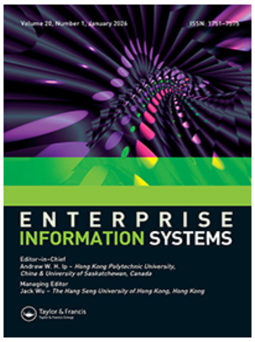

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Does data asset disclosure mitigate stock mispricing? A signalling perspective

Jian-Yong Liu[a], Feng-Xiao Jia[a], Yu-Ning Zhang[b], Zhen-Yuan (Ralph) Liu[a] and Ying Kei (Mike) Tse[c]

[a]Department of Accounting, School of Economics and Management, China University of Mining and Technology, Xuzhou City, China; [b]Department of International Trade, School of Business, Shanghai University of International Business and Economics, Shanghai City, China; [c]Department of Logistics and Operations Management, Cardiff Business School, Cardiff University, Cardiff, UK

ABSTRACT

Although data asset disclosure signals firms' competitive resource advantages, whether and how data asset disclosure influences investors' perceptions remains unclear. Using a unique dataset comprising A-share listed firms in China from 2008 to 2023, this study finds that data asset disclosure mitigates stock mispricing. Such the effect is stronger for self-use data asset disclosure than transactional ones, and for firms with higher internal control quality, media attention, and institutional ownership. Further analysis reveals that Only routine and truthful disclosure is effective, while exaggerated disclosure backfires. These findings yield important theoretical and managerial implications for firms formulating data asset disclosure strategies.

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Data assets disclosure; stock mispricing; signalling theory; internal control quality; media attention; institutional ownership

1. Introduction

Amid the rapid development of the digital economy and ongoing digital transformation globally, data assets have been widely recognised as the new oil that constitutes the fundamental component for firms' sustainable operations in the digitalisation era. Data assets refer to data resources an enterprise legally holds, utilises, and manages for generating business values, demonstrating have multiple merits of improving strategic resource allocations (Y. Li, Wang, and Zheng 2024), strengthening firm risk control (Dahiya, Le, and Kroll 2025), and enhancing managerial efficiency (Krause and Tse 2016). Hence, disclosing data assets to a broad range of stakeholders (data asset disclosure hereafter) can demonstrate firms' competitiveness and growth potential in the digital era, fostering stakeholder trust that brings future economic benefits (Tang 2024). For instance, in its 2023 annual report, Microsoft disclosed data assets of user data and transaction data generated throughout the processes of its products and services, including the specific items of user activity data, system log data, usage pattern data, cloud resource application data, and data sourced from operations and maintenance.[1] Meanwhile, Microsoft also emphasised that these data assets not only drive innovative applications like intelligent functionalities and real-time noise suppression features within Teams, but also enhance operations management through accurate demand forecasting, comprehensive capacity optimisation, and data centre expansion. In this sense, data asset disclosure clarifies firms' market growth potentials and anticipated future returns, mitigating information asymmetry among stakeholders and subsequently enhancing investor confidence.

Considering the surging importance of data asset disclosure in firms' both operations management and market values creation, the extant studies are striving to examine the consequences of data asset disclosure, especially in financial terms of credit allocation, stock price synchronicity, and stock return idiosyncratic volatility (Qian, Pan, and Liang 2025; Sun and Du 2024; Wei et al. 2025). However, scant attention has been paid to its role in mitigating firms' stock mispricing. Stock mispricing pertains to the particular phenomenon wherein a firm deviates from its intrinsic value (Lewis, Longstaff, and Petrasek 2021), posing considerable risks not only to investors and firms themselves but also to regulators via impairing resource allocation and even threatening the stability of financial system (Bofinger, Heyden, and Rock 2022). For instance,

CONTACT Ying Kei (Mike) Tse tsem1@cardiff.ac.uk Department of Logistics and Operations Management, Cardiff Business School, Cardiff University, Colum Road, Cathays, Cardiff CF10 3EU, UK

GigaDevice Semiconductor Inc. (603986.SH) benefited from surging demand for AI-related computing power and rapid advancements within the Chinese semiconductor sector, leading analysts to predict the net profit growth rate of GigaDevice would exceed 20% per annum over 2024–2026. However, the lack of data assets disclosure in GigaDevice's annual reports prevents investors from foreseeing its growth potential, resulting in a substantial underpricing of its price-to-earnings ratio, less than half the average of its peer firms in 2024. Such stock mispricing was later borne out by reality: on 25 April 2025, the company reported a net profit of RMB 1.103 billion for 2024, representing a year-on-year increase of 584.21%.[2]

Prior studies indicate that the core reasons of stock mispricing relates to information asymmetry among firms and capital market participants, which is much more evident in emerging markets such as China than in mature Western capital markets (W. Li and Zheng 2024). With the aim of exploring how to effectively minimise information asymmetry that leads to stock mispricing, building empirical evidences show that firm information disclosure could mitigate stock mispricing, such as corporate governance structure (Becker-Blease and Irani 2008), ESG practices (Lin, Zhu, and Meng 2023), and CSR initiatives (Wu et al. 2024). Nevertheless, we still do not know whether data asset disclosure can alleviate stock mispricing or not, especially given that such the information disclosure is neither formally recognised on balance sheets nor subject to mandatory disclosure regulations. When disclosing data assets, firms are confronted with contrasting scenarios wherein stock mispricing takes place caused by distinct interpretations of competitors, investors, and analysts. On the one hand, data asset disclosure facilitates firms to demonstrate their competitive advantages resulting from data resources and value creation potentials, expecting to relieve financial constraints and boost market valuations via conveying signals to the market (Ni et al. 2024; Qian, Pan, and Liang 2025). For instance, Guiyang Bank pioneered the global launch of 'data loan' that leverages firms' data asset disclosure to supplement commercial financing services for supporting corporate business operations. On the other hand, data asset disclosure may also pose the risk of exposing firms' data competencies to their competitors, which generates noise in the capital markets due to the competitive imitations among rivals. Such noise would increase stock mispricing (Xue, He, and Yun 2025). Therefore, the main objective of this study is to fill in this gap via unveiling the influence of data asset disclosure on stock mispricing, especially through the lens of signalling theory.

Signalling theory interprets the impact of firm information disclosure on reducing information asymmetry in the capital market through the process of sending, processing and countering signals (B. L. Connelly et al. 2011). Specifically, firms send signals to communicate their unique attributes to stakeholders and the public, who could be affected through the reduction of information asymmetry. In this sense, data asset disclosure can act as a signal not only to aid investors in evaluating the value-generating potential of data assets and assessing the firm's growth prospects (Hannila et al. 2022) but also to help them understand data-related risks, thereby enabling more accurate assessments of firms' intrinsic value. This facilitates more rational investment decisions and fosters a convergence between the market value and the fundamental value, ultimately reducing the degree of stock mispricing. More importantly, signals are costly to send as they enable investors to distinguish low- and high-quality firms in the capital market (Lam 2018). The more specific and valuable signals firms send, the more favourable attention investors pay to them. In this sense, we also categorise data asset disclosure into two different types according to firms' strategic utilisation preferences, i.e. self-use and transactional ones. Self-use data asset disclosure refers to firms announcing that they will integrate data assets into their own business operations process and improve operational efficiency and profitability. In contrast, transactional ones aim to provide or sell data assets to other business entities. Therefore, we tend to further examine the distinct effects of these two different disclosures on firms' stock mispricing.

Moreover, signalling theory also highlights the efficacy of a signal is contingent upon signaller and receiver characteristics as well as the signalling environment (Bafera and Kleinert 2022). Following this guidance, we take three critical features from each theoretical components of signalling theory that contingently affect the effect of data assets disclosure, i.e. firms' internal control quality, media attention, and institutional investors. Specifically, internal control refers to a set of governance mechanism for scrutinising, monitoring and safeguarding the details of information disclosure, reflecting the credibility of firm information disclosure and then influencing the effectiveness of these signals. With higher quality of internal control, firms' data asset disclosure can be more truthful and complete and thereby strengthen its mitigating effect on stock mispricing. In addition, prior research also suggests that both the characteristics of the signalling environment and the receivers significantly influence signal effectiveness through signal observability (Bafera and Kleinert 2022). Indeed, more observable signals to their intended recipients are more likely to exert a stronger influence (Lam 2018). Within this context, we propose that media attention constitutes a critical element of the signalling environment, as it enhances signal observability. Similarly, the information demand and the information-processing capacity of institutional investors can further amplify signal observability. Taking such three factors within the signalling theory, we argue that higher internal control quality, greater media attention, and increased institutional ownership can reinforce the effect of data asset disclosure on mitigating stock mispricing, respectively. To sum up, this research focuses on firms' data asset disclosure and aims to address the following research questions:

RQ1: How does data asset disclosure affect stock mispricing?

RQ2: How do firms' internal control quality, media attention, and institutional ownership moderate the effect of data asset disclosure on stock mispricing?

To empirically test the theoretical propositions outlined above, this study constructs a measure of data asset disclosure based on the text analysis approach and utilises data from Chinese A-share listed companies over the period from 2008 to 2023, and subsequently employs panel data regression models to examine the impact of data asset disclosure on stock mispricing. The empirical findings indicate that data asset disclosure significantly mitigates stock mispricing. This mitigating effect is evident in both overpricing and underpricing scenarios, and is more pronounced for self-use data assets than for transactional data assets. Furthermore, the analysis of moderating effects reveals that the mitigating effect could be strengthened when firms have higher levels of internal control quality, receive greater media attention, and have higher institutional ownership. Further analysis reveals that this effect is contingent on the normal data asset disclosure, and it is no longer observed when firms engage in exaggerated or overstated disclosure.

This study offers three marginal contributions. First, it enriches the literature on the determinants of stock mispricing. While previous research has primarily focused on the role of financial information (Berkman et al. 2009; Pantzalis and Park 2014) or mandatory non-financial disclosure (W. Li and Zheng 2024; Wu et al. 2024), this study shifts attention to the voluntary disclosure of non-financial information, revealing that data asset disclosure exerts a significant influence on stock mispricing. Second, it extends the research on the financial consequences of data asset disclosure. In contrast to existing studies that examine its effect on pricing efficiency via stock price synchronicity and stock return idiosyncratic volatility (Qian, Pan, and Liang 2025; Sun and Du 2024; Wei et al. 2025), this study adopts a stock mispricing perspective and finds that data asset disclosure can alleviate pricing inefficiencies and affirm its value relevance. Finally, by integrating signalling theory into the analytical framework, we conceptualise the disclosed data asset as a signalling mechanism and empirically test its effect on stock mispricing. We further explore the heterogeneity of this effect under varying contextual conditions, thereby identifying the contingencies under which data asset signals remain effective. In doing so, this study extends the application of signalling theory and offers a theoretical basis for understanding the capital market value of other forms of voluntary disclosure.

2. Literature review and theoretical background

2.1. Stock mispricing and information asymmetry

Stock mispricing reflects the extent to which information is accurately incorporated into market prices, and one of its fundamental causes lies in the information asymmetry between firms and investors (Caglayan et al. 2020). When investors lack access to comprehensive and reliable firm-specific information, they are unable to accurately assess the intrinsic value of a company's stock, resulting in market prices that deviate from their fundamental values (Lewis, Longstaff, and Petrasek 2021). Information disclosure serves as an essential mechanism for mitigating such asymmetries among capital market participants. Accordingly, a growing body of literature has examined the relationship between information disclosure and stock mispricing from various perspectives, including the content of information disclosure, the characteristics of the signaller, the information environment, and the receivers.

Regarding the content of disclosure, prior studies have found that the issues of CSR reports and key audit matters can reduce information asymmetry and alleviate stock mispricing (W. Li and Zheng 2024; Wu et al. 2024). However, the disclosure of ESG reports has been found to mitigate underpricing but not overpricing of stocks (Bofinger, Heyden, and Rock 2022; Lin, Zhu, and Meng 2023). Secondly, in terms of the signallers, firm ownership structure significantly affects corporate missions and resource allocation. Compared to state-owned enterprises, non-state-owned ones typically experience a greater degree of stock mispricing (C. Li et al. 2025). Furthermore, firms with stronger internal governance mechanisms tend to attract greater investor trust and attention, which may surprisingly give rise to more investor irrationality and thereby exacerbate pricing inefficiencies (Ruan, Li, and Huang 2025). Thirdly, the information environment plays a crucial role in shaping how information is transmitted and interpreted by investors. Media coverage, for instance, can influence stock mispricing, with negative news amplifying mispricing and positive news mitigating it (Narayan and Sharma 2023). Analyst recommendations affect the cost of information acquisition and interpretation by investors, but their impact on stock mispricing varies significantly across institutional settings. In underdeveloped markets and those with lower levels of individualism, such recommendations tend to be more valuable and can help reduce mispricing (Azevedo and Müller 2024). Social media with interactivity and dynamism characteristics facilitates information integration among retail investors and then contributes to the correction of stock mispricing (Shu 2024). Lastly, concerning the receiver, investor cognition, attention, and sentiment all exert significant influences on asset pricing (Caglayan et al. 2020). In particular, divergent investor cognition has been shown to amplify pricing errors (Han et al. 2022). Heightened investor attention tends to intensify emotional responses (Andrei and Hasler 2015), fuelling optimistic biases regarding firm prospects (Dong, Miao, and Wang 2020), which in turn drives stock prices above intrinsic value. Moreover, institutional herding behaviour among investors can further widen the gap between market prices and fundamental values (Hommes et al. 2008).

