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Reducing asymmetric cost behaviors: Evidence from digital innovation

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This study quantifies the impact of digital innovation on corporate performance, offering insights into the sustainability of digital innovation's impact and providing guidance for firms embarking on their digital innovation journey. We examine the effect of digital innovation on cost stickiness using patent reports spanning from 2007 to 2022. The baseline analysis results reveal that digital innovation significantly mitigates cost stickiness in companies. This finding remains robust after addressing endogeneity concerns and conducting various robustness tests. We probe potential mechanisms and discover that digital innovation reduces cost stickiness by enhancing the quality of internal controls, improving resource-adjustment efficiency, and addressing managerial over-optimism. Heterogeneity analysis indicates a more pronounced impact of digital innovation on reducing asymmetric cost behaviors in larger firms, those beyond the growth stage, and in regions with active digital procurement, well-developed digital taxation governance, and sound judiciary infrastructures. Additionally, our expanded analysis confirms the financial benefits of digital innovation in reducing cost stickiness. A notable discovery is the negative correlation between digital transformation and cost stickiness within digitally innovative firms, underscoring the greater significance of digital innovation over mere digitization. Overall, this study significantly advances our understanding of how digital innovation influences cost management strategies.

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Introduction

Against the backdrop of the persistent impact of the COVID-19 pandemic, the global economy is confronted with the looming threat of recession. The International Monetary Fund highlighted that measured by purchasing power parity (PPP), the global GDP shrank by approximately −4.4% in 2020, marking the most severe economic downturn of the century. However, bolstered by robust technological underpinnings, developmental resilience, and innovation capabilities, the digital economy has emerged as a critical force in reshaping global factor allocations, altering the economic contours of the world, and transforming the essence of international competition (Jiang et al. 2022; Luan et al. 2023; Chen et al. 2023). In the current digital era, the process of digital transformation at the company level stands as a key element for businesses to navigate the digital revolution effectively (Verhoef et al. 2021) and is identified as a crucial strategy for maintaining competitiveness (Skare and Soriano, 2021; Jiang et al. 2022; Ancillai et al. 2023; Feliciano-Cestero et al. 2023). With the deep integration of digital technology and business processes, companies are making significant progress in improving efficiency and creating more personalized innovative products (Chen and Jiang, 2024). Digital innovation is regaining attention among scholars (Huang et al. 2023; Liu et al. 2023a, 2023b; Wang et al. 2023). Distinct from the broader notion of digital transformation, which emphasizes the adoption of digital technologies across operations, digital innovation refers to the innovative process of combining digital technology with non-digital products or services to generate new products, processes, and business models (Lee and Berente, 2012; Hinings et al. 2018; Hanelt et al. 2021). This shift from transformation to innovation signifies a pivotal moment where companies not only adapt to the digital realm but also spearhead the creation of novel value propositions that have the potential to redefine markets and industries. Against this backdrop, exploring the nuances of corporate digital innovation and assessing its economic impacts becomes crucial.

Existing research has extensively examined digitalization's impact on various facets, including financial outcomes (e.g., Chen and Srinivasan, 2024; Malodia et al. 2023; Tian et al. 2023; Chen and Jiang, 2024), productivity enhancement (e.g., Gaglio et al. 2023; Du and Jiang, 2022), innovation capacity (e.g., Gaglio et al. 2023; Zhuo and Chen, 2023), financing accessibility (e.g., Skare et al. 2023; Zhou and Li, 2023), cost management (e.g., Jia et al. 2023; Voshaar et al. 2023; Chen and Xu, 2023), and environmental sustainability (e.g., Zhou et al. 2023; Bendig et al. 2023). However, the bulk of existing literature primarily focuses on the company's overall digital transformation, with less emphasis on how corporate digital innovation goes beyond mere digitization and its distinct significance. Moreover, the specific interplay between digital innovation and cost management strategies remains underexplored. This study seeks to bridge this gap by delving into the intricate connection between digital innovation and cost stickiness—a reflection of asymmetric cost behavior where costs rise more with increasing sales than they fall with decreasing sales (Anderson et al. 2003; Weiss, 2010; Banker and Byzalov, 2014). This phenomenon underscores the challenges firms encounter in achieving cost efficiency. Inefficiencies in cost management, stemming from crucial decisions about resource allocation, utilization, and budgeting in relation to revenue strategies, can substantially impact a firm's performance, affecting its sustainability and profitability. Inadequate cost management can erode a company's ability to price competitively, lead to resource wastage, and heighten financial risks (Zhang et al. 2019; He et al. 2020). This study unravels how digital innovation influences firm performance through resource management adjustments. Our objective is to underscore the strategic importance of digital innovation and establish its vital role in digitization.

Two recent studies exploring the correlation between corporate robot utilization and cost stickiness offer intriguing perspectives pertinent to our inquiry (Jia et al. 2023; Voshaar et al. 2023). However, these investigations reveal areas requiring improvement. Firstly, the dataset employed by Jia et al. (2023) fails to capture the era marked by extensive corporate digitalization, nor does it delve into mechanism analysis or probe into the mediating influence of mechanism variables. Secondly, Voshaar et al. (2023) explicitly examine labor cost stickiness, a narrower scope than the comprehensive operational cost stickiness that our research explores. Additionally, both studies limit their focus to robotic adoption, a singular aspect of digital transformation related to intelligent manufacturing. This method might overlook the significant impacts that other digital technologies such as blockchain technology applications, virtual reality and augmented reality, 5 G and 6 G communication technology, cloud computing and big data, artificial intelligence and machine learning have on transforming the cost structures and business models of companies. Particularly relevant to our study is Chen and Xu's (2023) exploration of the cost ramifications of corporate digitalization. Chen and Xu (2023) measure the extent of digital transformation by counting the occurrence of related keywords. While this technique is pragmatic, it comes with several constraints. While keyword frequency analysis serves as a feasible technique given data constraints, the chosen explanatory variables could benefit from refinement. The variability in annual report audiences poses a risk of measurement inaccuracies, as some reports are crafted with specific stakeholders in mind, potentially distorting the depiction of digital efforts. Moreover, due to technical and temporal limitations, the method may miss subtleties like modifiers or emotional nuances, affecting the weight of different textual elements. Furthermore, their model of cost stickiness, derived from Anderson et al. (2003),, introduces complexities when discussing model endogeneity, which may affect the empirical findings' credibility. In addition, their reliance on heterogeneity analysis to hint at influencing mechanisms, rather than directly examining the effects of corporate digitization on mechanism variables, complicates drawing solid conclusions about mechanisms. Most critically, Chen and Xu (2023) concentrate on general digital transformation rather than digital innovation, which is the focal point of our study. In the era where digital transformation is ubiquitous, the specific role of digital innovation in bolstering digital transformation remains an open question.

Compared to pertinent research (Chen and Xu, 2023; Jia et al. 2023; Voshaar et al. 2023), our study broadens the scope in terms of research subjects, indicators for measurement, methodologies, and theoretical frameworks. Addressing the gaps identified in existing research, our study employs an extensive dataset, advancing the evaluation of digital innovation by monitoring corporations' digital technology patent filings. This approach serves as a solid marker of a firm's innovative capability and knowledge accumulation in digital technologies, offering a tangible measure of its digital innovation efforts. Moreover, we adopt the model proposed by Weiss (2010) to examine asymmetric cost behaviors, particularly cost stickiness, incorporating data from firms that report negative values as evidence of cost stickiness. To strengthen the credibility of our results, we perform multiple tests designed to address endogeneity issues, including two-stage instrumental variable regression, propensity score matching (PSM), and placebo tests, thereby enhancing the methodological robustness and reliability of our findings. Our study incorporates an in-depth mechanism analysis, elucidating the shifts in mechanism variables following the advent of digital innovation.

The analysis of heterogeneity not only provides policy recommendations to boost the effects of digital innovation via government procurement, digital taxation, and judicial frameworks but also highlights the essential role of digital innovation in the overall digital transformation process.

The first contribution of our study lies in broadening the discourse on digital behavior and its relation to cost stickiness. Unlike prior research, which primarily focused on the adoption of robotics or the general intent towards digital transformation (Jia et al. 2023; Voshaar et al. 2023; Chen and Xu, 2023), our work provides a deeper analysis of how digital technologies empower various business domains such as production, management, and sales. We explore the significant factors that influence asymmetric cost behaviors, offering a detailed examination of the ways digital innovation impacts cost stickiness. Our research highlights the critical role of digital innovation in diminishing operational cost stickiness, identifying enhanced resource-adjustment capabilities, improved internal control quality, and reduced managerial overconfidence as key mechanisms facilitating this effect. Additionally, our findings equip corporate management with practical strategies derived from extensive cross-sectional analyses. Notably, our findings show that digital innovation's role in reducing cost stickiness is particularly pronounced in companies situated in areas with well-established digital governance, taxation, and judicial frameworks. This points to a wider call for national efforts to upgrade digital infrastructure, suggesting significant policy implications for regions still catching up in digital maturity. Moreover, our study makes a valuable addition to understanding the financial outcomes of corporate digital innovation. The performance implications of corporate digital innovation, particularly how cost adjustments post-innovation introduce uncertainties, have received less attention. We further analyze how digital innovation provides firms a competitive edge by analyzing its effects on cost stickiness, profitability, and risk management, thereby highlighting its strategic value in the digital age.

Our research also provides a substantial contribution by broadening our comprehension of the economic impacts of digital innovation. This study notably enriches the dialogue surrounding corporate digital innovation, which has previously focused on firm performance (Huang et al. 2023; Liu et al. 2023b; Hanelt et al. 2021), ESG (Environmental, Social, and Governance) achievements (Huang et al. 2023), and total factor energy efficiency (Lu and Li, 2024). By focusing on how cost management responds to digital innovation, our study fills a notable void in the existing literature and illuminates the wider implications of digital innovation on corporate strategies. Furthermore, we employ various methodological techniques to mitigate endogeneity issues, enhancing the credibility of our insights into how corporate digital innovation influences cost stickiness. Moreover, our study introduces indicators to assess the degree of corporate digitalization, providing a thorough and detailed analysis of digital innovation as a critical element of digital transformation. We investigate whether the impacts of digital innovation on cost stickiness are more significant compared to those stemming from non-innovative digital transformation initiatives. Our empirical findings reveal a notable negative association between digital innovation and cost stickiness in firms that actively pursue digital innovation—a relationship not observed in non-innovating firms. This highlights digital innovation's critical role in fostering value creation and empowerment, advocating for prioritizing it in companies' digitalization strategies.

The remainder of this paper is organized as follows: Section 2 provides a detailed review of relevant literature. Section 3 describes the data sources, variable definitions, and the methodologies used for empirical analysis. Section 4 displays the empirical findings. Section 5 delves into an in-depth examination of the mechanisms behind these results. Section 6 investigates heterogeneity across various cross-sections. Section 7 includes further discussions and insights. The paper concludes with Section 8, which summarizes the main findings and their implications.

