When Regulators Knock, Liquidity Rockets:

Evidence from China's Random Government Accounting Supervision

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Abstract: Exploiting the staggered introduction of the government's random accounting information quality inspection policy as an exogenous shock, we investigate the impact of government's randomized accounting supervision on stock liquidity. Our research shows that the randomized accounting supervision policy significantly increases stock liquidity. Our main findings are robust to controlling for firm characteristics, TWFE bias, and endogeneity concerns. Mechanism analysis reveals that the policy primarily enhances stock liquidity through three economic channels: reducing information asymmetry, offsetting agency costs and improving investor optimism. Additionally, the positive effect of government accounting supervision on stock liquidity is more salient among pilot firms with low ownership concentration, low industry competition and low investor attention. Importantly, we identify both intra-industry and intra-regional spillovers, which indicate positive policy externalities. Collectively, our findings contribute a new perspective on the economic consequences of government's random accounting supervision, emphasizing the crucial role of government direct regulation and its broader implications on enhancing market efficiency in emerging markets.

Keywords: Government accounting supervision; Stock liquidity; Information asymmetry; Agency costs; Spillover Effect.

JEL Codes: G14; G18; M48

1.Introduction

Effective regulation is essential for standardizing corporate behavior, achieving financial stability, and marinating sustainable growth, especially in developing countries that typically struggle with issues such as low liquidity, severe information asymmetry, and poor internal governance (Li et al., 2011). Accounting supervision plays an increasingly important role in inhibiting financial fraud (Lisic et al.,2015; Suryandari et al.,2019), preventing financial risks (Liu et al.,2014; Chen and Chen,2024), and maintaining economic stability (Bertomeu, et al.,2025). Accounting supervision takes a variety of forms, but relies primarily on internal corporate supervision, certified public accountants (CPA) supervision, and industry self-regulation in most countries. However, traditional accounting supervision is significantly limited by corporate governance issues (e.g., agency problems) and a lack of industry regulation, particularly in emerging markets where internal corporate governance and industry self-regulation are comparatively weak. This can result in issues such as insufficient deterrent force and delayed regulatory responses. Recent statistics show that, compared with developed countries, listed companies in the financial markets of developing countries frequently violate information disclosure and financial regulations[2]. Even worse, the actual rate of investigation and punishment is relatively low due to inadequate

2 See "Corporate Governance Disclosure in Emerging Markets: Statistical analysis of legal requirements and company practices" issued by the United Nations Conference on Trade and Development (UNCTAD) in 2011.

supervision. The establishment and improvement of an effective accounting supervision system has long been highlighted as a key issue for academics and practitioners worldwide (Liu et al., 2025). Building on this background, government regulatory interventions have become an increasingly crucial measure for enhancing the accounting supervision system over the past decade[3].

In response, China's Ministry of Finance (MOF) has conducted random inspections of the accounting quality of listed firms' financial statements since 1999, namely "double random, one public" inspections, on listed firms, exploring a critical and novel practice in strengthening financial and accounting supervision (Pan et al., 2023). By 2023, China's MOF had organized and issued 42 announcements, covering nearly 30,000 enterprises and institutions. Although similar government accounting supervision policies have been implemented in other countries (e.g., PCAOB), the uniqueness of China's random accounting inspection policy lies its regulatory practices, which are subject to direct government inspection and cover almost all listed companies. On the one hand, China's random accounting inspection policy directly reflects the government's regulatory intentions, giving it greater deterrent power. On the other hand, the random selection method of government accounting supervision system increases the uncertainty that listed firms face regarding regulatory scrutiny, thereby increasing the risks and costs associated with corporate violations. Overall, China's random accounting inspection policy could help to reduce the costs of the public enforcement in accounting supervision, enhance its efficiency and maximize the use of limited regulatory resources (Teng et al., 2022; Jiang et al., 2025).

Prior studies on the impacts of government's random accounting supervision (GAS) have mainly concentrated on corporate governance issues (Liu and Wang, 2021; Pan et al., 2023), corporate ethical conduct (Jiang, 2024), tax avoidance (Li et al., 2023), investment decisions (Wang et al., 2025), and stock price (Liu et al., 2024). However, as these studies have focused on corporate behavior, the role of GAS in capital market efficiency remains unexplored. Given that information disclosure by listed firms directly affects the transmission and reflection of accounting information in the stock market, it is imperative to examine the regulatory effects of the government's random accounting supervision on market efficiency.

Stock liquidity has long been recognized as having important implications for market efficiency. Liquidity is essential for the efficient functioning of financial markets and the allocation of resources, as well as for economic growth. As a key metric of capital market quality, it plays a vital role in evaluating market effectiveness (See Goyenko et al., 2009; Hasbrouck, 2009). In addition, stock liquidity is essential for investors to accurately evaluate a company's value, as it reflects market expectations regarding its prospects (Chen et al., 2023). Improving stock liquidity can significantly reduce corporate default risk (Brogaard et al., 2017), encourage research and development (R&D) investment (Wen et al., 2018), and enhance corporate performance (Fang et al., 2009), thereby

3 Regarding government accounting supervision, different countries have adopted differentiated practices at different stages. For example, in 2002, the U.S. established the PCAOB to undertake government accounting supervision activities. Unlike China, however, the PCAOB is an indirect regulator, primarily carrying out governmental accounting supervision by inspecting CPA firms' auditing activities rather than listed companies.

driving economic growth (Chipaumire and Ngirande, 2014; Levine and Zervos, 1998). However, China's A-share market has long been plagued by challenges such as low liquidity, severe information asymmetry and internal governance issues. These are typical dilemmas commonly encountered in other developing countries and highlight the need to strengthen financial and accounting supervision (Li et al., 2011). Building on this inquiry, a key question is whether and how GAS exerts an impact on market efficiency, particularly the stock liquidity.

This paper presents fresh evidence regarding the effect of GAS on stock liquidity, as well as on the channels through which GAS works. We first manually compile the Accounting Information Quality Inspection Announcements 3–43 of China's MOF and employ the staggered introduction of the government's random accounting information quality inspection as an exogenous shock to identify the causal effect of GAS. Using Chinese A-share listed companies during 2000 and 2022, we find that GAS significantly enhances stock liquidity. On average, the introduction of GAS is expected to increase stock liquidity by 26.800%. To ensure that the observed association reflects a positive policy impact rather than a spurious correlation, we further conduct a series of endogeneity tests to confirm the causality of our main findings as well as the validity of our identification strategy. Our main results remain robust after controlling for firm attributes, potential endogeneity concerns, TWFE bias, alternative measures, and model specifications.

To explore the economic channels via which GAS affects stock liquidity, we then examine three potential mechanisms. Specifically, we findings reveal that the positive impact of GAS on stock liquidity is mainly driven by a reduction in information asymmetry offsetting agency costs and improving investor confidence. Moreover, we further conduct a threefold heterogeneity analysis to understand how government accounting supervision (GAS) varies with the listed firm from firm-level perspective, industry-level perspective and market-level perspective, respectively. The heterogeneity analysis reveals that the positive impact of GAS on stock liquidity is more pronounced in firms with low ownership concentration, weak industry competition, and low investor attention. This suggests that China's random accounting inspections system plays an alternative regulatory governance role, effectively compensating for deficiencies in internal corporate supervision and industry self-regulation. Moreover, we adopt a spillover effect framework to examine whether the GAS policy has positive externalities from the industry-level and region-level perspective, respectively. Our findings show that the stock liquidity of uninspected listed firms would also improve if a higher proportion of pilot firms in the same industry/region were introduced, which suggests positive externalities. Overall, our findings uncover that GAS significantly increases stock liquidity, highlighting the positive impact of government regulation and monitoring on market efficiency in a representative emerging market such as China.

Our paper makes the following contributions to the existing literature. First, this study enriches the literature on government accounting inspection by shifting the focus from firm behavior to market efficiency, with a particular focus on stock liquidity. Previous studies have investigated the governance role of GAS and its effects on corporate governance stances (Liu and Wang, 2021; Pan

et al., 2023), ethical conduct (Jiang, 2024), and firm behaviors (Li et al., 2023; Wang et al., 2025). However, prior empirical evidence has focused primarily on internal governance rather than market-level outcomes, so the role of GAS in market efficiency is much less known. Complementary to their findings, our research aims to bridge this gap by evaluating the impact of GAS on stock liquidity. We provide direct empirical evidence of a positive regulatory effect from the perspective of corporate behavior towards market efficiency.

Our study also contributes to providing new evidence for evaluating the effectiveness of government accounting regulation system. Using the exogenous introduction of China's government's random accounting information quality inspection, we identify and assess the positive impact of GAS on stock liquidity as well as the potential channels, offering new insights into the ways government's random accounting supervision influences market efficiency. Our paper is also related to Lennox and Pittman (2010) and Stuber and Hogan (2021). They find that the market reaction to the U.S. PCAOB's system, which is an indirect regulation system, is limited, and thus raise the question the effectiveness of the government's accounting supervision for risks regulation. Fundamentally different from the existing evidence, our findings show that direct government regulation is more effective, carrying greater deterrent power, and offering stronger authority and enforcement capabilities. Therefore, the consequences of GAS are more far-reaching than research focusing solely on the PCAOB's regulations could reveal.

In addition, although several traditional theoretical studies argue that regulation usually restrict competition and foster corruption (see, for example, Stigler, 1971; Posner, 1974; and Djankov et al., 2022), Our findings provide a complementary perspective on the benefits of improvements in market efficiency, thereby expanding upon existing literature on the advantages of regulation (Leuz & Wysocki, 2016; Omarova & Steele, 2023; Gu et al., 2026).Our results provide practical implications for policymakers, and contribute to the ongoing debate about the unique role of government, particularly the direct government regulation, in enhancing information transparency and and maintaining market effectiveness. China's randomized accounting inspection system offers valuable insights into how economies can strike a balance between excessive intervention and regulatory leniency.

Finally, while our paper is firmly grounded in China's unique institutional background, our main findings offer fresh insights into the design of effective regulatory strategies and provide a solution to the long-standing governance dilemma in emerging markets. Developing countries typically struggle with issues such as low liquidity, severe information asymmetry, and poor internal governance (Li et al., 2011). However, comprehensive oversight typically implies high costs and the effectiveness of indirect supervision, e.g., U.S. PCAOB's system, is often significantly diminished. As noted by Ronconi (2019), the effective allocation of limited regulatory resources to enhance corporate compliance and market efficiency has long been a critical policy issue. The introduction of the government's random accounting inspection policy has significantly increased stock liquidity in China, achieving a low-cost, high-governance, high-deterrent effect. This sheds

light on establishing and reforming an effective accounting regulatory system.

The remainder of this paper organizes as follows: Section 2 introduce institutional background, and outlines our hypotheses development. Section 3 describes the sample selection procedure, variable construction as well as empirical strategies. Section 4 presents our main findings. Section 5 explores the potential channels, and Section 6 provides further analysis and Section 7 concludes.

2. Institutional Background and Hypotheses Development

2.1 Institutional background

As the largest emerging market, China's A-share market has long been plagued by challenges such as low liquidity, severe information asymmetry, and internal governance issues — a typical dilemma commonly encountered in other developing countries (Li et al., 2011), highlighted the need for strengthening financial and accounting supervision. More importantly, China's stock market is order-driven. Investors act as both suppliers and demanders of liquidity. Without market makers to provide stable liquidity, trading activity can be extremely low, causing trading costs to soar during market turmoil. With the intention to enhance information transparency and market efficiency, the Chinese government has introduced random inspection of accounting information quality by the Ministry of Finance for listed companies since 1999.

As a crucial external governance mechanism, government accounting supervision (GAS) is a critical practice that has been used to strengthen financial and accounting supervision. The core objective of GAS is to regulate accounting practices and ensure the authenticity, completeness and compliance of accounting information. GAS also aims to uphold national fiscal and financial order, protect the interests of investors and the public, and promote high-quality economic development (Lyu, 2025). GAS primarily targets enterprises, public institutions, accounting firms and other market participants, focusing mainly on the quality of accounting information, financial management, internal controls and auditing practices (Pan et al., 2023; Jiang, 2024). The mechanism of GAS includes two key components: (i) the random selection of inspectors and pilot firms[4] and (ii) the execution of public on-site inspections. Specifically, this involves "randomly selecting inspection targets, randomly assigning inspectors, and promptly disclosing inspection results".

The random supervision process begins with the calibration of a sampling threshold. Sample selection and inspector allocation are carried out using a stochastic lottery mechanism within the Ministry of Finance in China. Inspectors must comply with mandatory recusal provisions, which prevent them from being involved with the target firm if they have had a professional service relationship with it within the previous three years. The provisional inspection roster then undergoes manual adjudication to ensure regulatory compliance and eliminate ineligible candidates, particularly those currently involved in special treatment (ST) or delisting proceedings.

The on-site inspection process is carried out in confidence, as all inspectors are required to sign confidentiality agreements. The inspection process typically involves surprise audits, face-to-face

4 The inspectors include external accountants, legal experts, and regulatory officials. The supervision target includes almost all listed firms, except for those that are ineligible (e.g., those undergoing delisting procedures).

interviews, enquiries and various other procedures. Specifically, the inspection process mainly focuses on three parts: (i) Information Disclosure Standards, involve the procedural and documentary compliance within information disclosure; (ii) Corporate Governance Standards, involve the operational efficacy of the board and supervisory board, and verification of the checks and balances mechanisms across key functional departments; (iii) Financial Management Standards, involve the assessment of conformity with accounting policies and substantive accuracy in financial statement preparation, alongside auditing of capital allocation processes, connected transactions, and equity holder lending practices. This process usually takes 10–14 working days, but can take over 30 days for more complex cases. Finally, the inspection results will be publicized on the Accounting Information Quality Inspection Announcements by the Ministry of Finance.

Although similar government accounting supervision policies have been implemented in other countries, China's government accounting supervision is based on the "double random, one public" inspection principle and the policies are implemented randomly and suddenly to a large extent. For example, the U.S. established the U.S. Public Company Accounting Oversight Board (PCAOB), in 2002 to undertake government accounting supervision activities. Unlike China, the PCAOB is an indirect regulator, primarily responsible for supervising the accounting of public companies by inspecting CPA firms' auditing activities. Specifically, PCAOB is responsible for inspecting accounting firms and certified public accountants who audit public companies. These inspections focus on whether CPAs exercised due diligence and performed work procedures in accordance with auditing standards during the audit process. However, the scope of inspections by the PCAOB is also limited, resulting in gaps in the accounting oversight, e.g., banks industry (Lennox and Pittman, 2010). Moreover, as an independent accounting oversight body, the PCAOB lacks the necessary authority and enforcement power[5]. Therefore, GAS in China has a broader scope and more directly reflects the government's regulatory intentions. The PCAOB, however, places greater emphasis on independence and professionalization. This distinction reflects China's random government accounting supervision comprehensive regulatory mandate over the entire capital market, including listed firms, investors and auditors in accounting firms.