2.2. Data asset disclosure

Data assets refer to data resources that a firm legally holds, utilises and manages with the potential to generate future economic benefits (Tang 2024). As an emerging category of assets, data assets represent an enterprise's proprietary technological rights in digitalisation and data utilisation (Feng et al. 2025). For instance, firms leverage advanced information technologies and data analytics tools, such as data storage systems, information and communication infrastructure, and related technologies (Tian and Ou 2024) to accumulate, manage, and exploit vast volumes of data. These data resources generate value through their interaction with specific application scenarios (Pang et al. 2025), thereby giving rise to data assets. Scholars have found that data assets play a pivotal role in supporting corporate business intelligence decision-making and enhancing the agility and efficiency of business processes (Desgourdes and Ram 2024; Gupta et al. 2025; Scuotto et al. 2020; Singh, Sharma, and Dhir 2021). Moreover, they contribute to promoting green innovation (Zhang et al. 2025), reducing managerial costs (Bhatti et al. 2021; Thekkoote 2021), and strengthening firm-level market competitiveness (R. Chen et al. 2025).

Data asset disclosure constitutes an effective affirmation of the economic value embedded in data resources. By providing supplementary explanation and contextual elaboration, such disclosure enhances the transparency of listed firms (Kim and Yasuda 2019; Y. Li et al. 2022). Existing studies on data asset disclosure have primarily focused on its implications for corporate financing, stock price synchronicity, and stock return idiosyncratic volatility. Specifically, prior studies have shown that data asset disclosure improves information transparency, sustains long-term investor attention and facilitates greater access to bank lending (Qian, Pan, and Liang 2025). Meanwhile, data asset disclosure also mitigates information asymmetry. It promotes long-horizon institutional investment, thereby reducing stock price synchronicity (Sun and Du 2024). Then it further alleviates analyst forecast bias and noise trading-driven order imbalance, thereby dampening stock return idiosyncratic volatility (Wei et al. 2025). However, relatively limited attention has been devoted to examining the impact of data asset disclosure on stock mispricing. While extant research has investigated the effects of data asset disclosure on stock price synchronicity and stock return idiosyncratic volatility, these constructs diverge fundamentally from stock mispricing in terms of how they affect market pricing efficiency.

In light of this research gap, the present study seeks to investigate how data asset disclosure influences stock mispricing and under what conditions this relationship is subject to variation. Drawing on signalling theory, we conceptualise corporate data asset disclosure as a strategic signal transmitted by firms. We examine how these signals affect stock mispricing and whether the effects differ depending on the nature of the signal (namely, the self-use data asset disclosure or transactional data asset disclosure). Moreover, we aim to elucidate how the characteristics of the signaller (i.e. the internal control quality), the signalling environment (i.e. media attention), and the receiver (i.e. the institutional ownership) moderate the relationship between data asset disclosure and stock mispricing.

2.3. Signalling theory

Signalling theory applies to information asymmetry contexts wherein one party holds private information that is not readily observable by the other (Bafera and Kleinert 2022). Therefore, signalling theory emphasises three fundamental elements, i.e. signaller, signals and signal receivers (B. Connelly et al. 2024). The signaller, who holds complete information, transmits a signal to the receiver and helps to alleviate information asymmetry between the two parties (Nishant, Teo, and Goh 2017). Upon observing the signal, the receiver interprets it and makes subsequent decisions (Nishant, Teo, and Goh 2017).

Previous research has highlighted that the effectiveness of a signal hinges on two core attributes, i.e. its cost and its observability (B. Connelly et al. 2024). The former reflects the expenditure associated with generating a signal (e.g. the adoption costs of specific practices). At the same time, the latter indicates the extent to which the signal is observable and recognisable by the receiver (W. Liu et al. 2020). A signal must be costly to be considered credible (Drover, Wood, and Corbett 2017). In other words, the signal cost significantly influences the signalling effectiveness, with higher-cost signals being less susceptible to manipulation and thus considered more reliable (Narasimhan et al. 2015). Moreover, Narasimhan et al. (2015) noted that signal effectiveness improves when it conveys novel information to the receiver. In this sense, the more observable a signal is to its receiver, the greater its efficacy could achieve. The observability of a signal depends mainly on the signalling environment, which directly influences how effectively the signal is perceived (Lam 2018). In addition to the environment, the characteristics of the receiver also play a crucial role, given that the greater the receiver's willingness and capacity to interpret the signal, the more effective the signal becomes (Bafera and Kleinert 2022).

Grounded in the signalling theory, this study posits that firms' data assets disclosure conveys critical information to investors, thus reducing information asymmetry and mitigating stock mispricing. Such disclosure can serve as an effective signal because data asset information meets the two fundamental criteria of signalling theory: costliness and observability. Specifically, the formation of data assets requires considerable investment of time, financial resources, and intellectual capital. Moreover, such disclosure reveals information related to a firm's technological capabilities, value creation potential, and risk profile, all of which are recognisable and interpretable by relevant stakeholders. Based on this theoretical foundation, the following subsections examine how data asset signals affect stock mispricing by shaping investors' assessments, and how the characteristics of the signaller, the signalling environment, and the receiver further condition this relationship.

3. Hypothesis development

3.1. Data assets disclosure and stock mispricing

Drawing upon signalling theory, we argue that firms' data asset disclosure can mitigate information asymmetry between firms and investors. The spillover effect of information and its impact on decision-making have become core characteristics of the modern economic system. This characteristic is not only reflected in international cooperation within the real economy (Zhang et al. 2025), but also notably prominent in the information transmission of the capital market. Data asset disclosure enhances investors' understanding of the value-creating potential and inherent risks, supporting a more informed assessment of firms' intrinsic value and reducing stock mispricing (Clarkson et al. 2013).

First, data asset disclosure enhances investors' understanding of a firm's value creation capacity. Although data assets hold significant potential, their value is context-specific and emerges through particular application scenarios. By clarifying how data are collected, stored, and applied in production, operations, and decision-making (Rassier, Kornfeld, and Strassner 2019), firms can explain the concrete ways in which value is generated. Such transparent disclosure enables investors to understand these mechanisms better, reducing mispricing caused by informational opacity. For instance, when firms disclose how they use advanced data analytics to build customer profiles and implement precision marketing, they send a clear signal of their capacity to optimise decision-making, reduce marketing costs, and enhance economic returns (Hannila et al. 2022).

Second, data asset disclosure allows investors to better understand the risks associated with data assets. These risks often stem from technological vulnerabilities and regulatory compliance issues, both of which introduce substantial uncertainties to future cash flows (Balboni and Francis 2025; Cao, Phan, and Silveri 2024). Key disclosures should cover legal and technical disputes, data ownership, compliance in proprietary asset development, and high-risk activities such as securitisation, pledging, and trust-based financing. These adequate disclosures help investors avoid misjudging these risks, make more accurate investment decisions, and prevent mispricing. Taken together, data asset disclosure constitutes a credible signal that informs investors of both the value-generating potential and the inherent risks of data assets. By incorporating these dual aspects into firm valuation and trading decisions, investors can develop a more balanced understanding, promoting rational investment behaviour and mitigating stock mispricing.

H1a: **Voluntary data asset disclosure mitigates stock mispricing.**

Corporate data assets can be broadly categorised into self-use data assets (SDA) and transactional data assets (TDA) based on their intended use (L. Chen 2024). SDA are derived from a firm's internal operations and are subsequently collected, processed, and analysed to support production management, strategic decision-making, and business process optimisation. These assets play a key role in enhancing operational efficiency and profitability (Ning, Jiang, and Luo 2023) by serving as internal inputs rather than being sold or transferred externally. In contrast, TDA are created through processing, organising, and removing sensitive information from raw data, to provide services or generate revenues through external sale or licencing (Abrardi, Cambini, and Pino 2024; Fernandez, Subramaniam, and Franklin 2020). These assets contribute directly to a firm's income stream but generally do not constitute part of its core competitive resources.

Compared to TDA, SDA are more deeply embedded in a firm's production, operational, and decision-making processes and represent a core source of competitive advantage (Ruffoni and Reichert 2024). Firms may therefore adopt a more conservative disclosure strategy for SDA due to concerns over technology leakage. Disclosed SDA information often provides a greater degree of surprise and richer informational content for investors. Unlike TDA, SDA is typically tailored to a firm's internal needs. Its development involves more complex data acquisition and processing procedures, and incurs substantially higher costs. Firms bear full lifecycle responsibilities for these assets, including quality assurance, data security, regulatory compliance, and regular updates (Kruesi, Burstein, and Tanner 2020; Q. Zhang, Sun, and Zhang 2022). These obligations imply ongoing investment and high maintenance costs. According to the signalling theory, signals that involve higher costs are generally perceived as more credible (Drover, Wood, and Corbett 2017). As such, the disclosure of SDA information conveys a more credible signal to investors and is likely to exert a more substantial mitigating effect on stock mispricing.

H1b: Compared with transactional data assets, the disclosure of self-use data assets has a more pronounced mitigating effect on stock mispricing.

3.2. Moderating factors

According to the signalling theory, the characteristics of the signaller, the signal environment, and the receiver jointly influence the effectiveness of a signal (Bafera and Kleinert 2022), which in turn shapes the informational value it conveys. Hence, we investigate how the internal control quality, as a key attribute of the signaller, moderates the relationship between data asset disclosure and stock mispricing. Since the generation of data asset information must pass through a series of internal control processes within an enterprise (Abraham, Schneider, and Vom Brocke 2019), the effectiveness of the enterprise's internal control determines the reliability of the data asset signals. Furthermore, media attention, an essential component of the signal environment, plays a pivotal role in enhancing the observability of data asset signals. Thus, we explore how media coverage affects the efficacy of data asset disclosure in mitigating stock mispricing. Lastly, we examine how the characteristics of institutional investors (i.e. signal receivers) shape their perception and interpretation of data asset signals and, consequently, determine the extent to which such disclosure alleviates stock mispricing.

3.2.1. Internal control quality

Internal control refers to a structured set of processes and mechanisms to safeguard assets, ensure the accuracy and compliance of financial reporting, and enhance operational efficiency and organisational sustainability (Cheng, Goh, and Kim 2018). The high quality of internal control system typically comprises the following core components include the control environment, risk assessment, control activities, information and communication, and internal monitoring. Functioning as the foundational infrastructure of corporate governance, internal control provides the mechanism through which governance practices are operationalised and exert influence on corporate behaviour. As such, internal control directly contributes to the regulation of organisational decision-making and exerts a significant impact on firms' disclosure practices (Liao, Mukherjee, and Wang 2015).

Prior research has demonstrated that internal control contributes to enhancing both financial and non-financial information disclosure, thereby mitigating stock price crash risk and improving earnings quality (Ashbaugh-Skaife, Collins, and Kinney 2007; Callen and Fang 2015. Specifically, internal control can serve as a critical governance mechanism that effectively translates external pressures into substantive information disclosure practices, particularly when external media scrutiny or competitive market pressures are intensified (Elsayed and Elshandidy 2021; J. Zhang, Zhang, and Zhang 2024). Even though both China's *Basic Standards for Enterprise Internal Control* (2008) and the COSO Framework (2013) have extended the scope of internal control from its traditional focus on financial information to encompass both financial and non-financial information (Alshaiti 2023), it remains unclear whether the risk-reducing effect of data asset disclosure is amplified or not with the increasing of internal control strength. As data asset disclosure represents an extension of the corporate financial disclosure system and reflects corporate responses to the interests and concerns of various stakeholders, we posit that the effectiveness of a firm's internal control system plays a crucial role in shaping the quality of its data asset disclosure through at least two moderating mechanisms as below.

First, the influence is particularly evident in the role of internal control components such as the information and communication function, which reduces errors in information flow, enhances the efficiency and precision of signal transmission, and strengthens interdepartmental coordination. These functions provide robust support for the collection, organisation, and dissemination of information, thereby improving the overall quality of disclosure. Second, internal control functions as an internal governance mechanism that constrains opportunistic disclosure behaviour. It limits managerial manipulation and restricts the selective amplification of favourable information, which in turn enhances the credibility and reliability of the signals emitted to the market. According to the signalling theory, the signal reliability is a key determinant of signalling effectiveness. Therefore, firms with higher-quality internal control are more likely to issue reliable data asset disclosure, which improves signal effectiveness and enhances their ability to alleviate stock mispricing.

H2: Higher internal control quality strengthens the mitigating effect of data asset disclosure on stock mispricing.

3.2.2. Media attention

The media possesses professional advantages in gathering, interpreting, and disseminating information, and functions as an accelerator in the interpretation and diffusion process (Bhattacharya et al. 2009). Media coverage helps reduce information asymmetry between firms and investors and enhances pricing efficiency in capital markets by lowering the cost for investors to access relevant information. We posit that media attention can amplify the observability of signals as a fundamental component of the signal environment. As B. Connelly et al. (2024) highlighted, signals with greater observability tend to be more effective. Accordingly, firms that attract greater media attention are more likely to have their data asset disclosures interpreted and disseminated through media channels. This amplification increases the observability of data asset signals, enhances their signalling effectiveness, and thus more effectively mitigates stock mispricing.

In addition to its information-dissemination role, the media also serves a critical monitoring function by generating public resonance through news reporting. Prior studies have shown that managers may opportunistically manipulate data asset disclosure for personal gain in contexts characterised by weak internal governance. For example, before executive share sell-offs, executives may deliberately exaggerate data asset disclosure in an attempt to inflate stock prices, to facilitate disposals at elevated valuations for greater personal gain (Garcia Osma, Scarlat, and Shields 2020). In such cases, media coverage can exert a monitoring function and curb managerial opportunism through public scrutiny (Dai, Parwada, and Zhang 2015). This external governance improves the credibility of disclosures, enhances the reliability of data asset signals, and strengthens its effectiveness in alleviating stock mispricing.

H3: Media attention strengthens the mitigating effect of data asset disclosure on stock mispricing.