Review of literature and theoretical framework

Economic outcomes in corporate digitalization. Digitalization involves the incorporation of digital technologies into business operations, as defined by Ha (2022). In recent years, the digitalization of firms has garnered considerable academic attention, with numerous studies exploring the motivations for corporate digitalization efforts (Zhou et al. 2023; Jiang et al. 2024). Research has extensively examined various driving forces, including economic globalization (Skare and Soriano, 2021), changes in the taxation environment (Chen et al. 2023), impacts of the COVID-19 pandemic (Amankwah-Amoah et al. 2021), the pursuit of low-carbon initiatives (Chen et al. 2023; Ma et al. 2022; Wang et al. 2021), and governmental digitalization policies (Wang et al. 2023).

Previous studies have thoroughly investigated the economic impacts of firm digitalization, highlighting its crucial role in enhancing business operations. Technological advancements are linked to various improvements, including increased productivity (Brynjolfsson et al. 2019; Du and Jiang, 2022; Gaglio et al. 2023), boosted innovation capabilities (Ardito, 2023; Gao et al. 2023; Gaglio et al. 2023; Zhuo and Chen, 2023), improved financial performance (Peng and Tao, 2022; Malodia et al. 2023; Yang and Yee, 2022; Zhai et al. 2022; Tian et al. 2023; Chen and Jiang, 2024), enhanced operational resilience (Li et al. 2022; Zhai et al. 2022), greater value creation (Chen and Srinivasan, 2024), and better access to financing (Li et al. 2023; Skare et al. 2023; Zhou and Li, 2023). These benefits underscore the transformative potential of digital technologies across different dimensions of corporate management.

While corporate digital transformation has significantly improved economic performance, the swift pace of technological and market changes suggests that transformation alone may not be sufficient for businesses to maintain a competitive edge (Nambisan et al. 2017). In this scenario, digital innovation becomes a crucial element, not merely enhancing but also broadening these economic benefits, driving companies into new phases of growth, and generating more significant economic impacts. The academic community has yet to agree on a universal definition of digital innovation, as research encompasses a wide array of focuses. Nevertheless, a synthesis of the existing literature identifies three primary dimensions of corporate digital innovation: product and service innovation, operational process innovation, and business model innovation. Product and service innovation entails the introduction of novel or substantially improved offerings that leverage digital technologies such as AI, IoT, and blockchain (Nambisan et al. 2020). This facet of innovation emphasizes using technology to enhance product features, improve service quality, or create novel customer experiences. Balci (2021) suggested that innovations in products and services have the potential to enhance customer satisfaction, thereby cultivating loyalty. Huang et al. (2023) noted that pioneering products and services, such as autonomous vehicles and smart home solutions, allow firms to enter new markets or expand their current market footprint. Furthermore, Mariani and Nambisan's (2021) examination of Online Review Platforms indicates that unique products and services can significantly boost a brand's value and recognition in the market.

Within operational process innovation, digital innovation is leveraged to refine and optimize a company's internal operations, such as production, logistics, and human resources management, via digital tools. The objective is to boost efficiency, cut costs, and enhance flexibility by utilizing automation and intelligent solutions (Abrell et al. 2016; Mendling et al. 2020; Van Looy, 2021). For example, the implementation of robotics has streamlined operations by reducing the reliance on manual labor, shortening production cycles, and increasing overall productivity (Alguacil et al. 2022). A study analyzing Chinese listed companies over a period (Liu et al. 2023b) demonstrates that digital innovation markedly elevates operational efficiency within the manufacturing industry, highlighting its pivotal contribution to operational improvements.

From the perspective of business model innovation, digital innovation represents the introduction of novel business models that redefine how companies create, deliver, and capture value using digital technology. This encompasses devising innovative revenue streams, customer engagement strategies, and value distribution mechanisms. Erevelles et al. (2016) discovered combining big data analytics with artificial intelligence algorithms could reveal new risks and opportunities across industries by integrating varied data sources. Additionally, Ritter and Pedersen (2020) observed that groundbreaking business models emerging from digital innovation open up novel profit avenues and stimulate business growth opportunities.

To our knowledge, empirical research on digital innovation is relatively scarce, with a scant number of studies investigating the relationship between digital innovation and cost stickiness. Exploring how digital innovation can contribute to companies by facilitating efficient cost management represents a largely unexplored area within the existing body of scholarly work.

Factors influencing cost stickiness. Cost stickiness arises when managers retain surplus capacity during downturns in demand but expedite capacity increases in response to demand surges (Cannon, 2014). Various studies have documented and corroborated this asymmetrical cost behavior (Anderson et al. 2003; Weiss, 2010; Banker and Byzalov, 2014; He et al. 2020). Some scholars have applied the proportional cost model to clarify cost stickiness, positing that managerial decisions have no bearing on cost adjustments and that shifts in business volume are directly proportional to cost changes (Noreen, 1991). However, this model has faced criticism for overlooking managerial influence on cost adjustments (Noreen and Soderstrom, 1997). Banker and Byzalov (2014) contend that cost stickiness primarily arises from challenges in resource adjustment, skewed managerial expectations, and agency dilemmas. Specifically, constraints in resource adjustment compel managers to conserve excess resources during sales downturns, leading to asymmetric cost behaviors. For instance, Habib and Hasan (2019) found that commitments to corporate social responsibility (CSR) can limit a firm's flexibility in resource adjustment amidst revenue declines, thereby associating CSR engagement with heightened cost stickiness.

Moreover, managerial over-optimism regarding future performance can lead to sustained high costs, exacerbating cost asymmetry. Chen et al. (2019) identified a positive link between optimistic forecasts and cost stickiness, particularly when the costs associated with adjustments and idle capacities are substantial. Additionally, managers might adopt suboptimal strategies for resource adjustment driven by personal incentives. Enhanced corporate governance mechanisms that curb managerial latitude can alleviate these agency issues, thus reducing cost asymmetry. A seminal study by Chen et al. (2012) demonstrated that larger boards, the separation of CEO and chair roles, and board ownership are inversely related to cost stickiness. Further inquiries into corporate governance's impact on cost stickiness, especially via ownership structure, indicated that state ownership might elevate cost stickiness due to political influences (Prabowo et al. 2018). Chung et al. (2019) observed that scrutiny from long-term institutional investors might reduce cost stickiness. Additionally, specific incentive schemes can influence managerial decisions, affecting the level of cost stickiness. Kama and Weiss (2013) illustrated that managers' initiatives to avoid losses lead to cost reductions in the face of declining sales, thereby alleviating cost stickiness.

Conceptual framework: Exploring the nexus between digital innovation and cost stickiness. Given that the three primary determinants of cost stickiness are identified as agency problems, resource-adjustment costs, and managerial anticipation (Banker and Byzalov, 2014; Dai et al. 2023), we propose that a firm's digital innovation could influence cost stickiness by enhancing internal controls, boosting the efficiency of resource adjustments, and reducing managerial over-optimism.

As digital transformation becomes a critical strategy for organizations seeking to secure competitive advantages and foster differentiation (Mikalef and Pateli, 2017; Ferreira et al. 2019; Ancillai et al. 2023; Feliciano-Cestero et al. 2023), the reliance on adept information management becomes increasingly crucial for business operations (Howell et al. 2018). Within this framework, digital technological innovation—recognized as an advanced phase of digitization (Hanelt et al. 2021; Liu et al. 2023a)—is essential for integration processes. It facilitates the thorough incorporation of digital technology into existing products, services, and business models, significantly enhancing the quality of internal controls within the daily operations of companies. This comprehensive integration is pivotal for modernizing business practices and sustaining competitive advantages. Firstly, data analysis empowers firms to establish a quantitative risk assessment framework, pinpoint high-risk activities and processes, and identify critical areas for internal control and oversight (Jiang et al. 2022). Secondly, in the digital transformation era, companies can leverage information system privileges, electronic signatures, facial recognition, and other artificial intelligence technologies to introduce novel post-operational controls, significantly elevating the security and standardization of business operations and bolstering internal governance. Thirdly, a prevalent challenge for companies lies in designing comprehensive internal control systems that, in practice, often fail to be effectively implemented. This leads to a situation where internal control designs are merely ceremonial, not fulfilling their intended role in risk detection and prevention (Zhou et al. 2023). However, incorporating digital technology innovations into the design and execution of internal control systems can transform them into standardized procedures that are impervious to systematic manipulation or circumvention by individuals. Fourthly, digital technology innovation enhances the quality and efficiency of audits (Fedyk et al. 2022), thereby facilitating amplified oversight and verification of a company's internal operations. Given these considerations, we assert that digital innovation plays an indispensable role in augmenting the quality of their internal controls and mitigating asymmetric cost behaviors arising from agency dilemmas.

Efficient utilization of digital technology can improve internal operation efficiency (Tang et al. 2018; Enholm et al. 2022; Liu et al. 2023a; Zhou et al. 2023). Digital innovation guarantees intelligence and automation in a firm's production and business activities (Boland et al. 2007), thereby advancing the efficiency of resource adjustment (Cuevas-Vargas et al. 2022; Mouelhi, 2009) and mitigating cost stickiness. From one perspective, digital innovation can expedite asset utilization, lessen resource redundancy, and lower resource-adjustment costs, thus curbing asymmetric cost behavior. Take ERP systems, an important digital technology innovation for companies, for example, the application of an ERP enables real-time monitoring of firms' sales, production, inventory, and purchasing status and improves the transparency of corporate information (Chapman and Kihn, 2009). Therefore, when suffering from market demand declines, an ERP can help managers quickly and comprehensively understand the allocation of various resources, identify idle resources that can be reduced, and cut investments in a timely manner. Conversely, during market demand upsurges, ERP provides insights to aid managers in accurately predicting resource needs for production expansion and timely increasing resource inputs. From another perspective, the proliferation of digital innovation within companies results in enhanced efficiency of labor adjustments, which in turn mitigates cost stickiness (Anderson et al. 2003; Golden et al. 2020). Firms' implementation of digital technologies and their penetration can bring about innovation in human resources and major changes in original working methods and human resource management models. Companies can optimize the process of personnel management and recruitment by applying data analysis and, as a result, reduce labor-adjustment costs. At the same time, digital technologies have replaced some simple and tedious jobs with computers, artificial intelligence, robots, and so on, which have helped liberate productivity and improve labor efficiency (Li et al. 2022). Summing up, we argue that digital innovation promotes companies' resource-adjustment capabilities and further mitigates cost stickiness.

According to the managerial optimistic expectation theory, executives with an optimistic outlook are prone to maintaining a positive view of their firm's future operational prospects, often perceiving minor economic fluctuations as short-lived and temporary (Scheier et al. 1994; Graham et al. 2013). In the face of declining revenues and profits, these managers might eschew significant cuts in fixed asset or personnel investments. Conversely, they may be slow to react to increases in sales and overall market demand. Asymmetric cost behaviors partly stem from this subjective anticipation of future operational conditions. However, the innovation in operational models facilitated by digital innovation can amplify a company's capacity to leverage data analytics in operational management processes (Agrawal et al. 2019; Babina et al. 2020). The accumulation of business data gives managers feedback on internal resource allocation and product market supply and demand dynamics. Data analysis empowers managers to make well-informed resource allocation decisions, thus mitigating managerial overconfidence. Additionally, a company's commitment to digital innovation requires that managers develop digital competencies, prompting them to transform into skilled workers who complement digital advancements. Managers with superior expertise exhibit a more nuanced insight into the digital landscape, enabling them to render more precise forecasts of earnings and digital business contexts (Baik et al. 2011; Demerjian et al. 2013). Therefore, we posit that digital innovation at the firm level can temper managerial over-optimism and attenuate cost stickiness (Fig. 1).

