Alternatively, all of these measures are considered noisy to some extent. On the one hand, the MB ratio is referred to as mispricing, but is also characterized as a proxy for firm growth (Chen et al., 2019), and Tobin's Q is also considered for firm valuation (Barker et al., 2024). Similarly, Fama (1998) estimation of 'normal returns' reflected the pricing model, whereas 'abnormal returns' estimations are problematic. We observe that all these measures

[2] With the capital-raising strategy, compared with pre-issue firms in post-issue tenures, firms are likely to commence on multiple growth paths for effective evaluation regarding uncertainty about the future situation of the firm. Moreover, after SEO occurrence, the association of SEO timing with investment and financing becomes more complicated (Kim & Weisbach 2008; DeAngelo *et al.* 2010).

completely ignore market dynamics, investor sentiment, strategic objectives, and prospective firm performance, which are the key determinants of SEO timing. Additionally, the predictive capacity of these measures for corporate decisions to conduct SEOs is limited (Chen et al., 2019). Therefore, few studies exist and determining the consequences of SEO timing is challenging (Dittmar et al., 2020).

To fill these gaps, this study examines the causal effects of SEO timing using a newly developed instrumental variable of Dittmar et al. (2020) for SEO timing, which is the 'price ratio' that does not depend on mispricing. The price ratio (a proxy for SEO timing) is interpreted as the 'average share price of the last quarter to the most recent equity offer price', Hennessy and Chemla (2022) also prove the validity of this approach. Specifically, aligning with anchoring-based financing decision processes, we hypothesize that SEO timing has real and financial effects on the financial disclosure quality (FDQ).

Theoretically, this study is based on the role of stock price anchoring in strategic financing decision making and considers the last offered equity price as a threshold for FDQ valuation. When the stock market price touches or crosses the recently offered price (i.e., the SEO price), it can build positive investor sentiment and motivate investors to buy shares at least at the current market value. This price reference point encourages managers to artificially overvalue share prices by adjusting accounting numbers to collect higher proceeds from SEOs. Dittmar et al. (2020) reported that when the firm's share price touches or crosses the last offering price, firms prefer to issue more shares. Chen et al. (2023) claimed that prior to SEO, one-time disclosure can be reversed and is most often unlikely to be perceived by investors because this does not reflect the firm's disclosure commitment in the future. Furthermore, interest in borrowing is strongly affected by firms' historical borrowing rates (Dougal et al., 2015). These reference points clearly highlight that anchoring influences the most sophisticated agents, that is, managers. Hovakimian and Hu (2020) reported that the time spent on SEOs also leads to significant long-term modifications in a firm's capital structure. However, a change in capital structure impacts the discontinuity in managers' earnings fabrication behavior. Hence, based on the consequences of the reference point, we believe that FDQ discontinuously jumps around a price ratio cutoff value that is equal to 1 because if the share price is greater than or equal to the last offer price, it can lead the firm to be at risk of possible takeover attempts. Offering incentives to managers may increase earnings and dampen such bids. Similarly, if a firm plans an SEO shortly, its managers are motivated to achieve short-term orientation regarding stock overvaluation, which may compromise short-term accounting quality.

Following the above conjectures, the empirical part is initiated under a fuzzy regression discontinuity design (RDD) analysis with a comparison of the treatment group (price ratio ≥1) and control group firms (price ratio < 1). The RDD approach is based on a natural quasi-experiment in which the treatment is based on whether the assignment variable exceeds the threshold level (Calonico et al., 2014).[3] A key feature of RDD is their ability to address endogeneity concerns (Armstrong et al., 2013). This design also offers additional benefits, as Lee and Lemieux (2010) claimed and justified that this approach is not 'just another evaluation strategy'; causal estimations from RDD are more credible than other traditional natural experimental designs (i.e., difference-in-differences). Specifically, in our setting, it measures local randomness and the plausibly exogenous variation in managers' discretion toward the likelihood of FDQ when firms are just slightly above and slightly below the price ratio cutoff (cutoff equals to1). Our identification approach assumes that firms that are eligible and ineligible for treatment by a small margin would exhibit different managerial behaviors toward earnings adjustments. This assumption was verified using robust nonparametric inferences

[3] In our case, for implementation of the RDD approach, the threshold value of the *price ratio* equals 1. Treatment occurs when the price ratio ≥ 1.

within the fuzzy RDD framework. Following Bonfim et al. (2023), we consider firms that lie just below the threshold counterfactual for those that meet the threshold level by a small margin. Quantifying credible RDD estimates requires the selection of the polynomial order and optimal bandwidth. We used narrow bandwidths to present credible and precise estimations, which decreased the biases of the outcomes and further restricted the analysis to 1^{st-} and 2^{nd}-order polynomials because a higher level of polynomial order usually results in noisy outcomes (Gelman & Imbens, 2019).

Empirically, we perform several primary estimations under a restricted sample to narrow bandwidths, where the price ratio lies between 0.90 and 1.10.[4] We begin by establishing several novel empirical findings. First, across specifications and samples, our model predicts causal evidence that the treatment variable (equals 1 if the price ratio ≥ 1, 0 otherwise) has statistically positive coefficients with the likelihood of FDQ until two quarters prior to SEO occurrence. This finding indicates that when the share value touches and crosses the last offering price, managers readily attempt to adjust accounting numbers, which affects the quality of financial disclosure. The results also show that managers' incentives for the likelihood of FDQ are statistically indistinguishable in the SEO, post-SEO, and two quarters before the pre-SEO period. These intertemporal variations in FDQ imply that managers are not usually involved in long-term manipulations; they temporarily adjust accounting numbers to raise finances by issuing shares at high prices.

Furthermore, to validate the robustness of the main finding, we revisit the main hypothesis by controlling for Tobin's Q and MB in the model with the treatment variable. The newly

[4] In the main analysis, the sample is restricted to narrow bandwidths around the threshold level of the price ratio = 1, where the sample restricts firm quarter observations whose price ratio value lies between 0.90 and 1.10 because optimal narrow bandwidths reduce the biases and mean-square errors from estimations. This is done to compare the discontinuity of eligible (treatment group) firms that pass the eligibility criteria by a small margin with firms that are not eligible (control group) by a small margin. In other words, we compare when the price ratio is just above and below the threshold level.

developed instrumental variable *price ratio* might be correlated with past stock prices, mitigating the argument that managers' decisions are based on anchoring instead of past trends. To address this concern, estimations of the treatment variables were compared with existing SEO timing measures, that is, Tobin’s Q and MB. These are frequently used measures of SEO timing in the literature (Baker & Wurgler's, 2002; Dittmar et al., 2020). However, our results did not show any changes. The estimations reveal that, by controlling for Tobin’s Q and MB in the model, the treatment still has a statistically positive coefficient with the likelihood of FDQ until two quarters before the SEO.

Next, we extend the analysis under eight different subsamples based on several key firm characteristics with respect to their financing constraints situation, life cycle stage, and ownership status (state-owned vs. non-state-owned) that would be at play in the relationship between treatment variables and FDQ: (i) empirically predicts that treatment has a direct and statistically significant linkage with the FDQ in financially constrained firms, whereas in unconstrained firms, this association is not significant; these estimations show that, with financially constrained status, firms are more engaged in manipulative reporting practices; (ii) the results indicate that firms at the introduction and decline (growth and maturity) phase of their life have a significant (insignificant) positive linkage with the discontinuity of FDQ in estimated coefficients, which builds the notion that when firms’ size is smaller, then managers are intentionally inclined to significantly violate the ethical reporting standards and reveal a lower disclosure quality; and (iii) then, we add the state-owned (SO) enterprises' mechanism to explore whether this indicator affects the association between treatment and FDQ because this ownership (SO) is more common in the Chinese economy (Lennox & Wu, 2022). Our empirical analysis confirms that the treatment impact on non-state-owned enterprises is significant, with a positive coefficient, leading to lower financial reporting quality than in the context of state-owned firms, where this impact is statistically indistinguishable from zero.

Overall, our results imply that investors perceive firm SEOs favorably when stocks are overpriced. Specifically, this trend modifies managerial incentives for earnings manipulation. Given these intertemporal variations, we connect our study to the literature on periodic accounting adjustments. Additionally, we empirically report causal estimates that the propensity of treatment impacts disclosure quality is more pronounced when firms experience financing constraints, lie in the introduction and decline stages, and have a non-SO status.

Our contribution to the literature is twofold. First, we provide novel theoretical explanations for several empirical outcomes attributable to managers' decision making. First, our settings provide clear empirical causal evidence based on SEO timing with the likelihood of FDQ under the RDD mechanism, which closely extends prior literature on mispricing models and past stock price trends by using a novel instrumental measure for SEO timing, *the price ratio*, which mitigates the influence of historical trends and mispricing. Furthermore, this study enriches the literature on information asymmetry. Baker and Wurgler's (2002) market timing theory states that equity issuances are conducted mainly to increase existing stockholders' wealth at the expense of new investors who purchase shares through SEOs, because higher asymmetric information is associated with equity rather than debt. Combined with this fact, both Bharath et al. (2009) and Lee (2021) found that if a firm lies in an undervalued situation (when managers' information reflects that the firm value increases soon), firms avoid raising capital through SEOs. Hence, with more asymmetric information and expectations of overvaluation, firm managers are incentivized to adjust their accounting numbers, especially when they plan to issue SEOs. Therefore, given the belief that these asymmetries and timing conceptualizations in SEOs must be part of the intertemporal variation in managers' discretion in accounting numbers, this study evaluates SEO timing and FDQ by producing five event-time estimations (quarters before and after SEO occurrence) to quantify the exact extent of the likelihood of FDQ around SEO timing. Despite the level of 'occasional accounting adjustments,' our consistent evidence shows that these event-time variant estimations also extend the literature on 'periodic accounting adjustments' around key firm events (i.e., SEOs), which proves that, in our context, firm managers temporarily adjusted the accounting numbers to achieve short-term benefits.