3.2.3. Institutional ownership

According to the signalling theory, the characteristics of signal receivers significantly influence signal effectiveness (Bafera and Kleinert 2022). In capital markets, data asset signals are received by both individual and institutional investors. Institutional investors, in comparison to individual investors, typically hold larger shareholdings and possess greater resources, which makes them more willing and capable of bearing the considerable costs of acquiring and interpreting data asset disclosures.

First, in terms of informational receptiveness, institutional investors exhibit greater motivation to collect data asset information. Individual investors are generally less inclined to engage with data asset disclosures due to their smaller shareholdings and limited willingness to bear the substantial search and interpretation costs associated with the complex textual nature of such disclosures. By contrast, institutional investors prioritise long-term value and are generally more attentive to a firm's growth potential. Data assets, as strategic resources, reflect a company's technological capabilities and capacity for value creation, and align closely with the institutional investors' preferences (Goldfarb and Tucker 2019). Consequently, this alignment increases their incentive to acquire and interpret data asset information, enabling more informed investment decisions and contributing to the mitigation of stock mispricing.

Second, in terms of interpretive capacity, institutional investors typically possess superior access to information channels and professional analytical expertise compared with their retail counterparts. Their investment strategies are generally characterised by greater prudence and informed judgement (Hu et al. 2023; X. Liu et al. 2024). And they are better positioned to conduct professional analysis and due diligence, enabling them to identify the value-generating potential and inherent risks. As such, the signals embedded in the disclosure are more likely to be effectively assimilated into market prices through institutional investors' informed interpretation and rational trading activities, which further alleviate stock mispricing.

H4: Institutional ownership strengthens the mitigating effect of data asset disclosure on stock mispricing.

To summarise, the conceptual model is shown in Figure 1.

4. Research design

4.1. Sample selection and data sources

We sampled Chinese A-share listed firms from 2008 to 2023 to test the theoretical contentions above. Chinese samples provide a highly relevant context for us to test our hypotheses, given that China has witnessed rapid growth in its digital economy in recent years. Specifically, listed firms in China generated 8.1 zettabytes of data by the end of 2023, accounting for 10.5% of global data production and ranking second

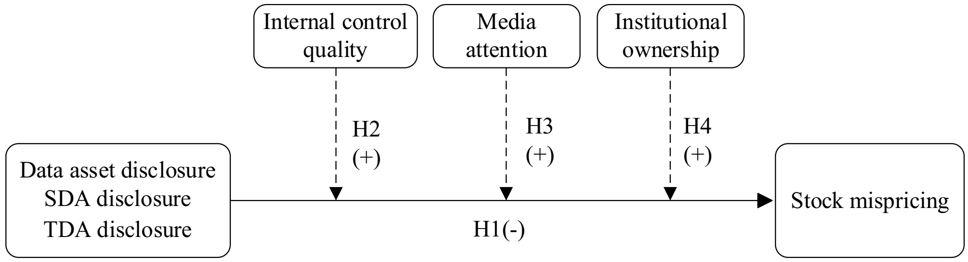

Figure 1. Research conceptual model.

worldwide. Moreover, these firms are increasingly disclosing data asset information in their annual reports, providing a highly appropriate empirical context for this research. Besides, the global financial crisis of 2008 and its aftermath exposed fundamental flaws in traditional asset valuation frameworks. In response, firms and regulatory authorities began to re-evaluate the value and associated risks with non-physical assets. This shift contributed to the growing recognition of data assets as strategically essential components of corporate value. Concurrently, the exponential growth of the internet and big data technologies has catalysed the development of digital infrastructure, which has facilitated the rapid growth of the digital economy and markedly expanded the scale of corporate data assets.

We apply the following sample refinement procedures to the initial dataset to enhance the robustness and reliability of the empirical analysis: (1) Firms in the financial and insurance sectors are excluded; (2) Firm-year observations within the first two years of listing are removed; (3) Observations with missing values are eliminated. And all continuous variables are winsorised at the 1st and 99th percentiles to mitigate the influence of outliers on the regression results. These screening procedures result in a final panel comprising 37,254 firm-year observations.

We measure the level of data asset disclosure using textual analysis of firms' annual reports, based on the frequency of data asset-related keywords. Media attention data are obtained from CNRDS, information on internal control quality is derived from the DIB database, and all remaining variables are collected from the CSMAR database.

4.2. Variable Measures

4.2.1. Dependent variable

Following (D. Liu, Sui, and Lung 2016), we measure stock mispricing (*Misp*) as the absolute deviation of a firm's market value (*P*) from its intrinsic value (*V*), defined as: *Misp*=|*1-V/P*|. A higher value of *Misp* indicates a greater degree of deviation, i.e. a higher level of mispricing. Specifically, when $V/P < 1$, the market value exceeds the intrinsic value, suggesting that the stock is overpriced. Conversely, when $V/P > 1$, the market value is below the intrinsic value, indicating underpricing. The market value (*P*) is computed as the average closing price over all trading days in a given year. The intrinsic value (*V*) is estimated using the Residual Income Model (RIM) proposed by Frankel and Lee (1998). The Residual Income Model expresses a company's intrinsic value as a function of its book value and future expected earnings, comprehensively incorporating information such as the company's financial condition, profitability, and growth potential. This approach is relatively comprehensive and intuitive, as specified in Equation (1). Furthermore, to ensure the robustness of the research conclusions, we also use the industry-relative valuation method in the subsequent text to estimate the company's intrinsic value for a replacement test.

$$V_t = b_t + \frac{f(1)_t - r * b_t}{(1+r)} + \frac{f(2)_t - r * b(1)_t}{(1+r)^2} + \frac{f(3)_t - r * b(2)_t}{(1+r)^2 * r} \tag{1}$$

In Equation (1), b_t denotes the book value of equity per share, and r represents the cost of capital. We adopt a fixed price of capital of 5% for r, as pioneering research in value investing has assumed a fixed cost of capital (Frankel & Lee, 1998). Moreover, the latest research literature based on China's capital market has also followed this practice (Ruan, Li, and Huang 2025). Therefore, this paper uses a cost of capital rate consistent with theirs to ensure the comparability of the research conclusions. The $f(.)_t$ corresponds to analysts' forecasts of future earnings. Drawing on the method proposed by (Hou, van Dijk, and Zhang 2012), we estimate *f(.)* using firm-level information to construct earnings forecasts, as specified in Equation (2):

$$Earnings_{i,t+j} = \alpha_0 + \alpha_1 Asset_{i,t} + \alpha_2 Dividend_{i,t} + \alpha_3 Earnings_{i,t} + \alpha_4 DD_{i,t} + \alpha_5 Loss_{i,t} + \alpha_6 Accrual_{i,t} + \varepsilon_{i,j} \tag{2}$$

In Equation (2), $Earnings_{i,\ t+j}$ represents the firm's projected earnings over the next one to three years, *j* takes values of 1, 2, and 3 respectively, the explanatory variables include: total assets per share (*Asset*), cash dividends per share (*Dividend*), earnings per share (*Earnings*), a dummy variable indicating whether dividends are paid (*DD*), a dummy variable indicating whether the firm has incurred a loss (*Loss*), and accruals per share (*Accrual*).

In addition, it is necessary to forecast the firm's book value of equity per share for the subsequent two periods, to operationalise Equation (1) and compute intrinsic value. The relevant forecast models are presented in Equations (3) and (4):

$$b(1)_t = b_t + Earnings_{t+1} - Dps_{t+1} \tag{3}$$

$$b(2)_t = b_t + Earnings_{t+2} - Dps_{t+2} \tag{4}$$

Where *Dps* denotes cash dividends per share.

4.2.2. Independent variable

Following the method proposed by Wei et al. (2025), we measure the level of data asset disclosure (*DAD)* by using the text mining approach with disclosure frequency serving as a proxy. One of the main challenges in identifying DAD is to disentangle its distinction from digital transformation and intellectual capital information disclosure. Unlike digital transformation and intellectual capital information disclosure, the purpose of data asset information disclosure is to demonstrate the scale, application scenarios, and potential economic benefits of data assets, thereby enhancing investor confidence and transparency by signalling firms' data resources and their intrinsic value (L. Chen 2024). On the other hand, digital transformation information disclosure focuses on the implementation progress and outcomes of firm overall digital strategy, aiming to illustrate the impact of digital transformation on business processes, business models, and long-term competitiveness (Merín-Rodrigáñez, Dasí, and Alegre 2024), whereas intellectual capital information disclosure emphasises the accumulation of organisational knowledge and core competencies, seeking to reflect the companies' long-term innovative capacity and sustainable development potential (Salvi et al. 2020). In this sense, one of the critical distinction between digital transformation and data asset disclosure lies in the emphasis of digital transformation on the application of digital technologies, which influences improvements in operational efficiency and cost reduction. In contrast, intellectual capital places greater emphasis on knowledge-based resources within a firm, as reflected through human capital (employee skills, innovation capabilities), market capital (customer relationships, brand value), and organisational capital (corporate culture, management processes). From this perspective, we focus on the disclosure of information pertaining specifically to data resources as a critical criterion to differentiate digital transformation and intellectual capital. This includes the types of data assets (e.g. user behaviour data, transaction data), methods for their valuation, and the extent and manner of their application in business operations.

We employ a four-step text mining approach to quantify sample firms' data asset disclosure, which includes keywords identification, expert validation, keywords matching based on Python programming, and frequency calculation. Specifically, we first begin with identifying 'data assets' and 'data resources' as seed terms. Following prior studies on information disclosure (Pant et al. 2025), we then use the deep learning technique of Word2Vec neural network model to generate a set of semantically similar terms to these seed terms. It is noticeable that all the keywords in the corpus are contextualised in Chinese as our samples are listed firms in Chinese A-share markets. Meanwhile, we also categorise two distinct corpora regarding self-use data assets (SDA) and transactional ones (TDA). In particular, SDA supports strategic decision-making and business process optimisation by serving as internal inputs, such as system log data, usage pattern data, and cloud resource application data. TDA contributes directly to a firm's income stream through external sales or licencing. For instance, Alibaba sold platform user data assets with removal of privacy-related information to other manufacturing enterprises for enhancing their marketing intelligence. Compared to TDA, SDA is more deeply embedded in a firm's production, operational, and decision-making processes and thereby represents a core source of competitive advantage (Ruffoni and Reichert 2024).

Secondly, we invited four experts from both industry and academia in the field of data assets to validate the effectiveness of identified keywords. We only adopted keywords when there is agreement among three-quarters of these experts. Third, we then employed Python programming to mine and analyse the frequencies of identified keywords in annual reports of sample firms. Finally, we compute the frequency of all seed and similar terms appearing in each firm's annual report. The data asset disclosure index is calculated according to Equation (5):

$$DAD_{i,t} = \frac{\sum Fre_{i,t,n}}{TotalFre_{i,t}} * 1000 \tag{5}$$

Where *Fre* denotes the exact frequency of the *n*-th term in the constructed dictionary appearing in firm *i*'s annual report in year *t*, and *TotalFre* represents the total word count of the yearly report of firm *i* in year *t*. A higher DAD value indicates a higher level of data asset disclosure. Figure 2 illustrates the four-step workflow we adopted in the identification of sample firms' data asset disclosure.

4.2.3. Moderating variables

We introduce three moderating variables to examine how the characteristics of the signaller, the signalling environment, and the receiver influence the relationship between data asset disclosure and stock mispricing (*Misp*).

First, we measure internal control quality (*IC*) by taking the natural logarithm of the internal control index disclosed in the DIB database, after adding one to the original index value. This variable captures the effectiveness of the firm's internal control system, i.e. the reliability of the signal. Higher values indicate better internal control quality and thus greater credibility of the data asset disclosure signal.

Second, we measure media attention (*Media*) by calculating the natural logarithm of the total number of online and print news reports mentioning the target firm, with one added to the count. This variable captures the transparency of the signalling environment (An et al. 2022). Higher values indicate greater media exposure, which enhances both the observability and transmission efficiency of the signal.

Finally, we use the institutional ownership (*Inst*) to capture the characteristics of the signal receiver. This variable reflects the willingness and capacity of investors to receive and process information. A higher

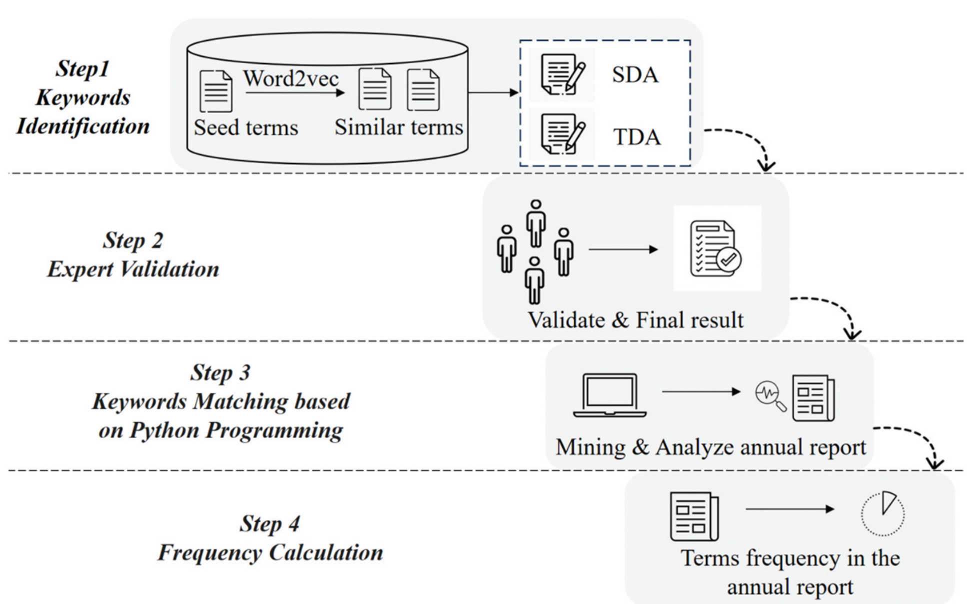

Figure 2. The four-step text mining strategy for data asset disclosure quantification.

institutional ownership implies stronger interpretive capabilities and greater sensitivity to data asset information, which facilitates more effective incorporation of the signal into market pricing.