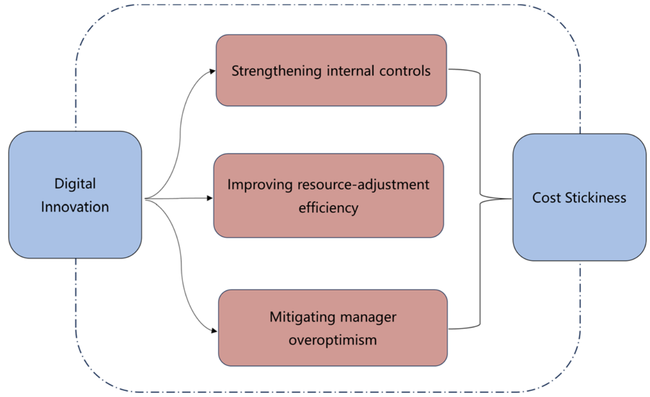

Fig. 1 The Nexus between digital innovation and cost stickiness.

Research design and data

Quantifying cost stickiness. Cost stickiness is delineated as the variation in the slope of the cost function between periods of sales increase and decrease within the first to the fourth quarter of year t. Consistent with the approach outlined by Weiss (2010), our quantification of cost stickiness involves estimating Eq. (1).

$$STICK_{i,t} = \log\left(\frac{\Delta COST}{\Delta SALE}\right)_{i,\underline{\tau}} - \log\left(\frac{\Delta COST}{\Delta SALE}\right)_{i,\bar{\tau}}, \underline{\tau}, \bar{\tau} \in \{t, \ldots, t-3\} \tag{1}$$

In this equation, $STICK_{i,t}$ represents the cost stickiness of firm i in year t, with the absolute value of $STICK$ considered in this study. $COST$ denotes the operating costs, and $SALE$ denotes the firm's sales. $\Delta SALE$ indicates the changes in sales from year $t-1$ to t, while $\Delta COST$ represents the changes in costs over the same period. $\underline{\tau}$ refers to the latest quarter that experienced a rise in sales from the first to the fourth quarter of a specific year, and $\bar{\tau}$ denotes the latest quarter that experienced a decrease in sales over the same period. Following Weiss (2010), a negative value for $STICK$ signifies that the decrease in costs when sales decrease is less than the increase in costs when sales increase, suggesting the existence of asymmetric cost behaviors. Therefore, we will exclude samples with positive $STICK$ values, indicating anti-sticky companies, and focus solely on samples with negative $STICK$ values, indicating cost stickiness. To clarify, we utilize the absolute value of $STICK$, denoted as Abs_STICK. An increased Abs_STICK value points to a greater extent of cost stickiness. In robustness checks, we utilize the ABJ model to quantify cost stickiness.

Quantifying firm digital innovation. Evaluating the level of digital innovation at the firm level stands as a central focus of this study. The count of patent applications is a commonly used symbol to depict a firm's innovation. Existing literature identifies firm-level digital patents by analyzing patent text information and constructing metrics for corporate digital innovation using the quantity of patent applications (Liu et al. 2023a). Studies have adopted similar methodologies focusing on artificial intelligence within digital technology, conducting patent text analyses, and developing corresponding indices (Yang and Yee, 2022). Inspired by these approaches, our investigation conducts a thorough keyword text analysis of the abstracts, descriptions, and claims of all patent filings for inventions and utility models filed by publicly listed companies to ascertain whether each patent pertains to key digital technologies. Specifically, we extract categories of key digital technology patents from the "Key Digital Technology Patent Classification System (2023)" published by the China National Intellectual Property Administration. We then match these categories with the patent classification and main classification numbers of the patents held by listed companies to filter for key digital technology patents. Ultimately, we aggregate each company's annual number of key digital technology patent applications. The logarithmically transformed count of key digital

Table 1 Summary statistics of key variables.

Variable	Observations	Mean	S.D.	Min	P25	P50	P75
Abs_STICK	10822	0.5737	0.6005	0.0229	0.1315	0.3495	0.7958
DI	10822	0.4094	0.7956	0.0000	0.0000	0.0000	0.6931
SIZE	10822	22.2833	1.1633	20.4959	21.3906	22.1137	23.0535
AGE	10822	2.8430	0.3227	2.1972	2.6391	2.8904	3.0910
TANG	10822	0.9220	0.0748	0.7185	0.8990	0.9484	0.9739
GrossProfit	10822	0.2826	0.1540	0.0689	0.1640	0.2544	0.3732
LIQUID	10822	2.1418	1.5357	0.6421	1.1351	1.6176	2.5514
IncomeDD	10822	0.0739	0.2617	0.0000	0.0000	0.0000	0.0000
INDIR	10822	37.0648	4.3889	33.3300	33.3300	33.3300	42.8600
DUALITY	10822	0.2629	0.4402	0.0000	0.0000	0.0000	1.0000
INST	10822	45.5478	24.9307	3.2879	25.2833	47.0213	66.0523
OER	10822	0.0829	0.0509	0.0177	0.0436	0.0709	0.1103

technology patents based on the main classification number plus one serves as this paper's proxy variable for digital innovation. For robustness checks, our study uses the logarithmically transformed count of pivotal digital technology patents based on the classification number plus one as an alternative indicator for digital innovation.

Setting of control variables. The analytical model incorporates company-level control variables. Firstly, firm-specific attributes are quantified through the logarithmically transformed total assets (*SIZE*) and the company's operational tenure (*AGE*). Secondly, variables measuring financial health consist of the ratio of tangible assets to total assets (*TANG*), gross profit margin (*GrossProfit*), the proportion of current assets to total assets (*LIQUID*), a binary indicator for successive sales declines (*IncomeDD*), and sales growth relative to the previous year (*GROWTH*). Lastly, variables related to corporate governance encompass the share of independent directors (*INDIR*), a binary indicator for a combined CEO-chairman role (*DUALITY*), the institutional ownership ratio (*INST*), and operating expense ratio (*OER*). Detailed variable definitions can be found in Table A1.

Methodology. In our baseline analysis, we aim to evaluate whether firm digital innovation influences the cost stickiness of companies. The subsequent model is formulated:

$$Abs\_STICK_{i,t} = \beta_0 + \beta_1 DI_{i,t} + \gamma X_{i,t} + \vartheta_t + \eta_j + \varepsilon_{i,t} \qquad (2)$$

where i and t represent the firm and the year, respectively. The term *Abs_STICK* is defined as the absolute value of *STICK*, as calculated by Eq. (1). The symbol $DI_{i,t}$ stands for the rank of digital innovation of firm i in year t. $X_{i,t}$ encompasses the firm-specific control variables previously outlined. The notation ϑ_t signifies the year-specific fixed effects, while η_j stands for the industry-specific fixed effects. The term $\varepsilon_{i,t}$ is the error term. Equation (2) further adjusts for firm-specific cluster-robust standard errors. Each variable with a continuous scale undergoes winsorization at the 5th and 95th percentiles to minimize the effect of outlier.

Data. This study investigates the consequence of digital innovation on cost stickiness in publicly traded Chinese firms from 2007 to 2022, utilizing a panel dataset derived from the CSMAR and Wind databases. This dataset comprises annual financial statements of companies listed on the Shanghai and Shenzhen stock exchanges. The analysis excludes companies demonstrating no cost stickiness—specifically, those within the financial sector, delisted firms, companies identified with *ST or ST, entities issuing both A and B shares, firms in their IPO year or earlier, companies with negative total assets and equity, and those lacking necessary data for baseline regression analysis. After applying these exclusions, the study focuses on 10,822 company-level yearly observations. Descriptive statistics, shown in Table 1, reveal a broad spectrum of cost stickiness and digital innovation levels across the sampled firms. Notably, about 7.39% of the sample underwent two consecutive years of declining sales, consistent with prior findings (Xin et al. 2021). Table A1 provides comprehensive definitions for each variable employed in the analysis.

How does digital innovation affect cost stickiness?

Baseline empirical findings. The findings from our preliminary model analysis are displayed in Table 2, which delineates the effects of digital innovation on mitigating cost stickiness in businesses. The examination is laid out over four columns, methodically adding control variables—from none to a full suite that includes aspects of firm characteristics, corporate governance, and fixed and random effects—to enhance the accuracy of the conclusions. The digital innovation coefficient ($\widehat{\beta_1}$) is uniformly negative and achieves statistical significance at the 1% level across every column, highlighting digital innovation's critical role in reducing cost stickiness. In particular, the findings in Column (4), which uses a model incorporating all adjustments, show a digital innovation coefficient ($\widehat{\beta_1}$) of -0.0233, with a t-statistic of -2.905. This points to the fact that an increment by one in the digital innovation ranking correlates with a 0.0233 reduction in cost stickiness. The gradual increase in the coefficient's absolute value from Column (1) to Column (4) underscores the significance of including control variables. These variables delineate the direct impact of digital innovation by mitigating the influence of other variables, offering a more accurate depiction of its repercussions on cost stickiness reduction.

The consistent and statistically significant negative connection between digital innovation and cost stickiness across all models accentuates the efficacy of digital innovation in enhancing cost management efficiency. In an era characterized by rapid technological advancements and digital transformations, particularly after the pandemic, this evidence implies that firms actively pursuing digital innovation may achieve a strategic edge by developing more flexible and resilient cost frameworks.

Endogeneity

Instrument variable regression. We employ instrumental variable analysis to mitigate potential endogeneity concerns. Our chosen instrument, denoted as $IV_{i,t}$, represents the average value of *DI* for other companies (excluding firm i itself) in the same city in year t. We argue that $IV_{i,t}$ is a suitable instrument as it is highly

Table 2 Baseline results for the degree of digital innovation and firm cost stickiness.

	(1) *Abs_STICK*	(2) *Abs_STICK*	(3) *Abs_STICK*	(4) *Abs_STICK*
DI	−0.0141* (−1.7166)	−0.0217*** (−2.6928)	−0.0370*** (−4.6820)	−0.0233*** (−2.9053)
SIZE		−0.0162** (−2.5220)	0.0060 (0.8362)	−0.0038 (−0.5357)
AGE		−0.0081 (−0.3357)	0.0341 (1.5840)	−0.0137 (−0.5611)
TANG		0.1275 (1.3499)	0.0740 (0.8341)	0.1870** (1.9773)
GrossProfit		0.6636*** (11.7125)	0.6494*** (11.5782)	0.5214*** (8.5461)
LIQUID		−0.0004 (−0.0791)	−0.0051 (−1.0334)	−0.0010 (−0.1970)
IncomeDD		0.0539** (2.3131)	0.0298 (1.2930)	0.0210 (0.8971)
INDIR		0.0016 (1.1421)	0.0005 (0.3156)	0.0015 (1.0542)
DUALITY			−0.0133 (−0.9176)	−0.0090 (−0.6413)
INST			0.0001 (0.5108)	0.0001 (0.3081)
OER			0.7856*** (4.7775)	1.1269*** (6.5191)
Constant	0.5795*** (81.4647)	0.5996*** (3.2898)	0.0296 (0.1597)	0.2388 (1.2320)
Industry Fixed Effects	Control	Control	Not-Control	Control
Year Fixed Effects	Control	Control	Not-Control	Control
Firm-Level Clustering	Control	Control	Control	Control
R-square	0.0585	0.0790	0.0383	0.0836
Observations	10821	10821	10822	10821

Bracketed figures represent the standard error of each coefficient. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations. Please refer to Table A1 for comprehensive descriptions of the variables.

