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資本市場投資者是否重視金融科技？—來自美國上市公司現金增資的證據

陳睿祥
國立成功大學會計學系暨財務金融研究所

龔芳
國立臺灣大學會計學系

朱玉芳*
國立臺灣大學會計學系

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摘要

本研究透過檢視投資人在面對公司宣告現金增資(Seasoned Equity Offerings, SEO)時的反應，以了解他們是否重視公司的金融科技(Financial Technology, FinTech)的發展。本研究蒐集 2019 至 2022 年期間美國 986 筆現金增資的觀察值，發現金融科技發展較強的公司能獲得更正面的市場反應。此正面效應在資訊不對稱程度較高的公司中更為顯著，這突顯金融科技在降低資訊不對稱方面的角色。擴展事件窗期的分析進一步顯示，採用金融科技所帶來的正向投資者情緒不僅限於現金增資宣告期間，還能持續發酵至後續時段。除了短期的市場反應以外，金融科技亦有助於公司長期績效的提升。此外，金融科技能力較佳的公司透過降低投資不足，來獲得更高的投資效率。即使在使用不同金融科技的替代衡量、控制 COVID-19 疫情期間、排除科技密集型公司以及考量潛在自我選擇偏誤之後，本研究結果仍維持穩健。整體而言，本研究結果顯示投資人高度重視金融科技發展，因其能有效降低資訊不對稱、改善投資效率與公司績效。

關鍵詞：金融科技(FinTech)、上市公司現金增資(SEO)、市場反應、投資效率、公司績效

JEL 分類碼：G34、G10、O33

* 通訊作者：朱玉芳 臺大會計系，聯絡地址：106319 臺北市大安區羅斯福路四段一號，電話：(02)3366-1117，E-mail: yufangchu@ntu.edu.tw。作者感謝總編輯與兩位匿名審查委員提供的寶貴意見。

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Do Capital Market Investors Value FinTech? Evidence from U.S. Seasoned Equity Offerings

Ruei-Siang Chen
Department of Accountancy and Graduate Institute of Finance, National Cheng Kung University

Fang Gong
Department of Accounting, National Taiwan University

Yu-Fang Chu*
Department of Accounting, National Taiwan University

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Abstract

This paper examines whether investors value financial technology (FinTech) development when reacting to seasoned equity offerings (SEOs). Using 986 observations of U.S. SEOs from 2019 to 2022, we find that firms with better FinTech experience more positive reactions than others. This positive effect is especially pronounced for firms with higher levels of information asymmetry, highlighting FinTech's role in reducing information asymmetry. An extended event window analysis further shows that FinTech adoption continues to generate positive investor sentiment beyond the SEO announcement period. Beyond short-term market reactions, FinTech also contributes to long-term firm performance. Moreover, firms with better Fintech demonstrate greater investment efficiency by reducing underinvestment. Our findings remain robust after testing alternative FinTech proxies, accounting for the COVID-19 period, excluding technology-intensive firms, and considering the potential self-selection bias. Overall, our findings indicate that investors highly value FinTech for its ability to reduce information asymmetry and improve investment efficiency and firm performance.

Keywords: Financial technology (FinTech); Seasoned equity offerings (SEO); Market reaction; Investment efficiency; Firm performance

JEL Classification Codes: G34, G10, O33

* Correspondence to Yu-Fang Chu, Address: Department of Accounting, National Taiwan University, No.1, Sec. 4, Roosevelt Road, Taipei, 106319 Taiwan; Tel: (02)3366-1117; E-mail: yufangchu@ntu.edu.tw. The authors sincerely appreciate the valuable feedback from the anonymous reviewers and the editors.

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1. Introduction

The purpose of this study is to understand how investors perceive firms that adopt financial technology (FinTech). Using seasoned equity offerings (SEOs) as clean exogenous events, we examine how varying levels of FinTech development influence market reactions to U.S. SEOs. The motivation for this study stems from FinTech's rapid development around the world, drawing a lot of attention from professionals worldwide, industry standards, and regulatory bodies.

What is FinTech? Chen et al. (2019a) argue that FinTech ultimately consists of the set of recently developed digital computing technologies that have been applied or are likely to be applied in the future to financial services. Broadly defined, FinTech refers to cybersecurity, mobile transactions, data analytics, blockchain, peer-to-peer (P2P) lending, robo-advising, and the Internet of Things(IoT). KPMG (2023) notes that "*2022 reached total global FinTech investment ($164.1 billion) and deal volume (6,006). 2022 was the third-best year for FinTech investment ever and the second-best year for deal volume*". As early as Oct. 18, 2018, to promptly respond to FinTech, the U.S. Securities and Exchange Commission (SEC 2018) launched a New Strategic Hub for Innovation and Financial Technology to provide regulatory oversight. Chair of the SEC, Gary Gensler, also said, "*Every five or 10 years, major new financial technologies come along to change business models. One thing that I've come to believe is that technology can bring greater access, efficiency, and innovation in our capital markets, as well as economic growth.*" (Gensler 2021) Such significant investment in FinTech and timely actions from regulators motivate us to examine how investors perceive FinTech.

Some studies show that applying FinTech has positive and negative impacts on companies. These studies mainly discuss a single context (e.g., China) and a specific industry (e.g., financial industry) (Gomber et al. 2018; Lv and Xiong 2022; Xu et al. 2022; Ding et al. 2022; Phan et al. 2020). As the Lucerne University of Applied Sciences and Arts Institute of Financial Services Zug (IFZ) points out, locations in the same country typically tend to show very similar performance in FinTech development, so those studies' findings inevitably have limitations.[1] Additionally, companies have widely invested in FinTech applications, which are no longer exclusive to the financial industry (Xu et al. 2022). Empirical evidence increasingly

[1] The IFZ of the Lucerne University of Applied Sciences and Arts uses factors related to driving entrepre¬neurship and innovation and PEST (politics, economics, society, and technology) analysis to analyze the overall indicators of each country to identify those regions with the most robust FinTech ecosystems. See the Institute for Financial Services Zug (IFZ) website for details, IFZ FinTech Study.

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highlights that FinTech adoption has broad implications beyond the financial sector. Prior studies suggest that FinTech enhances firm value (Chen et al. 2019a; Tang et al. 2025; Yang et al. 2023), improves access to external financing (Xu et al. 2022), and alleviates financial constraints (Guo and Zhang 2023). Additionally, FinTech has been shown to enhance corporate investment efficiency by reducing underinvestment and improving capital allocation (Ye et al. 2024). Firms leveraging FinTech also experience greater innovation output (Ding et al. 2022; Tan et al. 2023) and enhanced financial reporting quality (Wen et al. 2023), which in turn strengthens investor confidence. Furthermore, FinTech applications have been linked to improved internal controls and better risk management (He et al. 2023), mitigating operational uncertainties.

To comprehensively evaluate FinTech development, we utilize both firm-level and country-level measures. The firm-level measurement approach aligns with prior research that employs FinTech keyword searches to assess firm engagement in FinTech (Cheng and Qu 2020; Daud et al. 2022; He et al. 2023). We hand-collect Google search data by using two different sets of FinTech-related keywords, attempting to capture an approximation of each firm's involvement in FinTech development during a specific year. In a sensitivity analysis, we incorporate two country-level FinTech indicators to account for broader environmental influences. Following previous research (Liu and Chu 2024; Yang et al. 2023), we use IFZ's country-level FinTech rankings in our analysis. By using firm-level and country-level FinTech measures, we aim to explore how FinTech development influences market reactions to SEOs.

In addition to our main regression analysis, we conduct a series of analyses to further investigate the role of FinTech development and to ensure the validity of our results. We first conduct a cross-sectional analysis to explore how FinTech development influences market reactions to SEOs under varying levels of information asymmetry, distinguishing between high and low asymmetry scenarios. Next, we examine the impact of FinTech development on investment efficiency, assessing its role in optimizing capital allocation and mitigating inefficiencies in firms' investment decisions. Then, we extend the event window to incorporate longer trading periods, attempting a more comprehensive analysis of long-term investor reactions beyond the immediate announcement effect. Furthermore, we investigate the long-term impact of FinTech development on firm performance, using ROA and Tobin's Q as key performance indicators. To ensure robustness, we employ alternative FinTech proxies, account for the COVID-19 period, and exclude

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technology-intensive firms. Finally, to ensure the robustness of our findings, we employ propensity score matching (PSM) as a robustness test to address potential endogeneity issues caused by self-selection bias.

We employ the event study approach and SEOs as observed events for three reasons. First, SEO is an essential channel for companies to raise funds externally. It not only has a significant impact on the wealth of existing shareholders but also directly reflects the views of potential shareholders on the company's prospects. Second, various FinTech innovations essentially attempt to alleviate information asymmetry through technology (Chen et al. 2019a), and FinTech could reduce information asymmetry among various stakeholders in SEOs. Third, SEOs are cleaner exogenous and unanticipated events, alleviating the reverse causality problem and ensuring that our findings are less biased by endogeneity issues, similar to prior studies (Feng et al. 2018; Deng et al. 2013).

Using 986 observations of U.S. SEOs from 2019 to 2022, we find that FinTech development, measured through firm-level and country-level indicators, significantly enhances investor confidence and mitigates the negative effects typically associated with SEOs, particularly in firms with higher information asymmetry. Further, we find that FinTech development contributes to investment efficiency and firm performance. Lastly, to control for possible self-selection bias, we use a matched sample and the findings remain robust. Overall, this study indicates that, from investors' perspectives, FinTech plays an important role in decreasing asymmetric information and, in turn, improving company performance.

Our study contributes to the literature in several ways. First, our findings provide timely insights into the ongoing debate on firms' adoption of FinTech, offering empirical evidence on its market implications. Second, this study advances prior research by systematically examining the impact of FinTech development on market reactions to SEOs, investment efficiency (Ye et al. 2024), and firm performance (Ding et al. 2022), highlighting its role in enhancing transparency and reducing information asymmetry. Third, our findings carry significant policy implications, serving as a valuable reference for regulators and policymakers seeking to understand the broader economic effects of FinTech adoption. Fourth, our research aligns with the United Nations' call to action (UNEP 2021). FinTech could play a role in addressing the challenges of the sustainable development agenda. Finally, to the best of our knowledge, this study is the first to investigate stock market investors' perception of FinTech, and these findings could supplement the extant FinTech literature from the investors' view.