4.2.4. Control variables

Following the prior literature (Gao, Cui, and Xu 2025; Wang, Tang, and Li 2025; Yang et al. 2024), this study controls for basic firm characteristics and corporate governance attributes to account for other potential factors that may influence stock mispricing.

Basic firm characteristics comprise firm size (*Size*), leverage ratio (*Lev*), return on assets (*Roa*), cash flow ratio (*Cashflow*), revenue growth rate (*Growth*), book-to-market ratio (*BM*), ownership type (*Soe*), and listing age (*Age*). Specifically, firm size (*Size*) and ownership type (*Soe*) are associated with the firm's business scope. Leverage ratio (*Lev*), return on assets (*Roa*), cash flow ratio (*Cashflow*), and revenue growth rate (*Growth*) reflect financial capacity. Listing age (*Age*) proxies for the firm's stage in the life cycle, and book-to-market ratio (*BM*) captures the firm's investment value. These variables are included to control for basic firm characteristics that may affect the degree of stock mispricing.

Corporate governance attributes include the shareholding ratio of the top three shareholders (*Top3*), managerial ownership (*Mshare*), board size (*Board*), the ratio of independent directors (*Indep*), and CEO duality (*Dual*). *Top3* reflects ownership concentration and the control power of major shareholders. Managerial ownership (*Mshare*) represents the alignment of managerial interests with firm performance. Board size (*Board*) captures governance capacity. The ratio of independent directors (*Indep*) measures board independence. CEO duality (*Dual*) indicates the concentration of executive power. These variables are intended to control for managerial and supervisory influences on stock mispricing. The detailed definitions and measurements of all variables are provided in Table 1.

4.3. Model specification

We construct the following baseline regression model (Equation 6) to examine the effect of data asset disclosure on stock mispricing:

$$Misp_{i,t} = \beta_0 + \beta_1 DAD_{i,t} + \beta_j Controls_{i,t} + \Sigma Year + \Sigma Firm + \varepsilon_{i,t} \tag{6}$$

Where the dependent variable *Misp* represents the level of stock mispricing, and the key independent variable *DAD* denotes the extent of data asset disclosure. *Controls* denote the set of control variables, with j indexing the number of covariates, i and t indicating firms and years, respectively. *Firm* and *Year* represent two-way fixed effects, and the term ε is the random disturbance term. Standard errors are clustered at the firm level to account for within-firm correlation.

In Equation (6), a significantly negative coefficient for the data asset disclosure level (*DAD*) (i.e. $\beta_1 < 0$) supports Hypothesis H1a. We conduct subgroup analyses using the exact specification as Equation (6) to test H1b, H2, H3, and H4.

5. Empirical results and analysis

5.1. Descriptive statistics

Table 2 presents the descriptive statistics of all variables. The mean value of *Misp* is 0.669, and the standard deviation is 0.468. This reflects a notable deviation between market values and intrinsic values among sample firms, suggesting substantial heterogeneity in stock mispricing levels. These findings are broadly consistent with prior studies (C. Li et al. 2023; Lin, Zhu, and Meng 2023; Ruan, Li, and Huang 2025). The mean value of the data asset disclosure level (*DAD*) is 0.052, and the standard deviation is 0.148, suggesting that the overall level of data asset disclosure among Chinese listed firms is relatively low and exhibits considerable variation. The descriptive statistics for the remaining control variables are mainly consistent with prior empirical findings (Jiang, Zhu, and Li 2024; B. Qian and Tan 2024; Wang, Tang, and Li 2025).

From a temporal perspective, as shown in Figure 3, the number of enterprises disclosing data asset information has shown a significant overall upward trend. This trend intuitively reflects the increasing emphasis on data assets by enterprises. At the same time, the average value of enterprises' annual data

Table 1. Variable definition and measurement.

Variable	Symbol	Measurement	Data source
		Dependent variables	
Stock mispricing	*Misp*	|1- a firm's market value/average closing price across all trading days in a given year|	China Stock Market & Accounting Research (CSMAR)
Independent variables			
Data asset disclosure	*DAD*	Frequency of data asset terms/Total word count of annual report *1000	Chinese Research Data Services Platform (CNRDS)
Self-use data asset disclosure	*SDA*	Frequency of self-use data asset terms/Total word count of annual report *1000	
Transactional data asset disclosure	*TDA*	Frequency of transactional data asset terms/Total word count of annual report *1000	
Moderator variables			
Internal control quality	*IC*	Ln (1 + Internal Control Index)	DIB
Media attention	*Media*	Ln (1 + number of media reports on the firm)	CNRDS
Institutional ownership	*Inst*	Number of institutional ownership/Total shares outstanding	CSMAR
Control variables			
Firm size	*Size*	Natural logarithm of total corporate assets	CSMAR
Leverage ratio	*Lev*	The ratio of total liabilities to total assets at the end of the period	
Return on assets	*Roa*	The ratio of net profit to total assets of the enterprise	
Cash flow ratio	*Cashflow*	The ratio of net cash flows from operations to total assets	
Revenue growth rate	*Growth*	(current year's operating income − previous year's operating income)/ previous year's operating income	
Book-to-market ratio	*BM*	Ratio of book value to market value	
State-owned enterprise	*Soe*	State-owned enterprises are assigned a value of 1, and non-state-owned enterprises are assigned a value of 0	
Listing age	*Age*	Logarithm (current year−listed year +1).	
Ownership concentration	*Top3*	The shareholding ratio of the top three shareholders	
Managerial ownership	*Mshare*	Percentage of the total share capital of management-owned stations	
board size	*Board*	Natural logarithm of the total number of board members	
Ratio of independent directors	*Indep*	The ratio of the number of independent directors to the total number of board members	
Duality	*Dual*	The chairman of the board, who is also the general manager, takes a value of 1. Otherwise, it takes the value of 0	

asset information disclosure has also maintained steady growth, which means enterprises are more inclined to proactively release key information related to their own long-term growth potential and core development directions. This serves to convey enterprises' layout and value in the field of data assets, and alleviates information asymmetry between enterprises and their stakeholders.

5.2. Baseline regression results

The baseline regression results are presented in Table 3. Column (1) shows that data asset disclosure (*DAD*) is significantly negatively associated with stock mispricing (*Misp*) at the 1% level, indicating that a higher level of data asset disclosure corresponds to a lower degree of stock mispricing. From the perspective of economic significance, each standard deviation increase of data asset disclosure mitigates the mean of 2.3% decrease in sample firms' stock mispricing, bringing corporate market values closer to their intrinsic values. This effect enhances pricing efficiency in capital markets and, consequently, effectively safeguards investor interests. Specifically, data asset disclosure not only navigates investors to conserve investment costs to achieve expected returns when stock prices are overvalued, but also assists investors in identifying the firm's true market values and further maintaining investor confidence when stock prices are undervalued. Columns (2) and (3) of Table 3 report the results for overpricing and underpricing stocks, respectively, to further distinguish the direction of stock pricing deviation. The findings suggest that data asset disclosure helps to mitigate both stock overpricing and underpricing. By improving investors' ability to assess firms' intrinsic value, such disclosure supports more rational investment decisions, which in turn helps market prices better reflect fundamental value and mitigates stock mispricing. Hence, Hypothesis H1a is supported.

Hypothesis H1b is tested by replacing the data asset disclosure (*DAD*) variable in Equation (6) with self-use data asset (*SDA*) disclosure and transactional data asset (*TDA*) disclosure, which respectively capture the disclosure of self-use data assets and transactional data assets. The results are reported in Columns (4) and (5) of Table 3. The estimated coefficients are −0.562 for self-use data asset disclosure and −0.105 for

Table 2. Descriptive statistics and correlation matrix.

Variables	*N*	*Mean*	*SD*	*Misp*	*Da*	*Size*	*Lev*	*Roa*	*Cashflow*	*Growth*	*BM*	*Soe*	*Age*	*Top3*	*Mshare*	*Board*	*Indep*	*Dual*
Misp	37,254	0.669	0.468	1.000														
DAD	37,254	0.052	0.148	0.054*	1.000													
Size	37,254	22.250	1.309	0.024*	−0.012*	1.000												
Lev	37,254	0.453	0.211	0.178*	−0.083*	0.365*	1.000											
Roa	37,254	0.026	0.077	−0.448*	−0.047*	0.104*	−0.355*	1.000										
Cashflow	37,254	0.046	0.072	−0.202*	−0.057*	0.089*	−0.178*	0.376*	1.000									
Growth	37,254	0.158	0.467	−0.087*	−0.008	0.038*	0.020*	0.225*	0.028*	1.000								
BM	37,254	0.320	0.162	−0.183*	−0.004	0.137*	−0.509*	0.159*	0.066*	−0.061*	1.000							
Soe	37,254	0.383	0.486	0.003	−0.082*	0.289*	0.227*	−0.007	0.004	−0.030*	0.000	1.000						
Age	37,254	2.347	0.650	0.086*	−0.054*	0.312*	0.294*	−0.137*	−0.044*	−0.053*	−0.079*	0.397*	1.000					
Top3	37,254	0.465	0.154	−0.051*	−0.120*	0.233*	−0.016*	0.192*	0.129*	0.058*	0.113*	0.146*	−0.193*	1.000				
Mshare	37,254	0.106	0.172	−0.050*	0.092*	−0.230*	−0.279*	0.118*	0.033*	0.032*	0.122*	−0.453*	−0.547*	0.062*	1.000			
Board	37,254	2.123	0.201	−0.038*	−0.057*	0.239*	0.122*	0.064*	0.055*	0.005	0.038*	0.285*	0.126*	0.052*	−0.194*	1.000		
Indep	37,254	0.377	0.054	0.053*	0.040*	0.003	−0.010	−0.038*	−0.021*	−0.007	−0.031*	−0.070*	−0.026*	0.030*	0.071*	−0.534*	1.000	
Dual	37,254	0.265	0.441	0.003	0.062*	−0.128*	−0.108*	−0.002	−0.012*	0.004	−0.015*	−0.292*	−0.213*	−0.049*	0.228*	−0.189*	0.112*	1.000

Note: This table shows the Pearson correlation coefficients. Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

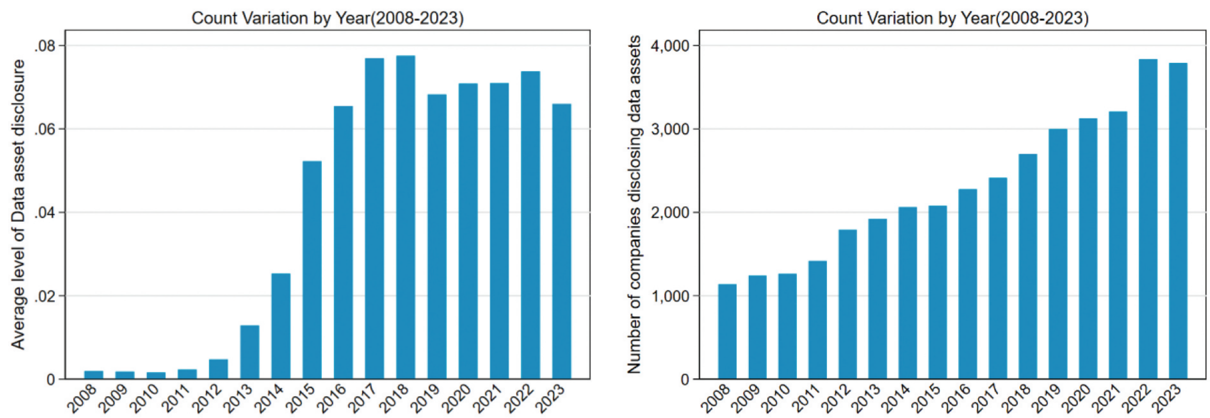

Figure 3. Count variation by year.

Table 3. Baseline regression results.