Table 3 Endogeneity: instrumental variable regression.

	(1) *DI*	(2) *Abs_STICK*
IV	0.0741*** (6.1942)	
DI		−0.1821** (−2.0463)
SIZE	0.1099*** (7.8569)	0.0152 (1.2027)
AGE	0.0055 (0.1281)	−0.0166 (−0.6355)
TANG	0.6632*** (4.0548)	0.2866** (2.5643)
GrossProfit	0.6165*** (6.9063)	0.6153*** (7.1928)
LIQUID	0.0039 (0.4822)	0.0033 (0.6271)
IncomeDD	−0.0456* (−1.7386)	0.0094 (0.3767)
INDIR	−0.0000 (−0.0121)	0.0011 (0.7640)
DUALITY	−0.0143 (−0.5973)	−0.0134 (−0.9098)
INST	0.0005 (0.9591)	0.0002 (0.7685)
OER	0.5275** (1.9972)	1.2237*** (6.4604)
Constant	−3.0006*** (−7.8305)	
Industry Fixed Effects	Control	Control
Year Fixed Effects	Control	Control
Firm-Level Clustering	Control	Control
Observations	10279	10279
Cragg-Donald Wald F statistic	97.256	
Kleibergen-Paap rk Wald F statistic	38.368	

Bracketed figures represent t-statistics of coefficients. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations.

correlated with firm digital innovation and only influences cost stickiness through this relationship. Firms in the same city typically share similar network infrastructure, leading to a strong correlation in their digital innovation processes.

The analysis employing an instrumental variable (*IV*) is executed through a two-step regression technique, detailed in Table 3. In the initial stage, depicted in Column (1), the *IV*'s estimated coefficient is positive and statistically significant at the 1% level, validating our hypothesis that there is a strong positive correlation between the *IV* and the independent variable, *DI*. Moving to the second stage, shown in Column (2), the analysis demonstrates that the *DI* coefficient continues to be negative and statistically significant. The Kleibergen–Paap Wald rk F-statistic stands at 38.368, and the Cragg–Donald Wald F-statistic reaches 97.256, both metrics suggesting that the *IV* serves as a robust instrumental variable. Consequently, this instrumental variable reinforces the central conclusion of our study: digital innovation by firms plays a crucial role in reducing cost stickiness.

Propensity score matching. This study further uses the propensity score matching (PSM) method to solve the endogeneity problems endogeneity issues originating from sample self-selection. Each observation in the digitalized firms (treated group) is matched with an observation in the control group using propensity scores (Armstrong et al. 2010; Jiang et al. 2024; Zhou et al. 2024). A dummy variable, DI_Dummy1, is created, assigned 1 when a firm's digital innovation level exceeds the 75% quantile, and 0 otherwise. The logit model estimated is:

$$DI\_Dummy1_{i,t} = \alpha_0 + \gamma \boldsymbol{X}_{i,t} + \vartheta_t + \eta_j + \varepsilon_{i,t} \tag{3}$$

where $\boldsymbol{X}_{i,t}$ is a set of covariates that is consistent with Eq. (2). Nearest-neighbor matching is utilized at a one-to-one ratio. The balance test outcomes, shown in Table A2, demonstrate no substantial bias following the implementation of Propensity Score Matching (PSM), indicating the effectiveness of the matching process. Figure 2 depicts the kernel density curves of propensity scores for both control and treated firms pre and post application of the 1:1 nearest-neighbor matching. The alignment of the probability density distributions for the two groups after matching suggests the successful execution of the matching procedure.

Upon re-estimating Model (2) with the post-matching sample, results in Table 4 Column (1) reveal a persistently negative coefficient for *DI*, reaffirming our initial conclusion. Alterations to the matching ratio do not affect this outcome.

Placebo test. To mitigate the potential impact of unobserved variables, we conducted a placebo test similar to the approach utilized by Du and Jiang (2022). This test involved randomly assigning digital innovation scores to firms and re-estimating Model (2) 1000 times. Illustrated in Fig. 3 are the probability

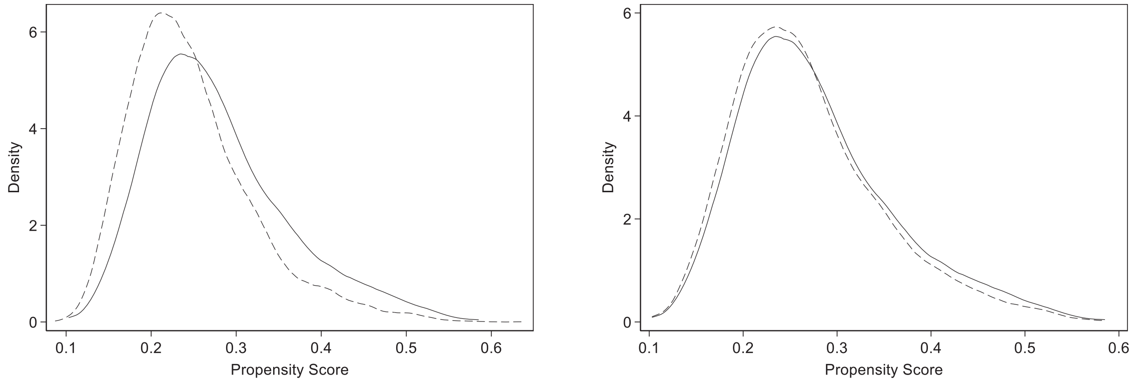

Fig. 2 Probability density distributions.

Table 4 Endogeneity: PSM method.

	(1) 1:1 *Abs_STICK*	(2) 1:2 *Abs_STICK*	(3) 1:3 *Abs_STICK*
DI	−0.0178* (−1.7110)	−0.0197** (−2.1607)	−0.0210** (−2.4434)
SIZE	−0.0169 (−1.5578)	−0.0100 (−1.0749)	−0.0091 (−1.0589)
AGE	−0.0371 (−0.9766)	−0.0383 (−1.2078)	−0.0123 (−0.4171)
TANG	0.3474** (2.4311)	0.4224*** (3.5000)	0.4307*** (3.8452)
GrossProfit	0.5125*** (5.5683)	0.5921*** (7.5776)	0.5783*** (8.0167)
LIQUID	−0.0005 (−0.0676)	−0.0072 (−1.2130)	−0.0039 (−0.7101)
IncomeDD	0.0593 (1.5054)	0.0331 (1.0427)	0.0362 (1.2248)
INDIR	0.0011 (0.5179)	0.0018 (1.0309)	0.0013 (0.8064)
DUALITY	−0.0121 (−0.5864)	−0.0123 (−0.6990)	−0.0086 (−0.5202)
INST	0.0007* (1.6721)	0.0003 (0.9653)	0.0001 (0.3470)
OER	0.9939*** (3.7073)	0.9362*** (4.3903)	1.0044*** (5.0570)
Constant	0.4399 (1.5172)	0.2113 (0.8494)	0.1251 (0.5395)
Industry Fixed Effects	Control	Control	Control
Year Fixed Effects	Control	Control	Control
Firm-Level Clustering	Control	Control	Control
R-square	0.0960	0.0971	0.0897
Observations	4380	6284	7463

Bracketed figures represent t-statistics of coefficients. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. The matching ratios of propensity score matching are 1:1, 1:2, and 1:3, respectively. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations.

density distributions and p-values for each regression's estimated coefficient. The coefficients $(\widehat{\beta}_1)$ tend towards zero and lack statistical significance, reaffirming the robustness of our initial findings and indicating they are not influenced by unobserved variables.

Additional robustness tests. To validate our findings, several robustness checks are conducted. Firstly, we use an alternative measure of firm digital innovation, denoted as *DIGITAL_r*, which calculates the logarithmically transformed count of key digital technology patents from an expanded classification, incremented by one. This alternative metric replaces *DIGITAL* in Eq. (2), and we recalibrate Model (2) and present the outcomes in Column (1) of Table 5. Subsequently, Model (2) undergoes re-estimation under varying fixed effects scenarios, with outcomes reported in Columns (2)–(4). Throughout these tests, digital innovation consistently exhibits significantly negative coefficients at the 5% significance level, strengthening the reliability of our initial conclusions.

Finally, we use the full sample with both positive *STICK* value and negative *STICK* value and adopt the ABJ model to assess cost stickiness behavior, referencing Anderson et al. (2003) and Li et al. (2022). The model is:

$$\begin{aligned} CostR_{i,t} = {} & \eta_0 + \eta_1 SaleR_{i,t} + \eta_2 SaleR_{i,t} \times IncomeD_{i,t} \\ & + \eta_3 SaleR_{i,t} \times DI_{i,t} + \eta_4 SaleR_{i,t} \times IncomeD_{i,t} \times DI_{i,t} \\ & + SaleR_{i,t} \times IncomeD_{i,t} \times (\gamma \boldsymbol{X}_{i,t}) \\ & + SaleR_{i,t} \times (\gamma \boldsymbol{X}_{i,t}) + \lambda_t + \eta_j + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where $CostR_{i,t}$ and $SaleR_{i,t}$ represent log-changes of firm costs and sales, respectively. *IncomeD* is a binary indicator set to 1 when a firm undergoes a year-on-year sales decline, and 0 otherwise. The set of control variables, $\boldsymbol{X}_{i,t}$, aligns with those specified in Model (2). The findings presented in Table 6 reveal that the estimated coefficient $(\widehat{\eta_2})$ is negative, while $(\widehat{\eta_1})$ is positive. These economically meaningful results indicate that the firm exists cost stickiness. The significant and negative $\widehat{\eta_4}$ indicates that digital innovation reduces cost stickiness, corroborating our initial conclusion.

Why can digital innovation improve cost management?