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2. Literature review and hypothesis development

2.1 SEOs and market reactions

Seasoned equity offerings (SEOs) are an essential mechanism for firms to raise additional equity capital. However, extensive research documents that SEO announcements often result in negative abnormal returns (Feng et al. 2018; Eckbo et al. 2007). These negative announcement returns are attributed to adverse selection, resulting from asymmetric information between issuers and outside investors (Myers and Majluf 1984; Lucas and McDonald 1990). Specifically, investors may interpret SEO announcements as a signal of overvaluation or the firm's inability to generate sufficient internal funds, leading to unfavorable market reactions. Thus, reducing information asymmetry is critical for mitigating the negative consequences of SEO announcements.

2.2 The mixed evidence on FinTech adoption

While a few studies regarding FinTech have been done, existing evidence is mixed. On the one hand, studies argue that FinTech adoption leads to more innovative output, improved access to bank loans, expanded business opportunities, reduced operating and transaction costs, and lessens the impact of negative events on company value and the country (Campanella et al. 2017; Chen et al. 2019a; Ding et al. 2022; Grennan and Michaely 2021; Huang 2022; Lee et al. 2021; Liu and Chu 2024; Lv and Xiong 2022; Xu et al. 2022; Yang et al. 2023). Additionally, empirical research suggests that FinTech enhances firms' investment efficiency (Ye et al. 2024), strengthens financial reporting quality (Wen et al. 2023), and improves internal control mechanisms, thereby reducing risk-taking behavior (He et al. 2023). These effects contribute to better governance and resource allocation, enhancing overall firm performance.

On the other hand, some research highlights potential downsides of FinTech adoption, including challenges related to reporting lags and cybersecurity risks. Liu and Chu (2024) explore whether FinTech applications improve the timeliness of financial reporting and audits. Using a dataset of 32,196 U.S.-listed firm-year observations from 2012 to 2021, they find that the Top 25 FinTech firms experience greater reporting lags compared to other firms. Ng and Kwok (2017) examine the cybersecurity risks associated with FinTech adoption in global financial centers, using Hong Kong as a case study. Their research discusses how financial regulators

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implement strategic, risk-based policies to address the potential cybersecurity challenges posed by FinTech innovations. Moreover, Phan et al. (2020) use bank-level data from Indonesia and find that the growth of FinTech firms negatively influences bank performance. Their study indicates that while FinTech innovations may offer opportunities, they can also introduce competitive pressures that challenge the profitability and performance of traditional financial institutions. The extent to which FinTech adoption benefits or harms firms depends largely on how strategically and effectively it is implemented. Therefore, the question of how FinTech influences firms, particularly during significant corporate events such as SEO, remains an area for exploration.

2.3 The role of FinTech in reducing information asymmetry

FinTech, encompassing technologies such as blockchain, big data, artificial intelligence, and cloud computing, has emerged as a transformative tool for reducing information asymmetry. Most studies argue that applying FinTech brings more innovative output (Chen et al. 2019a; Ding et al. 2022), gets more bank loans (Xu et al. 2022), expands more businesses (Campanella et al. 2017), enhances investment efficiency (Lv and Xiong 2022; Huang 2022), decreases operating and transaction costs (Lee et al. 2021; Grennan and Michaely 2021), and lessens the impact of negative events on company value and the country (Liu and Chu 2024; Yang et al. 2023). As a result, FinTech can address the adverse selection issue during SEOs by enabling real-time, transparent, and secure financial processes. FinTech applications improve corporate information transparency, allowing investors to make more informed decisions and reducing their reliance on negative signals associated with SEOs.

Considerable research has focused on the impact of SEO announcements, revealing predominantly negative abnormal returns (Feng et al. 2018; Eckbo et al. 2007). These negative announcement returns are attributed to adverse selection, resulting from asymmetric information between issuers and outside investors (Myers and Majluf 1984; Lucas and McDonald 1990). Lv and Xiong (2022) find that firms with FinTech applications enhance information transparency because various FinTech innovations essentially attempt to alleviate information asymmetry through technology (Chen et al. 2019a). For example, big data and blockchain technology could help companies improve forecast accuracy, lower costs, and make transactions safe and fast, thereby reducing information friction with stakeholders (Sanchez 2018).

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By mitigating information asymmetry, the use of FinTech enhances investment efficiency and increases financing channels. For example, FinTech promotes the positioning of funds and the transparency of investment projects when enterprises carry out investment activities (Huang 2022; Lv and Xiong 2022). The improvement of corporate information transparency is the basis for managers to distinguish good investment projects from bad investment projects. More detailed information disclosed enables companies to select investment projects better, and thus, companies have better investment efficiency (Bushman and Smith 2001; Lv and Xiong 2022; Huang 2022). Additionally, FinTech improves trust between banks and firms (Harhoff and Körting 1998; Wu and Xu 2020) and enhances firms' access to bank loans (Xu et al. 2022).

From the perspective of signaling theory (Spence 1974), adopting FinTech sends a positive signal to the market, reflecting a firm's innovation, adaptability, and strategic vision. Firms with advanced FinTech capabilities demonstrate their ability to leverage cutting-edge technologies for operational efficiency, risk management, and growth, which are critical factors in influencing investor sentiment. This signaling effect is particularly important during SEOs, as investors often scrutinize firms for signs of future potential and stability.

In summary, FinTech serves as a vital infrastructure for reducing information friction, improving transparency, and signaling innovation to investors. Therefore, we argue that firms with better FinTech development are better positioned to address the adverse selection problem inherent in SEOs, ultimately enhancing investor confidence and generating more favorable market reactions. Based on these theoretical and empirical insights, we propose the following hypothesis:

H1: SEO firms with better FinTech development experience have more positive market reactions than others.

3. Research design

3.1. Data and sample

This study employs the event study approach to analyze market reactions to SEO announcements (Chen and Church 1996; Feng et al. 2018; Menon and Williams 2010), and we obtain cumulative equal-weighted market index-adjusted returns (*CAR*) from the Event Study by *WRDS*. Moreover, financial data are obtained from Compustat and CRSP. Following prior literature (Baker and Wurgler 2006; Chen et al. 2019b; Ge et al. 2019), we obtain the investor sentiment data from

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Professor Jeffrey Wurgler.[2] This study focuses on SEO announcements from 2019 to 2022, as this period captures a time of rapid advancements in FinTech adoption, including digital finance, blockchain, artificial intelligence, and data analytics. Firms in the financial sector (SIC 6000-6999) and the utilities sector (SIC 4900-4999) are excluded. These exclusions are grounded in prior studies, which indicate that firms in these sectors exhibit fundamentally different characteristics. Specifically, Masulis and Korwar (1986) highlight that utility firms operate under distinct regulatory frameworks and financial structures, which may introduce biases into the analysis. Similarly, financial firms are excluded due to their unique capital structures and regulatory environments. In sum, after deleting the observations with missing financial data, our sample size is reduced to 986 observations (646 firms).

3.2. Methods

To examine our hypothesis, we develop the following regression model (1) to examine the market reactions to SEOs announced by firms with better and worse FinTech development (Tsai and Huang 2021; Singhvi et al. 2013; Feng et al. 2018).

$$\begin{aligned} SEOCAR_{it} = {} & \beta_0 + \beta_1 Fintech_{it} + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 Mtb_{it} + \beta_5 ROA_{it} \\ & + \beta_6 Share_{it} + \beta_7 ChgPrice_{it} + \beta_8 Nasdaq_{it} + \beta_9 Sent_t \\ & + Industry\ FE + Year\ FE + Country\ FE + \varepsilon_{it} \end{aligned} \quad (1)$$

A key component of this study is the measurement of FinTech development. While various approaches have been used in the literature to quantify FinTech adoption, there is no universally accepted standard. Appendix 3 presents a summary table of existing empirical research on FinTech measurement, demonstrating the diversity of methodologies applied in prior studies.

Previous research has used the presence of FinTech subsidiaries (Xu et al. 2022) and the frequency of FinTech-related keywords in financial reports (Guo and Zhang 2023; He et al. 2023). While these measures provide valuable insights into structural aspects of FinTech adoption, they may not fully capture a firm's visibility in the FinTech ecosystem, investor perception, or engagement in public discourse. In addition to firm-level measures, several studies have also assessed FinTech development using country-level FinTech rankings (Liu and Chu 2024; Yang et al. 2023) and FinTech indices based on regional or national data sources (Tang et al.

[2] The investor sentiment data source: https://pages.stern.nyu.edu/~jwurgler/

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2025; Ding et al. 2022). For instance, Liu and Chu (2024) employ FinTech development rankings published by IFZ to evaluate FinTech growth across 197 countries. To complement these methods, we develop a more dynamic and market-driven measurement framework where we consider both firm-level and country-level indicators to provide a more comprehensive evaluation of FinTech development.

At the firm level, our main approach is motivated by Cheng and Qu (2020). Cheng and Qu (2020) utilize FinTech-related keyword searches in articles to measure a firm's association with FinTech at the firm level. They classify Chinese bank FinTech into the following main categories: artificial intelligence technology, blockchain technology, cloud computing technology, big data technology, and internet technology. Similarly, Daud et al. (2022) also apply news-based FinTech keyword searches to capture FinTech-related developments in financial markets. Inspired by these methodologies, we develop two separate indices: *Fintech_Index1* and *Fintech_Index2*, based on the keywords proposed by Cheng and Qu (2020) and Daud et al. (2022). *Fintech_Index1* measures the annual Google search volume for a firm's name combined with FinTech-related synonyms, including *fintech*, *financial technology*, *digital finance*, or *financial innovation*. *Fintech_Index2* represents an expanded version of *Fintech_Index1*, capturing both broad FinTech discussions and specific technological advancements. *Fintech_Index2* measures Google search volume of firm i's name and Fintech synonyms (*fintech*, *financial technology*, *digital finance*, or *financial innovation*) and categories (*artificial intelligence*, *blockchain*, *cloud technology*, or *data technology*) in the SEO announcement year, scaled from 0 to 100.[3]

To obtain firm-level FinTech engagement data, we hand collect the firm-level Google search data following a structured Google search process. First, we conduct searches in Google by entering keywords that combine Fintech-related keywords with a specific firm name. Specifically, we conduct separate searches for *Fintech_Index1* and *Fintech_Index2*, ensuring that each index captures distinct aspects of FinTech engagement. The search format follows: (*Fintech_Index 1* or *2*)

[3] There are differences in measuring concepts of *Fintech_Index1* and *Fintech_Index2*. Inspired by the previous study (Hsu and Liao 2022), we construct *Fintech_Index2* by expanding on *Fintech_Index1*. *Fintech_Index1* aims to measure the general exposure of enterprises related to FinTech development in the media, reflecting their overall visibility on FinTech issues. By adding more FinTech tool terms as keywords, *Fintech_Index2* aims to observe whether a firm is connected to a specific FinTech tool and capture its technology-oriented FinTech activities.