Second, this study enriches the growing literature on the consequences of managers' decision-making processes based on stock price anchoring. Cen et al. (2013) report that anchoring bias affects investors, especially when determining a firm's future profitability level. Dougal et al. (2015) found that corporate interest rates vary subject to anchoring on past deal terms. Hovakimian and Hu (2020) highlighted the anchoring by investors on stock prices; as a result, managers make efforts to minimize issuance costs by adjusting the timing of SEO to periods when the share market is more receptive. These anchoring interpretations might be part of managers' discretion regarding misstatements, which is a key focus of our study. It also contributes to the understanding of the systematic consequences of the underlying mechanisms of the SEO timing and FDQ nexus by considering different theoretical channels that might empirically influence our relationship. As suggested by Linck et al. (2013), instead of being non-constrained, financially constrained firms are much more likely to engage in income-increasing accrual activities a quarter prior to investments to portray a positive signal in the market. DeAngelo et al. (2010) reported that firm life cycle phases and market timing are statistically associated with the likelihood of SEO conduction. Lennox and Wu (2022) reported that the Chinese government holds major swaths of its economy through direct state ownership and control of critical resources (i.e., financial and physical capital) in businesses. These arguments reveal that financing constraints, life cycle phases, and state ownership are key mechanisms that may explain the reshaping of the nature of the main findings that we consider in this study. We predicted that all three major mechanisms play a significant role in the relationship between SEO timing and FDQ. Our results confirm these insights in different scenarios and contribute to SEO implications for stakeholders in financial policy. Hence, our empirical evidence suggests that firms must be inclined to choose an auditing policy that identifies and discourages misstatements, and investors must consider reference points and scenarios in which these firms are most likely to be involved in earnings fabrication. From a normative perspective, the results suggest that the CSRC should reform SEO procedures, enforce private listings, and promote institutional investors and delist poorly governed firms.

Overall, we contribute to the literature on SEO and FDQ by hypothesizing a model that depends on managers' anchoring-based decision-making processes to inspect the financial and real causal influences of SEO timing. Furthermore, the use of a newly developed concrete SEO timing measure, the '*price ratio*', which does not rely on past stock price trends and mispricing, also sheds new light on the literature. Our study is related to the following nascent strands of research (Bazrafshan, 2025; Boulifa & Uchida, 2024; Chen et al., 2023; Chen et al., 2025; Cheng et al., 2022; Cohen & Zarowin, 2010; Dittmar et al., 2020; Kim & Weisbach, 2008; Lee & Masulis, 2009; Lee, 2021; Lennox et al., 2018; Teoh et al., 1998). We extend this literature by adding a timing element, quasi-natural experimental design, anchoring-based decisions, and theoretical mechanisms to determine the discontinuity of the FDQ around SEO timing.

This paper proceeds as follows: Section 2 describes the research design, empirical strategy, econometrics, and variables. A detailed description of the data and a descriptive analysis are presented in Section 3. Section 4 reports and discusses the empirical results. Finally, conclusions are presented in Section 5.

2. Research Design and Measurements

We use a single-dimensional regression discontinuity design (RDD) in accordance with our main motive to estimate the causal effects of treatment, and the treatment effect is heterogeneous across firms.[5] In a single-dimensional RDD, the cutoff for the forcing variables and bandwidths was defined using a single criterion. Hence, a single forcing variable and its cutoff value that uses natural variations in the forcing variables around the majority threshold must be defined. This approach has been implemented and validated by Dittmar et al. (2020), Hennessy and Chemla (2022), and Liu and Wu (2023). The naïve regression estimations of SEO timing and FDQ may produce biased outcomes because some unobservable characteristics may correlate with the explained and explanatory variables. Furthermore, a key challenge in interpreting simple OLS outcomes regarding spillover effects is the 'manifestation' of the 'reflection problem'. In these scenarios, the RDD approach is the best solution to resolve endogeneity concerns. Accordingly, to isolate quasi-randomized variation and report efficient and precise estimations, the analysis was restricted to a part of the sample that lies around the treatment cutoff. Analogously, to estimate the excellent effects, this study compares the firms that lie under the treatment group by passing the criteria by a small margin with those that do not qualify for the treatment group by a small margin. Because of ex-ante doubts concerning the responses at the threshold, the RDD approach provides quasi-variation in the FDQ with a truly fair treatment. The key assumption is that the clutch by RDD is the forcing variable (price ratio as a measure of SEO timing in our context) and should follow a continuous distribution around the majority threshold, as shown in Fig. 1. Let us assume that $Y_{i,t}(1)$ and $Y_{i,t}(0)$ represent the pair of outcome variables (FDQs in our context) of firm i at time t and reflect the FDQs with exposure to the treatment and without exposure to the treatment, respectively. Typically, RDD focuses on the difference $Y_{i,t}(1)$ - $Y_{i,t}(0)$ instead of the combined effect of $Y_{i,t}(1)$ and $Y_{i,t}(0)$ together. Therefore, it estimates the average treatment effect, that is, $Y_{i,t}(1)$ - $Y_{i,t}(0)$ over the cross sections instead of individual unit-level effects. For example, $D_{i,t}$

[5] Compared with other nonexperimental approaches, the key advantage of RDD is that it has proven much internal and external validity.

represents the treatment indicator with $D_{i,t} = 1$ if the firm is exposed to treatment; otherwise, $D_{i,t} = 0$, the observed outcome is written as:

$$Y_{i,t} = D_{i,t} \, . \, Y_{i,t}(1) + \left(1 - D_{i,t}\right) . \, Y_{i,t}(0) = \begin{cases} Y_{i,t}(1), & if\ D_{i,t} = 1, \\ Y_{i,t}(0), & if\ D_{i,t} = 0. \end{cases} \tag{1}$$

Specifically, we employ a fuzzy RDD approach to access clean estimates of the causal inferences of SEO timing on the FDQ. This nonparametric strategy investigates the treatment effect of firms close to a specific cutoff value. This effect is quite different for firms far from the specified cut-off values. Under fuzzy RDD, the probability of receiving treatment is not required to change from 0 to 1 at the cut-off point (W. Imbens & Lemieux, 2008). The fuzzy design allows small jumps at the threshold level in the likelihood assignment to treatment, and it requires only the following:

$$\lim_{\varepsilon \downarrow 0} prob\left(D_{i,t} = 1 | X_{i,t} = c + \varepsilon\right) \neq \lim_{\varepsilon \uparrow 0} prob\left(D_{i,t} = 1 | X_{i,t} = c + \varepsilon\right) \tag{2}$$

In fuzzy treatment, jumps do not have exactly 1 probability at the cutoff point; hence, the association between X and Y cannot be interpreted as the average treatment effect (Lee & Lemieux, 2010).[6] As an instrumented variable setting (in our case, the price ratio is constructed as an instrumental variable), the average treatment effect is retrieved by the ratio of jumps in the linkage between Y and X at the cutoff to the fraction induced to commence the treatment at the cutoff point.[7] Mathematically, the average treatment effect is written as

$$\tau_{Fuzzy} = \frac{\lim_{\varepsilon \downarrow 0} \mathbb{E}\left[Y_{i,t} | X_{i,t} = c + \varepsilon\right] - \lim_{\varepsilon \uparrow 0} \mathbb{E}\left[Y_{i,t} | X_{i,t} = c + \varepsilon\right]}{\lim_{\varepsilon \downarrow 0} \mathbb{E}\left[D_{i,t} | X_{i,t} = c + \varepsilon\right] - \lim_{\varepsilon \uparrow 0} \mathbb{E}\left[D_{i,t} | X_{i,t} = c + \varepsilon\right]} \tag{3}$$

[6] The use of the instrumented variable approach in fuzzy RDD is much more common, and different studies use this approach to interpret the average treatment effect under fuzzy RDD for precision and efficient estimations; see Dittmar *et al.* (2020) and Hennessy and Chemla (2022).

[7] In other words, it is recovered through the discontinuity in the association between D and X.

Many important points of debate exist concerning the explanation of the treatment effect under fuzzy RDD. Hahn et al. (2001) reported that the causal treatment effect under equation (3) above required the same Imbens and Angrist (1994) assumption as that is, '*monotonicity*' ($X_{i,t}$ exceeding the threshold does not simultaneously affect some to receive and others to reject for treatment) and '*excludability*' ($X_{i,t}$ beyond the threshold does not affect $Y_{i,t}$ except through affecting the receipt of treatment). When these assumptions are accepted, then, technically, it follows that

$$\tau_{Fuzzy} = \mathbb{E}\left[Y_{i,t}(1) - Y_{i,t}(0) \mid Units\ are\ Compiler, X_{i,t} = c\ \right], \quad (4)$$

where $Y_{i,t}$ and $X_{i,t}$ represent the outcome and running variable, respectively; c as the cutoff value, and compiler means the units/firms that receive treatment after satisfying the ($X_{i,t} \geq c$) condition.

Formally, under the RD design to access causal inferences, we estimate the following model:

$$Y_{i,t\pm\tau} = \alpha + \beta_1 D_{i,t} + \sum_{P=1}^{P}\{\alpha_{\rho 0} + \alpha_{\rho 1} \cdot D_{i,t}\}^{\rho} + \delta_{i,t} + \varepsilon_{i,t} \quad (5)$$

In Eq. 5, $Y_{i,t}$ represents our outcome variable (FDQ), measured through the proxy of earnings manipulation or earnings management, used interchangeably in the literature. τ denotes the quarters before and after the SEO is conducted. The FDQ proxy is constructed via Hribar and Collins (2002) discretionary accruals model, which relies on a modified Jones model (Dechow et al., 1995), consistent with Bose and Yu (2023) and Armstrong et al. (2024) recent studies. $D_{i,t}$ is an indicator variable that takes a value of 1 if the firm is eligible for treatment (price ratio ≥ 1); otherwise, it is 0. The price ratio is an instrumental variable constructed following Dittmar et al. (2020), and is defined as the ratio of the average share price in the last quarter to the most recent equity offer price.

The $\{\alpha_{\rho 0} + \alpha_{\rho 1} \cdot D_{i,t}\}^{\rho}$ is a function of the polynomial order of the distance to the cut-off. The coefficients of $\alpha_{\rho 0}$ and $\alpha_{\rho 1}$ can differ above and below the threshold. $\delta_{i,t}$ is a vector of fixed effects, specifically, i, and t represent firm and time fixed effects, respectively. Furthermore, to eliminate extrapolation bias and ensure comparability between the treatment and control groups, this study employed a local linear model and narrow bandwidths in our estimations to report precision outcomes. The coefficient of interest β_1 measures the average differential impact in $Y_{i,t}$ between the eligible and non-eligible groups.