	H1a			H1b	
	Full sample	Overpricing sample	Underpricing sample	Full sample	Full sample
	(1)	(2)	(3)	(4)	(5)
Variation	*Misp*	Misp	*Misp*	Misp	*Misp*
DAD	−0.103***	−0.049**	−0.279*		
	(−3.840)	(−2.431)	(−1.649)		
SDA				−0.562***	
				(−3.553)	
TDA					−0.105***
					(−3.592)
Size	0.057***	0.023***	0.248***	0.056***	0.057***
	(5.028)	(3.634)	(4.988)	(4.964)	(5.006)
Lev	−0.293***	−0.387***	2.837***	−0.293***	−0.292***
	(−8.805)	(−14.890)	(11.101)	(−8.804)	(−8.786)
Roa	−2.678***	−3.209***	7.904***	−2.678***	−2.677***
	(−38.410)	(−47.237)	(11.675)	(−38.404)	(−38.402)
Cashflow	−0.233***	−0.898***	2.616***	−0.231***	−0.232***
	(−4.285)	(−25.240)	(13.049)	(−4.245)	(−4.276)
Growth	−0.016***	−0.008**	−0.040*	−0.016***	−0.016***
	(−2.907)	(−2.045)	(−1.858)	(−2.915)	(−2.901)
BM	−0.624***	−0.757***	2.068***	−0.624***	−0.624***
	(−15.273)	(−30.785)	(10.935)	(−15.254)	(−15.265)
Soe	−0.021	−0.003	0.040	−0.022	−0.021
	(−1.144)	(−0.219)	(0.513)	(−1.179)	(−1.143)
Age	−0.150***	−0.126***	0.185**	−0.150***	−0.150***
	(−6.302)	(−9.072)	(2.402)	(−6.270)	(−6.301)
Top3	0.136**	−0.001	−0.133	0.139**	0.136**
	(2.331)	(−0.024)	(−0.696)	(2.401)	(2.337)
Mshare	0.078*	0.057**	0.202	0.079*	0.078*
	(1.705)	(1.985)	(0.770)	(1.741)	(1.708)
Board	0.020	0.003	−0.136	0.020	0.020
	(0.593)	(0.133)	(−1.311)	(0.586)	(0.594)
Indep	0.103	−0.034	−0.451	0.105	0.103
	(0.973)	(−0.558)	(−1.566)	(0.986)	(0.973)
Dual	0.003	−0.001	0.026	0.003	0.003
	(0.393)	(−0.243)	(0.686)	(0.388)	(0.399)
_cons	0.033	0.938***	−8.052***	0.050	0.037
	(0.131)	(6.984)	(−6.813)	(0.200)	(0.150)
Year&FirmFE	Yes	Yes	Yes	Yes	Yes
N	37,254	30,582	6672	37,254	37,254
r2	0.407	0.683	0.706	0.472	0.472
F	131.696	260.712	26.765	130.129	131.722

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

transactional type. This suggests that self-use data asset disclosure plays a stronger role in reducing stock mispricing than its transactional counterpart. These findings support Hypothesis H1b.

5.3. Regression results for moderating effects

We conduct a series of subgroup regressions to examine how the internal control quality, the media attention, and the institutional ownership moderate the relationship between data asset disclosure and stock mispricing. First, regarding the internal control index (*IC*), we split the sample into two groups according to the median value of annual industry: a high-IC group (greater than or equal to the median) and a low-IC group (below the median). Columns (1) and (2) of Table 4 report the regression results. We find that the regression coefficient of data asset disclosure on stock mispricing is significantly negative only in the high-IC group, and the difference between the two groups is statistically significant. This suggests that data asset disclosure is more credible when issued by firms with higher internal control quality. This improved credibility enhances the signalling effect and contributes more effectively to the mitigation of stock mispricing. These findings provide empirical support for Hypothesis H2.

Second, regarding the media attention (*Media*), we divide the sample into two groups according to the median level of annual industry: a high media-attention group (at or above the median) and a low media-attention group (below the median). Columns (3) and (4) of Table 4 report the regression results. We find that the regression coefficient of data asset disclosure on stock mispricing is significantly negative only in the high media-attention group, and the difference between the two groups is statistically significant. This suggests that greater media attention enhances the signal observability and improves the signalling environment, which in turn reinforces the mitigating effect of data asset disclosure on stock mispricing. These findings support Hypothesis H3.

Finally, concerning the institutional ownership (*Inst*), we divide the sample into two groups according to the median level of annual industry: a high institutional ownership group (greater than or equal to the median) and a low institutional ownership group (below the median). Columns (5) and (6) of Table 4 report the regression results. We find that the regression coefficient of data asset disclosure on stock mispricing is significantly negative only in the high institutional ownership group, and the difference between the two groups is statistically significant. This suggests that firms with a higher proportion of institutional ownership are more willing and better equipped to receive and interpret data asset information. As a result, such information is more likely to be incorporated into stock prices and will exert a more substantial mitigating effect on stock mispricing. These findings provide empirical support for Hypothesis H4.

5.4. Robustness checks

5.4.1. Alternative measurements of stock mispricing

Following the approach of (W. Li and Zheng 2024), we re-measure stock mispricing by calculating the deviation between a firm's market value and its intrinsic value. The deviation is denoted as *Misp1*, which is

Table 4. Regression results for moderating effects.

	H2		H3		H4	
	higher IC	lower IC	higher Media	lower Media	higher Inst	lower Inst
	(1)	(2)	(3)	(4)	(5)	(6)
Variation	*Misp*	*Misp*	*Misp*	*Misp*	*Misp*	*Misp*
DAD	−0.130***	−0.062	−0.142***	−0.054	−0.179***	−0.015
	(−3.637)	(−1.625)	(−3.723)	(−1.600)	(−4.165)	(−0.480)
controls	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.209	−0.029	0.143	−0.014	0.701*	−0.003
	(0.522)	(−0.114)	(0.390)	(−0.041)	(1.724)	(−0.011)
Year&FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
N	18,815	18,439	18,875	18,379	18,649	18,605
r2	0.477	0.583	0.514	0.530	0.490	0.549
F	10.598	135.501	62.860	77.321	45.949	86.051
Bdiff (p value)	0.054		0.028		0.000	

Note: ***p<0.01, **p<0.05, *p<0.1.

Table 5. Results for robustness tests.

Variation	(1) *Misp1*	(2) *Misp*	(3) *L.Misp*
DAD	−0.068***	−0.214***	−0.062*
	(−3.904)	(−2.758)	(−1.684)
Controls	Yes	Yes	Yes
_cons	0.979***	0.052	−1.351***
	(9.675)	(0.209)	(−4.788)
Year&FirmFE	Yes	Yes	Yes
N	37,254	37,254	31,523
r2	0.498	0.472	0.384
F	32.505	130.620	11.860

Note: ***p<0.01, **p<0.05, *p<0.1.

calculated as: *Misp1*=|*ln(M/V)*|. In this equation, *M* represents the firm's market value, defined as the sum of the market value of common equity and the book value of debt. We follow the method of (Rhodes–Kropf, Robinson, and Viswanathan 2005) and conduct regressions of model (7) by industry to estimate intrinsic value (*V*). We first estimate annual regression coefficients for each sector and then compute industry-level averages across years. Finally, based on these regression coefficients, each firm's data are substituted into the corresponding industry equation to calculate its intrinsic value (*V*). The core idea of this method is that a set of common fundamental factors drives the value of companies within the same industry.

$$LnM_{i,t} = \beta_{0jt} + \beta_{1jt}LnB_{i,t} + \beta_{2jt}Ln(NI+)_{i,t} + \beta_{3jt}I_{(<0)}Ln(NI+)_{i,t} + \beta_{4jt}Lev_{i,t} + \mu_{i,t} \tag{7}$$

In Equation (7), *M* is the firm's market value, *B* is the total assets, and *NI+* denotes the absolute value of net income. *I(< 0)* is a binary variable equal to 1 if net income is negative and zero otherwise. *Lev* represents the leverage ratio, *μ* is the residual term, *i*, *j*, and *t* denote firm, industry, and year, respectively. As reported in Column (1) of Table 5, data asset disclosure (*DAD*) is negatively and significantly associated with stock mispricing (*Misp1*) at the 1% level, thereby reaffirming support for Hypothesis H1a.

5.4.2. Alternative measurements of data asset disclosure

To address potential measurement errors in text-based disclosure metrics, the 'data assets' indicator from the CNRDS database is adopted to replace the measurement method of the independent variable. In the benchmark regression, we did not use CNRDS data as the primary measurement for two reasons: First, the database had a limited coverage scope in the early stage of the sample, which may lead to sample selection bias; Second, the total 'data assets' indicator it provides fails to be further divided into 'self-use data assets' and 'transactional data assets', making it impossible to accurately capture the differences in the impact of data assets on stock mispricing under different application scenarios. Despite the limitations above, as an independent third-party data source, the CNRDS database can effectively reduce systematic bias and enhance the reliability of the conclusions. The regression results in Column (2) of Table 5 show that both the coefficient direction and significance level of the explanatory variable are consistent with those of the benchmark regression.

5.4.3. Single-stage lag processing

We replace the dependent variable with its one-period lagged value (*L.Misp*) and re-estimate the baseline regression to account for possible lagged effects of data asset disclosure on stock mispricing. The coefficient of data asset disclosure (*DAD*) remains significantly negative, consistent with the previous findings, as presented in Column (3) of Table 5.

5.5. Addressing endogeneity concerns

5.5.1. Instrumental variable approach

We adopt an instrumental variable (IV) approach in line with prior studies (Chang, Jo, and Li 2018; Xu et al. 2014) to address potential endogeneity concerns arising from reverse causality. Two instruments are introduced. First, at the industry level, we use the annual industry-average data asset disclosure level (*DAD_mean*) as the first instrument, which is calculated by excluding the focal firm from the average. Specifically, the rationale is that when the focal firm faces competitive pressure from peer firms within the same industry that disclose more data asset information in a given year, it is incentivised to enhance its own data infrastructure and disclosure practices. However, the disclosure behaviour of other firms in the same industry and year does not directly influence the focal firm's stock mispricing. This independence satisfies the exclusion restriction. Second, at the provincial level, we use the number of years since the launch of a public data platform in the firm's registered province (*OL*) as the second instrument. This is measured by the elapsed years since the platform's launch. Specifically, the rationale is that the availability of public data resources is a key indicator of government support for data utilisation. The longer the duration of public data availability, the more developed the region's data ecosystem is likely to be. Consequently, firms located in such provinces are more likely to engage in data-driven practices and voluntarily disclose data asset information. In Table 6, the p-value of the *Hansen J-statistic* is 0.229, indicating that we fail to reject the null hypothesis that all instruments are exogenous. The *Kleibergen-PaaprkLM* and *Kleibergen-PaaprkWaldF* statistics suggest that the model passes the under-identification and weak identification tests, respectively. Column (1) of Table 6 reports the first-stage regression results, showing that both instruments are significantly associated with firms' data asset disclosure. Column (2) presents the second-stage regression results, where the coefficient of data asset disclosure remains significantly negative at the 1% level. These findings suggest that the main results are robust after addressing endogeneity concerns.

5.5.2. Heckman two-stage model

We implement the Heckman two-stage approach to address potential sample selection bias and validate the robustness of our results. In the first stage, we set the data asset disclosure as the dependent variable (*DAD_dummy*), assigning a value of 1 if data asset information is disclosed and 0 otherwise. The control variables from the original model are included as independent variables, and the industry-year average of data asset disclosure, excluding the focal firm (*DAD_mean*), is introduced as an exclusion restriction variable. This model is then estimated using Probit regression to obtain the inverse Mills ratio (*IMR*), with the results presented in column (1) of Table 7. In the second stage, we re-estimate the regression by including the IMR variable in model (4), as reported in column (2) of Table 7. The coefficient of the IMR is statistically significant, indicating the presence of selection bias. After controlling for this bias, the regression coefficient of data asset disclosure (*DAD*) about stock mispricing (*Misp*) remains significantly negative, thus reaffirming the robustness of the previous findings.

5.5.3. PSM estimation

This study employs the propensity score matching (PSM) method to conduct an endogeneity test, thereby mitigating potential interference from sample selection bias. The sample is divided into an experimental group and a control group based on whether firms disclose data asset information. The control variables from model (4) are selected as covariates, and nearest-neighbour matching is performed at a 1:2 ratio to identify a control group with similar characteristics to the treatment group. Table 8 presents the balance test results, where the absolute values of the standardised bias for the matching variables are all below 10%. The *t*-test results are not significant, indicating no systematic differences between the control and treatment groups. As shown in column (3) of Table 7, the results suggest that the data asset disclosure (*DAD*) remains significantly negatively correlated with stock mispricing (*Misp*), which is consistent with the previous findings, even after performing the PSM matching and controlling for sample selection bias.

Table 6. Results for the instrumental variable approach.

Variation	(1) *DAD*		(2) *Misp*
DAD			−0.369*** (−5.27)
DAD_mean	0.842*** (13.67)		
OL	0.006*** (2.71)		
Controls	Yes		Yes
Year&FirmFE	Yes		Yes
N	37,254		37,254
Kleibergen-PaaprkLM		93.397	
Kleibergen-PaaprkWaldF		98.292	
Hansen J-statistic (p value)		0.229	

Note: ***p<0.01, **p<0.05, *p<0.1.

Table 7. Results for Heckman and PSM tests.

Variation	(1) *DAD_dummy*	(2) *Misp*	(3) *Misp*
DAD		−0.147***	−0.113***
		(−4.814)	(−4.057)
DAD_mean	1.043***		
	(4.814)		
IMR		0.310***	
		(3.105)	
Controls	Yes	Yes	Yes
_cons	−6.140***	−1.215**	−0.181
	(−28.225)	(−2.367)	(−0.615)
Year&FirmFE	Yes	Yes	Yes
N	37,254	37,254	25,990
r2		0.473	0.411
F		125.860	107.277

Note: ***p<0.01, **p<0.05, *p<0.1.

Table 8. Sample balance test.