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AND [Firm Name].

Next, to ensure the search results are restricted to a specific time period, we apply a date filter within Google. This is done by selecting the custom date range option under the "Recent" dropdown menu and setting the time frame to match the desired calendar year (e.g., January 1, 2019 – December 31, 2019). This filtering allows us to capture firm-level FinTech-related discussions within a precise annual window.

Once the search is conducted, the total number of articles retrieved by Google is displayed in the top right corner of the results page. Then, the total number is scaled from 0 to 100, providing a normalized measure of a firm's FinTech visibility. This scaled value serves as our data point, representing the number of FinTech-related articles mentioned by the firm in that specific year. This approach ensures a consistent and replicable methodology for tracking firm-specific FinTech engagement over time. A detailed search instruction is provided in Appendix 2 for reference.

In addition to the firm-level measures, we also incorporate two country-level FinTech measures based on the insights from the literature. Following previous studies (Yang et al. 2023; Liu and Chu 2024), this study also uses two country-level FinTech development rankings in our additional analysis. By collecting SEO announcements by US-listed local and foreign companies from *SDC* between 2019 and 2022, we consider the firms located in ranking-listed countries as having better FinTech development, while the rest of the firms have poor FinTech development.

To ensure that the results are robust, we examine *SEOCAR* over the two event windows centered on the SEO announcement date: *SEOCAR* (-1, +1), covering one day before to one day after the announcement, and *SEOCAR* (-1, +2), covering one day before to two days after the announcement. Furthermore, the model includes a set of control variables to account for firm-specific, SEO-specific, and environment-specific characteristics, following the prior literature (Feng et al. 2018; Singhvi et al. 2013; Tsai and Huang 2021). Firm-specific controls include *Size* (logarithm of total assets), *Leverage* (long-term debt to total assets ratio), *Mtb* (market-to-book ratio), *ROA* (return on assets), and *ChgPrice* (stock price change over 250 trading days before the SEO announcement), reflecting size, capital structure, growth potential, profitability, and prior market performance. *Share*, representing the percentage of shares sold by existing shareholders in the SEO, captures ownership dilution effects. Environment-specific controls include *Nasdaq*, an indicator variable for firms listed on NASDAQ, and *Sent*, a composite measure of

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investor sentiment. We follow the prior literature (Baker and Wurgler 2006; Chen et al. 2019b; Ge et al. 2019) to measure investor sentiment.[4] In summary, Table 4 shows the predicted positive signs, including *Fintech_Index1*, *Size*, *ROA*, *ChgPrice*, *Nasdaq*, and *Sent*, while the variables expected to have negative signs are *Leverage*, *Mtb*, and *Share*.

Additionally, this study conducts further analyses to examine the impact of FinTech development on firm performance, focusing on measurements such as ROA and Tobin's Q. ROA is a widely recognized metric for measuring firm performance. Barber and Lyon (1996) use the ROA as the firm performance measure. Similarly, Phan et al. (2020) adopt ROA in their analysis of bank performance. Interestingly, research using bank-level data from Indonesia explores the hypothesis that FinTech development may negatively influence bank performance. This emphasizes the need for more insights into FinTech's diverse effects. Tobin's Q complements ROA by offering a market-based perspective, reflecting a firm's market value relative to the replacement cost of its assets. Wernerfelt and Montgomery (1988) underscore Tobin's Q in signaling a firm's potential to attract investments, while Bharadwaj et al. (1999) emphasize its ability to evaluate the contributions of technological advancements, such as information technology (IT), to a firm's future performance. Gompers et al. (2003) further highlight Tobin's Q as a critical tool in assessing governance and strategic impacts on market valuation. By examining *ROA* and *Tobin's Q*, this analysis investigates whether FinTech development enhances firms' performance in the future. Following the methodology outlined in prior literature (Bills et al. 2024), we apply the following model (2) to test long-term effects.

$$\begin{aligned} Firm_Performance_{it+1} = {} & \beta_0 + \beta_1 Fintech_{it} + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 RD_{it} \\ & + \beta_5 PPE_{it} + \beta_6 SalesGrowth_{it} + \beta_7 Share_{it} \\ & + Industry\ FE + Year\ FE + Country\ FE + \varepsilon_{it+1} \end{aligned} \quad (2)$$

For detailed definitions of all variables, please refer to Appendix 1, which provides a comprehensive explanation of their construction and application in the model. Specifically, *Firm_Performance* refers to *ROA* (Return on Assets) in year t+1 and *Tobin's Q* in year t+1, capturing both profitability and market valuation perspectives. We follow Bills et al. (2024) to include the control variables.

[4] Robust standard errors clustered at the industry level are used to deal with heteroscedasticity (Alhadab and Clacher 2018; Feng et al. 2018).

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4. Analysis and results

4.1. Sample selection and descriptive statistics

Table 1 summarizes the process of selecting the final sample and provides an overview of the sample distribution by year and industry. Panel A describes the steps used to refine the initial 5,512 seasoned equity offering (SEO) announcements from U.S. listed firms between 2019 and 2022, sourced from the *SDC* database. The sample excludes announcements offering prices below $5 (2,796 observations), firms in the financial and utilities industries based on their SIC codes (1,714 observations), and cases with missing data in *CRSP*, *Compustat*, or *SDC* databases (16 observations). We exclude financial and utilities firms because their capital structures and financing decisions are fundamentally different from those of non-financial firms. Our exclusion criteria maintain consistency in firm characteristics and ensure valid comparisons. After these exclusions, the final sample comprises 986 SEO announcements. Panel B shows the annual distribution of the final sample. The largest number of SEO announcements occurred in 2020, accounting for 36.10% of the total, followed by 31.85% in 2021 and 19.78% in 2019. The fewest announcements occurred in 2022, representing 12.27% of the sample. Panel C categorizes the sample by industry. Services firms contributed 16.94% of the sample, while other industries, such as transportation, retail trade, and mining, accounted for smaller proportions. Taken together, these panels provide a clear representation of the dataset's composition by time and sector.

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Table 1 Sample selection

Panel A: Sample Selection		
SEO announcements for U.S.-listed firms from 2019 to 2022 (*SDC)*		5,512
Less: Offering prices less than $5		(2,796)
Less: Financial (SIC: 6000-6999) and utilities (SIC: 4900-4999) industries		(1,714)
Less: Missing data (*CRSP*, *Compustat*, and *SDC*)		(16)
Final sample		986
Panel B: Sample distribution by year		
Year	N	%
2019	195	19.78
2020	356	36.10
2021	314	31.85
2022	121	12.27
Total	986	100.00
Panel C: Sample distribution by industries		
SIC CODE	N	%
Agriculture, Forestry, Fishing	3	0.31
Mining	14	1.42
Construction	7	0.71
Manufacturing	713	72.31
Transportation	38	3.85
Wholesale Trade	15	1.52
Retail Trade	29	2.94
Services	167	16.94
Total	986	100.00

Table 2 provides an overview of the descriptive statistics.[5] The table includes the number of observations (N), mean, standard deviation (SD), and quartile statistics (Q1, Median, Q3). The dependent variables, *SEOCAR* (-1, +1) and *SEOCAR* (-1, +2), represent the cumulative abnormal returns around SEO announcements for two event windows. Both have negative mean values (-0.013 and -0.009, respectively), suggesting an overall negative market reaction consistent with the literature (Asquith and Mullins Jr 1986; Masulis and Korwar 1986; Eckbo et al. 2007) on SEO announcements. Compared to Feng et al. (2018), where the mean *SEOCAR* was -0.014, our *SEOCAR* values are nearly identical. However, Feng et al. (2018) report a higher standard deviation, suggesting greater return volatility, which may be attributed to the differences in sample periods and the inclusion of the COVID-19 period in our dataset.

Our main variable of interest, *Fintech_Index1*, which measures FinTech development based on search volume data, has a mean of 50.325 and a median of

[5] All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of extreme values.

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51.000, with a standard deviation of 28.997. Additionally, the market-to-book ratio (*Mtb*) has a mean of 5.764, slightly lower than but broadly comparable to previous studies (e.g., Feng et al. (2018)). However, its higher standard deviation (16.847) suggests greater dispersion in firm valuation, potentially reflecting a more diverse sample composition that may include firms at different stages of growth and technological adoption. The mean *ROA* is -0.367, with a standard deviation of 0.514, which is lower than the -0.011 reported by Feng et al. (2018). This discrepancy is likely due to differences in sample selection, as our dataset includes a higher proportion of FinTech-driven firms that may face short-term profitability challenges during rapid expansion and innovation cycles.

Table 2 Descriptive statistics

Variable	N	Mean	SD	Q1	Median	Q3
SEOCAR (-1, +1)	986	-0.013	0.249	-0.125	-0.052	0.029
SEOCAR (-1, +2)	986	-0.009	0.254	-0.129	-0.050	0.045
Fintech_Index1	986	50.325	28.997	25.000	51.000	75.000
Size	986	5.996	1.841	4.838	5.742	6.983
Leverage	986	0.459	0.338	0.174	0.419	0.663
Mtb	986	5.764	16.847	2.127	3.884	7.058
ROA	986	-0.367	0.514	-0.550	-0.261	0.008
Share	986	0.111	0.062	0.069	0.101	0.139
ChgPrice	986	0.886	1.852	-0.008	0.374	1.020
Nasdaq	986	0.744	0.436	0.000	1.000	1.000
Sent	986	0.490	0.683	-0.094	0.181	1.037
InfoAsm	986	0.002	0.003	0.001	0.001	0.002

[a] Variable definition: See Appendix 1.

Table 3 presents the correlation matrix for the study's variables, showing Pearson (below the diagonal) and Spearman (above the diagonal) correlations. The cumulative abnormal returns around SEO announcements (*SEOCAR* (-1, +1) and *SEOCAR* (-1, +2)) exhibit a weak and statistically insignificant positive association with *Fintech_Index1*. However, *SEOCAR* (-1, +1) and *SEOCAR* (-1, +2) are positively associated with variables such as *ChgPrice*, *Nasdaq*, and *Sent*, indicating that prior stock price changes, NASDAQ listing, and market sentiment are positively related to market reactions to SEOs. Conversely, *SEOCAR* (-1, +1) and *SEOCAR* (-1, +2) are negatively associated with *Leverage* and *InfoAsm*, suggesting that higher leverage and greater information asymmetry correspond to less favorable market responses. There is no concern about multicollinearity among the variables.