GAS has several advantages over other forms of supervision[6]. First, the implementation of Government Accounting Supervision (GAS) adheres to the 'double random, one public' principle, which forms the basis of China's random accounting inspection system. As the objects of inspection and law enforcement personnel are randomly selected, this provides us with a natural exogenous event with which to address endogenous problems. Second, compared with traditional post-regulatory inspections or conventional regular inspections conducted on a fixed cycle, the randomly

[5] For example, Lennox and Pittman (2010) note that following an inspection by the U.S. PCAOB, the stock prices of listed companies have remained largely unaffected. In addition, Stuber and Hogan (2021) find that auditors of US public banks were the only ones to respond to inspections by the PCAOB. This further calls into question the effectiveness of the PCAOB's system for overseeing financial risks.

[6] Due to regulatory resources constraints, the number of enterprises included in random accounting supervision fluctuates annually, ranging from 1 in 2004 to 58 in 2010. According to our manual statistics, the number of firms listed under GAS has increased gradually, as shown in Figure 1.

implementation process of GAS effectively mitigates the endogeneity issues prevalent in existing research due to its unpredictability, as post-regulatory measures are usually introduced once potential risks of listed firms have been identified by regulators and regular inspections allow pilot firms to time their information disclosures strategically. In this case, GAS can identify accounting fraud at an early stage and act as a deterrent, facilitating the timely detection and prevention of problems. Therefore, pilot firms listed on GAS effectively gain a government audit guarantee, which significantly boosts investor confidence.

By 2023, China's Ministry of Finance had organized and issued 42 announcements regarding random inspections of accounting information quality, covering nearly 30,000 enterprises and institutions. Such regulatory efforts enable the Ministry to swiftly identify and address irregularities in corporate accounting disclosures and financial governance. This promotes the sound development of the accounting industry and provides institutional support for the stable operation of the national economy (Wang et al., 2025). We present the detailed distribution of these pilot firms in Figure 1. As shown, the number of firms listed under GAS has increased gradually, indicating that the scope of GAS is expanding, with a growing number of listed companies in the treatment group.

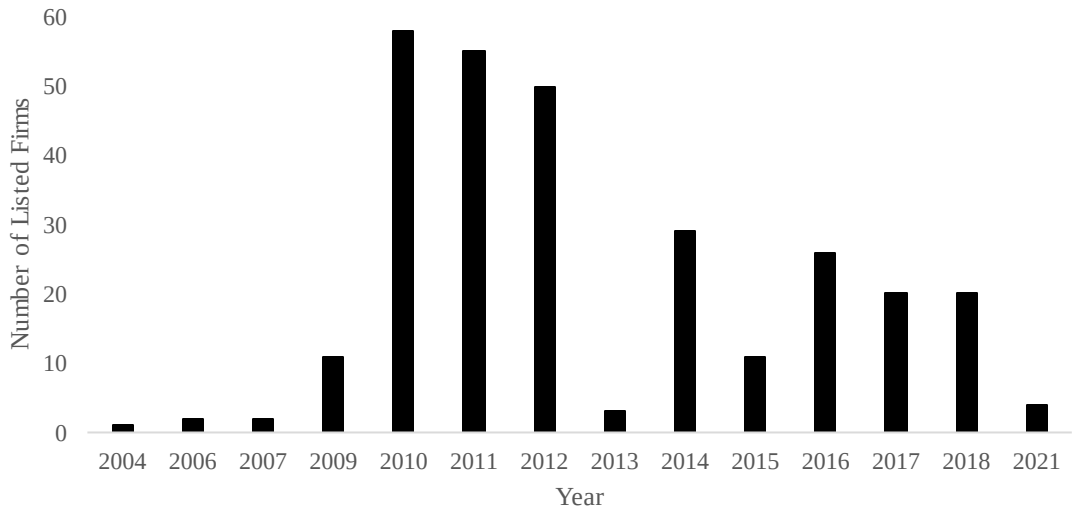


Figure 1 Temporal Distributions of Listed Firms under Government Accounting Supervision

Note: Figure 1traces the annual number of listed firms under government accounting supervision (GAS) during 2000 and 2022, with calendar years on the horizontal axis and the annual number of firms initially included in the government's random accounting information quality inspections on the vertical axis.

In addition, GAS covers nearly all industries, indicating a broader scope. For example, we compare the distribution of inspected firms across industries and regions further (see Appendix Tables A1 and A2). In terms of industry distribution, the pilot listed firms were spread across 134 different industries. This indicates that government accounting supervision inspections extend across multiple sectors, rather than being confined to specific fields. This demonstrates the policy's comprehensive coverage. From a regional perspective, the pilot listed firms that were subject to government accounting supervision by the Ministry of Finance (*treat* = 1) were distributed across 106 cities, revealing significant regional diversity. This coverage extends beyond developed regions

such as Beijing, Shanghai and Shenzhen to include multiple cities in western, central and north-eastern China, such as Lanzhou, Zhengzhou, Harbin, Guiyang, Urumqi and Yinchuan. Overall, the industry and regional distribution of the pilot listed firms indicates that the policy was implemented both comprehensively and randomly.

2.2 Theoretical analysis and Hypotheses Development

As a key indicator of market efficiency, stock liquidity is an issue of growing interest. Existing research has suggested several firm-level, institutional, industrial, and macroeconomic factors closely affect stock liquidity. For example, prior studies find that monetary policy (Sequeira, 2021), market uncertainty (Mbanyele, 2023), and legal and regulatory frameworks (Cumming et al., 2011; Trebbi and Xiao, 2019) have significant impacts stock liquidity, suggesting that changes in the macroeconomic environment can influence stock market trading activity and liquidity by affecting liquidity supply, risk premiums, and trading intensity. More recent studies have broadened this line of research from micro-level perspectives. Other studies have examined how investor sentiment (Liu, 2015; Kumari, 2019), corporate governance (Prommin et al., 2014), digital transformation (Liu and Liu, 2023) and innovation activities (Fang et al., 2014) affect stock liquidity through their impact on information disclosure transparency, governance efficiency and investor trading behaviors.

China is a typical emerging market, characterized by low liquidity, severe information asymmetry and internal governance issues (Li et al., 2011), as well as weak corporate governance and investor protection (Allen et al., 2005). Liang, D et al. (2024) find that liquidity and market uncertainty level are key driving forces of the large liquidity premium in China. China's capital markets have seen a number of financial fraud issues (e.g., Luckin Coffee in 2020 and LeTV in 2021), which have been a major obstacle to high-quality economic development (Lyu, 2025). To explore a new measure for enhancing the accounting supervision system, China’s MOF initiated random inspection of accounting quality on listed companies in 1999, based on the ‘double-random and public’ principle. This provides us with a unique institutional background to assess the impact of GAS on market efficiency.

Extant research has documented the economic consequences of GAS mainly on firm behavior and market performance. For instance, Liu and Wang (2021) first find that GAS can effectively mitigate firms' earnings management behavior. Similarly, a number of studies also document that the positive role of GAS in reducing firms' tax avoidance (Li et al., 2023), executive consumption (Pan et al., 2023), corporate stock price crash risk (Chen and Chen, 2024) and supply chain risks (Lyu, 2025). Moreover, Jiang (2024) finds that GAS significantly enhances the ESG performance. While the above evidence clearly demonstrates the impact of GAS on internal corporate governance, its role in market efficiency, particularly with regard to stock liquidity, remains unclear.

Motivated by the inquiry, we aim to exam the effect of government accounting supervision on the stock liquidity, the cornerstone for measuring market efficiency. The literature has long recognized that stock liquidity can be influenced by the quality and authenticity of information

disclosed by listed companies (Bhide,1993; Sengupta, 1998; Healy and Palepu,2001; Balakrishnan et al., 2014). Welker (1995) notes that a well-regarded disclosure policy reduces information asymmetry and increases liquidity in equity markets. Similarly, Balakrishnan et al. (2014) voluntarily disclosing more timely and informative information improves stock liquidity and, in turn, increases firm value.

A lack of liquidity in Chinese individual stocks is primarily caused by information concealment and inadequate disclosure (Li et al., 2011). As an external accounting supervision mechanism, the introduction of government's random accounting information quality inspection can compel listed companies to standardize their financial information disclosure practices. This ensures that financial reports are timely, truthful, complete, and transparent, thereby effectively reducing issues of financial fraud, and information manipulation. In addition, government accounting supervision can improve the quality of information disclosure, reducing market uncertainty and enabling investors to evaluate a company's intrinsic value more accurately. Based on the aforementioned studies, we predict that, GAS can enhance stock liquidity. We thus propose and test the main hypothesis as follows:

Hypothesis 1: The introduction of government accounting supervision is positively associated with stock liquidity.

The information asymmetry theory suggests that there is a significant difference in the extent to which listed companies and investors can acquire and possess information in capital markets (Chen and Liu, 2013). As the main demand side of information, investors rely heavily on the sufficiency, accuracy, and credibility of the financial information from earnings announcements of listed firms when making investment decisions. As the suppliers of information, listed companies often violate information disclosure regulations by disclosing information untimely, incompletely, or irregularly. Even more seriously, managers may disclose financial information selectively, conceal or distort unfavorable facts, or even commit financial fraud to mislead market expectations for their benefit. Information asymmetry between investors and listed firms increases market uncertainty (Welker,1995; Healy and Palepu,2001), reduces investors' ability to accurately evaluate company value (Krishnaswami and Subramaniam,1999; Armstrong et al.,2011), and undermines market trust and the willingness to trade company stocks (Zingales,2009; Zhang and Wiersema,2009). This ultimately results in a decline in stock market liquidity (Bhide,1993).

Previous theories of market microstructure also suggest that information asymmetry may reduce market trading depth and further aggravate market liquidity (Kyle, 1985; Welker, 1995). Recent studies show that stock liquidity is primarily driven by information asymmetry among investors, particularly between uninformed and informed traders (e.g., He et al., 2022). First, the introduction of the government's random accounting information quality inspection can compel pilot firms' compliance with accounting standards. The Ministry of Finance (MOF) of China and its subordinate institutions take a highly professional and systematic approach to monitoring information disclosure practices. They can identify and expose issues such as false disclosure and

earnings management, thereby strengthening financial reporting credibility and information disclosure quality. Besides its information monitoring, GAS plays an information governance role. By improving information disclosure precision, GAS reduce market uncertainty and information risk of pilot firms, allowing investors to evaluate the intrinsic firm value more accurately. Additionally, GAS also reduces the degree of information asymmetry between uninformed and informed traders regarding corporate value, thereby effectively combatting informed trading. The preceding analysis leads to the following hypothesis:

Hypothesis 2: The introduction of government accounting supervision has effectively reduced information asymmetry, thereby enhancing stock liquidity.

Agency theory provides another lens through which the influence of GAS on stock liquidity can be examined. Agency conflicts arise when managers act in their own interests at the expense of shareholders, which is usually through opportunistic disclosure or information withholding. Good corporate governance effectively mitigates agency problems, particularly those involving conflicts of interest between controlling shareholders and minority shareholders (see, for example, Shleifer and Vishny, 1997; Gillan, 2006). GAS regulates the behavior of managers and mitigates agency problems. Prior studies suggest that the interests of management and shareholders are not fully aligned, which can lead management to make investment or operational decisions that do not maximize shareholder value, but instead benefit them personally. Examples include overinvestment (Albuquerque and Wang, 2008), insider rent-seeking (Ahuja et al., 2005), and neglecting long-term corporate value (Renders and Gaeremynck, 2012). Suboptimal decisions resulting from the agency problem not only erode corporate value, but may also undermine financial stability, erode market confidence, and further decrease stock liquidity (Prommin et al., 2014).

On the one hand, the "external pressure–internal improvement" interaction of GAS strengthens requirements for financial information disclosure and standardized financial management and disclosure practices among pilot firms, as any deficiencies about information disclosure deficiencies regarding information disclosure are likely to be identified during the on-site inspection. On the other hand, the deterrence power of GAS increases the invisible costs and legal risks of violations for managers by introducing an external accounting monitoring mechanism, thereby inhibiting agency issues. By pursuing transparent disclosure policies and stronger governance practices, GAS reduces adverse selection and agency cost inequity in markets, thereby improving liquidity. Furthermore, we expect that GAS may also improve stock liquidity by mitigating agency conflicts. We thus propose the following hypothesis in alternative form:

Hypothesis 3: The introduction of government accounting supervision has a positive impact on corporate governance by reducing agency costs and thereby improving stock liquidity.

From the perspective of behavioral finance, investor sentiment can also affect firm liquidity (Baker and Stein, 2004; Chiu and Chung, 2012). For instance, Chiu and Chung (2012) find that a higher degree of bullish sentiment leads to improve equity liquidity and increase net buying volume

as well as more limit buy orders. Similarly, Asem et al. (2016) show that optimistic investor sentiment will significantly improve stock liquidity, especially when market sentiment is generally pessimistic. The inherent logic of how the government's random accounting supervision improves stock liquidity by boosting investor optimism is as follows:

First, as the government accounting supervision enhance the quality of information disclosure by pilot listed firms, thereby aligning investor expectations with firm fundamentals and enabling investors to estimate firm intrinsic value more precisely. The expansion of high-quality information disclosure due to GAS reduces retail investors' tendency to focus on "worst-case scenarios", prompting them to shift their stance from cautious observation to "optimistic buying". The resulting decline in information risk boosts investor confidence, leading to a more optimistic outlook and significantly increasing stock liquidity. In addition, under the scrutiny of government accounting oversight, listed companies receive an implicit seal of approval on the credibility of their disclosures; this regulatory endorsement acts as a powerful confidence shock, rapidly amplifying investor optimism and translating into markedly more bullish sentiment. Taken together, propose and test the following hypothesis:

Hypothesis 4: The introduction of government accounting supervision has boosted investor optimism and investment enthusiasm, thereby enhancing stock liquidity.

3. Data and Methodology

3.1 Data

Our initial sample covers all Chinese A-share listed companies from 2000 to 2022. We obtain all annual stock liquidity data and firm-level characteristic variables of listed firms from CSMAR. We manually collect the data from the Accounting Information Quality Inspection Announcements 3–43 of China's MOF[7]. For multiple inspected listed companies, we only retain the initial inspection. Although the MOF began organizing the quality inspection of accounting information in 1999, it did not publish a detailed report on the first two random inspections. We therefore started our sample period in 2000, compiling a manual list of the firms that were inspected[8]. For companies that have been inspected more than once, we only retain the initial inspection. To ensure consistency and representativeness of our sample data, financial firms and companies whose inspection year preceded their listing year were excluded. This filtering process removes duplicate data from multiple inspections, thereby improving the accuracy of our analysis.