Internal control channel. We examine the internal control channel, suggesting that digital innovation reduces cost stickiness

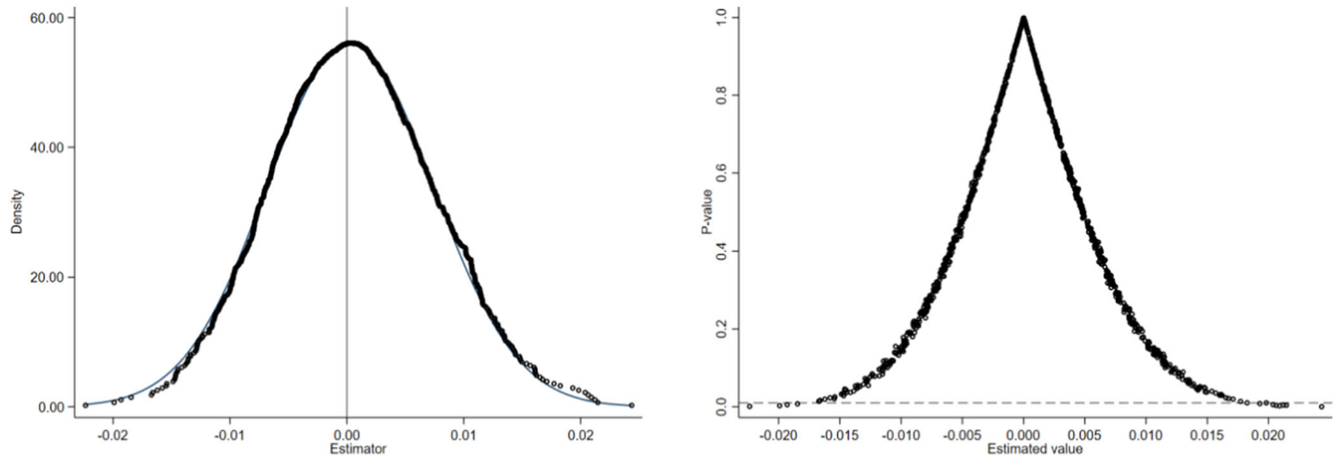

Fig. 3 Placebo Test.

Table 5 Additional Robustness Tests I.

	(1) Abs_STICK	(2) Abs_STICK	(3) Abs_STICK	(4) Abs_STICK
DI_r	−0.0146* (−1.9372)			
DI		−0.0221*** (−2.7340)	−0.0236*** (−2.8097)	−0.0372*** (−4.2925)
SIZE	−0.0048 (−0.6726)	0.0005 (0.0617)	−0.0046 (−0.6117)	0.0126 (1.4658)
AGE	−0.0132 (−0.5409)	−0.0295 (−1.1675)	−0.0181 (−0.7192)	−0.0152 (−0.5277)
TANG	0.1822* (1.9265)	0.1907* (1.9274)	0.2297** (2.3480)	0.1447 (1.3309)
GrossProfit	0.5160*** (8.4443)	0.5141*** (8.2552)	0.4683*** (7.2350)	0.5607*** (8.7343)
LIQUID	−0.0010 (−0.2099)	0.0025 (0.4914)	0.0001 (0.0116)	0.0040 (0.6878)
IncomeDD	0.0213 (0.9103)	0.0198 (0.8384)	0.0301 (1.2477)	0.0308 (1.1742)
INDIR	0.0015 (1.0421)	0.0007 (0.5261)	0.0007 (0.4520)	−0.0009 (−0.5301)
DUALITY	−0.0090 (−0.6431)	−0.0094 (−0.6574)	−0.0140 (−0.9677)	−0.0159 (−0.9945)
INST	0.0001 (0.2979)	0.0001 (0.3764)	0.0002 (0.7400)	0.0003 (0.8883)
OER	1.1173*** (6.4682)	1.2264*** (6.8057)	1.2628*** (6.9060)	1.1730*** (6.0103)
Constant	0.2637 (1.3624)	0.1962 (0.9653)	0.2537 (1.2561)	−0.0319 (−0.1419)
Industry Fixed Effects	Control	Control	Control	Not-Control
Year Fixed Effects	Control	Control	Control	Not-Control
City Fixed Effects	Not-Control	Not-Control	Control	Not-Control
Industry-Year Fixed Effects	Not-Control	Not-Control	Not-Control	Control
City-Year Fixed Effects	Not-Control	Not-Control	Not-Control	Control
Firm-Level Clustering	Control	Control	Control	Control
R-square	0.0832	0.1147	0.1553	0.1775
Observations	10821	10806	10668	9598

Bracketed figures represent t-statistics of coefficients. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations.

by enhancing internal controls. Following Zhou et al. (2022), we adopt the following mediation effect framework.:

$$CONTROL_{i,t} = \alpha_0 + \alpha_1 DI_{i,t} + \gamma X_{i,t} + \vartheta_t + \eta_j + \varepsilon_{i,t} \quad (5)$$

$$STICK_{i,t} = \beta_0 + \beta_1 DI_{i,t} + \gamma X_{i,t} + \vartheta_t + \eta_j + \varepsilon_{i,t} \quad (6)$$

$$STICK_{i,t} = \delta_0 + \delta_1 DI_{i,t} + \delta_2 CONTROL_{i,t} + \gamma X_{i,t} + \vartheta_t + \eta_j + \varepsilon_{i,t} \quad (7)$$

where *CONTROL* is a new variable representing the quality of firms' internal controls, denoted by the logarithmically transformed DiBo Internal Control Index scores. If $\widehat{\alpha_1}$ in Eq. (5) is significantly positive, digital innovation improves internal control quality. If the absolute value of $\widehat{\delta_1}$ in Eq. (7) is smaller than $\widehat{\beta_1}$ in Eq. (6), *CONTROL* has a mediating effect. Table 7 demonstrates the noteworthy and anticipated significance of the *DI* coefficient.. $\widehat{\beta_1}$ and $\widehat{\delta_1}$ are negative and the absolute value of $\widehat{\delta_1}$ is smaller than $\widehat{\beta_1}$. These results confirm that internal control is a key channel through which digital innovation can reduce cost stickiness.

Resource-adjustment channel. The resource-adjustment channel implies that firms' digital innovation alleviates cost stickiness by raising resource-adjustment efficiency. This subsection endeavors to validate the mediating role of resource-adjustment efficiency in the relationship between firm digital innovation and cost stickiness. Notably, we develop total asset turnover, *TURNOVER*, as a proxy for firm resource-adjustment efficiency. We replace *CONTROL* in Eq. (5) and Eq. (7) with *TURNOVER*, and reestimate Eqs. (5)–(7).

The findings are presented in Table 8. Firm digital innovation leads to higher resource-adjustment efficiency (from Column (1)). $\widehat{\alpha_1}$ is statistically significant at the 10% level, indicating a positive association. In Columns (3) and (4), $\widehat{\beta_1}$ and $\widehat{\delta_1}$ remain statistically negative. The absolute value of $\widehat{\delta_1}$ is smaller than $\widehat{\beta_1}$, which confirms that firm resource-adjustment efficiency may be another important channel.

Managerial optimism channel. As mentioned above, we believe that firm digital innovation alleviates cost stickiness by correcting managers' anticipations. In this subsection, we endeavor to prove this mediating effect. Following the methodology of Hilary et al. (2016), we develop a proxy, *STREAK*, for managers' overconfidence. Specifically, if a firm's actual net profit in quarter k meets or exceeds the managerial financial performance forecast, it can be defined as a successful managerial forecast. The number of consecutive successes in four quarters of year t is counted to measure managers' overoptimism (Hilary et al. 2016). To examine the managerial optimism channel, we replace *CONTROL* in Eq. (5) and Eq. (7) with *STREAK*, and subsequently re-estimate Eqs. (5)–(7).

Table 9 outlines the regression outcomes, demonstrating that the influence of digital innovation on managers' overconfidence is negatively significant, as shown in Column (1). The coefficients ($\widehat{\beta_1}$) and ($\widehat{\delta_1}$) highlight that digital innovation significantly curbs managers' overoptimism, thereby reducing cost stickiness. Furthermore, we adopt an alternate indicator for gauging managers' overoptimism, based on the approach of Hayward and Hambrick (1997), which utilizes CEO relative compensation (*Compen*). This metric calculates the compensation ratio of the aggregate compensation of the top three executives to the aggregate compensation of all executives. The analysis shows that digital innovation effectively lowers managerial overconfidence.

Table 6 Additional Robustness Tests II.

	(1) $CostR_{i,t}$
SaleR	1.1805*** (13.6181)
IncomeD× SaleR	−0.2247 (−1.0424)
SaleR× DI	0.0132*** (3.7845)
IncomeD× SaleR× DI	−0.0206** (−2.0268)
Other variables	Control
Industry Fixed Effects	Control
Year Fixed Effects	Control
Firm-Level Clustering	Control
R-square	0.8814
Observations	17731

Bracketed figures represent t-statistics of coefficients. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations. The sample adopted in the regression model is a full sample with both positive *STICK* value and negative *STICK* value.

What types of firms benefit more from digital innovation?

Our regression results confirm A reverse relationship between corporate innovation and asymmetric cost behavior. We delve deeper into how different types of firms, categorized by size, life cycle stage, and geographic region, respond to digital innovation in terms of cost stickiness.

Cross-sectional analysis by firm size. For large companies, effective resource allocation is paramount given their substantial resources and the complexity of their allocation challenges. Digital innovation, through data analytics and artificial intelligence, empowers these firms to improve demand forecasting, optimize inventory management, reduce waste, and ensure efficient resource utilization, thereby contributing to reduced cost stickiness. Additionally, the influence of managerial decision-making on resource allocation becomes more pronounced in larger organizations. Digital innovation provides sophisticated data analysis and predictive capabilities, enabling managers to make informed decisions grounded in accurate data rather than speculative forecasts. This mitigates the risk of resource overcommitment and subsequent increases in cost stickiness. Consequently, We posit that the influence of digital innovation on diminishing cost stickiness is notably pronounced in larger firms, as it improves resource allocation efficiency and aligns with managerial expectations.

The efficiency of resource allocation is particularly critical for large companies due to their abundant resources and more complex allocation needs. Digital innovations, such as technologies like data analytics and AI, could aid these corporations in

Table 7 Internal Control Channel.

	(1) *CONTROL*	(2) *Abs_STICK*	(3) *Abs_STICK*
DI	0.0258*** (3.3330)	−0.0237*** (−2.9517)	−0.0228*** (−2.8431)
CONTROL			−0.0338*** (−3.1246)
SIZE	0.1191*** (14.8225)	−0.0038 (−0.5242)	0.0003 (0.0344)
AGE	−0.0226 (−0.8954)	−0.0142 (−0.5770)	−0.0149 (−0.6084)
TANG	0.0109 (0.1193)	0.1876** (1.9837)	0.1879** (1.9924)
GrossProfit	0.8185*** (14.2311)	0.5244*** (8.5833)	0.5521*** (9.0085)
LIQUID	0.0205*** (4.6482)	−0.0012 (−0.2433)	−0.0005 (−0.0994)
IncomeDD	−0.2971*** (−13.6966)	0.0220 (0.9355)	0.0119 (0.4995)
INDIR	0.0012 (0.8918)	0.0014 (1.0169)	0.0015 (1.0483)
DUALITY	0.0206 (1.5019)	−0.0091 (−0.6486)	−0.0084 (−0.5995)
INST	0.0027*** (9.6136)	0.0001 (0.2480)	0.0002 (0.5635)
OER	−2.7852*** (−17.5346)	1.1317*** (6.5271)	1.0375*** (5.9597)
Constant	3.8275*** (18.2115)	0.2402 (1.2339)	0.3698* (1.8749)
Industry Fixed Effects	Control	Control	Control
Year Fixed Effects	Control	Control	Control
Firm-Level Clustering	Control	Control	Control
R-square	0.2676	0.0838	0.0846
Observations	10798	10798	10798

Bracketed figures represent t-statistics of coefficients. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations.