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Table 3 Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	*SEOCAR*(-1,+1)		0.954***	0.021	0.058*	-0.079**	0.086***	-0.038	-0.101***	0.164***	0.066**	0.049	-0.110***
(2)	*SEOCAR*(-1,+2)	0.984***		0.017	0.059*	-0.091***	0.076**	-0.035	-0.079**	0.168***	0.068**	0.041	-0.105***
(3)	*Fintech_Index1*	0.009	0.008		0.371***	0.107***	0.035	0.213***	-0.204***	-0.072**	-0.143***	0.016	-0.300***
(4)	*Size*	-0.031	-0.024	0.374***		0.300***	-0.221***	0.620***	-0.365***	-0.199***	-0.404***	0.081**	-0.594***
(5)	*Leverage*	-0.116***	-0.121***	0.062*	0.212***		-0.093***	0.256***	-0.116***	0.016	-0.360***	-0.014	-0.255***
(6)	*Mtb*	0.007	0.014	0.027	-0.062*	-0.070**		-0.185***	-0.199***	0.054*	0.146***	-0.074**	0.016
(7)	*ROA*	-0.061*	-0.051	0.237***	0.583***	-0.008	0.014		-0.252***	-0.022	-0.298***	0.125***	-0.384***
(8)	*Share*	0.038	0.038	-0.187***	-0.362***	-0.076**	-0.113***	-0.188***		-0.079**	0.151***	-0.02	0.328***
(9)	*ChgPrice*	0.202***	0.207***	-0.056*	-0.243***	0.016	0.02	-0.209***	0.000		0.063**	0.129***	0.029
(10)	*Nasdaq*	0.117***	0.117***	-0.143***	-0.411***	-0.316***	0.006	-0.189***	0.140***	0.113***		0.011	0.333***
(11)	*Sent*	0.075**	0.067**	0.010	0.067**	0.000	0.007	0.114***	0.024	0.019	0.009		0.152***
(12)	*InfoAsm*	-0.091***	-0.089***	-0.262***	-0.445***	-0.088***	-0.018	-0.271***	0.301***	0.028	0.149***	0.117***	

[a] Variable definition: See Appendix 1.
[b] Pearson (Spearman) correlations are below (above) the diagonal.
[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

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4.2. Main regression results

Table 4 provides the ordinary least squares (OLS) regression results to test the association between market reactions to SEO announcements, as measured by *SEOCAR* (-1, +1) and *SEOCAR* (-1, +2) and FinTech. The key independent variable, *Fintech_Index1*, is positively and significantly associated with both event windows, with coefficients of 0.001 (t = 2.60) and 0.001 (t = 2.20), respectively. These results support H_1, suggesting that market investors appreciate those firms with better FinTech development and react more positively. Among the control variables, *Size* and *ChgPrice* are also positively and significantly associated with *SEOCAR*, indicating that larger firms and those with stronger prior stock performance experience more favorable market reactions. Conversely, *Leverage* shows a significant negative relationship with *SEOCAR* in both windows, suggesting that higher debt levels negatively influence investor confidence. The model includes industry and year-fixed effects, with clustering by industry. We also find that the VIFs in the following regression results are all lower than 10, supporting the premise that the threat of multi-collinearity is not serious. Overall, the findings support our hypothesis that better FinTech development enhances positive market reactions to SEO announcements, likely due to reduced information asymmetry and improved stakeholder confidence.[6]

[6] Given that this paper constructs two measures of Fintech (*Fintech_Index1* and *Fintech_Index2*), we have considered incorporating both variables into the model simultaneously. However, we eventually use only *Fintech_Index2* as an alternative variable presented in Table 10 for two reasons. First, there is a high correlation between these two measures since their measured keywords are partially identical. Including both in the model may lead to collinearity and reduce explanatory power. Second, the literature that we follow in constructing variables also tests two highly correlated measures separately (Hsu and Liao 2022).

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Table 4 Regression results

		SEOCAR (-1, +1)		*SEOCAR* (-1, +2)	
Variable	Predicted sign	Coefficient	*t*-stat	Coefficient	*t*-stat
Fintech_Index1	+	0.001**	(2.60)	0.001**	(2.20)
Size	+	0.018**	(2.15)	0.020**	(2.11)
Leverage	-	-0.039***	(-6.19)	-0.048***	(-6.35)
Mtb	-	0.000	(0.16)	0.000	(0.77)
ROA	+	0.005	(0.21)	0.008	(0.36)
Share	-	0.198	(1.27)	0.224	(1.39)
ChgPrice	+	0.035***	(2.90)	0.035***	(3.36)
Nasdaq	+	0.032	(1.25)	0.036	(1.27)
Sent	+	0.063*	(1.83)	0.051	(1.61)
Constant	?	-0.269***	(-3.65)	-0.393***	(-4.44)
Observations		986		986	
Industry FE		Yes		Yes	
Year FE		Yes		Yes	
Country FE		Yes		Yes	
Cluster by industry		Yes		Yes	
Adj. R-squared		5.5%		5.6%	

[a] Variable definition: See Appendix 1.
[b] Robust *t*-statistics in parentheses.
[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

4.3 Cross-sectional tests

Table 5 presents the results of our cross-sectional tests. Prior research suggests that firms with advanced FinTech capabilities reduce information asymmetry, leading to increased innovation (Chen et al. 2019a; Ding et al. 2022) and business expansion (Campanella et al. 2017). Therefore, we further examine how the relationship between *Fintech_Index1* and market reactions to SEO announcements varies with the levels of information asymmetry. Specifically, we follow the literature (Ramalingegowda and Yu 2012; Ranaldo and Somogyi 2021; Romito and Vurro 2021) to measure the information asymmetry (*InfoAsm*). *InfoAsm* is defined as the average daily bid-ask spread of firm *i* over year *t* prior to the SEO announcement. The sample is divided into two groups based on the median: high and low information asymmetry. This provides insight into whether the effect of FinTech development is stronger when information asymmetry is greater. As shown in Table 5, for firms with high information asymmetry, *Fintech_Index1* is positively and significantly associated with both *SEOCAR* (-1, +1) (t = 2.37) and *SEOCAR* (-1, +2) (t=2.07). This indicates that FinTech development reduces information asymmetry, leading to more positive market reactions in such cases. Conversely, for firms with low information asymmetry, the association between *Fintech_Index1* and *SEOCAR* is insignificant, suggesting that the impact of FinTech is less pronounced when firms already have low information frictions. This result supports the notion that FinTech adoption is especially valuable in reducing investor uncertainty in firms

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with higher information frictions, thereby improving market confidence and reactions to SEOs.

In addition, Table 5 shows a contrast in the coefficients on *ROA* between the two groups. For firms with high information asymmetry, *ROA* is positively and significantly associated with *SEOCAR*, implying that investors rely more heavily on traditional financial indicators such as profitability to assess firm value when information is scarce. This finding is consistent with the argument of Healy and Palepu (2001) that financial disclosure becomes more critical when information asymmetry is high. In contrast, for firms with low information asymmetry, the coefficient on *ROA* is negative and significant, which may reflect a market preference for forward-looking indicators (e.g., innovation or growth potential) rather than current profitability. This is in line with Chan et al. (2001), who find that in more transparent environments, investors emphasize R&D expenditures and long-term potential over short-term accounting performance.

Table 5 Cross-sectional tests

		SEOCAR (-1, +1)		*SEOCAR* (-1, +2)	
		(1)	(2)	(3)	(4)
	Predicted sign	High *InfoAsm*	Low *InfoAsm*	High *InfoAsm*	Low *InfoAsm*
Fintech_Index1	+	0.001**	0.000	0.001*	0.000
		(2.37)	(0.36)	(2.07)	(0.47)
Size	+	0.027***	0.010***	0.030***	0.014*
		(8.51)	(4.05)	(10.06)	(1.90)
Leverage	-	-0.023***	-0.070***	-0.033***	-0.078*
		(-5.62)	(-5.27)	(-9.02)	(-1.85)
Mtb	-	-0.001	0.000	-0.001	0.000
		(-1.49)	(0.34)	(-1.49)	(0.98)
ROA	-	0.026***	-0.055***	0.030***	-0.049*
		(3.10)	(-4.09)	(3.35)	(-1.69)
Share	+	0.127**	0.394**	0.138**	0.468
		(2.98)	(2.79)	(2.25)	(1.29)
ChgPrice	+	0.044***	0.023***	0.044***	0.024**
		(45.02)	(10.92)	(29.79)	(2.51)
Nasdaq	+	0.007	0.017***	0.011	0.020
		(1.08)	(5.87)	(1.47)	(0.76)
Sent	+	0.121***	-0.009	0.097***	-0.006
		(9.19)	(-0.91)	(7.59)	(-0.41)
Constant	?	-0.302***	-0.424***	-0.426***	-0.446***
		(-14.61)	(-15.59)	(-17.82)	(-5.03)
Observations		491	495	491	495
Industry FE		Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes
Country FE		Yes	Yes	Yes	Yes
Cluster by industry		Yes	Yes	Yes	Yes
Adj. R-squared		6.7%	1.4%	6.6%	1.4%

[a] Variable definition: See Appendix 1.
[b] Robust *t*-statistics in parentheses.
[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

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4.4 Impact of FinTech development on investment efficiency

Investment efficiency plays a crucial role in corporate finance, shaping firm value, shareholder returns, and long-term sustainability. According to previous studies (Biddle et al. 2009; Richardson 2006; Ye et al. 2024), investment inefficiency arises when firms either overinvest—allocating excessive resources to low-return projects—or underinvest—failing to pursue profitable opportunities. These inefficiencies are quantified using the absolute residuals from an investment model that predicts the optimal level of investment based on firms' growth opportunities. To assess the influence of FinTech development on investment efficiency, this study decomposes investment inefficiency (*InvIneff*) into two components: *OverInvest*, which captures cases where firms invest beyond their optimal level (positive residuals), and *UnderInvest*, representing firms that fail to make sufficient investments in profitable opportunities (*absolute value of negative residuals*). By examining the impact of FinTech development on overall investment inefficiency (Table 6) and its distinct effects on overinvestment and underinvestment (Table 7), this study aims to determine whether FinTech enhances capital allocation and mitigates investment inefficiencies.