We followed the existing studies and filter out our sample data as follows: (1) we excluded firms in the financial industry; (2) we remove firms which are special treatment (ST) or facing delisting risk warning (*ST) or facing particular transfer (PT), or listed companies whose listing was suspended during the accounting year to mitigate the impact of financially distressed companies;

7 Source: The Accounting Information Quality Inspection Announcements 3–43 of China's Ministry of Finance during 2000 and 2022. (For example, see: https://www.mof.gov.cn/jrttts/202408/t20240805_3941091.htm).

8 The Accounting Information Quality Inspection Announcements 3 was released in 2004. Our sample period starts in 2000, four years before the initiation of the government accounting supervision in 2004, to trace dynamic patterns and verify the parallel-trend assumption.

(3) we exclude observations with missing values. All continuous measures are winsorized at the 1st and 99th percentiles to mitigate outlier influence. Table A4 in the Appendix details the sample selection process in this paper. Our final matched sample data includes 29,418 observations from December 2000 to December 2022, including 708 observations in treatment groups and 28710 in the control group.

3.2. Variable definition

Following with prior literature, we use the Amihud (2002) illiquidity measure $ILLIQ$ as our main proxy for stock liquidity. As shown in equation (1), $ILLIQ$is defined as

$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{k=1}^{D_{it}} \sqrt{\frac{|R_{it}(k)|}{V_{it}(k)}} \quad (1)$$

Secondly, following the previous studies (Lesmond et al.,1999; Chordia et al., 2002, Barinov, 2014), we use the annual turnover rate ($Turnover$) and zero yield index (*Zeros_Y)* as alternative measures of stock liquidity. Our findings remain robust with respect to alternative metrics for stock liquidity, which have also been widely employed in prior studies. These results are presented in Section 5.3.1.

Following the prior literature (e.g., Zhang and Sok, 2025; Majeed and Yan, 2022), we use several firm characteristics as control variables, including firm size (*Size*); leverage ratio (*Lev*); capital expenditure rate ($CAPEX$); the numbers of board members (*Board*); sales growth ($Growth$); cashflow ratio (*CF*); CEO duality (*Duality*). Table A3 presents the detailed definitions of each variable and the sources of the data.

3.3 Empirical methodology

Following Goodman-Bacon (2021), we use a staggered DID regression specification to examine the real impact of GAS on stock liquidity. The staggered introduction of the government's random accounting information quality inspections is adopted as a quasi-natural experiment, regarding the listed firms under GAS as the treatment group. Specifically, our baseline empirical model as follows:

$$ILLIQ_{it} = \alpha + \beta DID_{it} + \gamma X_{it} + \varphi_i + \mu_t + \varepsilon_{i,t} \quad (2)$$

where $ILLIQ_{it}$ denotes the dependent variable, which measures annual stock liquidity of firm *i* in year *t*. The main independent variable DID_{it}, is an indicator which takes the value one for the year in which a firm first becomes subject to government accounting supervision and for every year thereafter, and 0 otherwise. X_{it} is the vector of control variables.

Our coefficient of interest, namely β, estimates the treatment effect of the government's random accounting information quality inspection on stock liquidity. A negative β shows with improved stock liquidity of firms after GAS, consistent with Hypothesis 1.

3.4 Descriptive Statistics

Descriptive statistics for all variables of this study are reported in Table 1. In Panel A, we report the summary statistics of the main variables. The mean value of *ILLIQ* is -73.212, with a standard deviation of 43.336. The key independent variable, *DID*, exhibits a mean of 0.024, indicating that

approximately 2.400% of firm-year observations are treated by the government's random accounting information quality inspection. Overall, the descriptive statistics for our independent, dependent, and control variables are consistent with existing research (Li et al., 2011; Pan et al., 2023; Li et al., 2023; Liang, D et al., 2024).

Panel B of Table 1 reports pairwise correlations among dependent, independent, and control variables. As shown in Panel B, the correlation coefficients between the *DID* and stock liquidity measures *ILLIQ* are all statistically significantly negative, offering initial support for our hypothesis 1. In addition, correlations among key explanatory variables of stock liquidity and other firm characteristics are moderate, suggesting that multicollinearity is not a serious concern.

Table 1 Descriptive Statistics

Panel A: Summary Statistics

Variable	N	Mean	Median	SD	Max	Min
ILLIQ	29418	82.145-	-73.212	43.336	-13.024	-249.848
DID	29418	0.024	0.000	0.153	1.000	0.000
Size	29418	22.149	22.026	1.183	25.971	19.331
Lev	29418	0.437	0.432	0.200	0.987	0.056
CAPEX	29418	0.051	0.037	0.046	0.249	0.000
Board	29418	8.735	9.000	1.719	15.000	5.000
Growth	29418	0.159	0.113	0.342	3.133	-0.628
CF	29418	0.049	0.048	0.065	0.253	-0.176
Dual	29418	0.249	0.000	0.432	1.000	0.000

Panel B: Correlations

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	*ILLIQ*	1.000							
(2)	*DID*	-0.569***	1.000						
(3)	*Size*	-0.002	0.413***	1.000					
(4)	*Lev*	-0.021***	0.185***	0.141***	1.000				
(5)	*CAPEX*	-0.024***	-0.227***	-0.566***	-0.167***	1.000			
(6)	*Board*	-0.060***	0.017***	0.029***	0.011**	0.015***	1.000		
(7)	*Growth*	-0.105***	0.048***	-0.153***	0.052***	-0.153***	0.031***	1.000	
(8)	*CF*	0.006	-0.137***	-0.135***	-0.197***	0.115***	0.010*	-0.022***	1.000

Note: Table 1 summarizes the key variables used in our baseline regressions. Panel A displays the summary statistics. Table A3 in Appendix shows detailed definitions of all variables. Panel B reports pairwise correlations among dependent, independent, and control variables. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4. Regression Results

4.1 Baseline Regression

Table 2 presents the baseline regression results. As shown, the coefficient for *DID* is highly significant with a negative sign across all regression specifications at the 1% significance levels, indicating that government's random accounting information quality inspection significantly

enhance stock liquidity. In terms of economic magnitude, as the coefficient for DID is 11.614 in column 4 of table 1 (with a standard error of 0.153) and the standard error of the key dependent variable (*ILLIQ*) is 43.336, which means the introduction of GAS is expected to increase stock liquidity, on average, by 26.800% (= 11.614/43.336, relative to the standard deviation of annual stock liquidity). In addition, a one-standard-deviation improvement in government accounting supervision (GAS) will lead to a 0,041(=0.153*11.614/43.336)- standard-deviation decrease in *ILLIQ* (See Cohen and Zarowin, 2010). This relationship is economically significant.

Table 2 Baseline Regression

	(1) *ILLIQ*	(2) *ILLIQ*	(3) *ILLIQ*	(4) *ILLIQ*
DID	**-15.463*** **	**-20.298*** **	**-18.848*** **	**-11.614*** **
	(-5.380)	**(-7.788)**	**(-8.086)**	**(-4.531)**
Size		-31.409***	-20.948***	-23.439***
		(-55.067)	(-48.336)	(-34.129)
Lev		48.244***	44.196***	35.344***
		(19.355)	(22.298)	(15.808)
CAPEX		25.314***	-31.013***	-27.061***
		(4.266)	(-5.421)	(-5.222)
Board		1.584***	0.314	0.192
		(6.088)	(1.427)	(0.844)
Growth		-2.984***	-7.016***	-1.570***
		(-5.292)	(-11.881)	(-3.239)
CF		-21.749***	-29.581***	-30.082***
		(-5.770)	(-7.157)	(-9.290)
Dual		0.485	-1.871***	1.202*
		(0.588)	(-2.800)	(1.657)
_cons	-81.773***	579.265***	364.867***	422.983***
	(-1,182.211)	(45.030)	(41.006)	(28.220)
Year-FE	YES	NO	YES	YES
Firm-FE	YES	YES	NO	YES
N	29,418	29,418	29,418	29,418
R2	0.703	0.639	0.541	0.754

Note: Table 2 reports the baseline results from the staggered difference-in-differences estimations examining how government accounting supervision (GAS) affects stock liquidity. *ILLIQ* denotes the stock illiquidity measure following Amihud (2002). A Lower value of *ILLIQ* indicates higher stock liquidity. The *DID* indicator takes the value one for the year in which a firm first becomes subject to government accounting supervision and for every year thereafter, and 0 otherwise. The coefficients of *DID* estimate the treatment effect between firms which are exposed to government accounting supervision and other firms without government accounting supervision. The bold numbers indicate the key results. T values are in parentheses. The standard errors of all regressions are clustered at the firm level. ***, ** and * denote significance levels at 1%, 5%, and 10%, respectively. All subsequent tables adhere to the same format.

4.2 Goodman-Bacon Decomposition

Since conventional regression-based estimators may introduce potential bias on treatment-effect homogeneity in staggered DID estimates[9] (Callawayet al., 2021; Baker al., 2022; Borusyak and

[9] As Borusyak and Jaravel (2024) notes, when policy implementation occurs at different times or across different cohorts with varying treatment timings, the traditional TWFE estimator may may suffer from estimation bias due to weighting errors and negative weight issues. This issue can be diagnosed through Goodman-Bacon

Jaravel, 2024), we subsequently employ the Goodman-Bacon decomposition to investigate the relative contributions of each treatment timing cohort within the staggered difference-in-differences framework (Goodman-Bacon, 2021).

Table 3 Results of Goodman-Bacon decomposition

Bacon decomposition	Weight	Average DD estimator
Earlier Treatment vs. Later Comparison	0.007	0.340
Later Treatment vs. Earlier Comparison	0.005	-2.615
Treatment vs. Never Treated	**0.985**	**-15.408**
Treatment vs. Already Treated	0.002	8.797
TWFEDD Estimates	**-**	**-15.175**

Note: Table 3 displays the outcomes of the Bacon decomposition, comprising four constituent elements. "Earlier Treatment vs. Later Comparison" compares listed firms under GAS with those not yet affected. "Later Treatment vs. Earlier Comparison" compares listed firms introduced later to GAS with those already affected. "Treatment vs. Never Treated" compares listed firms under GAS with those never introduced. "Treatment vs. Already Treated" compares listed firms introduced to GAS at some point with those already affected. The two-way fixed-effects coefficient of −15.175 is obtained by weight-averaging the vertical-axis magnitudes using the horizontal-axis proportions.

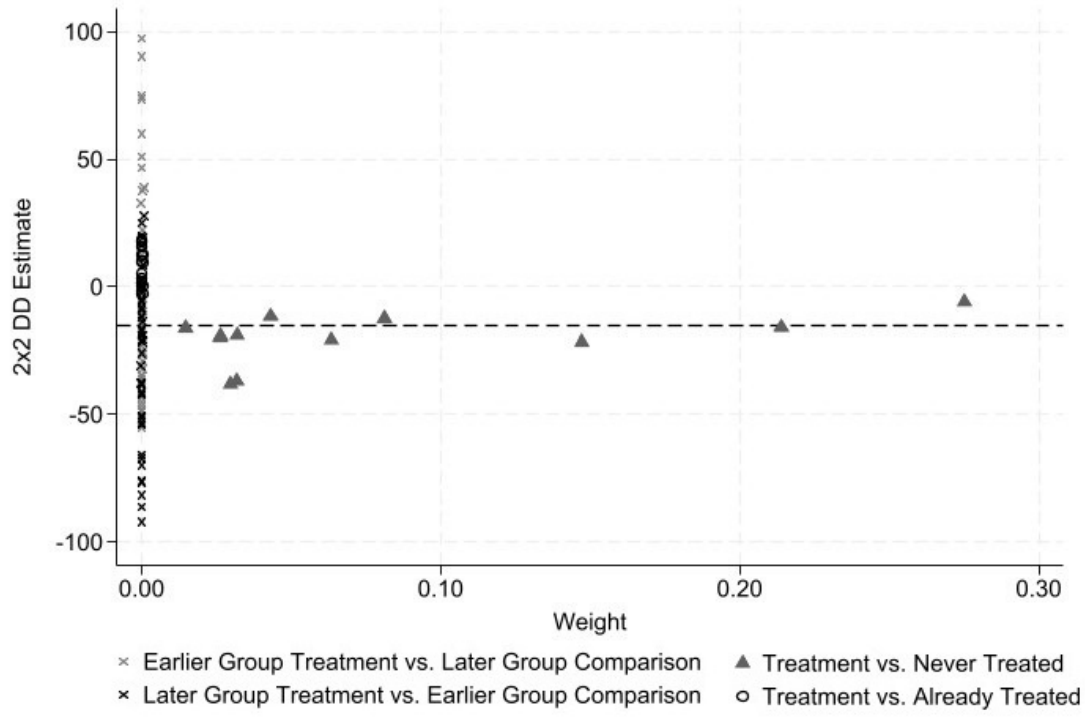


Figure 2 2×2 DID estimates

Note: Figure 2 plots each 2x2 DID component from the Goodman-Bacon decomposition, which includes four components. The vertical axis records the magnitude of each component, whereas the corresponding weight is plotted along the horizontal axis. "Earlier Treatment vs. Later Comparison" compares listed firms under government accounting supervision with those not yet affected. "Later Treatment vs. Earlier Comparison" compares listed firms introduced later to government accounting supervision with those already affected. "Treatment vs. Never Treated" compares listed firms under government accounting supervision with those never introduced. "Treatment vs. Already Treated" compares listed firms introduced to government accounting supervision at some point with those already affected.

decomposition..

As shown in Table 3, the Goodman-Bacon decomposition includes four components. “Earlier Treatment vs. Later Comparison” (Early-Late Group) compares listed firms under GAS with those not yet affected, with a weight of 0.70% and an average coefficient of 0.340. “Later Treatment vs. Earlier Comparison” (Late-Early Group) compares listed firms introduced to GAS later with those already affected, which mainly accounts for the bias in the overall DID estimate. The average coefficient is -2.615, accounting for only 0.50%. “Treatment vs. Never Treated” (treated-untreated group) compares listed firms under GAS with those never introduced, yielding an average coefficient of -15.408 and a weight of 98.50%.and account for the bias in the overall DD estimate “Treatment vs. Already Treated” (treated-already group) compares listed firms introduced of GAS at some point with those already affected, with an average coefficient of 8.797 and a weight of 0.20%. The bias resulting from HTE is also plotted in Figure 2.