Variable	Unmatched Matched	Mean Treated	Control	%bias	t-test t	p
Size	U	22.464	22.122	26.2	24.59	0.000
	M	22.463	22.468	−0.4	−0.3	0.764
Cashflow	U	0.046	0.046	−0.4	−0.4	0.687
	M	0.046	0.046	0.3	0.3	0.768
Growth	U	0.147	0.165	−3.9	−3.55	0.000
	M	0.147	0.147	0	0.01	0.992
Lev	U	0.441	0.460	−9.1	−8.47	0.000
	M	0.441	0.440	0.7	0.58	0.559
Roa	U	0.024	0.027	−4.7	−4.41	0.000
	M	0.024	0.025	−1.3	−1.02	0.308
Top3	U	0.461	0.468	−3.9	−3.68	0.000
	M	0.461	0.465	−2.3	−1.87	0.062
BM	U	0.326	0.316	6.6	6.18	0.000
	M	0.326	0.328	−0.8	−0.69	0.490
Age	U	2.334	2.355	−3.1	−2.94	0.003
	M	2.334	2.329	0.8	0.69	0.493
Mshare	U	0.128	0.093	20.3	19.16	0.000
	M	0.128	0.129	−0.6	−0.49	0.625
Board	U	2.107	2.134	−13.4	−12.59	0.000
	M	2.107	2.104	1.3	1.09	0.274
Indep	U	0.3806	0.374	11.7	10.98	0.000
	M	0.3806	0.381	−0.2	−0.17	0.862
Dual	U	0.307	0.239	15.2	14.36	0.000
	M	0.307	0.300	1.6	1.27	0.202
Soe	U	0.325	0.418	−19.4	−17.97	0.000
	M	0.325	0.325	0	−0.03	0.980

5.6. Further analysis

5.6.1. Strategic disclosure test

The above results confirm that data asset disclosure can alleviate stock mispricing. However, they do not necessarily indicate that this mitigating effect stems solely from the normal disclosure of information. Such information may also be subject to strategic disclosure behaviours. Data asset information represents valuable positive signals in the context of the digital economy. Managers may use the disclosure for personal gain, for example, they may strategically disclose data asset information to influence the capital market, steering decisions that favour their interests (Martinez-Ferrero, Suarez-Fernandez, and Garcia-Sanchez 2019) and enabling them to sell stocks at inflated prices. Additionally, data asset information disclosed by firms is mainly presented in complex textual form. This type of disclosure typically lacks relevant standards and is not subject to auditing procedures, which makes verification difficult (Fatemi, Fooladi, and Tehranian 2015). This situation grants managers considerable discretion. As a result, corporate managers may strategically disclose data assets to engage in concept marketing, divert stakeholder attention, and mislead investors' assessments of the company's value. To further examine whether the market can identify strategic data asset disclosure, this study, referring to Richardson (2006), constructs a model to determine the degree of data asset disclosure, as shown in Model (8). In regression models, the residual term reflects the difference between the observed values and the predicted values of the model, which represents the part that the independent variables and the model itself cannot explain. Based on this principle, in the context of this study, if the objective indicators of enterprises cannot explain the characteristics of data assets mentioned in the annual reports, this part of the difference will be presented as a residual term. Therefore, this study regards the abnormal disclosure of data assets in corporate annual reports as a specific manifestation of residuals and uses this to measure the subjective bias of enterprises in the disclosure of data assets.

$$DAD_{i,j,t} = \beta_0 + \beta_1 DAD\_mean_{i,j,t} + \beta_i Controls_{i,j,t} + \Sigma Year + \Sigma Firm + \varepsilon_{i,j,t} \tag{8}$$

Where the dependent variable in this model is the level of data asset disclosure (*DAD*), and the explanatory variable is the annual industry average of other firms' data asset disclosure (*DAD_mean*). The control variables (*Controls*) are consistent with the main test. Additionally, fixed effects for both firms and years are included. We estimate the normal level of data asset disclosure by using a regression model (8), with the residual (ε) representing the level of abnormal disclosure. A positive residual ($\varepsilon > 0$) indicates inflated disclosure, while a residual less than or equal to zero ($\varepsilon \leq 0$) indicates no inflated disclosure. In this study, we categorise the sample into two groups based on whether the residual (ε) is greater than zero: the inflated disclosure group and the normal disclosure group. We then conduct regressions on both groups using model (6), as shown in columns (1) and (2) of Table 9. The results reveal that only in the normal disclosure group is there a significant negative correlation between data asset disclosure (*DAD*) and stock mispricing (*Misp*). The inflated disclosure group does not pass the significance test, suggesting that the negative correlation between the two is not driven by inflated disclosure. It is only the normal data asset disclosure that exhibits signal validity.

5.6.2. Phased test

Considering the emergence of digital and intelligent technologies and the implementation of digital economy policies in China, we also conduct a dynamic analysis of the effect of data asset disclosure by dividing the sample into three sub-phases, i.e. 2008–2013, 2014–2019, and 2020–2023. Specifically, during the first period, as shown in column (3) of Table 9, the coefficient of DAD is negative but insignificant. One plausible explanation is that firms were undergoing informatisation transformation during this phase, while the strategic significance of data assets had not yet been recognised by the market. With the advent of emerging ABCD digital technologies and the rise of the Web 2.0 era, data was formally recognised as a critical factor of production, thereby attracting increased attention from the capital market to data asset disclosure. Consequently, in the second period, as shown in column (4) of Table 9, the DAD coefficient becomes significantly negative at the 10% level, indicating that data asset disclosure begins to fulfil its role as a value signal and exerts a significant corrective effect on asset mispricing. Notably, as shown in column (5) of Table 9, the absolute value of the DAD coefficient in the third phase further increases to 0.113 and remains significant at the 1% level. This is attributable to the accelerating circulation and market-oriented allocation of data resources, which are driven by technologies such as 5 G and artificial intelligence as well as national initiatives like Made in China 2025. Hence, data asset disclosure has become an increasingly salient and indispensable factor in investors' asset valuation processes with the proliferation of firm data resources and assets.

Table 9. Results for further analysis.

Variation	(1) Exaggerated sample *Misp*	(2) Normal sample *Misp*	(3) 2008–2013 *Misp*	(4) 2014–2019 *Misp*	(5) 2020–2023 *Misp*
DAD	0.060	−0.205**	−0.055	−0.075*	−0.113***
	(1.004)	(−2.177)	(−0.528)	(−1.884)	(−3.558)
Controls	Yes	Yes	Yes	Yes	Yes
_cons	1.126***	−0.790**	1.199***	0.720***	−1.036***
	(3.867)	(−2.060)	(15.727)	(2.826)	(−10.097)
Year&FirmFE	Yes	Yes	Yes	Yes	Yes
N	17,106	20,148	8771	14,526	13,877
r2	0.555	0.575	0.292	0.307	0.282
F	61.484	95.527	226.989	394.240	273.926
Bdiff(p value)	0.000			0.000	

Note: There are inter-group differences between every pair of the grouped data in (3), (4), and (5).
Note: ***p<0.01, **p<0.05, *p<0.1.

6. Discussions and conclusions

Even though the rapid development of the digital economy and digital transformation requires firms' data resources for gaining competitive advantages, we still lack knowledge about whether and how firms' data asset disclosure can mitigate stock mispricing. In this regard, this study draws upon signalling theory to explore the effects of data asset disclosure on stock mispricing. Using data from Chinese A-share listed companies between 2008 and 2023, we first apply the textual analysis method to extract and quantify sample firms' data asset disclosure from annual reports, and then empirically examine the effects of data asset disclosure on stock mispricing. The analysis results demonstrate that data asset disclosure can alleviate stock mispricing under both overpricing and underpricing scenarios. When categorising the context of data asset disclosure according to firms' concrete and strategic utilisation preferences, we found that self-use data asset disclosure exerts a more substantial effect in alleviating stock mispricing compared to transactional ones. Meanwhile, higher quality of firms' internal control, more media attention, and higher proportions of institutional ownership generate more pronounced mitigating effects of data asset disclosure on stock mispricing. Moreover, as firms may exaggerate their voluntary information disclosure for bragging advantages of data assets, we also investigate the potential effect of strategic data asset disclosure and found that inflated data asset disclosure does not exhibit signalling effects but only normal disclosure can alleviate stock mispricing. These findings provide several significant theoretical contributions and managerial and policy implications.

6.1. Theoretical contributions

This study contributes to the extant research from several aspects as follows. First, we extend the research on the crucial consequences of data asset disclosure by examining its effects on firms' stock mispricing. With the increasing importance of data assets for firms' operations management and decision-making, prior studies identified the significant potential of data assets to promote green innovation, reduce operational costs, and enhance corporate value (Goldfarb and Tucker 2019; Gunasekaran et al. 2017; Hannila et al. 2022; Ruffoni and Reichert 2024). However, data assets can not be recognised as strategic resource advantages by external stakeholders unless firms initiate relevant information disclosure voluntarily. Whether or not to disclose firms' data assets could bring firms both benefits and risks at the same time, given that rivals can easily imitate such data advantages. Therefore, a surge of literature investigates the financial consequences of data assets disclosure by primarily focusing on stock price synchronicity and stock return idiosyncratic volatility as indicators of capital market effects (Sun and Du 2024; Wei et al. 2025). We contribute to this stream of cutting-edge studies by revealing that data asset disclosure can alleviate stock mispricing across both overpricing and underpricing scenarios. Such that the effect adheres to firms' stock prices to their intrinsic market values and then improves pricing efficiency as well as financial stability in capital markets. More importantly, we further uncover that the mitigating effects of data asset disclosure are more pronounced when firms disclose self-use data assets rather than transactional ones, while strategic data asset disclosure in an exaggerated manner does not alleviate stock mispricing. In sum, we present fresh and novel empirical evidence regarding whether and how firms' data assets disclosure alleviates stock mispricing, primarily through investigating distinct disclosure contents and strategies.

Second, this study contributes to the existing literature by extending the antecedents of stock mispricing via identifying the novel voluntary information disclosure in terms of data assets. Previous research mainly relies on the effects of either firms' financial information disclosure (Berkman et al. 2009; Pantzalis and Park 2014) or mandatory non-financial information disclosure on stock pricing, such as key audit matters and social responsibility reports (W. Li and Zheng 2024; Wu et al. 2024). Even though voluntary information disclosure equips investors with extra knowledge for capturing firms' distinct competitive advantages, limited literature examines the impact of voluntary non-financial information disclosure on stock mispricing. In this sense, we fulfil the current research gap by shedding light on firms' data asset disclosure in a voluntary manner, which has not yet been formally recognised in financial statements but has been identified as the new oil propelling intelligent operations management in the digitalisation era. Our study finds that data asset disclosure significantly reduces stock mispricing, specifically alleviating both overpricing and underpricing situations. These results suggest that data asset disclosure, serving as a form of voluntary non-financial information disclosure, also constitutes a relevant driver for disentangling stock mispricing, thereby enriching the literature on its underlying causes.

Third, the comprehensive analytical framework underpinned by signalling theory also contributes to the current literature by resolving key factors that influence signal efficacy, including signal quality, signalling environment, and counter-signals from the capital market. Although previous research on the signalling theory has mainly concentrated on the moderating effects of signal attributes, little research has delved into the roles of signal quality, signaller characteristics, and the signalling environment in influencing signal efficacy (Lam 2018). To address this existing theoretical gap, we identify firms' data asset disclosure as essential signals sent to external stakeholders in the capital market, and further categorise these signals into distinct types according to firms' specific utilisation preferences regarding data assets, i.e. self-use and transactional ones. Such theoretical guidance helps us gain a better understanding of how distinct signal qualities influence investors' counter-signals in terms of stock pricing. More importantly, we also applied the theoretical constructs of signaller characteristics and signalling environment that moderate the relationship between data asset disclosure and stock mispricing. Specifically, we found that firms with higher internal control quality, more media exposure, and a higher proportion of institutional ownership could yield more favourable outcomes in terms of mitigating stock mispricing when voluntarily disclosing data assets. These findings highlight that the effectiveness of data asset signals is shaped by the characteristics of both the signaller and the receiver, as well as the signalling environment, providing a clearer understanding of how data asset disclosure affects stock mispricing. Therefore, our research extends the application of the signalling theory and provides an analytical framework for studying the value of voluntary information disclosure.

6.2. Managerial and policy implications

Our findings provide managerial guidance for firms when they implement data asset disclosure. First, data asset disclosure by firms can play a signalling role in capital markets and mitigate stock mispricing. Specifically, self-use data asset disclosure has a more pronounced effect. In light of this, we recommend that firms recognise the signalling function of data assets and actively disclose relevant information, with particular emphasis on self-use data assets that reflect their core business activities. For instance, Firms can refer to the framework of 'Data-Driven Enterprise Health Assessment' to systematically disclose information regarding their data resources, application capabilities, value creation, and other related aspects through annual reports, interim announcements (Zhu et al. 2025). They can also disclose their achievements in digital infrastructure development, digital technology application, and digitalisation efforts through investor relations platforms, social media, and official social media accounts. These disclosures would allow investors to assess firm value based on more comprehensive information, enabling more rational investment decisions and mitigating stock mispricing.

Second, our findings indicate that higher internal control quality, media attention, and institutional ownership enhance the effect of data asset disclosure on mitigating stock mispricing. Therefore, we recommend that firms establish dedicated teams for data management and disclosure, improve internal control mechanisms, and enhance the oversight of data asset disclosure. For example, strengthen information technology controls: ensure the integrity and security of the data disclosed by enterprises through system permission management, data encryption, and backup; establish an inter-departmental collaboration mechanism to realise the sharing of data asset information among the finance, IT, and legal departments, thereby ensuring the consistency of disclosed content. This would help ensure fair disclosure to capital markets and increase the credibility of data asset signals. Furthermore, we encourage media outlets to leverage their informational advantages to increase attention to corporate data asset disclosure, expand the dissemination channels, and reduce investors' costs in seeking and interpreting data asset information. Media could also expose any strategic data asset disclosure and enhance the effectiveness of data asset signals. Finally, we recommend that firms attract and cultivate long-term institutional investors who proactively collect and interpret disclosed data asset information. Investors should actively apply technologies such as big data analytics and text mining to conduct in-depth analysis of data asset information in corporate annual reports, identify the types of data assets disclosed by enterprises and their strategic disclosure behaviours, and dig into high-quality and differentiated information about the characteristics of data assets. By incorporating this information into stock prices, they can make more informed and rational investment decisions based on their professional expertise.