If the estimated coefficient β_1 is positive, when the share value reaches or crosses the last offering price (treatment group or price ratio ≥ 1), managers have much discretion to adjust the accounting numbers that diminish the quality of the firm's financial disclosure compared to the control group at a specific τ. Another primary feature of the RDD is the optimal selection of polynomial order and bandwidths. Calonico et al. (2014) recommended that for local-linear regressions, a 2nd-order weighted polynomial with optimal narrow bandwidths can create a trade-off between bias and efficiency. Referring to Gelman and Imbens (2019), this study used small narrow bandwidths ($\pm$ 0.10) around the cutoff and used only 1st and 2nd polynomial orders because higher-level polynomial orders in estimations usually result in noisy results. Cattaneo et al. (2020) reported that when the assignment of the treatment variable is random, the coefficient β_1 should be invariant to the addition of some control variables. To validate this assumption, we estimated Eq. 5, with and without firm-level control variables. In addition, we repeated the analysis of Eq. Table 5 partitions firm-quarters into eight subsamples based on different firm characteristics, including financing constraints, life-cycle stage, and ownership status, to statistically examine the magnitude of the treatment coefficient across these subsamples.

3. Data and Descriptive Analysis

a. Data

We use quarterly data of all Chinese nonfinancial A-listed firms listed on the '*Shenzhen and Shanghai stock exchanges.'* Considering China's unique jurisdiction inspired by the following impetus, unlike the stock markets of developed economies held by institutional investors, the institutional infrastructure of China is much different from that of other countries; retail investors denominate China's stock market (Leippold et al., 2022). A yearbook of the Shanghai Stock Market 2019 revealed that out of 214.5 million investors, 213.8 million (99.7%) were individual investors, whereas only 0.7 million were institutional investors. Furthermore, auditors might face less of a threat of being sued than in developed economies; therefore, there is no strong rationale to detect or discourage managers' involvement in FDQ (Lennox et al., 2018). Moreover, once a firm is listed in China, it must continuously maintain profitability threshold levels; otherwise, the CSRC will delist the firm if it reports losses over three consecutive years (Lennox & Wu, 2022).[8] Chinese firms also use the realized losses and gains of securities available for sale to smooth earnings (Lu et al., 2023). The unique jurisdiction of China, with its immense size, also has important implications for all countries worldwide because its domestic stock market affairs have key spillover effects on the stock markets of other regions, including the U.S. This spillover effect arises from many Chinese listed firms overseas. Furthermore, literature from non-Chinese countries raises the question of the 'efficacy of improving' reporting standards without strict enforcement and enhancement of

[8] As per the '*Chinese Securities Regulation Commission*' (CSRC) profitability benchmark, companies are much more stringent in maintaining the performance to raise the required capital through SEOs. This regulation motivates managers to violate ethical financial reporting standards.

incentives for preparers of financial reports in China (Christensen et al., 2013; Daske et al., 2013).[9]

Our data comprise seasoned equity offerings (SEOs) reported by the '*China Listed Firms Research Series – Seasoned Equity Offering'* database from 2002Q1-2023Q1. A total of 4,309 SEOs were reported during the selected time span, and the year-by-year SEO statistics are presented in Table 1. We then merged these data with firms' financial statement data assembled from the *China Stock Market and Accounting Research* (CSMAR) database. We further impose some restrictions on the sample, that is, we exclude financial firms and firms that must match SEO firms. Table 2 presents the detailed sample construction procedures.

Table 1. Summary of SEO's Conduct

Sr. No.	Year	SEO's	%
1	2002	20	0.46%
2	2003	14	0.32%
3	2004	11	0.26%
4	2005	10	0.23%
5	2006	44	1.02%
6	2007	122	2.83%
7	2008	107	2.48%
8	2009	106	2.46%
9	2010	154	3.57%
10	2011	172	3.99%
11	2012	143	3.32%
12	2013	249	5.78%
13	2014	361	8.38%
14	2015	544	12.62%
15	2016	602	13.97%
16	2017	413	9.58%
17	2018	221	5.13%
18	2019	174	4.04%
19	2020	231	5.36%
20	2021	350	8.12%
21	2022	195	4.53%
22	2023	66	1.53%
Total		**4,309**	**100%**

Notes. This table summarizes firms' SEOs' conduct during the selected period from 2002Q1 to 2023Q1. The table specifies the yearly number of SEOs conducted by Chinese nonfinancial A-listed firms with their respective % of each year against total SEOs during the selected period.

[9] Generally, China lacks the institutional settings that lead to a poor disclosed accounting information environment (Lennox & Wu 2022).

Table 2. Sample Construction Process

+/-	Description	Firm-Quarters	Firm's
	Initial data collection (2001Q1-2023Q1)	211,282	5,327
-	Financial firms	15,694	257
		195,588	**5,070**
-	Firms with ≤ 28 firm-quarters	61,343	2,347
		134,245	**2,723**
-	If year = 2001 (to overcome missing values, because lag is involved in the measurement of some key variables)	3,933	…
		130,312	**2,723**
-	Firms not matched with SEOs' data	1,510	666
	Final Sample	**128,802**	**2,057**

Notes. Table 2 presents the sample construction procedure. All the data are drawn from the financial statements, seasoned equity offerings, and stock trading heads of the CSMAR database.

b. Descriptive Analysis

Table 3 presents the summary statistics of all primary variables of our analysis with a comparison among panels A, B, C, and D. Panel A reports the descriptive statistics of the full sample observations, whereas panels B, C, and D present the statistics according to the value of the 'price ratio' variable.[10] In Panel A of Table 3, the outcome variable mean (standard deviation) is 0.05 (0.06), and the treatment variable has a median value of zero. In Panel B, the standard deviation of the explained (EM) variable is 0.0520, the lowest value among all other panels.

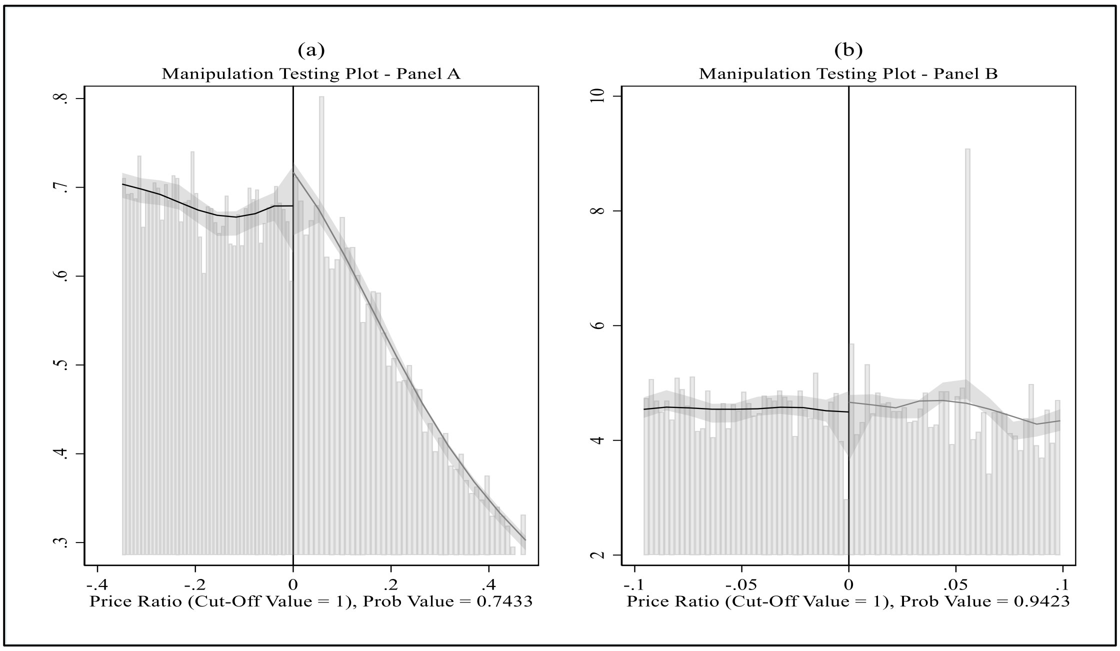
Interestingly, in a comparison of panels C and D of Table 3, the statistical values reveal that when the treatment is equal to 1, the mean value of 0.052 for the outcome variable is larger than the average value of 0.048 when the treatment is equal to 1.

[10] The Tobin's Q and MB (market-to-book) ratios are used as other timing proxies; however, the SFR (self-financing ratio), Tang (tangibility), QR (quick ratio), LEV (leverage), and EPS (earnings per share) are used as control variables in some validated analyses.

4. Results and Discussion

This section begins with a visual analysis of the regression coefficients of the main analysis for the RD design. The RDD approach is valid when it satisfies the *'local continuity assumption,'* which is that firm–quarter assignment around the cutoff for eligibility is random, and the outcome variable should show a smooth function around the cutoff absent treatment (W. Imbens & Lemieux, 2008). However, a formal test of this assumption cannot be performed. We check the distribution of the forcing variable (price ratio as a measure of SEO timing in our context) around the eligibility criteria using the McCrary (2008) method. In Fig. 1, both the '*a'* and '*b*' parts show *density* plots following McCrary (2008), which reflect the manipulation of the forcing variable around the cutoff value under different panels. The ρ value is highly insignificant in both parts, indicating that there is no systematic manipulation of the price ratio.