Table 6 presents the results of examining the impact of FinTech development on investment inefficiency (*InvIneff*), measured as the absolute value of residuals from an investment model based on prior literature (Biddle et al. 2009; Richardson 2006; Ye et al. 2024). A lower value of *InvIneff* indicates that a firm is making investment decisions closer to its optimal level, while a higher value suggests greater inefficiency, either through overinvestment or underinvestment. The coefficient on *Fintech_Index1* (t = -2.49) is negative and statistically significant, indicating that firms with higher FinTech development experience lower investment inefficiency. This supports the argument that FinTech adoption facilitates better capital allocation by enhancing financial transparency, improving forecasting accuracy, and reducing information asymmetry.

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Table 6 The impact of FinTech development on investment inefficiency

		$InvIneff_{t+1}$	
Variable	Predicted sign	Coefficient	*t*-stat
Fintech_Index1	-	-0.001**	(-2.49)
Size	+/-	-0.016***	(-2.96)
Leverage	-	0.022	(1.28)
Mtb	na	0.000***	(5.51)
PPE	+/-	0.035	(0.70)
Cash	+	0.021	(0.57)
Dividend	-	0.009	(0.45)
CFOSale	+	-0.000	(-0.58)
Loss	na	-0.011	(-0.71)
Constant	?	0.200***	(3.64)
Observations		705	
Industry FE		Yes	
Year FE		Yes	
Country FE		Yes	
Cluster by industry		Yes	
Adj. R-squared		4.2%	

[a] Variable definition: See Appendix 1.
[b] Robust *t*-statistics in parentheses.
[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

To further explore how FinTech development affects different types of investment inefficiency, we separately examine overinvestment (*OverInvest*) and underinvestment (*UnderInvest*). In Table 7, the coefficient on *Fintech_Index1* for *OverInvest* (t = -1.47) is negative but not statistically significant, suggesting that while FinTech adoption might help curb overinvestment, the effect is not strong enough to be conclusive. However, for *UnderInvest*, the coefficient of *Fintech_Index1* is negative and statistically significant (t = -2.27), indicating that FinTech significantly reduces underinvestment. This suggests that FinTech improves firms' ability to identify and pursue profitable investment opportunities, potentially by enhancing credit access, reducing financing constraints, and improving managerial decision-making. These results confirm that FinTech adoption helps firms overcome financing constraints and allocate resources more efficiently, particularly by reducing underinvestment in firms with historically limited access to capital.

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Table 7 The impact of FinTech development on overinvestment and underinvestment

		$OverInvest_{t+1}$		$UnderInvest_{t+1}$	
Variable	Predicted sign	Coefficient	*t*-stat	Coefficient	*t*-stat
Fintech_Index1	-	-0.001	(-1.47)	-0.001**	(-2.27)
Size	+/-	-0.046**	(-2.53)	0.005***	(3.95)
Leverage	-	0.071*	(1.79)	-0.006	(-1.14)
Mtb	na	0.000	(0.01)	-0.000	(-0.38)
PPE	+/-	0.055	(0.30)	-0.055**	(-2.48)
Cash	+	0.024	(0.53)	-0.022	(-1.33)
Dividend	-	0.053	(0.69)	0.002	(0.31)
CFOSale	+	0.000	(0.85)	0.000	(1.20)
Loss	na	-0.010	(-0.28)	0.008	(1.54)
Constant	?	0.513*	(1.75)	0.055***	(3.65)
Observations		298		407	
Industry FE		Yes		Yes	
Year FE		Yes		Yes	
Country FE		Yes		Yes	
Cluster by industry		Yes		Yes	
Adj. R-squared		22.1%		29.0%	

[a] Variable definition: See Appendix 1.
[b] Robust *t*-statistics in parentheses.
[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

Overall, the findings indicate that FinTech development is more effective at reducing underinvestment rather than overinvestment. This supports the hypothesis that FinTech enhances firms' ability to allocate capital efficiently by reducing financing frictions and improving decision-making processes.

4.5 The impact of FinTech development on market reactions to SEO announcements over an extended event window

A longer event window allows for a more comprehensive assessment of how investors process FinTech-related signals and adjust their expectations regarding a firm's future performance. Table 8 presents the regression results of analyzing the impact of FinTech development on market reactions to SEO announcements over two extended event windows: *SEOCAR* (-1, +7) and *SEOCAR* (-1, +30). This analysis builds upon prior results by incorporating longer event windows, addressing potential concerns that shorter-term cumulative abnormal returns (e.g., *SEOCAR* (-1, +1) and *SEOCAR* (-1, +2)) may not fully capture the market's adjustment to SEO-related information.

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Table 8 The impact of FinTech development on market reactions to SEO announcements over an extended event window

		SEOCAR (-1, +7)		*SEOCAR* (-1, +30)	
Variable	Predicted sign	Coefficient	*t*-stat	Coefficient	*t*-stat
Fintech_Index1	+	0.001**	(2.31)	0.001*	(1.76)
Size	+	0.017**	(2.08)	0.030**	(2.22)
Leverage	-	-0.057***	(-7.77)	-0.050***	(-3.60)
Mtb	-	0.000	(0.10)	0.000	(0.96)
ROA	+	0.013	(0.72)	0.017	(0.50)
Share	-	0.265	(1.16)	0.418***	(3.50)
ChgPrice	+	0.038***	(3.66)	0.032***	(3.27)
Nasdaq	+	0.042*	(1.85)	0.059*	(1.75)
Sent	+	0.054	(1.68)	0.066***	(3.16)
Constant	?	-0.479***	(-5.82)	-0.266***	(-2.81)
Observations		986		986	
Industry FE		Yes		Yes	
Year FE		Yes		Yes	
Country FE		Yes		Yes	
Cluster by industry		Yes		Yes	
Adj. R-squared		6.0%		4.3%	

[a] Variable definition: See Appendix 1.
[b] Robust *t*-statistics in parentheses.
[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

The results in Table 8 indicate that *Fintech_Index1* is positively associated with *SEOCAR* (-1, +7) (t = 2.31) and *SEOCAR* (-1, +30) (t = 1.76), suggesting that firms with stronger FinTech development experience more favorable and sustained investor sentiment following SEO announcements. These findings support our hypothesis that FinTech enhances firm transparency, reduces information asymmetry, and signals long-term growth potential, leading to more positive market reactions over extended periods. The positive market response further underscores the value of FinTech-driven financial innovation in improving investor confidence and mitigating concerns related to external financing decisions.

4.6 Impact of FinTech development on firm performance

Understanding how FinTech development influences firms' long-term performance is crucial, as it provides insights into whether investments in financial technology yield sustainable benefits beyond immediate market reactions.

For the measurement of firm performance, we draw on established frameworks from previous studies (Barber and Lyon 1996; Bharadwaj et al. 1999; Gompers et al. 2003; Phan et al. 2020; Wernerfelt and Montgomery 1988). Based on these prior studies, we employ *ROA* and *Tobin's Q* to evaluate firm performance. Following the prior literature Bills et al. (2024), Table 9 presents the results of the relationship

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between FinTech development (*Fintech_Index1*) and future firm performance measures (ROA_{it+1} and *Tobin's* Q_{it+1}). For ROA_{it+1}, the coefficient of *Fintech_Index1* is 0.001 (t = 2.17), while for *Tobin's* Q_{it+1}, the coefficient is 0.007 (t = 1.68). Regarding the impact of firms' capital-raising activities on ROA, we have included *Share*, which represents the percentage of seasoned equity offering shares sold by existing shareholders relative to total SEO shares in the announcement year, as a control variable. The models include industry, year, and country-fixed effects, with clustering by industry to ensure robust results. The results indicate that *Fintech_Index1* has a significant positive effect on both performance metrics. These findings suggest that higher FinTech development contributes to a firm's performance. The positive impact of FinTech on *ROA* and *Tobin's Q* suggests that FinTech adoption not only enhances short-term market reactions but also contributes to long-term profitability and firm value creation.

Table 9 The influence of FinTech development on firm performance

		ROA_{t+1}		$TobinQ_{t+1}$	
Variable	Predicted sign	Coefficient	*t*-stat	Coefficient	*t*-stat
Fintech_Index1	+	0.001**	(2.17)	0.006*	(1.68)
Size	+	0.060***	(3.87)	0.363***	(3.75)
Leverage	+/-	-0.061*	(-1.87)	1.534***	(4.79)
RD	-	-0.001***	(-17.10)	-0.004**	(-8.93)
PPE	+	0.139**	(2.32)	-1.696	(-0.98)
SalesGrowth	-	-0.001	(-1.11)	-0.013	(-1.46)
Share	+/-	-0.156	(-0.55)	5.383	(1.39)
Constant	?	-0.435*	(-1.72)	-2.866***	(-3.69)
Observations		986		986	
Industry FE		Yes		Yes	
Year FE		Yes		Yes	
Country FE		Yes		Yes	
Cluster by industry		Yes		Yes	
Adj. R-squared		20.1%		26.7%	

[a] Variable definition: See Appendix 1.
[b] Robust *t*-statistics in parentheses.
[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

5. Robustness of the results

To assess the robustness of our findings, we conduct sensitivity analyses by refining the measurement of FinTech development and exploring its association with market reactions to SEO announcements.

Table 10 presents a robustness check using alternative FinTech-related variables—*Fintech_Index2*, *Fintech_Listing*, and *Fintech_Ranking*—to assess the relationship between FinTech engagement and cumulative abnormal returns around SEO announcements. The results are estimated across two event windows, *SEOCAR* (-1,+1)

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and *SEOCAR* (-1,+2). *Fintech_Index2* measures Google search volume of firm *i*'s name and Fintech synonyms (fintech, financial technology, digital finance, or financial innovation) and categories (artificial intelligence, blockchain, cloud technology, or data technology) in the SEO announcement year, scaled from 0 to 100. This adjustment follows a refined methodology inspired by the studies by Cheng and Qu (2020) and Daud et al. (2022), which highlight the role of specific FinTech technologies in influencing firm outcomes. As shown in columns (1) and (4) in Table 10, the results reveal that *Fintech_Index2* is positively and significantly associated with market reactions to SEO announcements. For *SEOCAR* (-1, +1), the coefficient is 0.001 (t = 2.16), and for *SEOCAR* (-1, +2), it remains 0.001 (t = 1.96). The model includes industry, country, and year-fixed effects, with clustering by industry. These results confirm the relevance of FinTech technologies in shaping investor responses to corporate financial decisions.