Finally, our findings could also deliver critical policy implications for the governance of data asset disclosure. Given the merit of data asset disclosure for mitigating firms' stock mispricing via reducing information asymmetry in capital markets, governments should encourage such the novel pattern of information disclosure, especially through enacting disclosure regulations to spotlight the content, compliance, and form of data assets. In particular, content guidelines includes the scale and structure of data assets, value realisation methods, and valuation approaches, while compliance covers the compliance of data sources, security, and risk management. Moreover, disclosure form of data assets encompasses the location and frequency of data asset information disclosure, as well as standardised and digital disclosure templates. At the same time, governments could also set up grained accountability and communication mechanisms to facilitate investor appeals regarding the inaccurate disclosure of firms' data assets. In doing so, the edges of data asset disclosure at the very early stage could be further realised through government regulations, which significantly mitigates the concerns of data washing and exaggeration.

6.3. Limitations and future research

Akin to other research, this study has certain limitations as outlined below. First, the term 'data asset' and its related expressions used in our text dictionary may not fully capture all data asset information included in annual reports, due to the increasing diversification of data asset applications and the constant emergence of new terminology. Second, although we have found that data asset disclosure by listed companies can alleviate stock mispricing, we have not analysed the readability and complexity of this information. As such, we are unable to directly assess how the quality of data asset disclosure affects the pricing efficiency of capital markets. Finally, although the rapid development of digital economy and diverse characteristics of capital market in China propel us to focus on Chinese listed firms, such the sampling process relying on single market may limit the generalisation of our findings. Future research could further employ data from global markets to validate our results, shedding light on the differential impacts of data asset disclosure across diverse capital market settings.

Notes

1. Source available at: https://www.annualreports.com/HostedData/AnnualReportArchive/m/NASDAQ_MSFT_2023.pdf.
2. Source available at: https://finance.eastmoney.com/a/202504253388897875.html.

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ORCID

Ying Kei (Mike) Tse http://orcid.org/0000-0001-6174-0326

References

Abraham, R., J. Schneider, and J. Vom Brocke. 2019. "Data Governance: A Conceptual Framework, Structured Review, and Research Agenda." *International Journal of Information Management* 49:424–438. https://doi.org/10.1016/j.ijinfomgt.2019.07.008.

Abrardi, L., C. Cambini, and F. Pino. 2024. "Regulating Data Sales: The Role of Data Selling Mechanisms." *Telecommunications Policy* 48 (8): 102813. https://doi.org/10.1016/j.telpol.2024.102813.
Alshaiti, H. 2023. "Influences of Internal Control on Enterprise Performance: Does an Information System Make a Difference?" *Journal of Risk and Financial Management* 16 (12): 518. https://doi.org/10.3390/jrfm16120518.
An, Y., H. Jin, Q. Liu, and K. Zheng. 2022. "Media Attention and Agency Costs: Evidence from Listed Companies in China." *Journal of International Money and Finance* 124:102609. https://doi.org/10.1016/j.jimonfin.2022.102609.
Andrei, D., and M. Hasler. 2015. "Investor Attention and Stock Market Volatility." *The Review of Financial Studies* 28 (1): 33–72. https://doi.org/10.1093/rfs/hhu059.
Ashbaugh-Skaife, H., D. W. Collins, and W. R. Kinney. 2007. "The Discovery and Reporting of Internal Control Deficiencies Prior to SOX-Mandated Audits." *Journal of Accounting and Economics* 44 (1–2): 166–192. https://doi.org/10.1016/j.jacceco.2006.10.001.
Azevedo, V., and S. Müller. 2024. "Analyst Recommendations and Mispricing Across the Globe." *Journal of Banking & Finance* 169:107296. https://doi.org/10.1016/j.jbankfin.2024.107296.
Bafera, J., and S. Kleinert. 2022. "Signaling Theory in Entrepreneurship Research: A Systematic Review and Research Agenda." *Entrepreneurship Theory and Practice* 47 (6): 104225872211384. https://doi.org/10.1177/10422587221138489.
Balboni, P. D. P., and K. E. Francis. 2025. "Data Ethics and Digital Sustainability: Bridging Legal Data Protection Compliance and ESG for a Responsible Data-Driven Future." *Journal of Responsible Technology* 22:100099. https://doi.org/10.1016/j.jrt.2024.100099.
Becker-Blease, J., and A. Irani. 2008. "Do Corporate Governance Attributes Affect Adverse Selection Costs? Evidence from Seasoned Equity Offerings." *Review of Quantitative Finance and Accounting* 30 (3): 281–296. https://doi.org/10.1007/s11156-007-0051-x.
Berkman, H., V. Dimitrov, P. C. Jain, P. D. Koch, and S. Tice. 2009. "Sell on the News: Differences of Opinion, Short-Sales Constraints, and Returns Around Earnings Announcements." *Journal of Financial Economics* 92 (3): 376–399. https://doi.org/10.1016/j.jfineco.2008.04.009.
Bhattacharya, U., N. Galpin, R. Ray, and X. Yu. 2009. "The Role of the Media in the Internet IPO Bubble." *Journal of Financial and Quantitative Analysis* 44 (3): 657–682. https://doi.org/10.1017/s0022109009990056.
Bhatti, A., H. Malik, A. Kamal, A. Aamir, L. Alaali, and Z. Ullah. 2021. "Much-Needed Business Digital Transformation Through Big Data, Internet of Things and Blockchain Capabilities: Implications for Strategic Performance in Telecommunication Sector." *Business Process Management Journal, Ahead-of-Print* 27 (6): 1854–1873. https://doi.org/10.1108/BPMJ-12-2020-0553.
Bofinger, Y., K. J. Heyden, and B. Rock. 2022. "Corporate Social Responsibility and Market Efficiency: Evidence from ESG and Misvaluation Measures." *Journal of Banking & Finance* 134:106322. https://doi.org/10.1016/j.jbankfin.2021.106322.
Caglayan, M., T. Pham, O. Talavera, and X. Xiong. 2020. "Asset Mispricing in Peer-to-Peer Loan Secondary Markets." *Journal of Corporate Finance* 65:101769. https://doi.org/10.1016/j.jcorpfin.2020.101769.
Callen, J. L., and X. Fang. 2015. "Short Interest and Stock Price Crash Risk." *Journal of Banking & Finance* 60:181–194. https://doi.org/10.1016/j.jbankfin.2015.08.009.
Cao, H., H. V. Phan, and S. Silveri. 2024. "Data Breach Disclosures and Stock Price Crash Risk: Evidence from Data Breach Notification Laws." *International Review of Financial Analysis* 93:103164. https://doi.org/10.1016/j.irfa.2024.103164.
Chang, K., H. Jo, and Y. Li. 2018. "Is There Informational Value in Corporate Giving?" *Journal of Business Ethics* 151 (2): 473–496. https://doi.org/10.1007/s10551-016-3230-7.
Chen, L. 2024. "Does Data Assetisation Improve Corporate Liquidity and Corporate Growth? Evidence from "Hidden Champion" SMEs in China." *Borsa Istanbul Review* 24 (6): 24. https://doi.org/10.1016/j.bir.2024.07.008.
Chen, R., K. Tao, C. Jin, J. Zhang, and S. Zhang. 2025. "Navigating Uncertainty: The Impact of Economic Policy on Corporate Data Asset Allocation." *International Review of Economics & Finance* 97:103783. https://doi.org/10.1016/j.iref.2024.103783.
Cheng, Q., B. Goh, and J. Kim. 2018. "Internal Control and Operational Efficiency." *Contemporary Accounting Research* 35 (2): 35. https://doi.org/10.1111/1911-3846.12409.
Clarkson, P. M., X. Fang, Y. Li, and G. Richardson. 2013. "The Relevance of Environmental Disclosures: Are Such Disclosures Incrementally Informative?" *Journal of Accounting and Public Policy* 32 (5): 410–431. https://doi.org/10.1016/j.jaccpubpol.2013.06.008.
Connelly, B., T. Certo, C. Reutzel, M. DesJardine, and Y. Zhou. 2024. "Signaling Theory: State of the Theory and Its Future." *Journal of Management* 51 (1): 24–61. https://doi.org/10.1177/01492063241268459.
Connelly, B. L., S. T. Certo, R. D. Ireland, and C. R. Reutzel. 2011. "Signaling Theory: A Review and Assessment." *Journal of Management* 37 (1): 39–67. https://doi.org/10.1177/0149206310388419.
Dahiya, R., S. Le, and M. J. Kroll. 2025. "Big Data Analytics and Firm Performance: The Effects of Human Capital and Mediating Firm Capabilities." *Journal of Strategy & Innovation* 36 (1): 200535. https://doi.org/10.1016/j.jsinno.2025.200535.
Dai, L., J. Parwada, and B. Zhang. 2015. "The Governance Effect of the Media's News Dissemination Role: Evidence from Insider Trading." *Journal of Accounting Research* 53 (2): 331–366. https://doi.org/10.1111/1475-679X.12073.
Desgourdes, C., and J. Ram. 2024. "The Role of Big Data Analytics for Decision-Making in Projects: Uses and Challenges." *Enterprise Information Systems* 18 (4): 2317153. https://doi.org/10.1080/17517575.2024.2317153.

Dong, F., J. Miao, and P. Wang. 2020. "Asset Bubbles and Monetary Policy." *Review of Economic Dynamics* 37:S68–S98. https://doi.org/10.1016/j.red.2020.06.003.

Drover, W., M. Wood, and A. Corbett. 2017. "Toward a Cognitive View of Signalling Theory: Individual Attention and Signal Set Interpretation." *Journal of Management Studies* 55 (2): 209–231. https://doi.org/10.1111/joms.12282.

Elsayed, M., and T. Elshandidy. 2021. "Internal Control Effectiveness, textual Risk Disclosure, and Their Usefulness: U.S. Evidence." *Advances in Accounting* 53:100531. https://doi.org/10.1016/j.adiac.2021.100531.

Fatemi, A., I. Fooladi, and H. Tehranian. 2015. "Valuation Effects of Corporate Social Responsibility." *Journal of Banking & Finance* 59:182–192. https://doi.org/10.1016/j.jbankfin.2015.04.028.

Feng, Y., Z. Zhang, J. Zhang, and W. Zhou. 2025. "More Authentic Data Asset Disclosure by Myopic Managers: Evidence from China." *International Review of Financial Analysis* 104444:104444. https://doi.org/10.1016/j.irfa.2025.104444.

Fernandez, R., P. Subramaniam, and M. Franklin. 2020. "Data market platforms: Trading data assets to solve data problems." *Proceedings of the VLDB Endowment* 13 (12): 1933–1947. https://doi.org/10.48550/arXiv.2002.01047.

Frankel, R., and C. M. C. Lee. 1998. "Accounting Valuation, Market expectation, and Cross-Sectional Stock Returns." *Journal of Accounting and Economics* 25 (3): 283–319. https://doi.org/10.1016/S0165-4101(98)00026-3.

Gao, T., X. Cui, and L. Xu. 2025. "Does Investor Short-Horizon Affect Stock Mispricing? An Empirical Study Based on Higher Order Expectation Theory." *Finance Research Letters* 79:107202. https://doi.org/10.1016/j.frl.2025.107202.

Garcia Osma, B., E. Scarlat, and K. Shields. 2020. "Insider Trading Restrictions and Earnings Management." *Accounting and Business Research* 50 (3): 1–33. https://doi.org/10.1080/00014788.2020.1712650.

Goldfarb, A., and C. Tucker. 2019. "Digital Economics." *Journal of Economic Literature* 57 (1): 3–43. https://doi.org/10.1257/jel.20171452.

Gunasekaran, A., T. Papadopoulos, R. Dubey, S. F. Wamba, S. J. Childe, B. Hazen, and S. Akter. 2017. "Big Data and Predictive Analytics for Supply Chain and Organizational Performance." *Journal of Business Research* 70:308–317. https://doi.org/10.1016/j.jbusres.2016.08.004.

Gupta, B. B., A. Gaurav, V. Arya, and P. K. Panigrahi. 2025. "Big Data Innovations in Enterprise Information Systems: Strategies Formation for New Generation Entrepreneurs." *Enterprise Information Systems* 19 (1–2): 2449261. https://doi.org/10.1080/17517575.2024.2449261.

Han, Y., D. Huang, D. Huang, and G. Zhou. 2022. "Expected Return, Volume, and Mispricing." *Journal of Financial Economics* 143 (3): 1295–1315. https://doi.org/10.1016/j.jfineco.2021.05.014.

Hannila, H., R. Silvola, J. Harkonen, and H. Haapasalo. 2022. "Data-Driven Begins with DATA; Potential of Data Assets." *Journal of Computer Information Systems* 62 (1): 29–38. https://doi.org/10.1080/08874417.2019.1683782.

Hommes, C., J. Sonnemans, J. Tuinstra, and H. van de Velden. 2008. "Expectations and Bubbles in Asset Pricing Experiments." *Journal of Economic Behavior & Organization* 67 (1): 116–133. https://doi.org/10.1016/j.jebo.2007.06.006.

Hou, K., M. A. van Dijk, and Y. Zhang. 2012. "The Implied Cost of Capital: A New Approach." *Journal of Accounting and Economics* 53 (3): 504–526. https://doi.org/10.1016/j.jacceco.2011.12.001.

Hu, J., Y. Tang, N. Yin, and X. Guo. 2023. "Institutional Investor Information Competition and Accounting Information Transparency: Implications for Financial Markets and Corporate Governance in China." *Journal of the Knowledge Economy* 15 (2): 9629–9666. https://doi.org/10.1007/s13132-023-01482-8.

Jiang, M., B. Zhu, and L. Li. 2024. "Manager-Specific Manipulation of Tone and Stock Price Synchronicity." *Accounting & Finance* 64 (4): 3803–3821. https://doi.org/10.1111/acfi.13283.