4.3 Parallel Trends Test

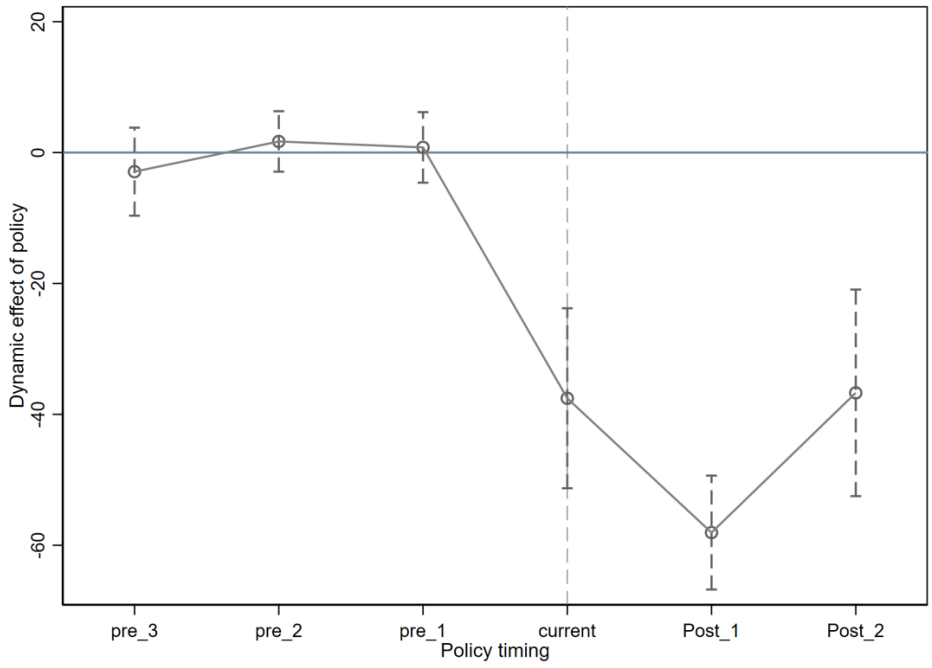


Figure 3 Parallel Trends Test

Note: Figure 3 illustrates the estimated dynamic effects of the government’s random accounting information quality inspection on annual stock liquidity in the treated and control groups at different periods around the government accounting supervision event. Pre_{it}^{-3}, Pre_{it}^{-2},Pre_{it}^{-1}, $Current_{it}^{0}$, $Post_{it}^{1}$ and $Post_{it}^{2}$ indicate the dummy variables, which equals one if the listed firms are included in the government’s random accounting information quality inspection: three or more, two, one year prior to the policy year, the policy year, the next year and the next two years, respectively.

The parallel trends assumption is crucial for accurately identifying the causal effect. Specifically, significant changes in the annual stock of listed firms in the treated and control groups should be significant only after the introduction of GAS, rather than before.

Following the prior studies (see Zhou et al., 2024; Dai et al., 2025), we decompose the effect of GAS into different time periods and replace the *DID* dummy with the following dummy variables:Pre_{it}^{-3}, Pre_{it}^{-2},Pre_{it}^{-1}, $Current_{it}^{0}$, $Post_{it}^{1}$ and $Post_{it}^{2}$. Next, we estimate the following

regression model:

$$Y_{it} = \alpha + \beta_1 Pre_{it}^{-3} + \beta_2 Pre_{it}^{-2} + \beta_3 Pre_{it}^{-1} + \beta_4 Current_{it}^{0} + \beta_5 Post_{it}^{1} + \beta_6 Post_{it}^{2} + \gamma X_{it} + \varphi_i + \mu_t + \varepsilon_{i,t} \quad (3)$$

Figure 3 illustrates the estimated dynamic effects of the government's random accounting information quality inspection on annual stock liquidity in the treated and control groups at different periods around the government accounting supervision event. It suggests that there were no significant differences in liquidity between the treated and control groups prior to the random accounting inspections. Column (1) in Table 5 reports the regression results of the parallel trends test. The coefficients of the interaction terms for the pre-treatment periods are all statistically insignificant, suggesting that the parallel trends assumption is satisfied. In addition, the coefficients on the interaction terms of $Post_{it}^{1}$ and $Post_{it}^{2}$ are significantly negative, indicating that the effect of the GAS on stock liquidity is not temporary but will last for several years. These findings not only confirm the the parallel trends assumption of our benchmark identification strategy, but also highlight the cumulative nature of the policy impact—stock liquidity has continued to improve since the randomized inspection was performed, which is likely due to the ongoing governance and deterrent effects.

4.4 Endogeneity Tests

4.4.1 Propensity Score Matching Analysis

Table 4 Diagnostic test for PSM

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
ILLIQ	Unmatched	-133.846	-80.870	-52.976***	1.619	-32.710
	After PSM	-133.846	-107.723	-26.123***	1.585	-16.490
Size	Unmatched	23.390	22.119	1.271***	0.044	28.650
	After PSM	23.390	23.304	0.085**	0.044	1.920
Lev	Unmatched	0.490	0.436	0.054***	0.008	7.130
	After PSM	0.490	0.487	0.003	0.007	0.390
CAPEX	Unmatched	0.045	0.051	-0.006***	0.002	-3.340
	After PSM	0.045	0.046	-0.001	0.002	-0.300
Board	Unmatched	8.982	8.729	0.252***	0.065	3.860
	After PSM	8.982	8.972	0.009	0.073	0.130
Growth	Unmatched	0.119	0.160	-0.042***	0.013	-3.210
	After PSM	0.119	0.122	-0.003	0.012	-0.250
CF	Unmatched	0.055	0.049	0.006***	0.002	2.620
	After PSM	0.055	0.056	-0.000	0.003	-0.100
Dual	Unmatched	0.196	0.250	-0.054***	0.016	-3.290
	After PSM	0.196	0.200	-0.004	0.015	-0.230

Note: Table 4 presents the diagnostic tests for the propensity-score matching (PSM) procedure. We apply a radius-matching algorithm with a caliper of 0.01. The propensity score is estimated based on probit model, the outcome of which is a binary indicator equaling 1 for firms that are first assigned to government accounting supervision (GAS) in a given year and in all subsequent years. Each treated observation is paired with the control firm within the same industry-year that exhibits the smallest absolute difference in estimated propensity scores.

The empirical findings so far suggest that under GAS, pilot listed firms experience a significant improvement in stock liquidity. However, although the MOF in China strictly conducts random accounting information quality inspections following the 'dual random inspections and one public disclosure' principle, thus exhibiting strong exogeneity, China's policy experiments may still exhibit

a sample selection issue. Specifically, listed firms selected by the government for random accounting information quality inspections may not be chosen at random, but rather due to their distinctive economic or political attributes.

To mitigate endogeneity arising from potential sample selection bias, we conduct a PSM analysis. First, we compare the firm characteristics of the listed firms in the treatment and control groups. Table 4 shows that the mean differences in these variables are overwhelmingly significant. Following the previous literature (Wen and Sun, 2023), we choose the radius matching method and the caliper set equal to 0.01. In the first stage, we use the covariates in our benchmark model as the matching covariates and estimate the propensity score through a probit regression. In the second stage, we use the first-stage propensity estimates to match pilot firms of similar characteristics.

Table 4 reports the diagnostic test for the accuracy of our PSM matching analysis. It shows that all firm characteristics between the treatment and control groups are insignificantly different after propensity score matching, suggesting that our matching process is effective for the observed firm characteristics. Importantly, *ILLIQ* is significantly lower for pilot firms at the 1% level (t = -16.490) even after imposing stringent controls on firm characteristics, suggesting that the difference in stock liquidity cannot be attributed solely to firm characteristics. Finally, we re-estimate the benchmark regression using the propensity score-matched sample. The results in column (2) of Table 5 show that the coefficient of the *DID* variable remains significantly negative. In addition, the magnitude of the coefficient (-11.631) is highly consistent with the baseline estimates, suggesting that our main results are are robust to potential sample selection bias.

4.4.2 Heckman Two-Stage Model

Another approach to addressing potential endogeneity is to use the Heckman two-stage method. We first construct an indicator variable *DID* as the dependent variable, which equals to 1 in the year of incorporation of GAS and in all subsequent years and 0 otherwise. Next, we run the Probit regression of *DID* in the first step regression of the Heckman two-stage model. Following the prior studies, we choose *FirmNum*[10], the total number of listed firms in a firm's headquarter city, as an additional factor that affects the probability of the introduction of government's random accounting information quality inspections in the first stage but does not have a direct impact on listed companies' subsequent stock liquidity (See Fan, et al., 2025). In the second stage, we further run the OLS regression with multiple firms controls, the same as in the benchmark regression, and the inverse Mills ratio (*IMR*), which is estimated in the probit regression.

Table 5 columns (3)-(4) present the results of the Heckman two-stage regression. In the first stage, as shown in Column (3), there is a significant negative effect of *FirmNum* on the key independent variable, *DID*, as expected. In Column (4), the coefficient of *DID* (-39.832) remains

10 We gather data on the headquarters locations of listed companies from CSMAR and compute the total count of listed firms in a company's headquarters city (in units of thousands). The larger the number of listed companies located in a firm's headquarters city, the lower the likelihood that the listed company will fall under government accounting supervision, owing to the limited attention of government regulators. Moreover, it is improbable to correlate with omitted variables that affect subsequent stock liquidity, as there is no clear direct economic link indicated by theory.

significantly negative (t =-2.852), and the positive impact of GAS on stock liquidity becomes even more pronounced. In sum, using Heckman 2-stage method to alleviate selection bias issue reinforces our main conclusion.

Table 5 Results of parallel Trends Test and Endogeneity Tests

	Parallel Trends Test	PSM	Heckman 2-Stage method	
	(1)	(2)	(3)	(4)
	ILLIQ	*ILLIQ*	*DID*	*ILLIQ*
Pre_3	**-2.742**			
	(-0.809)			
Pre_2	**1.875**			
	(0.788)			
Pre_1	**0.959**			
	(0.356)			
Current / DID	**-37.356*** **	**-11.631*** **		**-39.832*** **
	(-5.304)	**(-4.540)**		**(-2.852)**
Post_1	**-57.876*** **			
	(-13.461)			
Post_2	**-36.516*** **			
	(-4.651)			
FirmNum			**-4.154*** **	
			(-8.584)	
IMR				11.392*
				(1.833)
Size	-23.496***	-23.535***	0.343***	-25.933***
	(-34.304)	(-34.036)	(7.153)	(-26.886)
Lev	35.411***	35.728***	-0.110	33.443***
	(15.842)	(15.857)	(-0.423)	(11.252)
CAPEX	-26.794***	-27.045***	-0.304	-36.612***
	(-5.170)	(-5.206)	(-0.316)	(-5.168)
Board	0.206	0.185	0.021	0.719**
	(0.904)	(0.815)	(0.814)	(2.420)
Growth	-1.531***	-1.601***	-0.132	-2.511***
	(-3.160)	(-3.252)	(-1.614)	(-3.858)
CF	-30.003***	-30.367***	-0.033	-33.883***
	(-9.288)	(-9.366)	(-0.052)	(-7.825)
Dual	1.145	1.236*	-0.065	0.735
	(1.577)	(1.701)	(-0.732)	(0.898)
_cons	423.832***	425.035***	-9.025***	472.616***
	(28.336)	(28.172)	(-8.249)	(22.368)
Year-FE	YES	YES	YES	YES
Firm-FE	YES	YES	YES	YES
N	29,418	29,362	19,429	19,371
R2	0.754	0.753	0.213	0.756

Note: Column (1) of Table 5 estimates the dynamic effects of the government's random accounting information quality inspection on annual stock liquidity in the treated and control groups at different periods around the government accounting supervision event. Pre_{it}^{-3}, Pre_{it}^{-2},Pre_{it}^{-1}, $Current_{it}^{0}$, $Post_{it}^{1}$ and $Post_{it}^{2}$ indicate the dummy variables, which equals one if the listed firms are included in the government's random accounting information quality inspection: three or more, two, one year prior to the policy year, the policy year, the next year and the next two years, respectively. Table 5 also presents the endogeneity tests based on propensity score matching in column (2) and the Heckman 2-Stage method in columns (3) and (4). *ILLIQ* denotes the stock illiquidity measure following Amihud (2002). A Lower value of *ILLIQ* indicates higher stock liquidity. The *DID* indicator takes the value one for the year in which a firm first becomes subject to government accounting supervision and for every year thereafter, and 0 otherwise.

4.4.3 Placebo Test

Since some unobserved factors may also impact the estimation results, a possible alternative explanation is that the observed improvement in stock liquidity among pilot firms may not be due to the actual policy effect of GAS, but may instead reflect omitted macro trends or other underlying confounding factors. To strengthen our causal inference, we further perform placebo tests to show the robustness of our findings to unobserved random noise. Specifically, we randomize the policy shocks and randomly select the placebo-treated listed firms.

We repeat the placebo procedure 500 iterations, generating an equivalent number of coefficient estimates for *DID*, which equals to 1 if listed firms are chosen randomly into pseudo-treatment groups and 0 otherwise. We expect weak or no results if we use a placebo-treatment group sample. Specifically, if our main findings are causal, we would expect the placebo treatment coefficients to follow a normal distribution centered around zero, in the absence of an actual policy effect. Figure 4 displays the distribution of the placebo *DID* obtained by randomizing the policy shocks. As indicated, the distribution density is close to a Gaussian distribution centered at zero, and most of placebo treatment coefficients are statistically insignificant in the absence of actual intervention. Overall, the placebo test strengthens the credibility of our main finding and provides further evidence that our results are not due to unobserved factors.

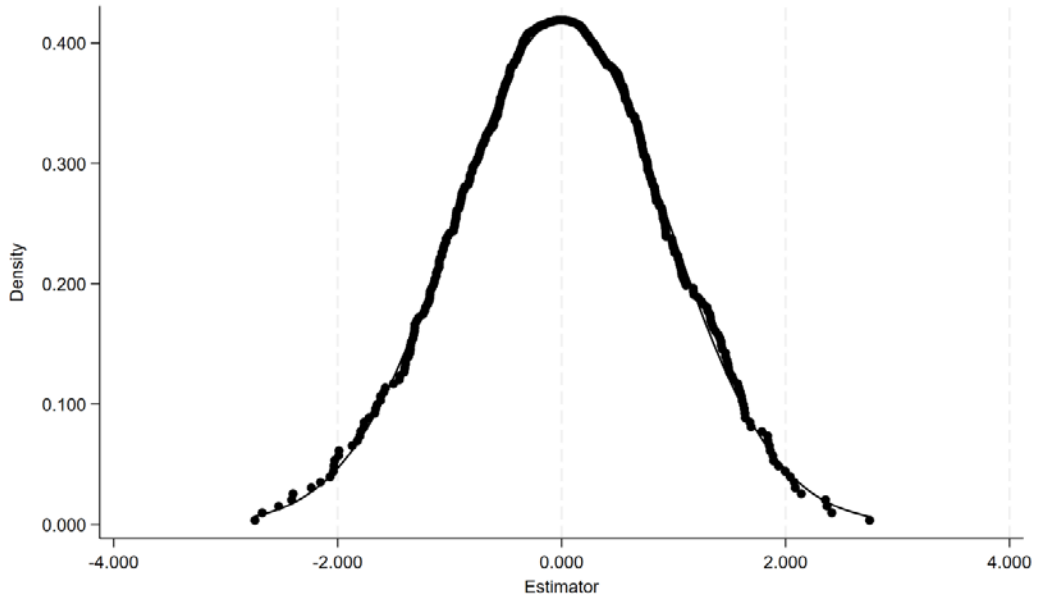


Figure 4 Placebo Test

Note: Figure 4 displays the distribution density of the placebo *DID* obtained by randomizing the policy shocks. The procedure of the placebo test is iterated five hundred times: in each iteration, firms are pseudo-randomly assigned to a pseudo-treatment groups (*DID*=1) or to the pseudo-untreated group (*DID*=0), and the corresponding regression coefficient is stored.