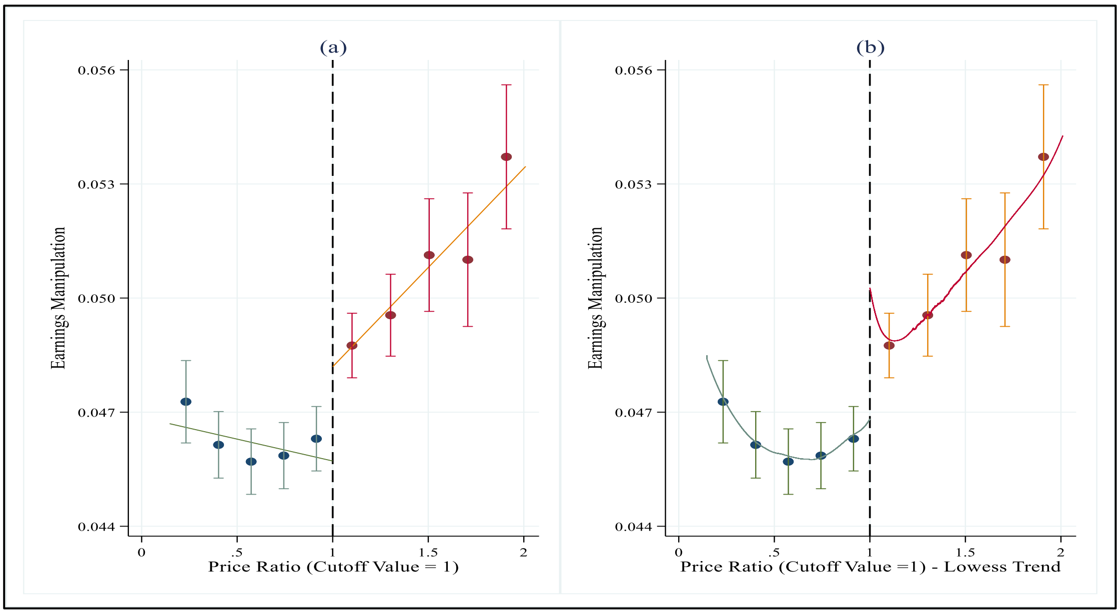
Figure 1. Manipulation Testing Plots of the Running Variable (*density*).



Note: This figure presents manipulation testing plots of the running variable (price ratio) around the cut-off value of 1. Part "a" considers the Panel A data (full data) of A-listed Chinese nonfinancial firms, and part 'b' contains the data of Panel B (which limits the sample to small bandwidths when the price ratio lies between 0.90 & 1.10) spanning from 2002Q1 to 2023Q1. Both parts, in the form of histograms, show the estimated density of the price ratio at the 95% confidence interval.

Fig. 2 presents the discontinuity in the outcome variable, that is, FDQ, around the SEO timing cutoff value in both parts '*a*' and '*b*' with only a difference in the graphical scheme. In Fig. 2, the x-axis shows the forcing variable (price ratio) and the y-axis shows earnings manipulation (a proxy for FDQ). The dots in the figure depict the average plotted outcome variable values in each bin, with a 95% confidence interval. Fig. 2 shows a clear discontinuity in the FDQ around the threshold value in the two quarters prior to SEO timing. This figure shows a significant increase in earnings manipulation when the price ratio moves from left to right at the cut-off value. This pattern suggests a poor FDQ two quarters prior to SEO timing.

Figure 2. Probability of Earnings Manipulation around the price-ratio cutoff.



Note. This reflects the probability of earnings manipulation around the price ratio cutoff/threshold value in the regression discontinuity design (RDD) analysis. Fig. 2 presents a graphical analysis of the cmogram of the RDD approach, whereas parts 'a' and 'b' show the lfit and lower trend functions of the cmogram, respectively. The cutoff value is 1, and if the price ratio is < 1, the firm lies under the control group; if the price ratio is ≥ 1, then the firm lies under the treatment group. The price ratio is our forcing variable, whereas the outcome variable–earnings manipulation or earnings management–is the FDQ proxy. All the variables are defined in Appendix A. This figure considers the outcome variable in the $t-2$ period relative to the SEO quarter. All dots represent the probability of the earnings manipulation bin against each level of the price ratio bin. This figure considers that Panel A (full data) ranges from 2002Q1 to 2023Q1.

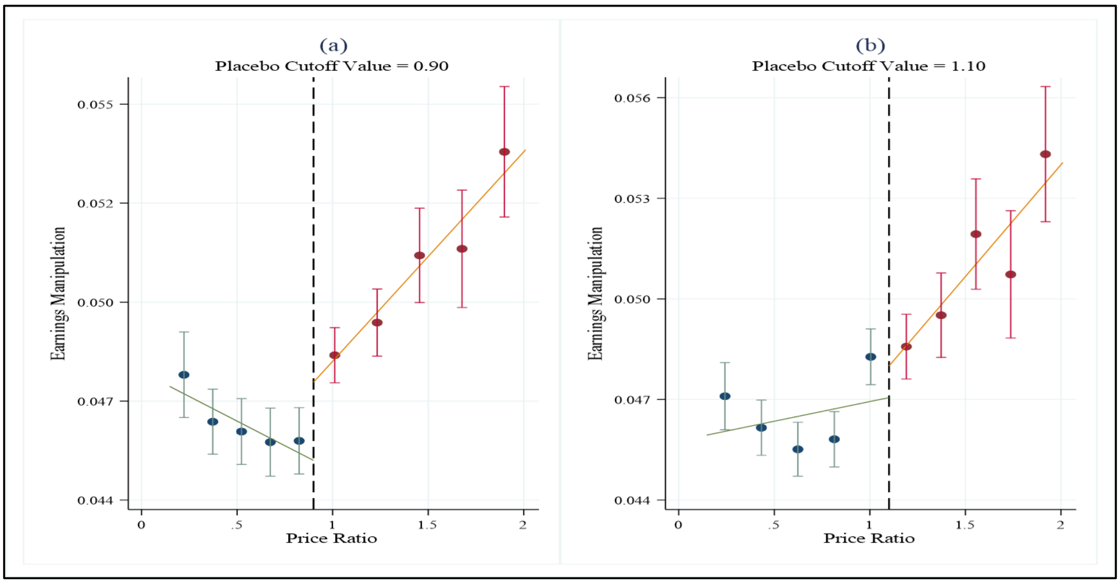
Table 3. Summary Statistics

	N	Mean	Median	SE	SD
	Panel A: Full Sample				
	N	Mean	Median	SE	SD
$EM_{i,t}$	128,802	0.050	0.033	0.000	0.063
$Treatment_{i,t}$	128,802	0.463	0	0.001	0.499
$PR\_1_{i,t}$	128,802	0.132	-0.065	0.002	0.838
$TobinQ_{i,t}$	125,158	1.827	1.478	0.003	1.088
$MB_{i,t}$	125,190	0.652	0.662	0.001	0.240
$SFR_{i,t}$	122,214	0.100	0.104	0.004	1.240
$Tang_{i,t}$	128,572	0.442	0.398	0.011	3.966
$QR_{i,t}$	128,241	1.683	1.042	0.007	2.317
$LEV_{i,t}$	128,765	0.495	0.463	0.005	1.694
$EPS_{i,t}$	128,438	0.207	0.121	0.001	0.370
	Panel B: If Small Bandwidths Price Ratio Between 0.9 & 1.10				
	N	Mean	Median	SE	SD
$EM_{i,t}$	18,947	0.048	0.033	0.001	0.052
$Treatment_{i,t}$	18,947	0.541	1	0.003	0.498
$PR\_1_{i,t}$	18,947	-0.001	-0.000	0.001	0.063
$TobinQ_{i,t}$	18,500	1.784	1.475	0.007	1.002
$MB_{i,t}$	18,507	0.650	0.657	0.002	0.233
$SFR_{i,t}$	18,035	0.116	0.102	0.008	1.086
$Tang_{i,t}$	18,909	0.439	0.399	0.023	2.977
$QR_{i,t}$	18,889	1.648	1.059	0.016	2.207
$LEV_{i,t}$	18,939	0.468	0.457	0.006	0.788
$EPS_{i,t}$	18,911	0.235	0.141	0.003	0.373
	Panel C: If Treatment = 1				
	N	Mean	Median	SE	SD
$EM_{i,t}$	59,635	0.052	0.035	0.000	0.057
$Treatment_{i,t}$	59,635	1	1	0	0
$PR\_1_{i,t}$	59,635	0.756	0.449	0.004	0.854
$TobinQ_{i,t}$	57,301	2.079	1.675	0.005	1.235
$MB_{i,t}$	57,311	0.573	0.573	0.001	0.227
$SFR_{i,t}$	57,264	0.085	0.109	0.005	1.277
$Tang_{i,t}$	59,541	0.438	0.386	0.019	4.628
$QR_{i,t}$	59,435	1.873	1.114	0.011	2.653
$LEV_{i,t}$	59,622	0.462	0.442	0.006	1.481
$EPS_{i,t}$	59,453	0.281	0.164	0.002	0.411
	Panel D: If Treatment = 0				
	N	Mean	Median	SE	SD
$EM_{i,t}$	69,167	0.048	0.032	0.000	0.068
$Treatment_{i,t}$	69,167	0	0	0	0
$PR\_1_{i,t}$	69,167	-0.407	-0.403	0.001	0.232
$TobinQ_{i,t}$	67,857	1.614	1.342	0.003	0.893
$MB_{i,t}$	67,879	0.719	0.739	0.001	0.231
$SFR_{i,t}$	64,950	0.114	0.101	0.005	1.206
$Tang_{i,t}$	69,031	0.446	0.409	0.013	3.290
$QR_{i,t}$	68,806	1.520	0.985	0.008	1.967
$LEV_{i,t}$	69,143	0.524	0.478	0.007	1.859
$EPS_{i,t}$	68,985	0.143	0.092	0.001	0.317

Notes. Descriptive statistics of the quarterly data from 2002Q1 to 2023Q1. Panel A presents the statistics of the full sample. Then, sample is split into different panels and presents the statistics of the firms under the small bandwidths when the price ratio is between 0.9 & 1.10, statistics for the firms when treatment is equal to 1, and for firms when treatment is equal to 0 in Panel B, C, and D, respectively. All the variables are defined in Appendix A.

Furthermore, Fig. 3 also presents the visual discontinuity in the outcome variable, but at different placebo cutoffs, by considering the ± 0.10 cutoff values in parts a and *b*. Fig. 3 reveals an expressive discontinuity in the FDQ at different placebo nearest cut-offs. Visual trends suggest that discontinuity increases when the price ratio exceeds the threshold. In both Figs. 2 and 3, the graphical trends support the argument that there is an apparent discontinuity in the outcome variables around the specific cutoff points and nearest-to-cutoff values. Hence, these trends forced us to approach a formal regression analysis under RDD to estimate causal inferences.

Figure 3. Probability of Earnings Manipulation around the Price Ratio at the Placebo Cutoffs.