Kim, H., and Y. Yasuda. 2019. "Accounting Information Quality and Guaranteed Loans: Evidence from Japanese SMEs." *Small Business Economics* 53 (4): 1–18. https://doi.org/10.1007/s11187-018-0106-5.

Krause, T. A., and Y. Tse. 2016. "Risk Management and Firm Value: Recent Theory and Evidence." *International Journal of Accounting and Information Management* 24 (1): 56–81. https://doi.org/10.1108/IJAIM-05-2015-0027.

Kruesi, L., F. Burstein, and K. Tanner. 2020. "A Knowledge Management System Framework for an Open Biomedical Repository: Communities, Collaboration and Corroboration." *Journal of Knowledge Management* 24 (10): 2553–2572. https://doi.org/10.1108/JKM-05-2020-0370.

Lam, H. 2018. "Doing Good Across Organizational Boundaries: Sustainable Supply Chain Practices and Firms' Financial Risk." *International Journal of Operations & Production Management* 38 (12): 2389–2412. https://doi.org/10.1108/IJOPM-02-2018-0056.

Lewis, K. F., F. A. Longstaff, and L. Petrasek. 2021. "Asset Mispricing." *Journal of Financial Economics* 141 (3): 981–1006. https://doi.org/10.1016/j.jfineco.2020.05.011.

Li, C., X. Liu, Z. Hou, and Y. Li. 2023. "Retail Investor Attention and Equity Mispricing: The Mediating Role of Earnings Management." *Finance Research Letters* 53:103621. https://doi.org/10.1016/j.frl.2022.103621.

Li, C., H. Yang, J. Li, C. Tao, and Y. Zhong. 2025. "Do Private Placements Exacerbate the Degree of Asset Mispricing? A Study Based on Theories of Information Asymmetry and Signaling." *Borsa Istanbul Review* 25 (2): 240–252. https://doi.org/10.1016/j.bir.2024.12.006.

Li, W., and X. Zheng. 2024. "Key Audit Matter Disclosure and Stock Mispricing: Evidence from China." *Finance Research Letters* 67:105843. https://doi.org/10.1016/j.frl.2024.105843.

Li, Y., C. Luo, L. Dong, and G. Meizeng. 2022. "Data Asset Disclosure and Nonprofessional Investor Judgment: Evidence from Questionnaire Experiments." *Mobile Information Systems* 2022:1–8. https://doi.org/10.1155/2022/8116063.

Li, Y., X. Wang, and X. Zheng. 2024. "Data Assets and Corporate Sustainable Development: Evidence from ESG in China." *Pacific-Basin Finance Journal* 85:102378. https://doi.org/10.1016/j.pacfin.2024.102378.

Liao, L.-K., T. Mukherjee, and W. Wang. 2015. "Corporate Governance and Capital Structure Dynamics: An Empirical Study." *Journal of Financial Research* 38 (2): 169–192. https://doi.org/10.1111/jfir.12057.

Lin, X., H. Zhu, and Y. Meng. 2023. "ESG Greenwashing and Equity Mispricing: Evidence from China." *Finance Research Letters* 58:104606. https://doi.org/10.1016/j.frl.2023.104606.

Liu, D., C. Sui, and P. Lung. 2016. "The Equity Mispricing: Evidence from China's Stock Market." *Pacific-Basin Finance Journal* 39:39. https://doi.org/10.1016/j.pacfin.2016.06.007.

Liu, W., W. Wei, C. Si, D. Xie, and L. Chen. 2020. "Effect of Supply Chain Strategic Collaboration Announcements on Shareholder Value: An Empirical Investigation from China." *International Journal of Operations & Production Management, Ahead-of-Print* 40 (4): 389–414. https://doi.org/10.1108/IJOPM-05-2019-0368.

Liu, X., J. Dai, X. Dong, and J. Liu. 2024. "ESG Rating Disagreement and Analyst Forecast Quality." *International Review of Financial Analysis* 95:103446. https://doi.org/10.1016/j.irfa.2024.103446.

Martinez-Ferrero, J., O. Suarez-Fernandez, and I.-M. Garcia-Sanchez. 2019. "Obfuscation versus Enhancement as Corporate Social Responsibility Disclosure Strategies [article]." *Corporate Social Responsibility and Environmental Management* 26 (2): 468–480. https://doi.org/10.1002/csr.1697.

Merín-Rodrigáñez, J., À. Dasí, and J. Alegre. 2024. "Digital Transformation and Firm Performance in Innovative SMEs: The Mediating Role of Business Model Innovation." *Technovation* 134:103027. https://doi.org/10.1016/j.technovation.2024.103027.

Narasimhan, R., T. Schoenherr, B. Jacobs, and M. K. Kim. 2015. "The Financial Impact of FSC Certification in the United States: A Contingency Perspective." *Decision Sciences* 46 (3): 527–563. https://doi.org/10.1111/deci.12141.

Narayan, P. K., and S. S. Sharma. 2023. "Understanding Mispricing in the Travel and Leisure Industry." *International Review of Financial Analysis* 90:102869. https://doi.org/10.1016/j.irfa.2023.102869.

Ni, X. M., T. T. Zheng, F. Gao, and H. M. Zhao. 2024. "Stimulating Start-Up Investment Through Government-Sponsored Venture Capital: Theory and Chinese Evidence." *Journal of Systems Science & Complexity* 37 (5): 2021–2053. https://doi.org/10.1007/s11424-024-3282-1.

Ning, J., X. Jiang, and J. Luo. 2023. "Relationship Between Enterprise Digitalization and Green Innovation: A Mediated Moderation Model." *Journal of Innovation & Knowledge* 8 (1): 100326. https://doi.org/10.1016/j.jik.2023.100326.

Nishant, R., T. Teo, and M. Goh. 2017. "Do Shareholders Value Green Information Technology Announcements?" *Journal of the Association for Information Systems* 18 (8): 542–576. https://doi.org/10.17705/1jais.00466.

Pang, B., J. Gou, L. M. Camarinha-Matos, J. Z. Zhang, and L. Zhang. 2025. "Scenario-Oriented Data Interoperability: Maximising the Connection Between Data and Users in Collaboration Environments." *Enterprise Information Systems* 19 (1–2): 2445604. https://doi.org/10.1080/17517575.2024.2445604.

Pant, P., R. Yadav, K. P. Niyas, M. Dadsena, K. K, S. Pratap, and A. Sachan. 2025. "Fake News Detection for Sustainable Supply Chain Management Using Deceptive Tones: An Application of ML, NLP and Explainable AI." *Enterprise Information Systems* 19 (9). https://doi.org/10.1080/17517575.2025.2510350.

Pantzalis, C., and J. C. Park. 2014. "Agency Costs and Equity Mispricing." *Asia-Pacific Journal of Financial Studies* 43 (1): 89–123. https://doi.org/10.1111/ajfs.12041.

Qian, B., and Y. Tan. 2024. "Firm-Specific Investor Sentiment and Stock Price Informativeness." *Finance Research Letters* 66, Article 105680. 105680. https://doi.org/10.1016/j.frl.2024.105680.

Qian, K., C. X. Pan, and X. Y. Liang. 2025. "Does Data Asset Disclosure Affect Bank Lending Acquisition?" *International Review of Financial Analysis* 97, Article 103834. 103834. https://doi.org/10.1016/j.irfa.2024.103834.

Rassier, D. G., R. J. Kornfeld, and E. H. Strassner. 2019. "Treatment of Data in National Accounts." *BEA Advisory Committee. U.S. Bureau of Economic Analysis*. https://www.bea.gov/sites/default/files/2019-05/Paper-on-Treatment-of-Data-BEA-ACM.pdf.

Rhodes–Kropf, M., D. T. Robinson, and S. Viswanathan. 2005. "Valuation Waves and Merger Activity: The Empirical Evidence." *Journal of Financial Economics* 77 (3): 561–603. https://doi.org/10.1016/j.jfineco.2004.06.015.

Richardson, S. 2006. "Over-Investment of Free Cash Flow." *Review of Accounting Studies* 11 (2): 159–189. https://doi.org/10.1007/s11142-006-9012-1.

Ruan, L., J. Li, and S. Huang. 2025. "ESG Rating Adjustment and Capital Market Pricing Efficiency: Evidence from China." *International Review of Economics & Finance* 98:103845. https://doi.org/10.1016/j.iref.2025.103845.

Ruffoni, E. P., and F. M. Reichert. 2024. "Exploring Configurations of Digital Servitization Capabilities for Value Creation: An fsQCA Approach." *Industrial Marketing Management* 122:131–144. https://doi.org/10.1016/j.indmarman.2024.08.010.

Salvi, A., F. Vitolla, A. Giakoumelou, N. Raimo, and M. Rubino. 2020. "Intellectual Capital Disclosure in Integrated Reports: The Effect on Firm Value." *Technological Forecasting and Social Change* 160:120228. https://doi.org/10.1016/j.techfore.2020.120228.

Scuotto, V., E. Arrigo, E. Candelo, and M. Nicotra. 2020. "Ambidextrous Innovation Orientation Effected by the Digital Transformation: A Quantitative Research on Fashion SMEs." *Business Process Management Journal* 26 (5): 1121–1140. https://doi.org/10.1108/BPMJ-03-2019-0135.

Shu, J. 2024. "Social Media, Investor–Firm Interactions and Informational Efficiency of Stock Prices: Evidence from China." *Finance Research Letters* 69:106059. https://doi.org/10.1016/j.frl.2024.106059.

Singh, S., M. Sharma, and S. Dhir. 2021. "Modeling the Effects of Digital Transformation in Indian Manufacturing Industry." *Technology in Society* 67:101763. https://doi.org/10.1016/j.techsoc.2021.101763.

Sun, X., and Z. Du. 2024. "Enhancing Capital Market Efficiency: The Role of Data Assets Disclosure in Reducing Stock Price Synchronicity." *International Review of Economics & Finance* 94:103351. https://doi.org/10.1016/j.iref.2024.05.030.

Tang, Z. 2024. "Research on the Accounting Recognition and Measurement Problems of Enterprise Data Assets." *International Journal of Global Economics and Management* 3 (2): 242–253. https://doi.org/10.62051/ijgem.v3n2.27.

Thekkoote, R. 2021. "Understanding Big Data-Driven Supply Chain and Performance Measures for Customer Satisfaction." *Benchmarking: An International Journal* 29 (8): ahead-of–print. https://doi.org/10.1108/BIJ-01-2021-0034.

Tian, Y., and L. Ou. 2024. "Exploring the Influencing Mechanisms of Different Digital Transformation Stages: An Industry Perspective." *Enterprise Information Systems* 18 (12): 2417407. https://doi.org/10.1080/17517575.2024.2417407.

Wang, Y., J. Tang, and C. Li. 2025. "Registration Reform and Stock Mispricing: Causal Inference Based on Double Machine Learning." *Research in International Business and Finance* 73:102668. https://doi.org/10.1016/j.ribaf.2024.102668.

Wei, Y., J. Zhang, M. Cheng, and T. Liu. 2025. "Does Data Asset Disclosure Contribute to the Market Efficiency? Evidence from China." *Research in International Business and Finance* 73:102549. https://doi.org/10.1016/j.ribaf.2024.102549.

Wu, D., Q. Sun, W. Zhang, G. Xu, K. C. Chan, and J. Qin. 2024. "Does Information Content of a Corporate Social Responsibility Report Matter for Stock Mispricing? Evidence from China." *International Review of Financial Analysis* 95:103507. https://doi.org/10.1016/j.irfa.2024.103507.

Xu, N., X. Li, Q. Yuan, and K. Chan. 2014. "Excess Perks and Stock Price Crash Risk: Evidence from China." *Journal of Corporate Finance* 25:419–434. https://doi.org/10.1016/j.jcorpfin.2014.01.006.

Xue, W., Z. He, and X. Yun. 2025. "The Effect of Mutual Fund Herding on Stock Mispricing." *Pacific-Basin Finance Journal* 93:102866. https://doi.org/10.1016/j.pacfin.2025.102866.

Yang, Z., P. Song, M. Xu, and Y. Li. 2024. "Environmental, Social and Governance Performance and Equity Mispricing: Does Embedded Information Mediation Matter?" *Finance Research Letters* 67:105922. https://doi.org/10.1016/j.frl.2024.105922.

Zhang, F., T. Yuzhu, L. K. W. Lam, and Z. Mian. 2025. "Analysis of the Influencing Factors of the Trade Potential Between Countries Along the 'Belt and Road' and China: A Study Based on Spatial Panel Data Model." *Enterprise Information Systems* 19 (1–2). https://doi.org/10.1080/17517575.2024.2448315.

Zhang, J., T. Xie, X. Kong, B. Liu, and W. Zhang. 2025. "Can Data Assets Promote Green Innovation in Enterprises?" *Finance Research Letters* 72:106554. https://doi.org/10.1016/j.frl.2024.106554.

Zhang, J., L. Zhang, and M. Zhang. 2024. "Media pressure, internal control, and corporate environmental information disclosure." *Finance Research Letters* 63:105369. https://doi.org/10.1016/j.frl.2024.105369.

Zhang, Q., X. Sun, and M. Zhang. 2022. "Data Matters: A Strategic Action Framework for Data Governance." *Information & Management* 59 (4): 103642. https://doi.org/10.1016/j.im.2022.103642.

Zhu, W., F. Yao, X. Zhan, Y. Lu, and L. D. Xu. 2025. "Data-Driven Corporate Health Assessment: An Analytical Framework for Strategic Management Information Systems." *Enterprise Information Systems* 19 (1–2). https://api.semanticscholar.org/CorpusID:280901813.