5. Mechanism Analysis

The prior analysis indicates that the positive impact of government's random accounting information quality inspection (GAS) on stock liquidity remains robust against potential

endogeneity problems. One unresolved question is how GAS alleviates stock illiquidity. In this section, we explore three possible channels through which the GAS affects stock liquidity: information asymmetry, agency costs, and investor optimism. We find evidence that all three channels work.

Table 6 Mechanism Analysis: Information Asymmetry Channel

	(1) *Quality*	(2) *ILLIQ*	(3) *ASY*	(4) *ILLIQ*
DID	**0.852****** **(6.953)**		**-0.059*** (-2.772)**	
$\widehat{Quality}$		**-10.187** (-2.447)**		
$\widehat{ASY}$				**196.112*** (4.531)**
Size	-0.612*** (25.575)	-17.977*** (-6.539)	-0.223*** (-35.208)	-31.409*** (-55.067)
Lev	-2.952*** (-22.212)	2.137 (0.167)	0.287*** (12.842)	48.244*** (19.355)
CAPEX	3.904*** (9.063)	17.024 (0.968)	-0.389*** (-6.801)	25.314*** (4.266)
Board	0.054*** (3.744)	1.041*** (2.985)	0.007*** (2.825)	1.584*** (6.088)
Growth	0.478*** (9.964)	2.870 (1.389)	-0.024*** (-4.853)	-2.984*** (-5.292)
CF	3.250*** (10.388)	5.915 (0.424)	-0.230*** (-6.452)	-21.749*** (-5.770)
Dual	0.005 (0.101)	1.213 (1.509)	0.022*** (2.610)	0.485 (0.588)
_cons	- -	437.515*** (23.039)	4.712*** (33.933)	579.265*** (45.030)
Year-FE	NO	YES	YES	YES
Firm-FE	NO	YES	YES	YES
N	21,913	21,658	29,418	29,418
R2	0.0782	0.768	0.702	0.639

Note: Table 6 explores one possible channel through which through which government accounting supervision (GAS) affects stock liquidity: the information asymmetry channel. Specifically, columns (1) and (2) report on how GAS improves stock illiquidity by enhancing information disclosure quality (*Quality*). *Quality* denotes the information disclosure quality rating evaluated by the Shanghai and Shenzhen Stock Exchanges. Rating grades are divided into four categories: A = Excellent, B = Good, C = Passing, D = Failing. Rating grades are divided into four categories: A = Excellent, B = Good, C = Passing and D = Failing. We then convert these categories into ordinal variables by assigning values of 3, 2, 1 and 0, respectively. A higher *Quality* value indicates greater reporting quality. Columns (3) and (4) report on how GAS improves stock illiquidity by reducing information asymmetry index (*ASY*). *ASY* denotes the asymmetric information index measure following Bharath et al. (2009), Abad et al. (2018) and Zhang & Sok (2025). Larger *ASY* scores denote a more pronounced degree of asymmetric information. *ILLIQ* denotes the stock illiquidity measure following Amihud (2002). A Lower value of *ILLIQ* indicates higher stock liquidity. The *DID* indicator takes the value one for the year in which a firm first becomes subject to government accounting supervision and for every year thereafter, and 0 otherwise.

To explore the three potential mechanisms through which government accounting supervision influences stock liquidity, we follow the previous research (Bertrand and Mullainathan, 2001; Di Giuli and Laux, 2022) by conducting a two-stage regression analysis to help mitigate potential endogeneity issues in the mechanism analysis.

Table 7 Mechanism Analysis: Agency Cost Channel

	(1) *AC1*	(2) *ILLIQ*	(3) *AC2*	(4) *ILLIQ*
DID	**-0.017****** **(-2.695)**		**-0.008**** **(-1.757)**	
$\widehat{AC1}$		**538.215****** **(3.160)**		
$\widehat{AC2}$				**1,100.456****** **(2.840)**
Optimism				
Size	-0.034**** (-6.163)	-5.776 (-0.988)	-0.028**** (-5.313)	7.478 (0.673)
Lev	0.037*** (1.844)	14.749**** (2.178)	0.040**** (2.131)	-8.943 (-0.573)
CAPEX	-0.004 (-0.195)	-30.210***** (-5.591)	-0.004 (-0.198)	-27.729***** (-4.981)
Board	0.002 (1.404)	-0.831**** (-2.206)	0.001 (0.993)	-1.082**** (-2.226)
Growth	-0.036***** (-10.840)	17.956***** (2.919)	-0.028***** (-11.676)	29.890***** (2.714)
CF	-0.127***** (-7.185)	37.769*** (1.730)	-0.109***** (-6.216)	89.592**** (2.110)
Dual	-0.003 (-0.523)	3.288***** (3.575)	-0.003 (-0.494)	4.305***** (3.472)
_cons	0.889***** (7.935)	-43.429 (-0.283)	0.703***** (6.471)	-341.094 (-1.243)
Year-FE	YES	YES	YES	YES
Firm-FE	YES	YES	YES	YES
N	27,319	27,319	27,671	27,671
R2	0.610	0.762	0.491	0.760

Note: Table 7 explores one possible channel through which through which government accounting supervision (GAS) affects stock liquidity: the agency cost channel. Specifically, we use two proxies for agency cost following the convention in corporate governance studies. Columns (1) and (2) report on how GAS improves stock illiquidity by reducing the operating expense ratio (*AC1*). Following Ang et al. (2000), *AC1* denotes the operating expense ratio, which is calculated by dividing operating expenses by sales revenue. A larger value of operating expense ratio indicates a higher agency cost. Columns (3) and (4) report on how GAS improves stock illiquidity by reducing administrative expense ratio (*AC2*). Following Singh and Davidson (2003), the administrative expense ratio is calculated as the ratio of firms selling, general, and administrative (SG&A) expenses divide by operating revenue. Similarly, a higher administrative expense ratio indicates higher agency costs. *ILLIQ* denotes the stock illiquidity measure following Amihud (2002). A Lower value of *ILLIQ* indicates higher stock liquidity. The *DID* indicator takes the value one for the year in which a firm first becomes subject to government accounting supervision and for every year thereafter, and 0 otherwise.

Specifically, we ran the following ordinary least squares (OLS) regressions using the mechanism variables as the dependent variable. This allowed us to obtain the predicted values of the mechanism variables, as shown in equation (4):

$$Mechanism_{i,t} = \alpha + \beta * DID + \gamma * X_{it} + \varphi_i + \mu_t + \varepsilon_{i,t} \quad (4)$$

where we employ all other explanatory variables in the baseline regression as controls.

In the second-stage estimation, we next perform a regression analysis between the dependent

variable, $ILLIQ_{it}$ and the predicted values of the mechanism variables, $\widehat{Mechanism}_{i,t}$. During this process, the regression coefficient between the predicted values of mechanism variables and the dependent variable, namely β in equation (5), will serve as an estimate of mechanism's causal effect on $ILLIQ_{it}$.

$$ILLIQ_{it} = \alpha + \beta * \widehat{Mechanism}_{i,t} + \gamma * X_{it} + \varphi_i + \mu_t + \varepsilon_{i,t} \quad (5)$$

5.1 Information Asymmetry

As information asymmetry is a key factor influencing stock liquidity, we first investigate the impact of GAS on the level of information asymmetry among listed firms-specifically, the information asymmetry channel (See Kyle, 1985; Glosten and Milgrom, 1985; Balakrishnan et al., 2014). If the introduction of government-random accounting supervision compels pilot listed companies to standardize their financial information disclosure practices, it is reasonable to anticipate an improvement in the quality of information disclosure, as well as a reduction in information asymmetry. The expected enhance in information disclosure and fall in information asymmetry would reflect improvements in stock liquidity. Thus, the expected enhanced information disclosure quality and reduced information asymmetry would reflect improvements in stock liquidity.

Specifically, the information disclosure quality (*Quality*) of listed firms is measured by their information disclosure rating evaluated by the Shanghai and Shenzhen Stock Exchanges[11], where a higher score indicates greater reporting quality. In columns (1), we examine the effect of GAS on listed firms' information disclosure quality[12]. The regression coefficients of *DID* is 0.852 (t statistic = 6.953), indicating economically meaningful effects. A one-standard-deviation increase in GAS leads to a 20.464% ($0.852 \times 0.153/0.637=20.464\%$) improvement in the standard deviation of *Quality*. In column (2), we regress *ILLIQ* on the predicted values of *Quality* ($\widehat{Quality}$)based on equation (4). Consistent with the literature, our result suggests that greater transparency in information disclosure is significantly associated with improved stock liquidity.

Drawing on earlier studies (see Bharath et al., 2009; Abad et al., 2018; Zhang and Sok, 2025), we next construct information asymmetry index (*ASY*) via PCA[13] to measure the degree of information asymmetry between uninformed traders and informed traders, which is calculated based on the daily trading data from from the CSMAR high-frequency archive. Higher *ASY* scores denote

11 Rating grades are divided into four categories: A = Excellent, B = Good, C = Passing, D = Failing. Rating grades are divided into four categories: A = Excellent, B = Good, C = Passing and D = Failing. We then convert these categories into ordinal variables by assigning values of 3, 2, 1 and 0, respectively.

12 As the dependent variable *Quality* is ordinal variables, we run an Order Logit regression and did not control for firm and year fixed effects due to the fact that including the fixed effects dummies in the Logit model can result in biased coefficient estimates and non-convergence of the regression, leading to parameter issues (see Bastos and Silva, 2012). We also employed OLS regression model including firm and year fixed effects as a robustness check. The unreported result shows similar finding.

13 Following the convention in the existing studies (Abad et al., 2018; Zhang and Sok, 2025), we selected three representative market microstructure metrics: liquidity ratio, price reversal indicator and illiquidity ratio, to capture the degree of information asymmetry between uninformed and informed traders regarding corporate value in stock market. We then constructed a comprehensive index of information asymmetry measures by retaining the first principal component (PCA).

a greater degree of information asymmetry. We then examine the effect of GAS on *ASY* using the same method. The regression results, presented in Table 6 column (3) where the key dependent variable is the *ASY*, show that the coefficient of *DID* is significantly negative, as expected. In columns (4), we further report the results of regressing *ILLIQ* on *ASY*, and demonstrate that the degree of information asymmetry is highly positively related to the stock illiquidity measure, suggesting that the introduction of GAS has indeed reduced information asymmetry by strengthening information disclosure quality and facilitating information transformation between uninformed traders and informed traders, subsequently improving stock liquidity. These results support Hypotheses 2.

In column (3) and (4) of Table 7 present the results of mechanism analysis using the administrative expense ratio as the proxy for the agency cost. The coefficient of *DID* is still significantly negative (-0.008), suggesting that the government's random accounting supervision significantly decreasing the managerial pay and perquisite consumption. Consistent with the previous results, columns (4) of Table 7 also show that the administrative expense ratio (AC2) is also positively associated with stock liquidity. Overall, these results further support Hypothesis 3, which states that the introduction of government accounting supervision reduce the agency cost and investment enthusiasm, thereby enhancing stock liquidity.

5.3 Investor Optimism Channel

Existing research suggests that higher investor sentiment generates greater noise trading, which in turn increases stock liquidity (Baker and Stein, 2004; Chiu and Chung, 2012). Optimistic investor sentiment will significantly improve stock liquidity, especially when market sentiment is generally pessimistic (Asem et al., 2016). As the government accounting supervision enhance the quality of information disclosure by pilot listed firms, thereby reducing market uncertainty and enabling investors to estimate firm intrinsic value more precisely. The resulting decline in information risk boosts investor confidence, leading to a more optimistic outlook and significantly increasing stock liquidity. To this end, we examine how firms with certain characteristics are more susceptible to changing lending dynamics. To this end, we consider the underlying investor sentiment mechanism by exploring how GAS improves stock illiquidity by boosting investor optimism.

As in previous studies (Jiang et al., 2022; Zhang et al., 2023), we use Guba's daily counts of posts and reads to construct our proxy for investor sentiment. Guba is a leading public internet stock discussion forum in China, where investors share and consume posts and replies specific to individual stocks. On Guba, individual investors share news, opinions and experiences via stock posts, which are the main type of content on the platform. Investors effectively disseminate news and investment insights about the broader market by engaging in activities such as posting, reading, and replying. We collect daily posts and reads data in Guba forum from Eastmoney[14].Each post is time-stamped for the first time and contains the author ID, title, body text, and number of reads. After removing duplicates, advertisements and stop words, the remaining text is tokenised using the

[14] See http://guba.eastmoney.com

Jieba parser and converted into TF-IDF vectors. Finally, a naïve Bayes classifier was trained using a manually labelled subset and was used to assign each post to one of three categories: optimistic, pessimistic, or neutral. The daily investor optimism (*Optimism*) is measured by taking the log of the number of optimistic posts clicked in an internet chat room, divided by the number of pessimistic posts. To derive the annual investor optimism, we calculate the average daily investor optimism values for individual stocks over each accounting year.

Table 8 Mechanism Analysis: Investor Optimism Channel

	(1) *Optimism*	(2) *ILLIQ*	(3) *OFI*	(4) *ILLIQ*
DID	**0.077***** **(5.420)**		**0.009***** **(4.267)**	
$\widehat{Optimism}$		**-151.218***** **(-4.531)**		
$\widehat{OFI}$				**-1,309.883***** **(-4.426)**
Size	0.028*** (7.664)	-19.226*** (-15.876)	0.007*** (11.449)	-14.166*** (-6.145)
Lev	-0.080*** (-6.151)	23.199*** (6.556)	0.003 (1.190)	38.711*** (16.420)
CAPEX	0.018 (0.604)	-24.383*** (-4.649)	0.007 (1.233)	-18.967*** (-3.304)
Board	0.000 (0.217)	0.235 (1.034)	-0.000 (-1.105)	-0.109 (-0.443)
Growth	0.033*** (11.449)	3.377*** (2.876)	0.005*** (7.286)	4.341*** (3.088)
CF	0.056*** (2.962)	-21.649*** (-5.770)	0.027*** (7.704)	4.631 (0.529)
Dual	0.006 (1.426)	2.125*** (2.857)	-0.000 (-0.212)	1.016 (1.385)
_cons	-0.371*** (-4.655)	366.955*** (18.027)	-0.204*** (-14.866)	158.858** (2.497)
Year-FE	YES	YES	YES	YES
Firm-FE	YES	YES	YES	YES
N	29,258	29,418	29,091	29,091
R2	0.610	0.754	0.579	0.752

Note: Table 8 explores one possible channel through which through which government accounting supervision (GAS) affects stock liquidity: the investor optimism channel. Columns (1) and (2) report on how GAS improves stock illiquidity by enhancing investor optimism (*Optimism*). *Optimism* denotes investor optimism proxy, which is measured by taking the average of the log of the number of optimistic posts clicked in an internet chat room, divided by the number of pessimistic posts. Columns (3) and (4) report on how GAS improves stock illiquidity by promoting the order flow imbalance of investors (*OFI*). Following Cont et al. (2014), we use order flow imbalance (OFI) as an additional proxy of investor optimism. We compute *OFI* in the following two steps: In the first step, each transaction is classified as either buyer-initiated (inflow) orders or seller-initiated (outflow) orders according to the Lee and Ready (1991) algorithm (Lee and Ready, 1991). Next, we calculate the daily net order flow as the difference between inflow and outflow, scaled by their sum: *OFI* = (*Inflow* −*Outflow*) / (*Inflow*+*Outflow*), where *Inflow* and *Outflow* are the daily buy-initiated and sell-initiated orders for each stock during each window period, respectively. The daily inflow and outflow are reported by the exchanges and collected by the CSMAR database. We collect the daily transaction data from the CSMAR database for each stock from 2003 to 2022. *ILLIQ* denotes the stock illiquidity measure following Amihud (2002). A Lower value of *ILLIQ* indicates higher stock liquidity. The *DID* indicator takes the value one for the year in which a firm first becomes subject to government accounting supervision and for every year thereafter, and 0 otherwise.