Note. This reflects the probability of earnings manipulation around the placebo cutoffs of the price ratio under RDD. In this use, different placebo cutoffs (nearest cutoffs) of the running variable, considered - or + 0.10 of the original cutoff value '1,' are used in parts 'a' and 'b' of Fig. 2. The price ratio is our forcing variable, whereas the outcome variable–earnings manipulation or earnings management–is the FDQ proxy. All the variables are defined in Appendix A. This figure considers the outcome variable in the $t - 2$ period relative to the SEO quarter. All dots represent the probability of the earnings manipulation bin against each level of the price ratio bin. This considers that Panel A (full data) ranges from 2002Q1 to 2023Q1.

Employing a naïve regression approach to investigate the influence of SEO timing on the FDQ may lead to biased inferences because certain unobserved characteristics may correlate with forcing and predicted variables. To address these concerns, Table 4 reports the regression estimations where Eq. 5 is formally executed with several specifications through a nonparametric local linear model with RDD to assess the discontinuity effects observed in Figs. 2 and 3. Table 4 presents the results, where earnings manipulation, as a proxy for FDQ, is regressed on the treatment effect with five event-time estimations (quarters before, during, and after SEO occurrence) to comprehensively determine the exact extent of the likelihood of earnings manipulation around the time of SEO. Concerning specifications, as RDD standards, largely isolating 'quasi-random variation' around the threshold mainly considers firm quarters that are very near the threshold (Panel B) within $\pm$ 0.10 of the original cutoffs (equals 1). Furthermore, columns 1–5 and 6–10 consider the 1st and 2nd levels of polynomial order, respectively.

The estimated coefficients in Columns 1 and 2 reveal that the average treatment coefficient is positive and significant for earnings manipulation at the $t-1$ and $t-2$ periods, respectively. However, Columns 3 to 5 report that in the SEO and periods $t-3$ and $t+1$, the treatment coefficients are statistically indistinguishable from zero. These outcomes indicate that for firms slightly above and below the cut-off, earnings manipulation is substantially greater in the two quarters, leading to the execution of SEO. This ultimately leads to poor FDQ, particularly during specific periods rather than others. The discontinuity in the FDQ around SEO timing in specific periods shows that when the price ratio moves from the left to the right of the threshold value, managers are incentivized to manipulate earnings in just two quarters before the SEO is conducted to issue securities at a high price. This outcome is consistent with the notion that when firms plan to raise financing quickly, they inflate earnings to build a positive image in front of stakeholders and overvalue their securities. In columns 6 to 10 of Table 4, our estimations remain the same when considering the 2nd level of polynomial order instead of the 1st.

Table 4. Treatment Impact Around Likelihood of Earnings Manipulation: An RDD Approach

	(1) $EM_{i,t-1}$	(2) $EM_{i,t-2}$	(3) $EM_{i,t-3}$	(4) $EM_{i,t}$	(5) $EM_{i,t+1}$	(6) $EM_{i,t-1}$	(7) $EM_{i,t-2}$	(8) $EM_{i,t-3}$	(9) $EM_{i,t}$	(10) $EM_{i,t+1}$
$Treatment_{i,t}$	0.003*	0.003*	0.002	-0.002	-0.002	0.003*	0.003*	0.002	-0.001	-0.002
	(1.77)	(1.79)	(1.16)	(-1.03)	(-1.13)	(1.75)	(1.82)	(1.22)	(-1.07)	(-1.15)
Polynomial Order	1	1	1	1	1	**2**	**2**	**2**	**2**	**2**
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.28	0.28	0.27	0.30	0.30	0.28	0.28	0.27	0.30	0.30
RMSE	0.046	0.049	0.052	0.046	0.049	0.046	0.049	0.052	0.046	0.049
N	18,890	18,890	18,890	18,890	18,890	18,890	18,890	18,890	18,890	18,890

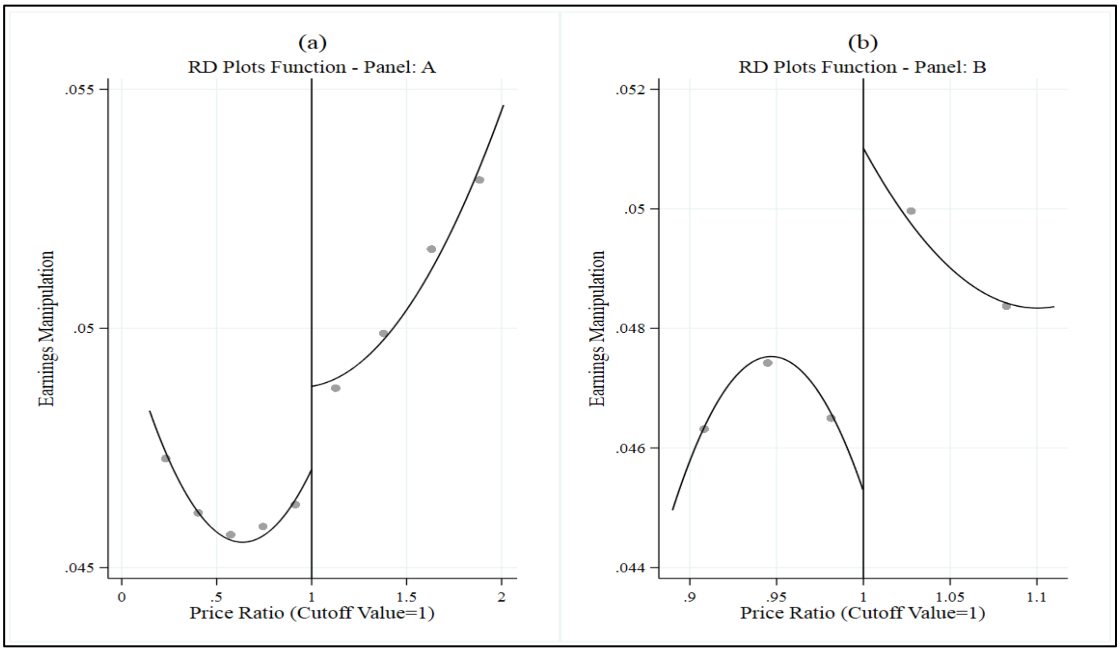
Notes. This table shows the treatment effect around the probability of earnings manipulation practices, and *Treatment* is an indicator variable equal to 1 if the price ratio is ≥ 1 and zero otherwise. The outcome variable *EM* is the earnings manipulation or earnings management (a proxy for FDQ). The quarter prior to SEO and next to SEO is labeled as t-1 and t+1, respectively, with the outcome variable, and all other quarters are labeled accordingly. As per the RDD standard in the main analysis, this study limits the sample to small bandwidths where the price ratio lies between 0.90 & 1.10 (Panel B). Columns 6-10, the same analysis is revised at 2nd level polynomial order. All the variables are defined in Appendix A. The t-statistics are mentioned in parentheses, and the significance level is denoted as follows: ***, **, and * are significant at 1%, 5%, and 10%, respectively.

Indeed, the above outcomes support our argument that managers' decisions are based on anchoring rather than on past price trends. Furthermore, to robustly validate this phenomenon, Table 5 reports the treatment effect by controlling for the most widely used traditional SEO timing measures, Tobin's Q and MB (Baker & Wurgler's, 2002; Dittmar et al., 2020). In columns 1 to 5 (report estimations under Panel B), the findings are still consistent in that managers have more discretion to manipulate earnings two quarters before SEO is conducted, and in the same period of SEO and periods $t-3$ and $t+1$, there is no statistical effect of treatment on FDQ. Furthermore, in columns 6–10, the same analysis is repeated by considering the full sample in panel A and obtaining similar and distinct results. Tobin's Q is often driven out in small bandwidths where the sample is restricted to a price ratio between 0.9 and 1.10. Based on the estimations in Tables 4 and 5, we conclude that owing to the unique jurisdiction system, in our context, firm managers only temporarily (not in the long term) manage earnings to meet the stringent requirements for raising financing through SEOs.

Next, to test the assumption of Cattaneo et al. (2020) that when the assignment of the treatment variable is random, the coefficient β_1 should be invariant to the addition of control variables. Therefore, this study re-estimates Eq. 5. Table 5 shows the addition of a continuous price ratio variable and several other firm-level control variables, that is, SFR, Tang, QR, LEV, and EPS, which represent the self-financing ratio, tangibility, quick ratio, leverage, and earnings per share, respectively.

In columns 1–5 of Table 6, we find consistent results that the treatment coefficient is positive with FDQ until two quarters before the SEO occurrence ($p<0.05$, and $p<0.10$, respectively). The results are also similar in columns 6–10, where the analysis is performed considering the 2nd level of the polynomial order. This result from the RDD of the likelihood of earnings manipulation around SEO timing in particular periods shows that managers are more motivated to fabricate accounting numbers when stock prices exceed the recent offer price, intending to raise financing from the public by issuing stock at a higher price relative to its fair value. Concerning the control variables, compared with the 1st and 2nd levels of the polynomial-order estimations in Table 6, the sample observations in Panel B report the same magnitude of the coefficients. The identified RD estimations are also visually presented in Fig. 4 through the RD (regression discontinuity) plots. The y-axis shows the outcome variable earnings manipulation in quarter $t-2$ relative to the SEO quarter. According to the regression estimations, the graphical analysis also shows clear discontinuous jumps around the price-ratio cut-off. Part *'b'* of Fig. 4 restricts the sample to firm quarters that barely pass and fail the eligibility criteria for treatment by a small margin (the price ratio lies between 0.90 and 1.10). The outcome variable exhibits a larger discontinuous jump around narrow bandwidths.

Figure 4. RD Plot Function.



Note. This figure presents RD plots using evenly spaced estimators that mimic multiple distinctive bins at the 95% confidence interval and 2nd-order polynomial order. The price ratio is our forcing variable, whereas the outcome variable– earnings manipulation or earnings management– is the FDQ proxy. All the variables are defined in Appendix A. This figure considers the outcome variable in the $t-2$ period relative to the SEO quarter. Part 'a" considers Panel A data (full data) ranging from 2002Q1 to 2023Q1, and part 'b' uses the data of Panel B (which limits the sample to small bandwidths when the price ratio lies between 0.90 and 1.10).