Table 8 Resource-adjustment Channel.

	(1) *TURNOVER*	(2) *Abs_STICK*	(3) *Abs_STICK*
DI	0.0333*** (6.9231)	−0.0234*** (−2.9121)	−0.0186** (−2.2983)
TURNOVER			−0.1446*** (−6.3795)
SIZE	−0.0368*** (−6.3970)	−0.0037 (−0.5183)	−0.0090 (−1.2458)
AGE	−0.0045 (−0.2581)	−0.0133 (−0.5443)	−0.0140 (−0.5712)
TANG	0.0685 (1.1805)	0.1852* (1.9582)	0.1951** (2.0731)
GrossProfit	−0.4774*** (−11.7627)	0.5218*** (8.5516)	0.4527*** (7.3141)
LIQUID	−0.0176*** (−5.5459)	−0.0009 (−0.1933)	−0.0035 (−0.7145)
IncomeDD	−0.1063*** (−10.4084)	0.0209 (0.8929)	0.0056 (0.2366)
INDIR	0.0007 (0.6999)	0.0015 (1.0464)	0.0016 (1.1156)
DUALITY	−0.0032 (−0.3646)	−0.0090 (−0.6403)	−0.0094 (−0.6751)
INST	0.0014*** (7.1218)	0.0001 (0.3169)	0.0003 (1.0276)
OER	−2.9489*** (−26.3728)	1.1302*** (6.5387)	0.7037*** (3.8286)
Constant	1.7351*** (11.3093)	0.2365 (1.2202)	0.4874** (2.4630)
Industry Fixed Effects	Control	Control	Control
Year Fixed Effects	Control	Control	Control
Firm-Level Clustering	Control	Control	Control
R-square	0.5265	0.0837	0.0874
Observations	10820	10820	10820

Bracketed figures represent t-statistics of coefficients. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations.

Table 9 Managerial Optimism Channel.

	(1) *STEAK*	(2) *Abs_STICK*	(3) *Abs_STICK*
DI	−0.0241*** (−2.9302)	−0.0274** (−2.5575)	−0.0262** (−2.4433)
STREAK			0.0528*** (2.8794)
SIZE	0.0007 (0.0827)	−0.0242** (−2.2181)	−0.0243** (−2.2172)
AGE	−0.0590** (−2.1653)	−0.0416 (−1.2634)	−0.0385 (−1.1694)
TANG	−0.2782*** (−2.9162)	0.0713 (0.6057)	0.0860 (0.7309)
GrossProfit	−0.5296*** (−8.4212)	0.3593*** (4.1754)	0.3873*** (4.5062)
LIQUID	−0.0203*** (−4.0063)	−0.0008 (−0.1168)	0.0003 (0.0470)
IncomeDD	0.0370 (1.5217)	0.0163 (0.5072)	0.0144 (0.4467)
INDIR	0.0015 (0.9827)	0.0003 (0.1729)	0.0003 (0.1327)
DUALITY	0.0080 (0.5357)	−0.0179 (−0.9655)	−0.0183 (−0.9888)
INST	−0.0013*** (−4.1124)	0.0002 (0.6102)	0.0003 (0.7805)
OER	1.1849*** (6.6493)	1.1277*** (4.7725)	1.0651*** (4.4714)
Constant	0.7837*** (3.3565)	0.9682*** (3.3326)	0.9268*** (3.1894)
Industry Fixed Effects	Control	Control	Control
Year Fixed Effects	Control	Control	Control
Firm-Level Clustering	Control	Control	Control
R-square	0.0755	0.0885	0.0899
Observations	5304	5304	5304

Bracketed figures represent t-statistics of coefficients. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations.

more accurately forecasting demand, optimizing inventory management, reducing waste, and achieving optimal resource deployment, thereby lowering cost stickiness. Furthermore, in large companies, managerial decisions have a more significant impact on resource allocation. Digital innovation can provide more precise data analysis and forecasting tools, assisting managers in making decisions based on factual data rather than overly optimistic expectations, thus avoiding overinvestment in resources and the escalation of cost stickiness. Hence, we contend that via mechanisms such as resource allocation and managerial anticipations, the alleviating impact of digital innovation on cost stickiness could be more pronounced in larger corporations. A binary variable, named *Big*, is formulated to identify whether a firm's size surpasses the median within its industry, with a value of 1 indicating sales above the median and 0 otherwise. Segmenting our dataset according to the *Big* variable and reapplying Model (2), the outcomes detailed in Table 10, specifically in Columns (1) and (2), reveal a more substantial and significant coefficient ($\widehat{\beta_1}$) for larger firms, underscoring the intensified effect of digital innovation in these entities.

Cross-sectional analysis by firm life cycle. Studies indicate that companies evolve through life-cycle phases, transitioning from growth to maturity (Helfat and Peteraf, 2003; Dickinson, 2011). Companies in non-growth stages typically encounter slow market growth or find themselves in mature business phases, where the emphasis shifts from pursuing rapid expansion to maintaining profitability and competitiveness. Improving internal control efficiency, fine-tuning resource allocation, and minimizing

Table 10 Cross-sectional Analysis in Firm Size.

	(1)	(2)
	$Big = 1$	$Big = 0$
	Abs_STICK	*Abs_STICK*
DI	−0.0278*** (−2.9650)	−0.0146 (−0.9583)
SIZE	−0.0038 (−0.3598)	0.0151 (0.6477)
AGE	0.0070 (0.2299)	−0.0598 (−1.5502)
TANG	0.1871 (1.5606)	0.1991 (1.3058)
GrossProfit	0.5772*** (7.5026)	0.4582*** (4.7591)
LIQUID	0.0066 (0.8899)	−0.0080 (−1.2237)
IncomeDD	−0.0073 (−0.2407)	0.0612* (1.6463)
INDIR	−0.0002 (−0.1320)	0.0056** (2.4907)
DUALITY	−0.0012 (−0.0656)	−0.0286 (−1.3473)
INST	0.0001 (0.3064)	0.0001 (0.2285)
OER	1.0959*** (4.5926)	1.1426*** (4.4905)
Constant	0.2200 (0.8328)	−0.1732 (−0.3199)
Industry Fixed Effects	Control	Control
Year Fixed Effects	Control	Control
Firm-Level Clustering	Control	Control
R-square	0.0986	0.0797
Observations	6596	4223

Bracketed figures represent t-statistics of coefficients. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations.

Table 11 Cross-sectional Analysis in Firm Life Cycle.

	(1)	(2)
	$Growth = 1$	$Growth = 0$
	Abs_STICK	*Abs_STICK*
DI	−0.0025 (−0.1792)	−0.0332*** (−3.3499)
SIZE	−0.0062 (−0.5088)	−0.0040 (−0.4708)
AGE	−0.0306 (−0.7654)	−0.0062 (−0.2157)
TANG	0.2084 (1.3757)	0.1587 (1.3121)
GrossProfit	0.6241*** (5.8979)	0.4730*** (6.4899)
LIQUID	−0.0122 (−1.2593)	0.0026 (0.4536)
IncomeDD	−0.0082 (−0.1705)	0.0265 (0.9985)
INDIR	0.0004 (0.1868)	0.0021 (1.2390)
DUALITY	0.0217 (0.9371)	−0.0274 (−1.5725)
INST	0.0002 (0.4844)	0.0000 (0.0178)
OER	0.9431*** (3.0750)	1.1963*** (5.9257)
Constant	0.3467 (1.0920)	0.2346 (0.9966)
Industry Fixed Effects	Control	Control
Year Fixed Effects	Control	Control
Firm-Level Clustering	Control	Control
R-square	0.0953	0.0928
Observations	3559	7257

Bracketed figures represent t-statistics of coefficients. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-Level Clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations.

superfluous expenses through digital innovation becomes increasingly crucial in these phases. Meanwhile, companies in the growth stage might prioritize investments and expansion, showing a relatively lower emphasis for immediate cost efficiency and stickiness.

Moreover, managers in non-growth stages might adopt more cautious budgeting and cost management approaches to forestall overexpansion and unnecessary expenditures. Digital innovation facilitates this by offering managers more precise and timely insights, enabling them to adjust their forecasts to be more realistic and in tune with market dynamics, thus mitigating the risk of optimistic cost projections and the resultant cost stickiness. Consequently, non-growth companies, driven by a quest for stability and efficiency, are likely to leverage digital innovation to optimize their cost structures and management techniques. This inclination reflects the distinct challenges and characteristics of various stages in a company's life cycle, which emphasize the role of digital innovation in diminishing cost stickiness for certain companies.

To investigate this aspect, we employ Dickinson's (2011) framework for segmenting companies into life-cycle phases according to cash flow trends, identifying growth firms as those with positive operating and financing cash flows but negative investment cash flow. Subsequently, we categorize our dataset using a newly created binary variable, *Growth*, to differentiate between growth and non-growth firms and rerun Model (2). The outcomes, outlined in Table 11, affirm our hypothesis, demonstrating a more significant influence of digital innovation on lowering cost stickiness among non-growth firms.

Cross-sectional analysis by region. Considering regional diversity, establishing digital government infrastructure significantly impacts the potential of digital innovation to generate value. Governments exert a pivotal role in fostering the digital economy, creating digital government systems requiring local authorities to engage in digital contract procurement. Such involvement expands the market for corporate digital technology offerings and strengthens the potential for digital technology to add value. Consequently, The evolution of digital governance structures is projected to augment the efficacy of digital innovation in diminishing firm cost stickiness. This study introduces a binary variable, $did1_{i,c,t}$, to indicate the consequence of China's Information Benefit Pilot Policy on a firm, determined by the interaction between $du1_c$ (a dummy variable for cities) and $dt1_t$ (a dummy variable for time). Initiated in January 2014, this policy is a key step toward modernizing China's governance system and boosting governance capabilities as part of the drive to establish a digital China. The National Development and Reform Commission, along with twelve other departments, jointly released the "Notice on Accelerating the Implementation of the Information Benefit Project," designating 80 cities as national pilot cities. This initiative aims to dismantle "information silos," enhance interconnectivity, information sharing, and business collaboration across all government levels and departments, and explore innovative mechanisms and models for public resource optimization, social management, and public services through big data, with the ultimate goal of benefiting the public and businesses (Gao et al. 2023). For a list of cities in the treatment and control groups, refer to Table A3. Therefore, when city c is a national pilot city, $du1_c$ is set to 1; otherwise, it is 0. Similarly, $dt1_t$ is set to 1 for the years 2014 and onwards; otherwise, it is 0. $dt1_t$ is set to 1; otherwise, it is 0. Utilizing the variable $did1_{i,c,t}$ to denote the consequence of China's digital government policy on a firm based on its location in the city c during year t, we categorize the firms into groups reflecting high and low levels of digital government infrastructure development. This classification enables a detailed comparison, with Model (2) reapplied for each group. Results, displayed in Table 12 Columns (1) and (2), indicate that in regions with advanced digital government infrastructure, digital innovation significantly reduces cost stickiness, as evidenced by a notably negative coefficient for DI in Column (1). However, in areas with less developed digital government, the effect of digital innovation on cost stickiness, while still negative, does not reach statistical significance. This suggests that the efficacy of digital innovation in mitigating cost stickiness depends on the extent of digital government infrastructure development.