Most current studies on FinTech use alternative measures, such as a province or city-level FinTech development, to indirectly capture the application of FinTech by companies located in these regions (Lv and Xiong 2022; Ding et al. 2022; Xie and Zhu 2022). However, since IFZ is concerned that locations in the same country typically tend to show very similar performance in FinTech development, IFZ uses factors related to driving entrepreneurship and innovation and the PEST (politics, economics, society, and technology) approach to analyze the overall indicators of each country to identify those countries with the most robust FinTech ecosystems. We follow previous studies (Yang et al. 2023; Liu and Chu 2024) to construct the country-level FinTech development rankings (i.e., *Fintech_Listing* and *Fintech_Ranking*). The FinTech country rankings used in this analysis are detailed in Appendix 5.

Columns (2) and (5) in Table 10 present the results of a sensitivity analysis investigating whether a firm located in a country included in a global FinTech ranking (*Fintech_Listing*) influences market reactions to SEO announcements. *Fintech_Listing* is a dummy variable that equals 1 if a firm is based in a FinTech-ranked country and 0 otherwise. The results demonstrate that *Fintech_Listing* has a positive and statistically significant association with cumulative abnormal returns during both event windows. For *SEOCAR* (-1, +1), the coefficient is 0.034 (t = 1.92), significant at the 10% level. For *SEOCAR* (-1, +2), the coefficient is 0.081 (t = 2.29), significant at the 5% level. These findings suggest that firms located in FinTech-advanced countries experience more favorable investor reactions to SEO announcements, likely due to the perceived advantages of operating within a strong FinTech ecosystem.

Finally, *Fintech_Ranking* is a continuous variable representing the relative ranking of countries based on their FinTech development levels. In columns (3) and (6) of Table 10, the results show that *Fintech_Ranking* is positively and significantly associated with *SEOCAR* in both event windows. For *SEOCAR* (-1, +1), the coefficient is 0.005 (t =

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2.01), and for *SEOCAR* (-1, +2), the coefficient is 0.005 (t = 1.89), both significant at the 10% level.[7] These findings suggest that firms located in countries with higher FinTech rankings receive more favorable investor reactions to SEO announcements, likely due to perceived advantages in technological capabilities and financial infrastructure.

Table 10 Robustness analysis using another set of FinTech proxies

		SEOCAR (-1,+1)			*SEOCAR* (-1,+2)		
Variable	Predicted sign	(1)	(2)	(3)	(4)	(5)	(6)
Fintech_Index2	+	0.001**			0.001*		
		(2.16)			(1.96)		
Fintech_Listing	+		0.034*			0.081**	
			(1.92)			(2.29)	
Fintech_Ranking	+			0.005*			0.005*
				(2.01)			(1.89)
Size	+	0.018**	0.019**	0.018*	0.020**	0.021**	0.020*
		(2.25)	(2.16)	(1.96)	(2.16)	(2.15)	(1.82)
Leverage	-	-0.038***	-0.046***	-0.046***	-0.047***	-0.055***	-0.055***
		(-6.21)	(-5.23)	(-4.10)	(-6.38)	(-4.98)	(-3.80)
Mtb	-	0.000	0.000	0.000	0.000	0.000	0.000
		(0.12)	(0.34)	(0.36)	(0.75)	(0.83)	(0.89)
ROA	+	0.005	0.001	-0.003	0.008	0.002	-0.000
		(0.21)	(0.04)	(-0.14)	(0.36)	(0.09)	(-0.02)
Share	-	0.198	0.184	0.172	0.224	0.204	0.198
		(1.26)	(1.22)	(1.03)	(1.39)	(1.34)	(1.13)
ChgPrice	+	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***
		(2.91)	(2.76)	(2.70)	(3.36)	(3.15)	(3.07)
Nasdaq	+	0.032	0.027	0.030	0.036	0.033	0.034
		(1.27)	(1.14)	(1.16)	(1.28)	(1.21)	(1.19)
Sent	+	0.063*	0.059	0.059	0.051	0.047	0.045
		(1.83)	(1.60)	(1.52)	(1.62)	(1.33)	(1.23)
Constant	?	-0.271***	-0.262**	-0.223*	-0.394***	-0.325**	-0.285**
		(-3.61)	(-2.12)	(-1.97)	(-4.38)	(-2.50)	(-2.30)
Observations		986	986	933	986	986	933
Industry FE		Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Country FE		Yes	No	No	Yes	No	No
Cluster by industry		Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared		5.5%	6.4%	5.7%	5.6%	6.3%	5.6%

Notes：

[a] Three alternative variables are employed: *Fintech_Index2*, *Fintech_Listing*, and *Fintech_Ranking*. Following Cheng and Qu (2020) and Daud et al. (2022), *Fintech_index2* measures Google search volume of firm i's name and Fintech synonyms (*fintech*, *financial technology*, *digital finance*, or *financial innovation*) and categories (*artificial intelligence*, *blockchain*, *cloud technology*, or *data technology*) in the SEO announcement year, scaled from 0 to 100. *Fintech_Listing* is a dummy variable equal to 1 if firm i is located in a country included in the global FinTech ranking list prior to the SEO year, and 0 otherwise. *Fintech_Ranking* reflects the FinTech rank of the firm's country prior to the SEO year, multiplied by -1 so that a higher value represents a better rank. Other variable definitions: See Appendix 1.

[b] Robust t-statistics in parentheses.

[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

[7] In Table 12, the sample size is reduced to 933 from the original 986 in Table 4. This reduction occurs because the analysis relies on the FinTech ranking list (IFZ), which excludes firms from countries not included in the list.

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Table 11 presents the results of a robustness test that examines whether the observed relationship between firm-level FinTech development (*Fintech_Index1*) and market reactions to SEOs remains significant after controlling for country-level FinTech measurement (*Fintech_Ranking*). The results indicate that Fintech_Index1 remains positively associated with *SEOCAR* (-1, +1) (t = 1.89) and *SEOCAR* (-1, +2) (t = 2.15), suggesting that firms with higher FinTech adoption continue to experience more favorable market reactions to SEOs.

Table 11 Sensitivity analysis controlling for country-level FinTech ranking

		SEOCAR (-1, +1)		*SEOCAR* (-1, +2)	
Variable	Predicted sign	Coefficient	*t*-stat	Coefficient	*t*-stat
Fintech_Index1	+	0.001*	(1.89)	0.001*	(2.15)
Size	+	0.017*	(1.94)	0.019*	(1.82)
Leverage	-	-0.046***	(-3.90)	-0.055***	(-3.71)
Mtb	-	0.000	(0.32)	0.000	(0.89)
ROA	+	-0.003	(-0.13)	-0.000	(-0.00)
Share	-	0.174	(1.04)	0.199	(1.14)
ChgPrice	+	0.034***	(2.70)	0.035***	(3.08)
Nasdaq	+	0.029	(1.18)	0.034	(1.21)
Sent	+	0.059	(1.55)	0.045	(1.24)
Fintech_Ranking	+	0.002	(0.56)	0.002	(0.97)
Constant	?	-0.216*	(-1.98)	-0.280**	(-2.33)
Observations		933		933	
Industry FE		Yes		Yes	
Year FE		Yes		Yes	
Cluster by industry		Yes		Yes	
Adj. R-squared		5.6%		5.5%	

[a] Variable definition: See Appendix 1.
[b] Robust *t*-statistics in parentheses.
[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

Table 12 reports the findings of examining whether the relationship between FinTech development and market reactions to SEOs remains robust after accounting for the effects of the COVID-19 crisis. The *Pandemic* variable is defined as an indicator variable that takes the value of 1 for the years 2020, 2021, and 2022 and 0 otherwise, allowing us to capture the potential effects of the COVID-19 crisis on investor responses to SEOs. The results show that *Fintech_Index1* remains positively and significantly associated with *SEOCAR* (-1, +1) (t = 2.60) and *SEOCAR* (-1, +2) (t = 2.20), confirming that firms with higher FinTech adoption continue to experience more favorable investor reactions to SEOs, even during periods of heightened market uncertainty. The *Pandemic* variable is statistically insignificant, implying that SEO market reactions during the pandemic were primarily driven by firm-level characteristics rather than the broader macroeconomic crisis. These findings reinforce the notion that FinTech-enabled firms were better positioned to maintain market trust and adapt to financial disruptions during

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times of uncertainty.

Table 12 Sensitivity analysis controlling for the COVID-19 pandemic effect

		SEOCAR (-1, +1)		*SEOCAR* (-1, +2)	
Variable	Predicted sign	Coefficient	*t*-stat	Coefficient	*t*-stat
Fintech_Index1	+	0.001**	(2.60)	0.001**	(2.20)
Size	+	0.018**	(2.15)	0.020**	(2.11)
Leverage	-	-0.039***	(-6.19)	-0.048***	(-6.35)
Mtb	-	0.000	(0.16)	0.000	(0.77)
ROA	+	0.005	(0.21)	0.008	(0.36)
Share	-	0.198	(1.27)	0.224	(1.39)
ChgPrice	+	0.035***	(2.90)	0.035***	(3.36)
Nasdaq	+	0.032	(1.25)	0.036	(1.27)
Sent	+	0.063*	(1.83)	0.051	(1.61)
Pandemic	-	0.010	(0.71)	0.017	(1.19)
Constant	?	-0.269***	(-3.65)	-0.393***	(-4.44)
Observations		986		986	
Industry FE		Yes		Yes	
Year FE		Yes		Yes	
Country FE		Yes		Yes	
Cluster by industry		Yes		Yes	
Adj. R-squared		5.5%		5.6%	

[a] Variable definition: See Appendix 1.
[b] Robust *t*-statistics in parentheses.
[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

Table 13 presents the results of a robustness test in response to the concern that technology firms and digital service providers may inherently have higher FinTech-related visibility, potentially biasing the results. To address this issue, we exclude firms classified under SIC codes 737 (computer programming, data processing, and other computer-related services) and 731 (advertising and digital marketing services), which are industries naturally associated with greater FinTech adoption and online search activity. By removing these firms, we ensure that the observed relationship between FinTech development and market reactions to SEOs is not driven by industry-specific effects but rather reflects a broader, cross-industry phenomenon.