The regression result, detailed in column (1) and (2) of Table 8, investigates how GAS improves stock illiquidity by enhancing investor optimism. The coefficient of *DID* in Column (5) is 0.077, which is statistically significant at the 1% level, suggesting that the introduction of GAS effectively boost investor optimism. The regression results also reflect economically meaningful effects. A one-standard-deviation increase in *DID* leads to a 5.43% increase in the standard deviation of investor optimism. In column (6), we further regress *ILLIQ* on investor optimism (*Optimism*) controlling for all the other variables in the baseline model. As indicated, investor *ILLIQ* is significantly and negatively associated with investor optimism, which is consistent with previous findings (Baker and Stein, 2004; Chiu and Chung, 2012; Asem et al., 2016). This underscores an important channel through which GAS appears to promote stock liquidity is by improving investor optimism.

In column (3) and (4) of table 8, we examine how GAS improves stock illiquidity by promoting the order flow imbalance of investors (*OFI*). As *OFI* serves as a critical metric for understanding investor sentiment in high-frequency. It captures the net difference between buy and sell orders, offering insights into market pressure and enabling the anticipation of future price fluctuations. Following Cont et al. (2014), we use order flow imbalance (*OFI*) as an additional proxy of investor optimism. According to the Lee and Ready (1991) algorithm (Lee and Ready, 1991), daily net order flow as the difference between inflow and outflow, scaled by their sum[15]. We take the annual average of the daily *OFI* values and then match them with our sample. The regression coefficients for *DID* in column (3) (0.009) is still positive and statistically significant at 1% level, indicating that GAS is more likely to improve order flow imbalance. As shown in column (4), the coefficients of the $\widehat{OFI}$ obtained in the first-stage regression still have their expected signs and are significantly negative. These results further support Hypothesis 4.

Taken together, there is evidence that the potential effect of GAS on stock liquidity can, in part, work through three potential economic mechanisms: the information asymmetry channel, the agency cost channel and the investor optimism channel. Our findings show that GAS significantly reduces information asymmetry, alleviating agency costs within listed firms and boosting investor optimism, which in turn enhances stock liquidity.

6. Further Research

6.1 Heterogeneity Analysis

[15] We compute *OFI* in the following two steps: In the first step, each transaction is classified as either buyer-initiated (inflow) orders or seller-initiated (outflow) orders according to the Lee and Ready (1991) algorithm (Lee and Ready, 1991). Next, we calculate the daily net order flow as the difference between inflow and outflow, scaled by their sum: $OFI = (Inflow - Outflow) / (Inflow + Outflow)$, where *Inflow* and *Outflow* are the daily buy-initiated and sell-initiated orders for each stock during each window period, respectively. A transaction is designated as buy-initiated if it is executed at the selling price, which is above the quote midpoint and designated as sell- initiated if it is executed at buying price, which is below the quote mid- point. If a transaction is executed at the quote midpoint, similar to Liu et, al (2020), the exchanges apply the tick rule: it is buy-initiated if the transaction price is above or equal to the last executed transaction price, otherwise it is sell-initiated. The daily inflow and outflow are reported by the exchanges and collected by the WIND database. We collect the daily transaction data from the WIND database for each stock from 2003 to 2022, since the earliest transaction data in the WIND database dates back to 2003.

We next conduct a threefold heterogeneity analysis to examine how the treatment effect of government accounting supervision (GAS) on stock liquidity is moderated by several factors. First, we examine how ownership concentration moderates the positive impact of GAS on stock liquidity, focusing on the firm-level perspective. Next, we examine the moderating effect of industry competition, as exerted by a pilot firm's external market environment, on stock liquidity, adopting an industry-level perspective. Finally, we test the moderating effect of investor attention at the market-level perspective. These analyses of heterogeneity strengthen the external validity of our main findings and help to clarify the boundary conditions of the policy's effect.

Table 9 Heterogeneity Analysis

	(1) *High Ownership ILLIQ*	(2) *Low Ownership ILLIQ*	(3) *High HHI ILLIQ*	(4) *Low HHI ILLIQ*	(5) *High SVI ILLIQ*	(6) *Low SVI ILLIQ*
DID	**-16.637*** **	**-6.928** **	**-8.031** **	**-14.783*** **	**-7.797**	**-11.266*** **
	(-3.704)	**(-2.241)**	**(-2.077)**	**(-4.158)**	**(-1.612)**	**(-3.389)**
Size	-24.872***	-24.460***	-22.813***	-24.179***	-30.311***	-16.991***
	(-22.563)	(-27.433)	(-24.937)	(-23.787)	(-23.047)	(-24.033)
Lev	41.382***	36.569***	38.858***	33.997***	33.188***	28.029***
	(11.356)	(13.005)	(12.932)	(10.388)	(7.950)	(13.234)
CAPEX	-13.253*	-42.503***	-26.131***	-27.385***	-64.879***	-9.187**
	(-1.802)	(-5.878)	(-3.693)	(-3.690)	(-5.991)	(-1.995)
Board	0.199	0.367	0.543*	-0.333	0.969**	-0.044
	(0.557)	(1.375)	(1.759)	(-1.020)	(2.350)	(-0.202)
Growth	-1.937***	-2.013***	-1.526**	-1.612**	-3.512***	-1.298**
	(-2.702)	(-3.006)	(-2.307)	(-2.162)	(-3.726)	(-2.535)
CF	-35.326***	-21.697***	-31.724***	-30.246***	-43.958***	-18.670***
	(-7.698)	(-5.040)	(-7.192)	(-6.513)	(-7.170)	(-6.166)
Dual	1.426	0.746	0.822	0.999	0.617	0.877
	(1.226)	(0.828)	(0.823)	(0.965)	(0.535)	(1.188)
_cons	456.438***	439.653***	404.231***	444.974***	565.820***	293.590***
	(18.853)	(22.726)	(20.085)	(20.202)	(19.164)	(19.193)
Year-FE	YES	YES	YES	YES	YES	YES
Firm-FE	YES	YES	YES	YES	YES	YES
N	14,143	14,613	14,580	14,139	11,576	17,107
R2	0.783	0.787	0.778	0.772	0.758	0.780
Empirical *p-value*	**0.010** **		**0.090***		**0.030** **	

Note: Table 9 displays the results of heterogeneity analysis examining how government accounting supervision (GAS) varies with the listed firm. Columns (1)- (2) present estimation results of subsample regression by using high and low ownership concentration groups. Columns (3) - (4) present the estimation results of the heterogeneity test by using high and low analyst coverage subsamples. Columns (5) -(6) present the estimation results of the heterogeneity test based on high and low stock price synchronicity subsamples. *ILLIQ* denotes the stock illiquidity measure following Amihud (2002). A Lower value of *ILLIQ* indicates higher stock liquidity. The *DID* indicator takes the value one for the year in which a firm first becomes subject to government accounting supervision and for every year thereafter, and 0 otherwise. The coefficients of *DID* estimate the treatment effect between firms which are exposed to government accounting supervision and other firms without government accounting supervision.

6.1.1 Firm-Level Heterogeneity Analysis: Ownership Concentration

As our previous results show, GAS significantly enhances stock liquidity by reducing information asymmetry, alleviating agency cost and booting investor optimism. As the largest emerging market and the second-largest stock market in the world, one of the main distinctive features of listed firms in China is the high equity concentration compared with other developed countries. Prior literature suggests that ownership concentration, a key factor for ownership structure, not only directly affects the information asymmetry and the efficiency of corporate governance (e.g., Omran et al., 2008; Hu and Izumida,2008), but also has a significant impact on stock liquidity (See Rubin,2007; Staglianò et al., 2018). In general, firms with high ownership concentration tend to be associated with governance issues and poor information transparency, as decision-making power is concentrated in the hands of a few major shareholders (Lemmon and Lins, 2003). In contrast, dispersed ownership is more likely to result in market-oriented decision-making. This effectively reduces information asymmetry issues among listed companies and curbs corporate governance problems within enterprises.

Since GAS significantly mitigates internal corporate governance issues (e.g., Pan et al., 2023) and strengthen external monitor monitoring mechanism, especially reducing agency costs, we posit that the positive effect of GAS on stock liquidity will be more pronounced for listed firms with high ownership concentration. These firms are more likely to be associated with weaker internal controls and financial transparency, thereby leading to high information asymmetry and agency costs.

To explore how the treatment effect of GAS is moderated by ownership concentration, we use the fraction of outstanding equity controlled by the top shareholder as the measure for ownership concentration. Column (1) and (2) of Table 9 shows that GAS has a more pronounced effect on enhancing stock liquidity in firms with high ownership concentration, and passes the between-group coefficient difference test at the 1% significance level. The results of subsample regression highlight how ownership concentration influences the impact of GAS and support our framework. As an effective external governance mechanism, GAS effectively addresses deficiencies in corporate governance structures. By regulating firms' accounting and information disclosure practices, and standardizing management governance norms, GAS significantly enhances financial transparency and inhibits opportunistic behaviors, thereby improving stock liquidity.

6.1.2 Industry-Level Heterogeneity Analysis: Industry Concentration

Recent evidence suggests that the intensity of competition has significant implications for corporate governance and market efficiency. Specifically, higher industry competition, as measured by the Herfindahl–Hirschman Index (*HHI*), reduces information asymmetry and effectively curbs agency problems (Giroud and Mueller, 2011; Valta, 2012). By comparison, absent competitive pressure from the product market, weak governance gives rise to agency costs. This indicates that industry competition can partially substitute for corporate governance mechanisms.

Following prior literature, we use the Herfindahl–Hirschman Index (*HHI*) to measure industry concentration and divide the full sample into high- and low-industry competition groups for a

heterogeneity analysis. We hypothesize that the positive impact of the government's random accounting information quality inspections on stock liquidity is more pronounced for pilot firms operating in a low-competitive environment. Columns (3) and (4) report the results of the subsample regressions, showing that GAS has a more significant effect on improving stock liquidity for firms in the low industry competition group. Cross-group coefficient difference tests show that the coefficients differ significantly between high- and low-industry competition subsamples (empirical p-value = 0.090), suggesting that GAS has a more pronounced impact on pilot firms in low-industry competition.

In line with previous findings, our results suggest that the government's random accounting supervision can also serve as a partial substitute for corporate governance mechanisms, particularly when industry competition is weak. As with listed companies in other emerging markets, China's listed companies often face issues of insufficient industry competition and inadequate industry regulation. Our findings provide potential insights for other developing countries, showing how government accounting oversight can address shortcomings in industry regulation and internal governance.

6.1.3 Market-Level Heterogeneity Analysis: Investor Attention

Extensive literature argued that investor attention is gradually playing a more crucial role in the information acquisition and decision-making process, thereby higher investor attention help reduce information asymmetry and improve investor confidence (Barber and Odean, 2008; Chen and Wu, 2022). Our main argument is that GAS significantly enhances stock liquidity by reducing information asymmetry and alleviating agency costs within listed firms, thereby boosting investor optimism. If our argument is reasonable, we would expect the effect of random government inspections on stock liquidity to be weaker for pilot firms that attract less investor attention. We next examine the heterogeneity of investor attention to the policy impact.

To test the investor attention's governance role, we collect the daily Internet Search Volume Index (*SVI*) of Chinese listed companies from CNRDS database[16]. The SVI index (*SVI*) uses keywords such as stock codes, company abbreviations and full company names to aggregate search values. Next, we calculate average of daily SVI index for each fiscal year and divide our sample into high and low investor attention groups by the median value of *SVI*, a proxy for investor attention (Chi, et al., 2017; Gao et al., 2020). We then run a subsample regression.

As shown in Column (5) and (6) of Table 9, While the *DID* coefficient remains negative and significant in both subsamples, its magnitude is much lower for firms with high investor attention group (the p value of between-group coefficient difference test is 0.030), indicating that the impact of GAS is more pronounced for firms with low investor attention. Lower investor attention is often associated with greater information risk, as well as a decrease in investor conviction and confidence.

[16] The Web Search Volume Index (WSVI) of Chinese listed companies combines various web search indices and integrates news sentiment in order to capture public opinion and the intensity of corporate searches. As a key barometer of investor attention and its dynamics, the database has recorded daily search volumes for all A-share firms since 2011 using stock codes, short names and full corporate names as keywords.

Our findings suggest that, as an external governance mechanism, GAS can effectively address issues of information asymmetry arising from low investor attention. It can also boost investor optimism by mandating financial disclosure practices and strengthening financial transparency, thereby promoting stock liquidity.

Overall, the results of the heterogeneity analysis in Table 9 suggest that the treatment effect of GAS is more significant for pilot firms operating in an environment with weaker pre-existing oversight, namely low ownership concentration, low industry competition, and low investor attention, as the marginal eeffects of the government's random accounting inspections in boosting stock liquidity is stronger in such environments.