Secondly, the digital taxation system has facilitated improvements in companies' management of internal financial data. The

Table 12 Cross-sectional Analysis in Region.

	(1) $did1 = 1$ *Abs_STICK*	(2) $did1 = 0$ *Abs_STICK*	(3) $did2 = 1$ *Abs_STICK*	(4) $did2 = 0$ *Abs_STICK*	(6) $did3 = 1$ *Abs_STICK*	(5) $did3 = 0$ *Abs_STICK*
DI	−0.0247** (−2.2619)	−0.0179 (−1.4200)	−0.0245** (−2.2020)	−0.0160 (−1.2854)	−0.0255** (−2.5212)	−0.0150 (−0.9806)
SIZE	0.0044 (0.4110)	−0.0071 (−0.7239)	−0.0016 (−0.1493)	−0.0029 (−0.2938)	0.0011 (0.1095)	−0.0047 (−0.4308)
AGE	−0.0104 (−0.3051)	−0.0448 (−1.3204)	−0.0025 (−0.0715)	−0.0380 (−1.1735)	−0.0314 (−0.9657)	−0.0210 (−0.5250)
TANG	0.2306* (1.7523)	0.2216 (1.5766)	0.1446 (1.1411)	0.3745** (2.5750)	0.1989* (1.6648)	0.2843* (1.7040)
GrossProfit	0.3370*** (3.7804)	0.6697*** (7.8081)	0.3820*** (4.3081)	0.5676*** (6.7603)	0.3988*** (4.9011)	0.5989*** (6.1020)
LIQUID	−0.0023 (−0.3007)	0.0011 (0.1667)	−0.0026 (−0.3374)	0.0056 (0.8844)	0.0004 (0.0623)	0.0029 (0.3897)
IncomeDD	0.0114 (0.3467)	0.0082 (0.2498)	0.0228 (0.6634)	0.0013 (0.0417)	0.0258 (0.8399)	−0.0259 (−0.6972)
INDIR	0.0015 (0.7391)	0.0019 (0.9488)	0.0010 (0.5051)	0.0017 (0.9106)	0.0013 (0.7068)	−0.0003 (−0.1121)
DUALITY	0.0169 (0.8309)	−0.0328* (−1.6970)	0.0263 (1.3093)	−0.0483** (−2.4072)	−0.0010 (−0.0519)	−0.0059 (−0.2564)
INST	0.0001 (0.2949)	0.0001 (0.3279)	0.0003 (0.7825)	0.0001 (0.2828)	−0.0002 (−0.3851)	0.0009* (1.8266)
OER	1.5679*** (6.2230)	0.7817*** (3.2432)	1.2974*** (4.8983)	1.1089*** (4.6072)	1.3695*** (5.9037)	1.0639*** (3.7882)
Constant	0.0106 (0.0356)	0.3347 (1.2881)	0.2504 (0.8533)	0.0485 (0.1879)	0.1922 (0.7108)	0.1838 (0.6200)
Industry Fixed Effects	Control	Control	Control	Control	Control	Control
Year Fixed Effects	Control	Control	Control	Control	Control	Control
Firm-Level Clustering	Control	Control	Control	Control	Control	Control
R-square	0.0929	0.0941	0.0827	0.1054	0.0977	0.0994
Observations	4839	5737	5087	5489	5709	4351

Bracketed figures represent t-statistics of coefficients. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations.

digital tax project introduced a risk early-warning module that utilizes big data analytics to provide early warnings for high-risk areas and entities. By integrating and comparing financial indicators and tax-related information of companies within the same industry, businesses can more effectively monitor and manage costs, reduce unnecessary expenditures, and enhance the quality of internal controls. From this standpoint, implementing digital taxation can guide and compel companies to maximize the utilization of the dynamic energy released by digital innovation, thereby improving the cost stickiness issues of firms through internal control channels. To examine our hypothesis further, we incorporate a binary variable, $did2_{i,c,t}$, to assess the impact of China's digital taxation governance policy on firms. This variable is determined by the interaction of $du2_c$ (city-specific dummy) and $dt2_t$ (time-specific dummy). Launched in 2013, the Golden Tax Phase III project aimed at enhancing the informatization, accessibility, and efficiency of tax collection and administration, guided by the principle of "one platform, two-level processing, three coverages, and four systems" (Li et al. 2020). A city c participating in the Golden Tax Phase III pilot is marked by $du2_c = 1$, and a year t during or after the pilot phase is marked by $dt2_t = 1$. For a detailed listing of pilot and control cities, refer to Table A4. Using this classification, we calculate the policy influence, $did2_{i,c,t}$, for firms based in city c in year t and categorize the firms into groups with high and low digital tax system development levels before reapplying Model (2). The findings, displayed in Table 12 Columns (3) and (4), suggest that in areas with advanced digital tax systems, digital innovation significantly aids in reducing cost stickiness, as evidenced by a strongly negative *DI* coefficient in column (3). Conversely, in areas with less developed digital tax systems, the *DI* coefficient remains negative but lacks statistical significance, suggesting that the effectiveness of digital innovation in reducing cost stickiness is impacted by the level of digital taxation infrastructure.

Finally, property rights protection is crucial for corporate innovation. A robust intellectual property (IP) protection system can safeguard businesses' rights to digital innovations, encouraging them to develop diverse and localized technological innovations to empower production and operations. High judicial protection incentivizes firms to invest in research, development, and innovation. Such innovation includes improving products and services, optimizing operational efficiency, and reducing costs through digital technology. A robust level of judicial protection is hypothesized to bolster the impact of digital innovation in diminishing firm cost stickiness. To explore this theory, the study introduces a binary variable, $did3_{i,c,t}$, to denote the influence of China's intellectual property (IP) pilot policy on firms, determined by the interaction of $du3_c$ (a city-specific dummy) with $dt3_t$ (a time-specific dummy). Aiming to reinforce IP protection, China's National Intellectual Property Administration released the "National Intellectual Property Pilot and Demonstration Cities (Districts) Evaluation Methods" in 2011. This initiative began the selection process for IP demonstration cities, with the first group of 23 cities announced on April 27, 2012. By 2021, a total of six cohorts of IP demonstration cities had been acknowledged, comprising 76 cities (districts). Over the years, these cities have shown early signs of success in building effective IP protection frameworks. Echoing the approach of Fang et al. (2017), when a city c is recognized as an IP demonstration city, thereby indicating enhanced IP protection, $du3_c$ is assigned a value of 1; otherwise, its value is 0. Similarly, if year t falls within or after the inception of the IP demonstration cities, $dt3_t$ is set to 1; otherwise, its value remains 0. For a detailed list of cities categorized under the treatment and control groups, refer to Table A5. With this methodology, the study calculates the policy impact, $did3_{i,c,t}$, for a firm located in city c during year t, subsequently categorizing the firms based on high or low IP protection levels before reassessing Model (2). As depicted in Table 12, Columns (5) and (6), the findings reveal that in areas boasting superior IP protection, digital innovation significantly aids in curtailing firm cost stickiness, as evidenced by a strongly negative *DI* coefficient in column (5). Conversely, among firms in locales with weaker IP protection, the influence of digital innovation on cost stickiness remains negative, albeit without statistical significance, suggesting that the degree of IP protection can indeed affect how digital innovation influences cost stickiness.

Further analysis

Benefits of reducing cost stickiness. In this segment, we delve into the implications of cost stickiness and examine the competitive edge that digital innovation brings to firms regarding cost management. On the one hand, cost stickiness restricts companies' ability to adjust resources efficiently. Reducing cost stickiness directly improves the flexibility of company cost management, reduces unnecessary cost expenditure, and improves business performance. Cost reduction also helps companies reduce cash flow pressure and weaken financial risks. On the other hand, flexible cost management enables companies to respond effectively to external changes and reduce market risks. Consequently, we contend that digital innovation improves financial performance and reduces risk levels by mitigating cost stickiness. We further examine this assumption. Specifically, we concentrate on ROA volatility (representing firm risk) and profitability. Employing the methodology from Zhou et al. (2022), we assess the variability in financial performance by computing both the dispersion and the range of industry-adjusted Return on Assets (ROA) across a three-year timeframe. These measures, denoted as *RISK*1 and *RISK*2, respectively, serve to capture the volatility and risk profile of a firm's earnings relative to its industry peers. *RISK*1 reflects the variability in earnings through the standard deviation, providing insight into the stability of a firm's performance. *RISK*2, calculated as the range, offers a perspective on the breadth of performance fluctuations, indicating the distance between the highest and lowest performance outcomes. Together, these metrics provide a comprehensive view of firms' financial risk and performance stability, adjusted for industry-specific factors. Higher ROA volatility suggests heightened external operational risks faced by the company. Firm profitability can be measured by net profit margin (net profits over sales, denoted as *PREF*1) and ROA (denoted as *PREF*2), respectively.

In line with the approach outlined by Kim et al. (2021), we implement a two-stage model to explore how digital innovation affects cost stickiness and, in turn, impacts firm risk and profitability. In the initial stage, we revisit Eq. (2) to recalibrate it and acquire the estimated value of the dependent variable, symbolized as $Abs\_\widehat{STICK}$. This procedure ensures that we capture the effect of digital innovation on cost stickiness with greater precision.

Proceeding to the second stage, our focus transitions to elucidating the ramifications of cost stickiness—quantified by $Abs\_\widehat{STICK}$—on the risk and profitability metrics of the firm. This sequential approach allows for a nuanced analysis, wherein the first stage identifies the degree to which digital innovation can mitigate cost stickiness, and the subsequent stage evaluates the broader implications of these cost behavior patterns on the firm's financial health and operational risk. By dissecting the relationship in two stages, we can isolate the direct and indirect effects of digital innovation on firm dynamics, providing insightful conclusions about the strategic value of digital innovation in enhancing financial performance and managing operational risk.

$$RISK_{i,t}\ or\ PREF_{i,t} = \beta_0 + \beta_1 Abs\_\widehat{STICK}_{i,t} + \gamma X_{i,t} + \vartheta_t + \eta_j + \varepsilon_{i,t} \tag{8}$$

Table 13 showcases the findings from the two-stage analysis. In Columns (1) and (2), the coefficients of $Abs\_\widehat{STICK}$ are positively correlated with firm risk and statistically significant, suggesting that elevated levels of cost stickiness are linked to diminished risk for firms. This might suggest that firms with sticky costs are potentially more cautious in their operational and financial management, leading to lower variability in their financial performance.