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Table 13 Sensitivity analysis excluding technology-Intensive industries

		SEOCAR (-1, +1)		*SEOCAR* (-1, +2)	
Variable	Predicted sign	Coefficient	*t*-stat	Coefficient	*t*-stat
Fintech_Index1	+	0.001**	(2.30)	0.001**	(2.02)
Size	+	0.022***	(3.53)	0.026***	(3.39)
Leverage	-	-0.041***	(-7.09)	-0.048***	(-6.44)
Mtb	-	-0.000	(-0.16)	0.000	(0.38)
ROA	+	0.000	(0.00)	0.003	(0.12)
Share	-	0.258*	(1.91)	0.298**	(2.31)
ChgPrice	+	0.037***	(3.14)	0.037***	(3.48)
Nasdaq	+	0.044	(1.65)	0.048	(1.61)
Sent	+	0.077**	(2.66)	0.064**	(2.41)
Constant	?	-0.307***	(-4.07)	-0.437***	(-5.01)
Observations		886		886	
Industry FE		Yes		Yes	
Year FE		Yes		Yes	
Country FE		Yes		Yes	
Cluster by industry		Yes		Yes	
Adj. R-squared		5.5%		5.6%	

[a] Variable definition: See Appendix 1.
[b] Robust *t*-statistics in parentheses.
[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

The results in Table 13 indicate that *Fintech_Index1* remains positively and significantly associated with *SEOCAR* (-1, +1) ($t = 2.30$) and *SEOCAR* (-1, +2) ($t = 2.02$), suggesting that FinTech development continues to enhance investor confidence in SEOs even after excluding technology-intensive firms. The consistency of the coefficient magnitude and statistical significance with previous findings further supports the robustness of our results. These findings confirm that the observed FinTech effect is not solely driven by technology firms but is applicable across a broader range of industries, strengthening the generalizability and reliability of our conclusions.

Table 14 presents the results of a robustness check using Propensity Score Matching (PSM) to address potential selection bias in the relationship between FinTech development and cumulative abnormal returns around SEO announcements. To address potential self-selection bias, we categorize *Fintech_Index1*, originally a continuous variable, into two groups based on its median value. Firms with higher FinTech development are assigned a dummy variable of 1, while those with lower FinTech development are assigned 0. Next, we estimate a logit model, where this binary FinTech development indicator serves as the dependent variable, and all control variables from the main regression model act as explanatory factors. Using the estimated propensity scores, we conduct caliper matching, ensuring that each firm in the high FinTech development group is matched with a firm in the low FinTech development group with a similar propensity score. Firms without suitable matches are excluded, resulting in a final

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matched sample of 945 observations.

This approach ensures that firms with comparable characteristics—except for their level of FinTech development—are analyzed together, reducing concerns regarding omitted variable bias. The robustness of our results after matching further strengthens the causal interpretation of FinTech's impact on market reactions to SEOs.

The key independent variable, *Fintech_Index1*, measures firm-specific Google search volume for FinTech-related terms. The results confirm that *Fintech_Index1* is positively and significantly associated with *SEOCAR* in both event windows. For *SEOCAR* (-1, +1), the coefficient is 0.001 (t = 2.22), significant at the 5% level. For *SEOCAR* (-1, +2), the coefficient is also 0.001 (t = 1.92), significant at the 10% level.[8] These findings reinforce the conclusion that firms with higher FinTech engagement experience more favorable investor reactions to SEO announcements.

Table 14 PSM results

		SEOCAR (-1, +1)		*SEOCAR* (-1, +2)	
Variable	Predicted sign	Coefficient	*t*-stat	Coefficient	*t*-stat
Fintech_Index1	+	0.001**	(2.22)	0.001*	(1.92)
Size	+	0.019*	(1.98)	0.022*	(2.00)
Leverage	-	-0.039***	(-5.12)	-0.049***	(-5.65)
Mtb	-	0.000	(0.13)	0.000	(0.81)
ROA	+	0.003	(0.13)	0.007	(0.36)
Share	-	0.197	(1.14)	0.231	(1.32)
ChgPrice	+	0.036***	(2.99)	0.037***	(3.56)
Nasdaq	+	0.034	(1.20)	0.039	(1.25)
Sent	+	0.063*	(1.80)	0.050	(1.56)
Constant	?	-0.278***	(-3.19)	-0.408***	(-4.01)
Observations		945		945	
Industry FE		Yes		Yes	
Year FE		Yes		Yes	
Country FE		Yes		Yes	
Cluster by industry		Yes		Yes	
Adj. R-squared		5.4%		5.6%	

[a] Variable definition: See Appendix 1.
[b] Robust *t*-statistics in parentheses.
[c] The notation *, **, *** indicate two-tailed significance levels at 10%, 5%, and 1%, respectively.

Overall, these results emphasize the critical role of FinTech—both at the firm and country levels—in shaping investor responses to SEOs, providing robust support for the relevance of FinTech ecosystems in corporate financial decision-making. Additionally, the PSM results validate the robustness of the relationship between FinTech

[8] In Table 14, the sample size decreases to 945 due to the use of Propensity Score Matching (PSM). The PSM method matches firms based on the model's control variables, and observations without suitable matches are dropped, leading to a reduced sample.

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development and investor reactions, mitigating concerns about potential selection bias.

6. Conclusion

This study aims to investigate whether well-applied FinTech firms experience a difference in the market reaction to SEOs compared to others. Using 986 observations of U.S. SEOs from 2019 to 2022, this study provides evidence that FinTech development, both at the firm and country levels, plays a crucial role in mitigating information asymmetry. These findings suggest that FinTech reduces information asymmetry and enhances stakeholder confidence, particularly for firms operating in environments with greater information frictions.

To further explore the impact of FinTech development, we conduct a series of analyses and robustness tests to ensure the validity of our results. Our findings indicate that FinTech adoption plays a more significant role in mitigating negative market reactions to SEOs when firms face higher information asymmetry. Moreover, firms leveraging financial technology demonstrate greater investment efficiency by reducing underinvestment, suggesting that FinTech enhances capital accessibility and optimizes resource allocation. To assess whether the benefits of FinTech extend beyond the immediate SEO announcement, we conduct an extended event window analysis covering longer trading periods (-1, +7) and (-1, +30) days. The results remain robust, showing that FinTech development continues to positively influence post-SEO market performance, reinforcing the notion that investors perceive FinTech adoption as a value-enhancing factor.

Beyond short-term market reactions, we examine the long-term implications of FinTech adoption on firm performance, as measured by profitability (ROA) and market valuation (Tobin's Q). The findings suggest that FinTech contributes to sustained firm growth and financial stability over time. To ensure the robustness of our findings, we employ alternative FinTech proxies, control for the COVID-19 period, and exclude technology-intensive firms. The consistent results confirm that the observed FinTech effects are not merely driven by industry-specific characteristics but instead reflect broader cross-sector benefits, highlighting FinTech's role in enhancing transparency, reducing financing constraints, and strengthening firm value in capital markets.

The findings of this study offer valuable insights for policymakers, firms, and investors. They underscore the strategic value of FinTech adoption in enhancing transparency, improving capital market efficiency, and strengthening firm value. As FinTech continues to reshape financial markets, firms that effectively integrate

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financial technology into their operations may gain a competitive advantage in securing investor trust and optimizing long-term growth.

It should be noted that our study has limitations. The limitations of our study also provide opportunities for future research. First, we acknowledge that the event-study approach limits sample size. Our sample size is inevitably reduced due to the SEO and FinTech data. FinTech encompasses a broad range of technologies and applications. However, due to the limitations of the data utilized in this study, it is not feasible to differentiate these individual technologies and applications. Future studies could use larger samples, different FinTech data, and samples from other countries to assess the generalizability of our findings. Second, although the *Fintech_Index2* we constructed includes various technologies related to financial technology, whether different financial technologies (e.g., artificial intelligence, blockchain, cloud technology, or data technology) bring different impacts is still an issue worth exploring. Future research can further extend our findings. Third, while our FinTech index (*Fintech_Index1* and *Fintech_Index2*) captures the volume of FinTech-related news coverage by firm-year, it does not account for the sentiment or tone (e.g., positive versus negative) of the news content. Future research could adopt textual analysis methods to refine this proxy and capture the qualitative aspects of FinTech-related discourse. Fourth, we acknowledge that there may still be uncaptured effects of missing confounding events. Future studies could consider other relevant events and different periods to gain further validation and extend the findings of this study. Despite these limitations, our empirical results provide important views beyond the extant literature and should be of interest to companies, regulators, and academic researchers.

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Appendix 1 The definition of variables

Variable		Definition
Dependent variable		
SEOCAR	=	Abnormal (index-adjusted) market returns cumulated over three periods around the SEOs announcement day (*t*): *t*-1 to *t*+1 and *t*-1 to *t*+2.
Independent variable		
Fintech_Index1	=	Google search volume of firm *i*'s name and Fintech synonyms (fintech, financial technology, digital finance, or financial innovation) in the SEO announcement year, scaled from 0 to 100.
Control variable		
Size	=	Natural logarithm of the book value of total assets for firm *i* in the year prior to the SEO announcement.
Leverage	=	The ratio of the book value of long-term debt to the book value of total assets for the firm *i* in the year prior to the SEO announcement.
Mtb	=	The market value of equity is divided by the book value of equity for the firm *i* in the year prior to the SEO announcement.
ROA	=	Return on assets (net income scaled by lagged total assets).
Share	=	Percentage of SEO shares being sold by existing shareholders to total SEO shares offered for firm i in the SEO announcement year.
ChgPrice	=	Change in stock prices 250 days before the SEO announcement day.
Nasdaq	=	Indicator variable that takes the value of 1 for NASDAQ-listed firms and 0 otherwise for firm i in the SEO announcement year.
Sent	=	Composite Baker and Wurgler index of sentiment for firm *i* announcing SEO during the month.
InfoAsm	=	Average daily bid-ask spread of firm *i* over year *t* prior to the SEO announcement.
TobinQ	=	The market value of stocks plus the book value of liabilities is all divided by total assets.
RD	=	Research and development (R&D) expenditures are divided by sales and set the missing value of R&D expenditures as 0.
PPE	=	Property, plant, and equipment divided by total assets.
SalesGrowth	=	The growth rate of net sales over the previous year.

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InvIneff	=	The absolute value of residual from the investment model (Biddle et al. 2009) that predicts the level of investment based on growth opportunities. Deviations from the model based on the Fama-French 30-industry classification, as reflected in the error terms of the investment model, represent the investment inefficiency.
OverInvest	=	The positive firm-year residual from the investment model (Biddle et al. 2009).
UnderInvest	=	The absolute value of the negative firm-year residual from the investment model (Biddle et al. 2009) .
Cash	=	The ratio of cash to total assets.
Dividend	=	Indicator variable that takes the value of 1 if the firm paid a dividend, and zero otherwise.
CFOSale	=	The ratio of cash flow from operations to sales.
Loss	=	The indicator variable that takes the value of 1 if "net income before extraordinary items and current R&D expenses" is negative, and zero otherwise.
Pandemic	=	Indicator variable that takes the value of 1 if the year is 2020, 2021, or 2022 and 0 otherwise.
Alternative variable		
Fintech_Index2	=	Google search volume of firm *i*'s name and Fintech synonyms (fintech, financial technology, digital finance, or financial innovation) and categories (artificial intelligence, blockchain, cloud technology, or data technology) in the SEO announcement year, scaled from 0 to 100.
Fintech_Listing	=	The indicator variable takes the value of 1 for firms located in Fintech ranking-listed countries and 0 otherwise for firm *i* prior to the SEO announcement year.
Fintech_Ranking	=	FinTech ranking for firm *i* prior to the SEO announcement and multiply by -1 for ease of interpretation.