6.2 Spillover effects of GAS

Table 10 Industry Spillover Effects and Regional Spillover Effects

	(1) *ILLIQ*	(2) *ILLIQ*
Spillover_Industry	**-5.996***	
	(-1.910)	
Spillover_Region		**-15.259****
		(-2.212)
Size	-23.536***	-23.553***
	(-34.247)	(-34.303)
Lev	35.480***	35.557***
	(15.859)	(15.907)
CAPEX	-27.074***	-27.044***
	(-5.221)	(-5.210)
Board	0.210	0.211
	(0.923)	(0.926)
Growth	-1.505***	-1.499***
	(-3.101)	(-3.085)
CF	-29.711***	-29.979***
	(-9.181)	(-9.254)
Dual	1.164	1.171
	(1.600)	(1.613)
_cons	424.947***	425.848***
	(28.334)	(28.408)
Year-FE	YES	YES
Firm-FE	YES	YES
N	29,418	29,418
R2	0.753	0.753

Note: Table 10 presents the test for the industry spillover effects and regional spillover effects of government accounting supervision (GAS) policy. Columns (1) reports the results of industry-level spillover effects. Following Seo (2021) and Jiang et al. (2025), we construct a proxy *Spillover_Industry* to measure intra-industry spillovers. Specifically, *Spillover_Industry* denotes the proportion of focal firms (excluding firm *i*) within the same industry and year that were subject to the government's randomized accounting inspections. Columns 2 report the results of the tests for intra-regional spillovers. Similarly, we construct a measure *Spillover_Region* to capture intra-regina1 spillovers. *Spillover_Region* denotes the proportion of focal firms (excluding firm *i*) within the same province or municipality directly under the central government (e.g. Beijing, Shanghai, Chongqing and Tianjin) and year that were subject to the government's randomized accounting inspections. *ILLIQ* denotes the stock illiquidity measure following Amihud (2002). A Lower value of *ILLIQ* indicates higher stock liquidity. The *DID* indicator takes the value one for the year in which a firm first becomes subject to government accounting supervision and for every year thereafter, and 0 otherwise.

The preceding results show the positive effect of government's randomized accounting supervision (GAS) in boosting stock liquidity, primarily by reducing information asymmetry, offsetting agency costs and improving investor optimism. If the policy does indeed enhance the stock liquidity of pilot firms, then even listed firms that are not directly inspected in a given year may be deterred from improving the quality of their internal governance, given that regulatory policies may exhibit positive externalities (Jiang et al., 2025). To further explore whether the government's randomized accounting supervision (GAS) exhibits positive externalities, we next examine the industry-level spillover effects and regional-level spillover effects. Following Seo (2021) and Jiang et al. (2025), we construct two proxies to measure intra-industry spillovers and intra-reginal spillovers, respectively, which denotes the proportion of focal firms (excluding firm *i*) within the same industry/region and year that were subject to the government's randomized accounting inspections. As shown in Equation (6):

$$Spillover_{it} = \frac{TreatNum_{it-DID_{it}}}{FirmNum_{jt}-1} \quad (6)$$

where $TreatNum_{it}$ denotes the total number of firms in industry / region j in year t; $FirmNum_{jt}$ denotes the total number of listed firms in / region j that were inspected by GAS in year t; DID_{it} equals 1 if firm i was subject to GAS and for every year thereafter, and 0 otherwise.

We next regress *ILLIQ* on spillover measures and regression results are reported in Table 10. As shown in column (1) and (2) in Table 10, the coefficients on *Spillover_Industry* and *Spillover_Region* are statistically negative, exhibiting the positive industry-level spillover effects and regional-level spillover effects. Importantly, we find that the stock liquidity of non-inspected firms in the same industry or region also tends to increase, indicating the deterrent effect of random supervision policy. In other words, GAS not only directly shapes the stock liquidity of pilot firms, but also affects the stock liquidity of non-inspected firms indirectly through industry or regional networks. These findings enable us to examine the policy impact comprehensively and conduct accurate policy evaluations. Additionally, authorities may pay more attention to the positive spillover effect in order to strike a better balance between supervisory effectiveness and limited regulatory resources.

6.3 Robustness checks

6.3.1 Alternative Stock Liquidity Measure

As a robustness check, we first employ the turnover rate (*Turnover*) and Zeros index (*Zeros_Y*) as our alternative measures, and then use these alternative measures to re-estimate our baseline model. Following the existing studies (Lesmond et al.,1999; Chordia et al. 2002; Barinov, 2014), we use the annual stock turnover rate as the first alternative proxy for stock liquidity.

The results are shown in column (1) in Table 11, the coefficients on the key independent variable, *DID*, are significantly positive, suggesting that the GAS has a significant positive impact on enhancing stock liquidity. Secondly, following Lesmond et al. (1999), we change our dependent variable and use *Zeros_Y*. A zero yield is regarded as evidence that transaction costs exceed trading benefits, and thereby *Zeros_Y* is one measure of illiquidity. The results in column (2) of Table 11

suggest that the estimated coefficients on *DID* are -10.286, significant at the 1% level.

Table 11 Robustness Tests

	(1) *Turnover*	(2) *Zeros_Y*	(3) *ILLIQ*	(4) *ILLIQ*	(5) *ILLIQ*	(6) *ILLIQ*
DID	58.521***	-0.005***		-11.614***	-9.169***	-9.184***
	(4.110)	(-3.003)		(-3.807)	(-3.893)	(-3.856)
DID2			-10.286***			
			(-3.892)			
Size	-31.559***	-0.003***	-23.459***	-23.439***	-23.337***	-23.467***
	(-8.621)	(-6.984)	(-34.148)	(-16.707)	(-34.995)	(-35.160)
Lev	-15.971	0.014***	35.360***	35.344***	34.770***	35.469***
	(-1.190)	(8.989)	(15.818)	(9.078)	(15.990)	(16.405)
Capex	165.851***	-0.036***	-27.145***	-27.061***	-23.310***	-23.005***
	(4.481)	(-10.129)	(-5.237)	(-3.181)	(-4.514)	(-4.374)
Board	-1.492	-0.000	0.196	0.192	0.021	-0.035
	(-1.040)	(-1.081)	(0.861)	(0.891)	(0.097)	(-0.163)
Growth	14.484***	-0.003***	-1.563***	-1.570*	-0.441	-0.371
	(3.928)	(-8.239)	(-3.223)	(-1.846)	(-0.891)	(-0.752)
Cf	61.705***	-0.009***	-30.007***	-30.082***	-26.494***	-26.320***
	(2.651)	(-3.809)	(-9.264)	(-5.882)	(-8.209)	(-8.189)
Dual	4.342	-0.000	1.196*	1.202	0.903	0.821
	(0.931)	(-0.793)	(1.648)	(1.614)	(1.365)	(1.244)
_cons	1,147.244***	0.092***	423.353***	422.983***	421.624***	424.658***
	(14.511)	(10.181)	(28.237)	(13.882)	(28.841)	(28.966)
Year-FE	YES	YES	YES	YES	YES	YES
Firm-FE	YES	YES	YES	YES	YES	YES
Industry × Year FE	NO	NO	NO	NO	YES	YES
Province × Year FE	NO	NO	NO	NO	NO	YES
Industry-Firm Two-way Cluster	NO	NO	NO	Yes	NO	NO
N	29,418	29,418	29,418	29,418	28,624	28,575
R2	0.470	0.544	0.754	0.754	0.801	0.808

Note: Table 11 displays the results of multiple robustness checks examining how government accounting supervision (GAS) affects annual stock liquidity. Columns (1)-(2) demonstrate that our baseline results remain unchanged when alternative stock liquidity proxies are substituted for the benchmark measure. *Turnover* denotes the annual stock turnover rate, calculated as the sum of daily turnover rates. *Zeros_Y* denotes another illiquidity measure, which is calculated as the number of days with zero returns during the year, divided by the total number of trading days in that year. Columns (3) report the robustness tests of the measure for the independent variable. *DID2* is the alternative measure for the *DID* indicator, which takes the value one in the year following the incorporation of government accounting supervision and in all subsequent years, and equals 0 otherwise. In Column (4), we re-estimate the benchmark model with standard errors clustered at both the industry and firm level. Columns (5) and (6) present the results for robustness tests with multidimensional fixed effects. We add Industry × Year fixed effects in Column (5), and include both Industry × Year and Province × Year fixed effects in Column (6). *ILLIQ* denotes the stock illiquidity measure following Amihud (2002). A Lower value of *ILLIQ* indicates higher stock liquidity. The *DID* indicator takes the value one for the year in which a firm first becomes subject to government accounting supervision and for every year thereafter, and 0 otherwise.

6.3.2 Alternative Measure for DID Dummy

In the preceding analysis, we measure *DID* as a dummy which equals to 1 in the year of incorporation of GAS and all subsequent years, and 0 otherwise. However, if a listed firm is introduced in the government's random accounting information quality inspection in December, then the pilot firm is impacted since the following year. To better capture the temporal effects of

GAS, we redefine the key independent variable (*DID2*), which equals 1 in the year following the incorporation of GAS and in all subsequent years, and equals 0 otherwise. We re-estimate our baseline regression by replacing the independent variable in *DID2*, and the result is presented in Table 11 Column (3). The coefficient on *DID2* is still significantly negative.

6.3.3 Two-Way Cluster

Given that our baseline regression model only clusters robust standard errors at the firm level, it may overlook error correlations at broader levels. To adjust for the possible error correlations, we implement two-way clustering at both the industry and firm level level. As shown in Column (4) of Table 11, the coefficient of *DID* remains significantly negative, and the magnitude of the coefficient is almost unchanged. We can conclude that clustering methods do not affect the robustness of our main findings.

6.3.4 Multidimensional Fixed Effects

Although our benchmark specification has already controlled for several firm-level attributes as well as firm- and year-fixed effects, it is still possible that the estimation of the *DID* coefficient in the regression could be biased due to omitted common industry or location-specific factors. To mitigate the potential omitted variable bias, we also incorporate traditional multidimensional fixed effects into our benchmark regression. Specifically, we add Industry × Year fixed effects in Column (5), and include both Industry × Year and Province × Year fixed effects in Column (6). Columns (5)-(6) of Table 11 show that GAS still has a significantly positive influence even after controlling for multidimensional fixed effects, suggesting that omitted variable bias poses only a negligible threat to our specification.

7. Conclusion

This paper examines the impact of GAS on stock liquidity. Leveraging the staggered introduction of the government's random accounting information quality inspection as an exogenous shock, we find that GAS significantly enhances stock liquidity, primarily through three potential mechanisms: reducing information asymmetry, offsetting agency costs and improving investor optimism. Furthermore, the positive effect is more pronounced in firms with low ownership concentration, weak industry competition, and low investor attention. Importantly, we find that the impact of GAS extends positive externalities, exhibiting the positive industry-level spillover effects and regional-level spillover effects. Overall, there is clear evidence that GAS significantly increases stock liquidity, highlighting the positive impact of government regulation and monitoring on market efficiency in a representative emerging market such as China.

This paper adds to the body of literature on GAS and market efficiency by offering a fresh angle on the economic implications of GAS. Prior research has examined the governance function of GAS and its impacts on corporate ethical behavior, investment choices, and governance practices. Yet, the role of GAS in market efficiency remains far less understood. Our study seeks to address this gap by evaluating the potential impact of GAS on stock liquidity. Moreover, our paper explores how the government's random accounting information quality inspection promotes market

efficiency, notably in stock liquidity, by reducing information asymmetry, inhibiting agency costs and boosting investor confidence. This broadens our understanding of the important role of government regulation in maintaining market efficiency, and contributes to the broader debate on regulatory design.

Importantly, our results have several potential practical and policy implications. The improvement in stock liquidity following the GAS strongly suggests the crucial role of direct government regulation in market efficiency, especially in emerging markets where internal monitoring and governance in listed firms are comparatively weak, as opposed to indirect government regulation. Additionally, it strikes a balance between the prominent contradiction of limited regulatory resources and regulatory effectiveness. Consequently, the government, especially in emerging markets, may strengthen direct accounting supervision by conducting random inspections and publicly announcing the results, as well as implementing regulatory reforms that facilitate positive externalities and guide targeted policy and supervisory measures. Our findings also indicate that GAS mechanisms may serve as a partial substitute for corporate governance mechanisms, particularly when internal governance and industry monitoring systems are inadequate. Meanwhile, regulators may consider issuing directives to guide the implementation of the accounting information quality inspection pilot program, with the aim of improving market efficiency and protecting investor interests more accurately, which is vital for future regulatory reforms aimed at enhancing information transparency and stock liquidity.

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Appendix A

Table A1 Industry Distribution of Samples with Treat = 1

Industry Name	Share	Industry Name	Share
Pharmaceutical Manufacturing	5.49%	Synthetic Materials Manufacturing	0.32%
Real Estate Industry	5.28%	Petroleum Products Industry	0.32%
Automobile Manufacturing	4.56%	Water Production and Supply	0.29%
Computer, Communication & Other Electronic Equipment Manufacturing	3.65%	Television Industry	0.29%
Retail Industry	3.49%	Specialty Chemical Products Manufacturing	0.29%
Chemical Raw Materials & Products Manufacturing	3.28%	Electronic Components Manufacturing	0.29%
Real Estate Development & Operation	3.09%	Pulp Manufacturing	0.29%
Non-ferrous Metal Smelting & Rolling Processing	2.85%	Other Transportation Industries	0.29%
Coal Mining & Washing	2.56%	Cement Manufacturing	0.29%
Electric Power & Thermal Production and Supply	2.45%	Electrical Machinery Manufacturing	0.29%
Electrical Machinery & Equipment Manufacturing	2.26%	Household Electronic Appliances Manufacturing	0.27%
Road Transportation	2.13%	Business Services	0.27%
Ferrous Metal Smelting & Rolling Processing	2.10%	Urban Public Transport	0.27%
Rubber & Plastic Products	1.92%	Poultry Farming	0.27%
Non-metallic Mineral Products	1.73%	Other Communication & Cultural Services	0.27%
Wholesale Industry	1.71%	Rare & Rare-earth Metal Smelting	0.27%
Software & Information Technology Services	1.71%	Agricultural & Sideline Food Processing	0.27%
Civil Engineering & Construction	1.68%	Paper & Paper Products Manufacturing	0.27%
Electric Power Production	1.57%	Telecommunication Services	0.27%
Specialized Equipment Manufacturing	1.52%	Basic Chemical Raw Materials Manufacturing	0.27%
General Merchandise Retail	1.49%	Medical Equipment Manufacturing	0.27%
Pharmaceutical Preparations Manufacturing	1.47%	Railway, Highway, Tunnel & Bridge Construction	0.27%
Coal Mining	1.47%	Food, Beverage & Tobacco Wholesale	0.24%
Comprehensive Industry	1.44%	Non-ferrous Metal Rolling Processing	0.24%
Steelmaking	1.20%	Printing & Reproduction of Recorded Media	0.24%
Telecom, Broadcasting & Satellite Transmission Services	1.17%	Coal Washing	0.24%
News & Publishing	0.93%	Gas Production & Supply	0.21%
Highway Management & Maintenance	0.88%	Health Services	0.21%