Table 5. Treatment Impact by Controlling Other Timing Variables

	Small Bandwidths (Price Ratio between 0.9 & 1.10)					Full Sample				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$EM_{i,t-1}$	$EM_{i,t-2}$	$EM_{i,t-3}$	$EM_{i,t}$	$EM_{i,t+1}$	$EM_{i,t-1}$	$EM_{i,t-2}$	$EM_{i,t-3}$	$EM_{i,t}$	$EM_{i,t+1}$
$Treatment_{i,t}$	0.002**	0.002***	0.001	-0.001	-0.000	0.001	0.003***	0.002***	0.000	0.000
	(2.27)	(2.67)	(0.64)	(-0.58)	(-0.21)	(1.45)	(3.54)	(2.76)	(0.26)	(0.37)
$TobinQ_{i,t}$	-0.002	0.001	0.000	-0.001	0.007***	0.002**	0.002***	0.003***	0.004***	0.009***
	(-1.22)	(0.50)	(0.24)	(-0.85)	(5.39)	(2.12)	(4.07)	(3.82)	(3.23)	(12.06)
$MB_{i,t}$	-0.043***	-0.021***	-0.012*	-0.052***	-0.022***	-0.038***	-0.023***	-0.021***	-0.039***	-0.018***
	(-6.83)	(-4.24)	(-1.95)	(-8.46)	(-5.50)	(-15.23)	(-9.99)	(-8.89)	(-9.94)	(-6.58)
Polynomial Order	1	1	1	1	1	1	1	1	1	1
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R2	0.300	0.292	0.274	0.315	0.315	0.190	0.162	0.156	0.202	0.207
RMSE	0.045	0.048	0.051	0.045	0.048	0.056	0.053	0.060	0.056	0.060
N	18,437	18,437	18,437	18,437	18,437	125,157	125,157	125,157	125,157	125,157

Notes. This table shows the treatment effect around the probability of earnings manipulation practices by controlling for other market timing variables (i.e., Tobin's Q and MB). *Treatment* is an indicator variable equal to 1 if the price ratio is ≥ 1 and zero otherwise. The predicted variable *EM* is the earnings manipulation or earnings management (a proxy for FDQ). The quarter prior to SEO and next to SEO is labeled as t-1, and t+1, respectively, with the outcome variable, and all other quarters are labeled accordingly. Tobin-Q and MB are considered the other market timing variables. Tobin-Q equals the ratio of the market value of assets to the book value of assets; *MB* is the market-to-book ratio equal to total assets minus book equity plus market equity over total assets. In columns 1-5, the sample is limited to small bandwidths where the price ratio lies between 0.90 & 1.10 (Panel B), while in columns 6 to 10, estimations are produced considering the full sample (Panel A). All the variables are defined in Appendix A. The t-statistics are mentioned in parentheses, and the significance level is denoted as follows: ***, **, and * are significant at 1%, 5%, and 10%, respectively.

Table 6. Treatment Impact by Adding Control Variables

Panel B: Small Bandwidths (Price Ratio between 0.9 & 1.10)										
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	$EM_{i,t-1}$	$EM_{i,t-2}$	$EM_{i,t-3}$	$EM_{i,t}$	$EM_{i,t+1}$	$EM_{i,t-1}$	$EM_{i,t-2}$	$EM_{i,t-3}$	$EM_{i,t}$	$EM_{i,t+1}$
$Treatment_{i,t}$	0.003**	0.003*	0.002	-0.002	-0.002	0.003**	0.003*	0.002	-0.002	-0.003
	(2.19)	(1.86)	(0.85)	(-1.02)	(-1.38)	(2.17)	(1.89)	(0.93)	(-1.07)	(-1.41)
$PR-1_{i,t}$	-0.011	-0.008	-0.014	0.017	0.016	-0.006	-0.004	-0.007	0.009	0.008
	(-0.84)	(-0.65)	(-0.88)	(1.35)	(1.41)	(-0.83)	(-0.69)	(-0.96)	(1.42)	(1.45)
$SFR_{i,t}$	-0.003***	-0.002**	-0.001	-0.003***	-0.002***	-0.003***	-0.002**	-0.001	-0.003***	-0.002***
	(-4.21)	(-2.47)	(-0.83)	(-3.29)	(-2.64)	(-4.21)	(-2.47)	(-0.83)	(-3.29)	(-2.64)
$Tang_{i,t}$	-0.014*	-0.012**	-0.009*	-0.012*	-0.004	-0.014*	-0.012**	-0.009*	-0.012*	-0.004
	(-1.80)	(-2.45)	(-1.86)	(-1.78)	(-0.96)	(-1.80)	(-2.45)	(-1.86)	(-1.78)	(-0.96)
$QR_{i,t}$	-0.000	-0.001	-0.000	-0.000	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000
	(-0.57)	(-0.53)	(-0.94)	(-1.12)	(-0.57)	(-0.56)	(-0.53)	(-0.94)	(-1.12)	(-0.57)
$LEV_{i,t}$	0.004	0.007*	0.006*	0.007	0.009***	0.004	0.007*	0.006*	0.007	0.009***
	(0.74)	(1.91)	(1.76)	(1.54)	(4.96)	(0.74)	(1.91)	(1.76)	(1.54)	(4.96)
$EPS_{i,t}$	-0.001	0.009***	0.007***	0.004*	0.008**	-0.001	0.009***	0.007***	0.004*	0.009**
	(-0.45)	(4.84)	(3.95)	(1.67)	(2.14)	(-0.45)	(4.84)	(3.95)	(1.67)	(2.14)
Polynomial Order	1	1	1	1	1	**2**	**2**	**2**	**2**	**2**
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R2	0.299	0.291	0.273	0.308	0.298	0.299	0.291	0.273	0.308	0.298
RMSE	0.045	0.047	0.051	0.044	0.045	0.045	0.047	0.051	0.044	0.045
N	17,866	17,866	17,866	17,866	17,866	17,866	17,866	17,866	17,866	17,866

Notes. This table shows the treatment effect around the probability of earnings manipulation practices by considering a set of control variables (SFR, Tang, QR, LEV, and EPS). *Treatment* is an indicator variable equal to 1 if the price ratio is ≥ 1 and zero otherwise; PR-1 represents the price ratio minus the cutoff value. The predicted variable *EM* is the earnings manipulation or earnings management (a proxy for FDQ). The quarter prior to SEO and next to SEO is labeled as t-1, and t+1, respectively, with the outcome variable, and all other quarters are labeled accordingly. SFR, Tang, QR, LEV, and EPS represent the coefficients of the self-financing ratio, tangibility, quick ratio, leverage, and earnings per share, respectively. In columns 1 to 5, estimations are produced in 1st order polynomial while in columns 6 to 10, estimates are made in 2nd order polynomial. All the variables are defined in Appendix A. The t-statistics are mentioned in parentheses, and the significance level is denoted as follows: ***, **, and * are significant at 1%, 5%, and 10%, respectively.

Next, under the extension of the analyses, Tables 7-9 empirically report the causal estimates for the treatment effect on FDQ under three unique theoretical scenarios: financing constraints versus non-financing constraints across corporate life-cycle stages and state-owned versus non-state-owned enterprises. This was done to investigate whether the identified treatment effect is replicated under these subsamples.

In Table 7, we examine whether the status of firm financing constraints (FCs) affects the role of treatment in earnings manipulation practices. Table 7 reports the estimations of Panel B with the partition of firms into financially constrained and non-constrained firms. The division of firms with FC vs. without FC is performed using two approaches: the KZ index and size approach. The measurements of these approaches are presented in Appendix A. Columns 1 to 4 present the estimations following the Kaplan and Zingales (1997) approach by following the financing constraints literature (Bartram et al., 2022; Law & Mills, 2015; Lin, 2023). Specifically, columns 1 and 2 report the results under the subsample of firms with FC, and in this treatment, β is statistically positive in quarters -1 and -2 relative to SEO conduction (ρ<0.05, & ρ<0.10, respectively). Columns 3 and 4 report the results without FC firms, in which the treatment impact is insignificant. In Columns 5–8 of Table 7, an analysis is performed using the SIZE approach to measure firm FC status. However, our results did not show any changes. These results show that if financially constrained firms disclose their actual performance before the SEO, it is challenging for them to increase their financing through SEOs. Hence, managers use accounting numbers to artificially disclose better financial positions, especially before an SEO event. In line with this view, non-constrained firms already have sufficient financial positions and public trust; therefore, managers are not required to adjust their accounting numbers.

Furthermore, firms were split into four new subsamples based on their life cycle stages (i.e., introduction, growth, maturity, and decline). In Table 8, we estimate separate regressions across the corporate life-cycle (CLC) stages. The CLC stages are measured using Dickinson (2011) firm-level model, which is based on accounting and finance measurements, and the validity of this model is supported by Anderson et al. (2023) and Liang (2023). This model uses distinct cash flow patterns to define each CLC stage. The measurement of each stage is described in Appendix A. Columns 1 to 4 present the treatment effect on outcome variables across diverse CLC stages by taking the 1st level of polynomial order; however, in columns 5 to 8, the estimations are based on the 2nd level of polynomial order. Considering the shake-out stage as a benchmark, the results of the introduction, growth, maturity, and decline stages are reported in Columns 1–4 of Table 8. The results revealed that the treatment effect was positive and statistically significant in the initial and decline stages; however, in the growth and maturation stages, the treatment effect was statistically indistinguishable from zero. The estimations hold the same conclusion in columns 5 to 8, where the same analysis is performed considering the 2nd level of the polynomial order. In summary, Table 8 shows that during the introduction and decline stages, due to lower sales volume, profitability, market share, erosion of business concepts, products, innovation, and internal inefficiencies, management is more severe toward earnings manipulation practices in quarters, especially prior to SEO. The intention of exploiting investment opportunities and expanding a firm's operations is to issue shares. These outcomes are also executed because younger firms are most often issued equity to raise financing, but owing to their lower public awareness and reputation, they are highly engaged in artificially presenting a better financial position.