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Appendix 2 Measurement of the FinTech index at the firm level

To collect firm-level FinTech engagement data, we hand collect the firm-level Google search data following a structured Google search process.

First, we conduct searches in Google by entering keywords that combine Fintech-related keywords with a specific firm name. Specifically, we conduct separate searches for *Fintech_Index1* and *Fintech_Index2*, ensuring that each index captures distinct aspects of FinTech engagement. The search format follows: (*Fintech_Index1* or *2*) AND [Firm Name]. *Fintech_Index1* measures the annual Google search volume for a firm's name combined with FinTech-related synonyms, including fintech, financial technology, digital finance, or financial innovation. *Fintech_Index2* represents an expanded version of *Fintech_Index1*, capturing both broad FinTech discussions and specific technological advancements. *Fintech_index2* measures Google search volume of firm *i*'s name and Fintech synonyms (fintech, financial technology, digital finance, or financial innovation) and categories (artificial intelligence, blockchain, cloud technology, or data technology) in the SEO announcement year, scaled from 0 to 100.

Next, to ensure the search results are restricted to a specific time period, we apply a date filter within Google. This is done by selecting the custom date range option under the "Recent" dropdown menu and setting the time frame to match the desired calendar year (e.g., January 1, 2019 – December 31, 2019). This filtering allows us to capture firm-level FinTech-related discussions within a precise annual window.

Once the search is conducted, the total number of articles retrieved by Google is displayed in the top right corner of the results page. Then the total number is scaled from 0 to 100, providing a normalized measure of a firm's FinTech visibility. This result serves as our data point, representing the number of FinTech-related mentions for the firm in that specific year. This approach ensures a consistent and replicable methodology for tracking firm-specific FinTech engagement over time.

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Appendix 3 Existing research on the impact of FinTech on firms

#	Authors	Country	Industry	Sample period	Outcome(s)	Major Findings	Impact
1	Chen et al. (2019a)	US	General	2003-2017	Firm value	Most FinTech innovations yield substantial value to innovators.	Positive
2	Yang et al. (2023)	US	General	2020	Firm value	FinTech applications alleviate the negative impact of the COVID-19 pandemic on firm value.	Positive
3	Xu et al. (2022)	China	General	2013-2018	Bank loan	Fintech positively contributes to firm access to bank loans.	Positive
4	Ding et al. (2022)	China	General	2011-2019	Innovation	Financially constrained firms exhibit a higher innovation level in cities with better-developed FinTech services.	Positive
5	Wen et al. (2023)	China	General	2010-2020	Reporting quality	FinTech development improves corporate financial reporting quality.	Positive
6	Guo and Zhang (2023)	China	General	2011-2018	Financing constraint	The development of FinTech can significantly reduce firms' financing constraints.	Positive
7	Ye et al. (2024)	China	General	2013-2021	Investment efficiency	FinTech can effectively reduce underinvestment.	Positive
8	Wang et al. (2024)	China	General	2011-2022	Productivity	FinTech has a positive effect on enhancing firm productivity.	Positive
9	Tang et al. (2025)	China	General	2011-2021	Firm value	FinTech development increases tax avoidance, facilitating firm value.	Positive
10	Cheng and Qu (2020)	China	Finance	2008-2017	Credit risk	Bank using FinTech significantly reduces credit risk in banks.	Positive
11	Wang et al. (2021)	China	Finance	2008-2017	Operating efficiency	Development of FinTech leads to increased profitability, financial innovation, and improved control of risk.	Positive
12	Tan et al. (2023)	China	Finance	2010-2020	Innovation	Bank using FinTech positively affects corporate innovation.	Positive
13	He et al. (2023)	China	Finance	2011-2021	Risk taking	The use of fintech improves the quality of banks' internal controls, thereby reducing risk-taking.	Positive
14	Zhao et al. (2022)	China	Finance	2003-2018	Performance	FinTech innovation reduces banks' profitability and asset quality in the aggregate, but it improves banks' capital adequacy and management efficiency	Positive/ Negative
15	Liu et al. (2023)	US	General	2012-2021	Reporting lag	Top 25 FinTech firms experience greater reporting audit and financial lags than other firms.	Negative

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Appendix 4　Measurements used in existing empirical research on FinTech

#	Authors	Journal	Context	Measurement	Level
1	Daud et al. (2022)	Finance Research Letters	63 countries	Number of articles based on the country and FinTech keywords search	Country
2	Liu and Chu (2024)	Asia Pacific Management Review	197 countries	FinTech development rankings published by IFZ	Country
3	Tang et al. (2025)	International Review of Financial Analysis	China	FinTech index published by PKU-DFIIC	Province
4	Ding et al. (2022)	Journal of Corporate Finance	China	FinTech index published by PKU-DFIIC	City
5	Wen et al. (2023)	Economic Modelling	China	Number of FinTech patent filings	City
6	Ye et al. (2024)	Finance Research Letters	China	Number of FinTech enterprises located in the city	City
7	Wang et al. (2024)	Finance Research Letters	China	Number of FinTech enterprises located in the city	City
8	Cheng and Qu (2020)	Pacific-Basin Finance Journal	China	Number of articles based on the firm and FinTech keywords search	Firm
9	Xu et al. (2022)	Accounting & Finance	China	Firms with or without FinTech subsidiaries	Firm
10	Tan et al. (2023)	Finance Research Letters	China	Number of FinTech patents held by firm	Firm
11	Guo and Zhang (2023)	Research in International Business and Finance	China	Number of occurrences of FinTech keywords in financial report	Firm
12	He et al. (2023)	Finance Research Letters	China	Number of occurrences of FinTech keywords in financial report	Firm
13	Chen et al. (2019a)	Review of Financial Studies	US	Number of FinTech patent filings	Firm
14	Liu et al. (2023)	Review of Pacific Basin Financial Markets and Policies	US	IDC FinTech rankings	Firm
15	Yang et al. (2023)	Review of Quantitative Finance and Accounting	US	FinTech development rankings published by IFZ	Firm

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Appendix 5 Fintech country rankings from IFZ (2018–2022)

Year	Ranking	Country
2018	1	Singapore
2018	2	Switzerland
2018	3	UK
2018	4	Netherlands
2018	5	Canada
2018	6	Sweden
2018	7	US
2018	8	Hong Kong
2018	9	Germany
2018	10	Australia
2018	11	Norway
2018	12	Austria
2018	13	Japan
2018	14	Ireland
2018	15	France
2018	16	Luxembourg
2018	17	Israel
2018	18	United Arab Emirates
2018	19	Italy
2018	20	China
2018	21	Poland
2018	22	Russian Federation
2018	23	South Africa
2018	24	Brazil
2018	25	India
2018	26	Argentina

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Appendix 5 Fintech country rankings from IFZ (2018–2022) (Continued)

Year	Ranking	Country
2019	1	Singapore
2019	2	Switzerland
2019	3	UK
2019	4	Netherlands
2019	5	Canada
2019	6	US
2019	7	Hong Kong
2019	8	Sweden
2019	9	Japan
2019	10	Australia
2019	11	Germany
2019	12	Austria
2019	13	Norway
2019	14	Ireland
2019	15	South Korea
2019	16	France
2019	17	Luxembourg
2019	18	Estonia
2019	19	United Arab Emirates
2019	20	Israel
2019	21	Italy
2019	22	China
2019	23	Poland
2019	24	Russian Federation
2019	25	Chile
2019	26	South Africa
2019	27	Brazil
2019	28	India
2019	29	Argentina

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Appendix 5 Fintech country rankings from IFZ (2018–2022) (Continued)

Year	Ranking	Country
2020	1	Singapore
2020	2	Switzerland
2020	3	Sweden
2020	4	Netherlands
2020	5	Canada
2020	6	US
2020	7	Hong Kong
2020	8	UK
2020	9	Germany
2020	10	Australia
2020	11	Germany
2020	12	Norway
2020	13	Japan
2020	14	Austria
2020	15	South Korea
2020	16	Ireland
2020	17	France
2020	18	Luxembourg
2020	19	Estonia
2020	20	Spain
2020	21	United Arab Emirates
2020	22	Israel
2020	23	Italy
2020	24	Poland
2020	25	China
2020	26	Russian Federation
2020	27	Chile
2020	28	South Africa
2020	29	India
2020	30	Brazil
2020	31	Argentina

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Appendix 5 Fintech country rankings from IFZ (2018–2022) (Continued)

Year	Ranking	Country
2021	1	Singapore
2021	2	Switzerland
2021	3	Sweden
2021	4	Netherlands
2021	5	US
2021	6	UK
2021	7	Hong Kong
2021	8	Canada
2021	9	Germany
2021	10	Australia
2021	11	Norway
2021	12	Ireland
2021	13	Japan
2021	14	Austria
2021	15	South Korea
2021	16	Luxembourg
2021	17	France
2021	18	Estonia
2021	19	Spain
2021	20	Israel
2021	21	United Arab Emirates
2021	22	Lithuania
2021	23	Italy
2021	24	Poland
2021	25	China
2021	26	Chile
2021	27	Russian Federation
2021	28	South Africa
2021	29	India
2021	30	Brazil
2021	31	Argentina

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Appendix 5 Fintech country rankings from IFZ (2018–2022) (Continued)

Year	Ranking	Country
2022	1	Singapore
2022	2	Switzerland
2022	3	Sweden
2022	5	US
2022	6	Netherlands
2022	7	UK
2022	9	Canada
2022	10	Hong Kong
2022	11	Germany
2022	12	Australia
2022	14	Norway
2022	15	South Korea
2022	16	Austria
2022	17	Japan
2022	18	Ireland
2022	19	Estonia
2022	20	Luxembourg
2022	21	France
2022	22	Spain
2022	23	United Arab Emirates
2022	24	Israel
2022	25	Lithuania
2022	26	China
2022	28	Italy
2022	29	Poland
2022	30	Chile
2022	31	Russian Federation
2022	32	South Africa
2022	33	India
2022	34	Brazil
2022	35	Argentina

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