On the other hand, Columns (3) and (4) display negative coefficients for $Abs\_\widehat{STICK}$, suggesting that a decrease in cost stickiness correlates with increased profitability. This indicates that firms that successfully manage to reduce their cost stickiness can achieve better financial performance, likely due to improved operational efficiency and flexibility in cost management.

These outcomes reinforce our initial hypothesis, positing that digital innovation holds the potential to diminish firm risk while simultaneously enhancing profitability. This is accomplished by mitigating cost stickiness, underscoring the strategic significance of digital innovation in contemporary business practices. It highlights how leveraging digital technologies refines cost management strategies and aligns closely with achieving broader financial objectives.

Superiority of digital innovation. To illuminate the exceptional role of digital innovation in enabling value creation and enhancing corporate empowerment, distinguishing its effects on firm cost stickiness from other digital transformation efforts. We posit that digital innovation is vital to a firm's digital strategy, warranting prioritization within corporate digitalization endeavors. Our goal is to ascertain if digital transformations that embrace digital innovation exert a more substantial effect on mitigating cost stickiness in companies than those without digital innovation.

For this analysis, we introduce a new binary variable, DI_dummy2, to differentiate firms based on their digital innovation activity. Firms actively engaged in any level of digital innovation are assigned a value of 1, whereas firms with no digital innovation activity are marked as 0. This classification enables us to divide the firms into two categories: those implementing digital innovation and those that are not. Leveraging this division, we evaluate the consequence of digital innovation on the cost stickiness of firms by applying the following model (9):

$$Abs\_STICK_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \gamma X_{i,t} + \vartheta_t + \eta_j + \varepsilon_{i,t} \tag{9}$$

In the model, $DT_{i,t}$ represents the level of digital transformation for firm i in year t. To quantify this, we utilize the logarithmically transformed frequency of digital-related keywords found in the Management Discussion and Analysis sections of firms' annual reports (identified as *DT*), following the approach by Du and Jiang (2022). Additionally, we include the proportion of digital intangible assets relative to total assets (referred to as *DA*), as suggested by Jiang et al. (2022), to further encapsulate a firm's digital transformation efforts. The data for this comprehensive analysis are sourced from the CSMAR database. The specifications for Model (9) are consistent with those outlined in Model (2), ensuring methodological coherence and the reliability of our conclusions.

The results in Table 14 uncover notable trends. In columns (1) and (2), where $DI\_dummy2 = 1$ signifies firms actively engaging in digital innovation, $\widehat{\beta_1}$ is negative and achieve statistical

Table 13 Benefits of reducing cost stickiness.

	(1) *RISK1*	(2) *RISK2*	(3) *PERF1*	(4) *PERF2*
$\widehat{Abs\_STICK}$	0.9498* (1.7487)	0.6995** (2.3887)	0.1136** (2.5573)	−0.0736*** (−2.7845)
SIZE	0.0282* (1.7606)	0.0065 (0.8958)	0.0064*** (5.9434)	−0.0011* (−1.7290)
AGE	0.1322*** (2.7770)	0.0682*** (2.9727)	0.0023 (0.6474)	−0.0004 (−0.2116)
TANG	−0.0846 (−0.4952)	−0.1351 (−1.3205)	0.0023 (0.1454)	0.0323*** (3.6671)
GrossProfit	−0.4115 (−1.4222)	−0.2362 (−1.4460)	0.3868*** (15.4990)	0.2179*** (15.0368)
LIQUID	0.0072 (0.7560)	−0.0050 (−0.8299)	0.0142*** (18.4186)	0.0049*** (12.7689)
IncomeDD	−0.0203 (−0.5763)	0.0700*** (3.0468)	−0.0284*** (−8.1828)	−0.0168*** (−10.6181)
INDIR	−0.0030 (−0.9827)	−0.0004 (−0.2412)	−0.0003 (−1.1767)	−0.0000 (−0.1259)
DUALITY	0.0462* (1.6505)	−0.0121 (−0.8634)	−0.0002 (−0.1132)	−0.0004 (−0.3429)
INST	−0.0007 (−1.2022)	−0.0006** (−2.0416)	0.0003*** (7.1856)	0.0003*** (11.9292)
OER	−0.1887 (−0.2782)	−0.2982 (−0.7665)	−0.6269*** (−10.4973)	−0.3017*** (−9.1245)
Constant	−0.5442 (−1.2915)	−0.0547 (−0.2506)	−0.2272*** (−6.8804)	0.0235 (1.2683)
Industry Fixed Effects	Control	Control	Control	Control
Year Fixed Effects	Control	Control	Control	Control
Firm-Level Clustering	Control	Control	Control	Control
R-square	0.5512	0.6142	0.5464	0.4320
Observations	10811	9853	10821	10820

Bracketed figures represent t-statistics of coefficients. Significance levels are as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations.

Table 14 Superiority of digital innovation.

	(1)	(2)	(3)	(4)
	DI_dummy2 = 1		*DI_dummy2* = 0	
	Abs_STICK	*Abs_STICK*	*Abs_STICK*	*Abs_STICK*
DT	−0.0224* (−1.8347)		−0.0035 (−0.4780)	
DA		−0.0197* (−1.8421)		−0.0070 (−1.1687)
SIZE	−0.0256* (−1.8123)	−0.0115 (−0.5867)	0.0029 (0.3571)	0.0061 (0.5428)
AGE	−0.0477 (−0.9289)	−0.0685 (−1.1587)	−0.0021 (−0.0763)	−0.0042 (−0.1319)
TANG	0.4155** (2.2602)	0.4961** (2.4809)	0.0841 (0.7819)	0.0946 (0.7731)
GrossProfit	0.4009*** (3.1553)	0.3937*** (2.6084)	0.5600*** (8.2587)	0.5987*** (7.6138)
LIQUID	−0.0141 (−1.4974)	−0.0201* (−1.8488)	0.0047 (0.8514)	0.0021 (0.3104)
IncomeDD	0.0719 (1.3570)	0.0636 (1.0291)	0.0055 (0.2108)	0.0363 (1.1786)
INDIR	0.0012 (0.4448)	0.0011 (0.3634)	0.0019 (1.2063)	0.0033* (1.7552)
DUALITY	−0.0053 (−0.1913)	−0.0124 (−0.3871)	−0.0053 (−0.3303)	−0.0060 (−0.3256)
INST	0.0004 (0.7047)	0.0004 (0.6083)	−0.0001 (−0.2991)	−0.0002 (−0.4456)
OER	1.4128*** (3.8383)	1.8919*** (4.3627)	1.0827*** (5.5533)	1.1226*** (4.7956)
Constant	0.6380 (1.5918)	0.5504 (1.1970)	0.1313 (0.5950)	0.1030 (0.3812)
Industry Fixed Effects	Control	Control	Control	Control
Year Fixed Effects	Control	Control	Control	Control
Firm-Level Clustering	Control	Control	Control	Control
R-square	0.0854	0.1064	0.0934	0.1008
Observations	2772	2058	8047	5882

Bracketed figures represent t-statistics of coefficients. Significance levels are denoted as follows: *** for 1%, ** for 5%, and * for 10%. Industry Fixed Effects and Year Fixed Effects pertain to industry-specific and temporal variations controls, respectively. Firm-level clustering indicates using cluster-robust standard errors at the firm level to account for within-group correlations. For comprehensive descriptions of the variables, see Table A1.

significance at the 10% level. This indicates that digital transformation substantially reduces cost stickiness in firms incorporating digital innovation into their operations. On the other hand, in columns (3) and (4), marked by $DI\_dummy2 = 0$ for firms not undertaking digital innovation, $\widehat{\beta}_1$ is negative but do not reach statistical significance. This suggests that digital transformation initiatives exert a negligible effect on the cost stickiness of firms lacking in digital innovation activities.

These findings emphasize digital innovation's critical role in diminishing cost stickiness, affirming its vital place within the broader digital transformation efforts. The findings bolster the notion that digital innovation, more so than other forms of digital transformation, is key to boosting firm efficiency and driving empowerment. This underscores the strategic significance of digital innovation in corporate digital strategy development.

Conclusion

In the post-pandemic landscape, digitalization has emerged as a pivotal driver of corporate evolution, propelled by the growing integration of technology into business practices and the quest for innovative avenues of growth. Amid this wide-ranging embrace of digitalization, digital innovation has taken center stage as a strategic priority. Utilizing a comprehensive dataset of Chinese companies spanning from 2007 to 2022, our study delves into the effects of digital innovation on cost stickiness. By examining corporate digital technology patent applications data, we develop proxy measures for digital innovation and uncover a notable decrease in cost stickiness associated with such initiatives. To mitigate potential biases and substantiate our results, we employ a suite of robust analytical methods, including two-stage instrumental variable regression, PSM, and placebo tests. These methodologies bolster the credibility of our findings, highlighting the transformative impact of digital innovation on reducing cost stickiness.

The study delves deeper into the mechanisms through which digital innovation influences cost stickiness, highlighting improvements in internal controls, the agility of resource reallocation, and the adjustment of managerial over-optimism. Our findings reveal that digital innovation significantly curtails cost stickiness by fortifying internal control systems, elevating the effectiveness of resource distribution, and curbing managerial over-optimism. A heterogeneity analysis further elucidates that the efficacy of digital innovation in mitigating asymmetric cost behaviors is especially marked in larger firms, those at advanced lifecycle stages, and entities located in regions endowed with robust digital governance, taxation, and judicial infrastructures.

Moreover, our analysis extends to the broader implications of digital innovation on firm risk and profitability, finding that digital innovation leads to risk reduction and improved financial performance by decreasing cost stickiness. Additionally, we find that digital innovation is associated with reduced cost stickiness in firms actively pursuing digital innovation, whereas this association is not observed in firms without such initiatives.

Drawing from the empirical insights of this investigation, which highlight the significant role of digital innovation in reducing cost stickiness, enhancing internal controls, and improving resource adjustment and financial performance in Chinese firms, we put forth the following policy prescriptions. First, Governments and policymakers should place digital innovation at the forefront across diverse sectors. This can be facilitated by providing R&D incentives, offering tax incentives for digital initiatives, and allocating direct funding for digital transformation projects. Second, while digital innovation yields benefit across the board, our analysis indicates its powerful impact on larger firms and those beyond their growth phase. Policy measures should be customized to aid these entities in their digital evolution, acknowledging their substantial economic impact. Third, The benefits of digital innovation are notably greater in areas with developed digital governance, taxation, and legal frameworks. Therefore, enhancing digital infrastructure on a regional scale is crucial to fostering a conducive environment for corporate digital innovation and transformation. Fourth, given that digital innovation contributes to risk reduction and better financial outcomes, companies should be encouraged to weave digital innovation strategies into their risk management and financial planning. This might include the development of digital risk management guidelines and frameworks. Finally, ensuring the workforce is equipped to back and advance digital innovation efforts call for significant investment in education and training focused on digital skills. These initiatives should cater to both newcomers and current emp loyees, promoting the upskilling and reskilling necessary for digital proficiency.

Data availability

The datasets generated during and/or analyzed during the current study are available in the Harvard Dataverse repository, https://doi.org/10.7910/DVN/5KBCTD.

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