Table 7. Treatment Impact under Financing Constraints Issue

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FC Approach	KZ Index				SIZE			
FC Status	Firms With FC		Firms Without FC		Firms With FC		Firms Without FC	
	$EM_{i,t-1}$	$EM_{i,t-2}$	$EM_{i,t-1}$	$EM_{i,t-2}$	$EM_{i,t-1}$	$EM_{i,t-2}$	$EM_{i,t-1}$	$EM_{i,t-2}$
$Treatment_{i,t}$	0.005**	0.003*	0.002	0.002	0.007**	0.006**	0.001	0.001
	(2.06)	(1.71)	(1.06)	(1.09)	(2.36)	(2.30)	(0.31)	(0.27)
$PR-1_{i,t}$	-0.026	-0.015	0.006	0.004	-0.036	-0.040*	0.016	0.018
	(-1.58)	(-0.87)	(0.30)	(0.21)	(-1.50)	(-1.86)	(1.05)	(1.20)
$SFR_{i,t}$	-0.003**	-0.001	-0.003***	-0.003***	-0.002	-0.003**	-0.003***	-0.001
	(-2.16)	(-0.58)	(-3.32)	(-2.72)	(-1.49)	(-2.35)	(-4.59)	(-1.45)
$Tang_{i,t}$	0.003	0.001	-0.022**	-0.021**	0.003	-0.001	-0.035***	-0.030***
	(0.35)	(0.18)	(-2.16)	(-2.52)	(0.32)	(-0.17)	(-4.61)	(-4.72)
$QR_{i,t}$	0.001	0.000	-0.001	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.49)	(0.09)	(-0.93)	(-0.40)	(-0.29)	(-0.13)	(-0.68)	(-0.45)
$LEV_{i,t}$	0.001	0.006	0.014*	0.019**	0.000	0.005	0.004	-0.001
	(0.28)	(1.64)	(1.75)	(2.48)	(0.06)	(1.65)	(0.66)	(-0.09)
$EPS_{i,t}$	-0.008***	0.008***	0.008**	0.009***	-0.017**	0.019***	0.001	0.005**
	(-2.85)	(3.82)	(2.16)	(2.64)	(-2.36)	(4.35)	(0.50)	(2.30)
Polynomial Order	1	1	1	1	1	1	1	1
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
R2	0.367	0.349	0.401	0.400	0.408	0.401	0.369	0.387
RMSE	0.044	0.049	0.044	0.045	0.048	0.051	0.038	0.039
N	8,212	8,212	9,184	9,184	7,834	7,834	9,691	9,691

Notes. This table shows the treatment effect around the probability of earnings manipulation practices when the treatment variable is regressed on the outcome variable with a set of control variables (SFR, Tang, QR, LEV, and EPS) by splitting the sample into firms with and without financing constraints (FC) issue for Panel B. *Treatment* is an indicator variable equals to 1 if price ratio is ≥ 1 and zero otherwise and PR-1 represents the price ratio minus the cutoff value. The predicted variable *EM* is the earnings manipulation or earnings management (a proxy for FDQ). The quarter prior to the SEO quarter is labeled as t-1, and t-2 is labeled with the value of the predicted variable two quarters prior to the following the SEO quarter. SFR, Tang, QR, LEV, and EPS represent the coefficients of the self-financing ratio, tangibility, quick ratio, leverage, and earnings per share, respectively. Columns 1 to 4 use the KZ index to categorize the sample into firms subsamples with and without financing constraint issues, while columns 5 to 8 use the SIZE approach to divide the sample into firms with and without FC issues. Variables are defined in Appendix A. The t-statistics are mentioned in parentheses, and the significance level is denoted as follows: ***, **, and * are significant at 1%, 5%, and 10%, respectively.

Table 8. Treatment Impact across Corporate Life Cycle

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Life Cycle Stage	*Intro.*		*Growth*		*Maturity*		*Decline*	
	$EM_{i,t-1}$	$EM_{i,t-2}$	$EM_{i,t-1}$	$EM_{i,t-2}$	$EM_{i,t-1}$	$EM_{i,t-2}$	$EM_{i,t-1}$	$EM_{i,t-2}$
$Treatment_{i,t}$	0.0053*	0.0096*	-0.0025	0.0005	0.0035	-0.0035	0.0092	0.0159**
	(1.76)	(1.91)	(-1.09)	(0.20)	(1.57)	(-1.25)	(1.41)	(2.08)
$PR-1_{i,t}$	-0.0177	-0.0486	0.0268	-0.0133	-0.019	0.0424*	-0.0049	-0.0555
	(-0.58)	(-1.25)	(1.55)	(-0.66)	(-0.98)	(1.86)	(-0.08)	(-0.72)
$SFR_{i,t}$	-0.0138***	-0.0052**	0.0080***	0.00303	0.0148***	0.0056**	-0.0088***	-0.0062**
	(-6.70)	(-2.10)	(3.27)	(1.58)	(4.95)	(2.44)	(-3.70)	(-2.05)
$Tang_{i,t}$	-0.0048	-0.0080	-0.0173*	-0.0150	-0.0190**	-0.0165	0.0181	0.0103
	(-0.29)	(-0.44)	(-1.77)	(-1.45)	(-2.20)	(-1.60)	(1.06)	(0.26)
$QR_{i,t}$	-0.0004	-0.0000	-0.0001	-0.0006	0.0001	0.0004	0.0013	-0.0029*
	(-0.59)	(-0.12)	(-0.23)	(-1.07)	(0.10)	(0.80)	(0.99)	(-1.94)
$LEV_{i,t}$	-0.0329***	-0.0160	0.0283**	0.0127	0.0255***	0.0310***	-0.0090	-0.0023
	(-2.80)	(-1.09)	(2.47)	(1.50)	(2.91)	(2.96)	(-0.71)	(-0.08)
$EPS_{i,t}$	0.0092	0.0191***	0.00131	0.0055*	-0.0073**	0.0110***	-0.0012	0.0041
	(1.35)	(3.35)	(0.33)	(1.75)	(-2.16)	(3.14)	(-0.17)	(0.32)
Polynomial Order	1	1	1	1	1	1	1	1
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
R2	0.532	0.493	0.397	0.409	0.469	0.454	0.756	0.723
RMSE	0.054	0.037	0.039	0.039	0.043	0.041	0.047	0.054
N	2,630	2,630	5,296	5,296	5,164	5,164	645	645

Notes. This table shows the treatment effect around the probability of earnings manipulation practices when the treatment variable is regressed on the outcome variable with a set of control variables (SFR, Tang, QR, LEV, and EPS) across the different corporate life cycle stages (introduction, growth, maturity, and decline) for Panel B. *Treatment* is an indicator variable equals to 1 if price ratio is ≥ 1 and zero otherwise and PR-1 represents the price ratio minus the cutoff value. The predicted variable *EM* is the earnings manipulation or earnings management (a proxy for FDQ). The quarter prior to the SEO quarter is labeled as t-1, and t-2 is labeled with the value of the predicted variable two quarters prior to the following SEO quarter. SFR, Tang, QR, LEV, and EPS represent the coefficients of the self-financing ratio, tangibility, quick ratio, leverage, and earnings per share, respectively. In columns 1 to 4, estimations are produced in 1st order polynomial while in columns 5 to 8, the same analysis is revised in 2nd order polynomial. All the variables are defined in Appendix A. The t-statistics are mentioned in parentheses, and the significance level is denoted as follows: ***, **, and * are significant at 1%, 5%, and 10%, respectively.

Table 9 evaluates whether the average treatment effect of timing on FDQ changes in response to changes in firm status, that is, state-owned versus non-state-owned. For this, earnings manipulation is a proxy for FDQ in quarters -1 and -2 relative to SEO timing is regressed on the treatment variable along with a set of control variables under the classification of firms with respect to their status: state versus non-state-owned subsamples. The first two columns are compared with the last two columns in Table 9 by classifying firms into state- and non-state-owned firms. In Columns 1 and 2 of Table 9, treatment β is statistically insignificant. However, the estimated coefficient of the average treatment effect on FDQ is significant and positive in Columns 3 and 4 (for non-state-owned firms). This treatment effect on FDQ under this scenario shows that, instead of being state-owned, stateate-owned firms face intense market pressure and require more stringent financial health conditions to raise additional financing through SEOs, which encourages managers to use their discretion on accounting numbers before SEOs. Firms with a state-owned status are less transparent and riskier, revealing low informativeness regarding stock prices and receiving more protection from the state. These characteristics do not motivate managers to engage in earnings fabrication practices in order to present a better financial image.

Finally, in Table 10, we investigate the average treatment impact on the different firm outcome variables under Panel B. Columns 1-7, our core explanatory variable is the treatment indicator. In each column, the separate firm outcome is a dependent variable in a quarter $t-1$ relative to the SEO quarter is regressed on the treatment indicator after controlling for the price ratio. The results show that the estimated coefficients of the treatment indicator in columns 1-7 are never statistically significant. These indistinguishable findings prove the underlying assumption that there is no other discontinuous jump around the price ratio cutoff value, except for our main dependent variable, that is, earnings manipulation as a proxy for FDQ.

Table 9. Treatment Impact under SO vs. Non-SO Firms

	(1)	(2)	(3)	(4)
	State-Owned		Non-State-Owned	
	$EM_{i,t-1}$	$EM_{i,t-2}$	$EM_{i,t-1}$	$EM_{i,t-2}$
$Treatment_{i,t}$	0.003	0.006	0.004**	0.003*
	(0.67)	(1.39)	(2.07)	(1.83)
$PR-1_{i,t}$	0.018	-0.017	-0.014	-0.007
	(0.53)	(-0.42)	(-1.05)	(-0.54)
$SFR_{i,t}$	0.000	0.002	-0.005***	-0.005***
	(0.16)	(0.69)	(-5.69)	(-6.03)
$Tang_{i,t}$	-0.036***	-0.026***	-0.027***	-0.027***
	(-6.46)	(-3.95)	(-4.98)	(-5.79)
$QR_{i,t}$	0.000	0.001	0.000	-0.000
	(0.30)	(0.70)	(0.08)	(-0.18)
$LEV_{i,t}$	-0.002	0.008	0.008*	0.009**
	(-0.27)	(0.78)	(1.74)	(2.22)
$EPS_{i,t}$	-0.005	-0.005	0.004	0.003**
	(-1.41)	(-1.22)	(1.63)	(2.14)
Year FE	✓	✓	✓	✓
R2	0.023	0.016	0.027	0.026
RMSE	0.051	0.056	0.050	0.052
N	2,401	2,401	15,501	15,501