Glass & Glass Products	0.80%	Lighting Equipment Manufacturing	0.21%
Other Specialized Equipment Manufacturing	0.80%	Biopharmaceutical Manufacturing	0.21%
Food Manufacturing	0.77%	Other Electronic Equipment Manufacturing	0.21%
Computer Software Development & Consulting	0.75%	Chemical Fiber Manufacturing	0.21%
Light Non-ferrous Metal Smelting	0.72%	Precious Metal Smelting	0.21%
Daily Chemical Products Manufacturing	0.72%	Chemical Fertilizer Manufacturing	0.21%
Alcohol, Beverage & Refined Tea Manufacturing	0.72%	Primary Processing of Fiber Raw Materials	0.21%
Public Facility Management	0.72%	Crop Farming	0.21%
Communication Equipment Manufacturing	0.69%	Livestock Farming & Grazing	0.21%
Petroleum Processing, Coking & Nuclear Fuel Processing	0.69%	Textile & Apparel Industry	0.21%
Instruments & Meters Manufacturing	0.69%	Professional Technical Services	0.19%
Commercial Brokerage & Agency	0.64%	Pharmaceutical & Medical Equipment Wholesale	0.19%
Other Manufacturing	0.64%	Water Transportation	0.19%
Public Utility Services	0.61%	Ferrous Metal Mining	0.19%
Railway Transportation	0.61%	Computer Network Development, Maintenance & Consulting	0.16%
Non-ferrous Metal Mining	0.61%	Air Passenger & Cargo Transportation	0.16%
Pharmaceutical Raw Materials Manufacturing	0.61%	Textile, Apparel, Footwear & Hat Wholesale	0.16%
Housing Construction	0.59%	Transportation Equipment Manufacturing	0.16%
Aviation Transportation	0.56%	Precious Metal Mining	0.16%
General Equipment Manufacturing	0.56%	Radar Manufacturing	0.16%
Internet & Related Services	0.56%	Fishery	0.13%
Comprehensive	0.53%	Casting Manufacturing	0.13%
Animal Husbandry	0.53%	Grain & Feed Processing	0.13%
Chemical Pesticide Manufacturing	0.53%	Broadcasting, Film, Television & Recording Production	0.13%
Heavy Non-ferrous Metal Smelting	0.53%	Other Retail Industries	0.11%
Traditional Chinese Medicine Processing	0.53%	Cement & Asbestos Cement Products Manufacturing	0.11%
Electricity, Steam & Hot Water Production and Supply	0.48%	Papermaking Industry	0.11%
Tire Manufacturing	0.48%	Plastic Sheets, Pipes & Rods Manufacturing	0.08%
Power Transmission & Control Equipment Manufacturing	0.48%	Specialized Instruments & Meters Manufacturing	0.08%
Tourism Industry	0.48%	Books, Newspapers, Magazines & Data Publishing	0.08%
Agriculture	0.45%	Other Food Manufacturing	0.05%

Alcohol & Beverage Manufacturing	0.45%	Heavy Non-ferrous Metal Mining	0.05%
Ecological Protection & Environmental Governance	0.40%	Other Bioproducts Manufacturing	0.05%
Textile Industry	0.37%	Printing Industry	0.05%
Forestry	0.35%	Other Plastic Manufacturing	0.05%
Furniture Manufacturing	0.35%	Other Computer Application Services	0.05%
Electronic Device Manufacturing	0.35%	Bioproducts Industry	0.03%
Steel Rolling Processing	0.35%	Motorcycle Manufacturing	0.03%
Airport & Aviation Transport Support	0.32%	Communication Services	0.03%

Note: Table A2 shows the distribution of inspected firms across industries in China's A share stock market. A total of 134 different industries, including the pharmaceutical manufacturing industry, the real estate industry, the automobile manufacturing industry and so on. The broad industry coverage suggests that government accounting supervision is not limited to specific fields, but instead spans multiple sectors, reflecting its universality.

Table A2 City Distribution of Samples with Treat = 1

City	Share	City	Share
Shenzhen	8.47%	Jiaozuo	0.51%
Shanghai	5.84%	Yongcheng	0.51%
Beijing	5.44%	Xingtai	0.51%
Nanjing	4.08%	Guilin	0.51%
Xiamen	2.72%	Lingyuan	0.51%
Dalian	2.42%	Yangquan	0.51%
Taiyuan	2.24%	Guixi	0.51%
Tianjin	2.21%	Tongling	0.51%
Guangzhou	2.13%	Zibo	0.51%
Hefei	2.13%	Yuncheng	0.48%
Haikou	2.10%	Yantai	0.48%
Chengdu	2.08%	Baotou	0.48%
Chongqing	1.95%	Luohe	0.48%
Qingdao	1.92%	Mudanjiang	0.48%
Changchun	1.92%	Yangzhou	0.48%
Changsha	1.89%	Sanhe	0.48%
Ningbo	1.89%	Shaoguan	0.45%
Zhengzhou	1.52%	Zhenjiang	0.43%
Lanzhou	1.52%	Zhaoqing	0.43%
Harbin	1.52%	Fushun	0.43%
Hangzhou	1.49%	Datong	0.43%
Wuhan	1.49%	Zhangjiagang	0.40%
Fuzhou	1.41%	Jinjiang	0.40%
Deyang	1.36%	Changzhi	0.40%
Nanchang	1.33%	Baiyin	0.37%
Nanning	1.17%	Cangzhou	0.37%
Kunming	1.09%	Tianshui	0.37%
Guiyang	1.01%	Ulanqab	0.37%

Taizhou	0.96%	Shenyang	0.37%
Jinan	0.96%	Nanchong	0.35%
Pingdingshan	0.93%	Ningguo	0.35%
Shantou	0.80%	Yulin	0.32%
Urumqi	0.75%	Kunshan	0.32%
Yinchuan	0.64%	Wuhu	0.32%
Yueyang	0.61%	Ezhou	0.32%
Ganzhou	0.61%	Liaoyuan	0.29%
Xi'an	0.59%	Jinzhong	0.29%
Dongguan	0.59%	Huzhou	0.29%
Liaocheng	0.56%	Panshi	0.29%
Shizuishan	0.56%	Suzhou (Anhui)	0.27%
Xiangyang	0.56%	Zhumadian	0.27%
Lianyungang	0.56%	Tai'an	0.19%
Anshun	0.56%	Changjiang County	0.19%
Fuqing	0.56%	Baishan	0.16%
Huangshi	0.56%	Dezhou	0.16%
Yong'an	0.53%	Heze	0.16%
Huangshan	0.53%	Jianyang	0.08%
Suzhou (Jiangsu)	0.53%	Linyi	0.08%
Longkou	0.53%	Emeishan	0.08%
Wuzhou	0.53%	Hong Kong SAR	0.08%
Ma'anshan	0.53%	Zhuhai	0.05%
Wuxi	0.51%	Nantong	0.03%
Shijiazhuang	0.51%	Qiqihar	0.03%

Note: Table A3 shows the distribution of inspected firms across 106 cities. The coverage extends not only to developed eastern coastal regions (e.g., Beijing, Shanghai and Shenzhen), but also to multiple cities in the western, central, and northeastern parts of China, including Lanzhou, Zhengzhou, Harbin, Guiyang, Urumqi, and Yinchuan. This indicates that government accounting supervision has achieved strong nationwide coverage, not limited to economically and financially developed areas, but also taking into account regional differences in development

Table A3 Variable Definitions

Variables	Measurement
	Panel A: Dependent Variable
ILLIQ	*ILLIQ* is calculated as the average ratio of absolute daily returns divided by trading volume in year t. The economic implication of *ILLIQ* denotes the price change per unit of RMB trading volume. The smaller the *ILLIQ*, the better the liquidity. Detailed calculation is shown in Equation (1). Source: Amihud (2002), Acharya and Pedersen (2005), CSMAR-Corporate Stock Liquidity Database.
Turnover	Annual turnover rate. The sum of the daily turnover rates (based on the number of shares outstanding) within the accounting year. Source: Lesmond et al.(1999), Chordia et al. (2002), Barinov (2014), CSMAR-Corporate Stock Liquidity Database.
Zeros_Y	Zero yield index. *Zeros_Y* is calculated as the number of days with zero returns during the year, divided by the total number of trading days in that year. A zero yield is regarded as evidence that transaction costs exceed trading benefits, and thereby *Zeros_Y* is a proxy of illiquidity. Source: Lesmond et al. (1999), CSMAR-Corporate Stock Liquidity Database.
ASY	Comprehensive index of information asymmetry measures. We selected three representative market microstructure metrics from the CSMAR high-frequency archive: liquidity ratio, price reversal indicator and illiquidity ratio. We then constructed a comprehensive index of information asymmetry measures by retaining the first principal component (PCA). Larger *ASY* scores denote a more pronounced degree of asymmetric information. Source: Bharath et al. (2009); Abad et al. (2018); Zhang and Sok (2025); CSMAR-Corporate Stock Liquidity Database.
Quality	The information disclosure quality rating evaluated by the Shanghai and Shenzhen Stock Exchanges. Rating grades are divided into four categories: A = Excellent, B = Good, C = Passing, D = Failing. Rating grades are divided into four categories: A = Excellent, B = Good, C = Passing and D = Failing. We then convert these categories into ordinal variables by assigning values of 3, 2, 1 and 0, respectively. A higher *Quality* value indicates greater reporting quality. Source: Shanghai and Shenzhen Stock Exchanges; CSMAR-Analyst Forecast Database.
AC1	The operating expense ratio, which is calculated by dividing operating expenses by sales revenue. A larger value of AC indicates the higher the agency costs. Source: Ang et al. (2000); CSMAR-Corporate Distress Database.
AC2	The administrative expense ratio is calculated as the ratio of firms selling, general, and administrative (SG&A) expenses divide by operating revenue. Similarly, a higher administrative expense ratio indicates higher agency costs. Source: Singh and Davidson (2003); CSMAR-Corporate Distress Database.
Optimism	The investor optimism proxy, which is measured by taking the average of the log of the number of optimistic posts clicked in an internet chat room, divided by the number of pessimistic posts (ln (1+Postive posts)/(1+Negative posts)). Source: Eastmoney Guba (See: http://guba.eastmoney.com). Firstly, each post is time-stamped and contains the author ID, title, body text and number of reads. After removing duplicates, advertisements and stop words, we use the Jieba parser to tokenise the remaining text and convert it to TF-IDF vectors. Finally, a naïve Bayes classifier was trained using a manually labelled subset and was used to assign each post to one of three categories: optimistic, pessimistic or neutral. Source:Jiang et al. (2022); Zhang et al. (2023); Eastmoney;
OFI	Order flow imbalance of investors. Following Cont et al. (2014), we use order flow imbalance (OFI) as an additional proxy of investor optimism. We compute *OFI* in the following two steps: In the first step, each transaction is classified as either buyer-initiated (inflow) orders or seller-initiated (outflow) orders according to the Lee and Ready (1991) algorithm (Lee and Ready, 1991). Next, we calculate the daily net order flow as the difference between inflow and outflow, scaled by their sum: $OFI = (Inflow - Outflow) / (Inflow+Outflow)$, where *Inflow* and *Outflow* are the daily buy-initiated and sell-initiated orders for each stock during each window period, respectively. A transaction is designated as buy-initiated if it is executed at the selling price, which is above the quote midpoint and designated as sell- initiated if it is executed at buying price, which is below the quote mid- point. If a transaction is executed at the quote midpoint, similar to Liu et, al (2020), the exchanges apply the tick rule: it is buy-initiated if the transaction price is above or equal to the last executed transaction price, otherwise it is sell-initiated. The daily inflow and outflow are reported by the exchanges and collected by the WIND database. We collect the daily transaction data from the WIND database for each stock from 2003 to 2022, since the earliest transaction data in the CSMAR database dates back to 2003. Source: Lee and Ready (1991), Cont et al. (2014), Liu et, al (2020); Zhang and Sok (2025); CSMAR-Order Imbalance Database
	Panel B: Independent Variable
DID	The *DID* indicator takes the value one for the year in which a firm first becomes subject to government accounting supervision and for every year thereafter, and 0 otherwise. The coefficients of *DID* estimate the treatment effect between firms which are exposed to government accounting supervision and other firms without government accounting supervision. Source: We manually collect the data from the Accounting Information Quality Inspection Announcements 3–42 of China's Ministry of Finance. For multiple inspected listed companies, we only retain

	the initial inspection. (For example, see: https://www.mof.gov.cn/jrttts/202408/t20240805_3941091.htm).
Spillover_Industry	*Spillover_Industry* denotes the proportion of focal firms (excluding firm *i*) within the same industry and year that were subject to the government's randomized accounting inspections. Source: Seo (2021), Jiang et al. (2025).
Spillover_Region	*Spillover_Region* denotes the proportion of focal firms (excluding firm *i*) within the same province or municipality directly under the central government (e.g. Beijing, Shanghai, Chongqing and Tianjin) and year that were subject to the government's randomized accounting inspections. Source: CSMAR-China Listed Firm's Basic Information Database
	Panel C: Firm-Level Control Variables
$Size$	*Ln* (market capitalization+1). Source: CSMAR-Financial Statement Database.
Lev	The ratio of total liabilities to total assets. Source: CSMAR- Financial Indicators Analysis Database.
$CAPEX$	The ratio of capital expenditures to total assets. Source: CSMAR-Financial Statement Database.
$Board$	The number of board members. Source: CSMAR-Corporate Distress Database.
$Growth$	Sales revenue growth rate. Source: CSMAR- Financial Indicators Analysis Database.
CF	Cash flow from operations divided by total assets (OANCF/total assets). Source: CSMAR-Corporate Distress Database.
$Duality$	CEO duality is an indicator which equals to 1 if the CEO simultaneously occupies as the board chairman at the same listed company, and zero otherwise.Source: CSMAR-Corporate Distress Database.

Notes: Table A3 presents the detailed definitions of the main variables. Panel A outlines the definitions of the dependent variables. Panel B provides the construction of the key independent variable (*DID*), which allows us to quantify the real impact of government accounting supervision on stock liquidity. Panel C lists the definitions of firm-level control variables.

Table A4 Sample Selection Process.

Sample selection process	No. of observations
China Stock Market & Accounting Research (CSMAR) database Stock Liquidity File with Annual liquidity for individual stocks during 2000 and 2022	58,501
Less: Listed companies in the financial services industry	(1,666)
Less: Chinese B-share listed firms	(2,415)
Less: Listed companies which are special treatment (ST) or facing delisting risk warning (*ST) or facing particular transfer (PT), or listed companies whose listing was suspended during the accounting year	(2,590)
Less: the missing observations of control variables	(22,412)
Equals: the final matched sample from 2000 and 2022 accounting reporting year	29,418

Notes: Table A4 details the compilation of the final sample. We collect all annual stock liquidity data from the CSMAR database for the years from 2000 through 2022. To begin with, we match the annual stock liquidity files with other financial statement information from the CSMAR database. Next, we followed the existing studies and filter out our sample data as follows: (1) all the financial listed firms; (2) Chinese B-share listed firms; (3) listed companies that were special treatment (ST), facing delisting risk warning (*ST) or facing particular transfer (PT), or listed companies whose listing was suspended during the accounting year; (4) listed firms with missing relevant data of control variables. All continuous variables are winsorized at the 1st and 99th percentiles. After eliminating the duplicate observations and our final matched sample consists of 29,418 firm-year observations from December, 2000 to December, 2022, including 708 observations in treatment groups and 28710 in the control group.