Notes. This table shows the treatment effect around the probability of earnings manipulation practices when the treatment variable is regressed on the outcome variable with a set of control variables (SFR, Tang, QR, LEV, and EPS) by splitting the sample into SO and non-SO firms for Panel B. *Treatment* is an indicator variable equals to 1 if price ratio is ≥ 1 and zero otherwise and PR-1 represents the price ratio minus the cutoff value. The predicted variable *EM* is the earnings manipulation or earnings management (a proxy for FDQ). The quarter prior to the SEO quarter is labeled as t-1, and t-2 is labeled with the value of the predicted variable two quarters prior to the following the SEO quarter. SFR, Tang, QR, LEV, and EPS represent the coefficients of the self-financing ratio, tangibility, quick ratio, leverage, and earnings per share, respectively. Variables are defined in Appendix A. The t-statistics are mentioned in parentheses, and the significance level is denoted as follows: ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Table 10. Treatment Impact on Other Firm-Level Outcome Variables

	Other Firm Level Dependent (Outcome) Variables						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	$TobinQ_{i,t-1}$	$MB_{i,t-1}$	$SFR_{i,t-1}$	$Tang_{i,t-1}$	$QR_{i,t-1}$	$LEV_{i,t-1}$	$EPS_{i,t-1}$
$Treatment_{i,t}$	0.012	0.002	-0.000	-0.005	0.074	-0.004	0.006
	(0.66)	(0.61)	(-0.00)	(-1.51)	(1.50)	(-1.08)	(0.81)
$PR-1_{i,t}$	0.236*	0.120***	-0.152	0.011	-0.197	0.011	0.207***
	(1.71)	(4.37)	(-0.59)	(0.49)	(-0.91)	(0.40)	(3.38)
Polynomial Order	1	1	1	1	1	1	1
Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
R2	0.632	0.740	0.343	0.748	0.618	0.708	0.578
N	18,890	18,258	18,217	18,659	18,638	18,688	18,655

Note. This table shows the treatment effect on different firm-level outcome variables when the treatment variable is regressed on different outcome variables separately under Panel B, where the sample is limited to small bandwidths when the price ratio lies between 0.90 & 1.10. *Treatment* is an indicator variable equal to 1 if the price ratio is ≥ 1 and zero otherwise. PR-1 represents the price ratio minus the cutoff value. The outcome variables are Tobin Q, MB, SFR, Tang, QR, LEV, and EPS, representing the coefficients of Tobin Q, market-to-book ratio, self-financing ratio, tangibility, quick ratio, leverage, and earnings per share, respectively. In parentheses, t-statistics are mentioned, and the significance level is denoted as follows: ***, **, and * are significant at 1%, 5%, and 10%, respectively.

5. Conclusion

Skepticism about the quality of disclosed information increased, especially around firm-specific events (i.e., SEOs); hence, we hypothesize that FDQ jumps discontinuously around SEO timing at a specific reference point. By holding stock price anchoring and considering the recently offered price as a benchmark for examining the discontinuity in disclosure quality, we provide causal estimates by documenting that when the share value reaches or crosses the recent offering price, the average treatment impact shows statistically positive coefficients until two quarters prior to SEO implementation. In contrast, the likelihood of FDQ is statistically indistinguishable from zero in the quarter, quarter relative to post-SEO, and before the two quarters of the pre-SEO period. This finding indicates that owing to the unique jurisdiction system, managers are transitory and involved in income-increasing practices to meet the stringent requirements of raising funds through SEOs. Specifically, we detect intertemporal managers' behavior toward earnings fabrication around the intertemporal variations in SEO timing. These results are robust across alternative specifications (i.e., different bandwidths, polynomial orders, panels, and FDQ measures). Our econometric approach (i.e., *regression discontinuity design*) offers many contributions that have not been previously part of the empirical systematic literature, despite traditional investigations of SEOs' return volatilities, liquidity risk, and earnings management as core ideas in the literature for at least two decades. In multiple avenues, this approach extends the literature: timing discontinuity for FDQ, anchoring-based managerial decisions, partitioning of firms on the basis of firm characteristics, and empirical proof of periodic manipulations are the main avenues through which our econometric approach extends the framework.

Furthermore, for the subsample estimations, the discontinuous impact of SEO timing on FDQ is much more pronounced in firms that are financially constrained and non-state-owned, and in firms in the introductory and decline phases of their life cycle. Collectively, our results show that a specific reference point for SEO timing is a key factor in determining FDQ. Additionally, firms in the introduction and decline stages of their life and status as financially constrained and non-state-owned are signals for investors about the adverse consequences of the disclosed information of a firm.

This study's results have several implications. Investors must rely on the information disclosed by firms to make investment decisions. This study's reference point leads to a noticeable change in the quality of accounting information. Thus, practitioners should weigh the reference points to determine a firm's transparency level. The more pronounced income-increasing accounting adjustments in the case of financing constraints and firms in the introduction and decline phases suggest that investors accessing such scenarios could have a greater estimate of the likelihood of FDQ. Furthermore, the statistically positive impact of treatment on earnings manipulation in the context of non-state-owned firms is due to intense market pressure and the requirement for more stringent financial stability conditions to acquire more money through the issuance of shares. This suggests that regulatory bodies should provide a *'level playing field'* to all enterprises without any distinction between state-owned and non-state-owned firms. From a managerial perspective, research suggests that managers must prioritize disclosure quality because poor quality breaks stakeholders' trust, which can adversely affect a firm's prospective success by damaging its reputation.

Although we documented novel results and answered several previously unanswered questions, our study leaves multiple avenues open. First, we acknowledge that our findings are not generalizable to other economies because the Chinese financial system is distinct from that of other jurisdictions. The threat of legal liability in China is relatively low, which has led firm managers to inflate earnings. Future studies may consider other countries to assess whether the reference point (i.e., price ratio equals 1) encourages managers to be temporarily (not in the long term) involved in income-increasing practices in pre-SEO periods. Furthermore, we do not provide any evidence regarding the reversal impact on FDQ after more than one-quarter of SEO conduct, and this effect may potentially exist. Another generalizability concern related to the RDD framework is that the findings are attributable to a small sample of firms that are slightly above and below the threshold. Future research could identify alternative settings by examining shocks to address these concerns.

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APPENDIX A

Variables	Theoretical and Operational Definition(s)
PR	The price ratio is defined as the: 'average stock price of the last quarter to the firm's most recent equity offering price'.
PR_1	Price ratio minus cutoff value (cutoff equals 1 in our context).
$Treatment$	= 1 if the running variable (price ratio) is greater or equal to the cutoff point, = 0 otherwise.
FDQ	Financial disclosure quality, it is measured through earning manipulation or earnings management by employing the Hribar and Collins (2002) model. $\frac{TA_{it}}{Assets_{it-1}} = \beta_0\left(\frac{1}{Assets_{it-1}}\right) + \beta_1\left(\frac{\Delta REV_{it}}{Assets_{it-1}}\right) + \beta_2(PPE_{it}/Assets_{it-1}) + \epsilon_{i.t}$ Where TA_{it} is accruals total, computed by subtracting operating cash flow from operating income. $Assets_{it-1}$ = lagged total assets and ΔREV_{it} is the change in sales revenues minus the change in accounts receivables. PPE_{it} = total of Plant, Property, and Equipment. $u_{i,t} + \epsilon_{i.t}$ are residual terms, which actually detect the discretionary accruals. Furthermore, to improve the robustness, this study used two other measures of earnings manipulation by employing the following Kothari et al. (2005) and Raman and Shahrur (2008), respectively: $\frac{TA_{it}}{Assets_{it-1}} = \beta_0\left(\frac{1}{Assets_{it-1}}\right) + \beta_1\left(\frac{\Delta REV_{it}}{Assets_{it-1}}\right) + \beta_2\left(\frac{PPE_{it}}{Assets_{it-1}}\right) + \beta_3(ROA_{it-1}) + u_{i,t} + \epsilon_{i.t}$ ROA is the return on assets = net income÷average total assets. All others are the same as described in the previous model. $TA_{it}/Assets_{it-1} = \beta_0(1/Assets_{it-1}) + \beta_1(\Delta REV_{it}/Assets_{it-1}) + \beta_2(PPE_{it}/Assets_{it-1}) + \beta_3(ROA_{it-1}) + \beta_4 BM_{it} + u_{i,t} + \epsilon_{i.t},$ BM is a book-to-market ratio, calculated as the ratio of total assets to total assets minus the book value of equity plus the firm market value. All others are the same as described in the previous model.
$TobinQ$	Tobins' Q, is = assets market-value ÷ assets book-value
MB	Market-to-book ratio is measured as total market capitalization divided by total book value.
SFR	Self-financing ratio equals operating cash-flows ÷ net fixed assets.
$Tang$	The tangibility ratio measures as, net property, plant, and equipment/book total assets value.
QR	The quick ratio is defined as current assets minus inventory/current liabilities.
LEV	Leverage is measured as total debt to total book value of assets.
EPS	Earnings per share are directly taken from firm financial statements.
KZ	$KZ_{i,t} = -\left(1.002\frac{CF}{K_{t-1}}\right)i,t + (0.283TQ)i,t + \left(3.139\frac{D}{Total\ Cap}\right)i,t - \left(39.368\frac{Dividend}{K_{t-1}}\right)i,t - \left(1.315\frac{C}{K_{t-1}}\right)i,t$ Where CF is cash-flows which are equal to net profit + amortization & depreciation; K is capital stock, equals to the total of net plant, property, and equipment; TQ represents Tobin Q= assets market-value ÷ assets book-value; D = short-term debt + long-term debt; $Total\ Cap$ is total capitalization, computed through total debt + shareholders' equity; $Dividend$ shows dividend payments and; C=cash + short-term investment. We categorize the firms into constraints versus non-constraints with regard to financings based on the 50th percentile value of the KZ index. If the KZ value in the respective year is> its 50th percentile, then the firm-year is recognized as a financially constrained firm; otherwise, it is vice versa.
$SIZE$	Natural logarithm of total assets. The firm is recognized as financially constrained if the SIZE value in the respective year is < its tercile value; otherwise, vice versa.
$CLC\ Stages$	Corporate life cycle stages, as per Dickinson (2011) model, classified the firms into five stages through distinctive combinations of cash-flows from operating (OCF), investing (ICF), and financing (FCF) activities. Introduction = OCF<0, ICF<0, FCF>0; Growth = OCF>0, ICF<0, FCF>0 ; Maturity = OCF>0, ICF<0, FCF<0; Decline = OCF<0, ICF>0, FCF>0 or<0; and Shake-out = all remaining firm-quarters.
$State\_Owned$	Equals to 1, if the firm is recognized as a state-owned enterprise; and 0 for non-state-owned enterprise.