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Does commercial reform embracing digital technologies mitigate stock price crash risk?☆

Guanming He[a,*], Zhichao Li[b], Ling Yu[c], Zhanqiang Zhou[d]

[a] Department of Accounting, Business School, Durham University, Durham, UK
[b] Department of Finance and Accounting, Business School, University of Exeter, Exeter, UK
[c] National School of Development, Peking University, Beijing, China
[d] School of Economics, Central University of Finance and Economics, Beijing, China

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ABSTRACT

Over the recent decade or so, the Chinese government implemented a commercial reform that features governmental application of digital technologies to acquire and process firm information. The core objective of commercial reform is to improve information transparency and monitoring on corporate commercial activities. To explore the economic effectiveness of the reform, we examine how it impacts firms' stock price crash risk. We find robust evidence that the commercial reform that digitalizes government regulatory activities mitigates stock price crash risk and achieves so via enhancing information environment and monitoring for firms. This finding is more prominent for firms with higher levels of digitalization and innovation and those with weaker internal governance. Overall, our findings highlight a potential benefit of applying digital technologies to regulatory reform, encouraging governments to adopt digital tools to improve information environments and monitoring for firms, and thereby promoting a more stable and efficient capital market.

1. Introduction

In the era of digitalization, the Chinese government has adopted digital technologies for commercial reform. It features the governmental utilization of digital technologies to acquire and process firm information for purpose of facilitating real-time

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* Corresponding author.
E-mail addresses: guanming.he@durham.ac.uk (G. He), z.li10@exeter.ac.uk (Z. Li), yling@pku.edu.cn (L. Yu), zhouzhanqiang@cufe.edu.cn (Z. Zhou).

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monitoring on commercial activities under transparent information environments. The primary goals of the reform are to provide commercial convenience for enterprises, ensure fair and transparent regulation of corporate activities, and promote healthy development of commercial activities within a country. In this study, we investigate the effectiveness of the commercial reform by providing evidence from stock price crash risk.

The digitalization-applied commercial reform involves the utilization of digital technologies by the government to transform and upgrade government activities, with the primary objective of facilitating and regulating corporate commercial activities. The application of digital technologies is an integral part of commercial reform and serves two crucial roles in making the reform plausibly effective. First, it may improve information transparency of firms' commercial activities. By providing convenient digital commercial registration and approval services, the government can efficiently collect an extensive array of commercial information, integrate it into a comprehensible form, promptly analyze this big data, and accurately transmit it among government departments, firms, and the public. Second, digitalization may also enhance the monitoring of firms' commercial activities. Implementing digital and intelligent monitoring in the commercial reform allows the government to improve interdepartmental regulatory cooperation, promote diverse monitoring approaches, and raise firms' awareness of commercial credit. These digital monitoring tools would help standardize firm-relevant commercial conducts, and prevent firms from engaging in suboptimal, illegal, or value-destroying commercial activities.

However, the application of digital technologies in commercial reform may be ineffective in increasing information transparency and enhancing the monitoring of firms' commercial activities if we consider the associated risks and costs. Prior studies document that technological obsolescence (Acemoglu, 2002), privacy concerns (Dinev and Hart, 2006), and cybersecurity risks (Rosati et al., 2022), which are involved in the practices of digitalization, may deter firms from enhancing information transparency and monitoring. In addition, applying digital technologies to commercial reform requires considerable time and entails substantive expenses, learning costs, and uncertainties (Luo, 2022). Therefore, it is unclear whether digitalization-involved commercial reform would improve the information environment and enhance the monitoring of firms' commercial activities.

To address the open question, we investigate the impact of digitalization-applied commercial reform on stock price crash risk. Such risk results from manager opportunism that leads to overvaluation of stocks (e.g., Hutton et al., 2009; Kim et al., 2011), and is closely bound up with both information opacity and inadequate monitoring of corporate activities (e.g., Hutton et al., 2009; Kim et al., 2011). Therefore, by examining the effect of digitalization-involved commercial reform on stock price crash risk, we may shed light on the effectiveness of the government's adoption of digital technologies in commercial reform. If the digitalization-involved commercial reform improves information transparency and monitoring of firms' commercial activities, stock price crash risk is supposed to decrease.

We focus on the digitalization-involved commercial reform in China for two reasons. First, it provides a nice institutional setting for a quasi-natural experiment. Since 2014, the Chinese government has initiated a commercial reform, wherein the Market Supervision Administration (MSA) in each city is established over different years and takes the main responsibility for implementing the commercial reform. For the reform, the municipal MSA actively adopted digital technologies to streamline corporate online applications, acceptances, reviews, license issuances, and publicity for enterprise commercial activities and to process relevant commercial information intelligently for monitoring the activities. This setup provides a reasonable context for employing a stacked difference-in-differences research design to establish causality. Second, the information environment and monitoring of commercial activities are relatively weak in China compared with those of developed countries (e.g., Piotroski and Wong, 2012). Hence, a study on the effectiveness of Chinese commercial reform that embraces digital technologies is potentially generalizable to other countries, especially the developing ones.

We manually collected data on the timing of establishing the MSA in each city to proxy for the timing of enacting the digitalization-involved commercial reform across cities. A difference-in-differences regression model is applied on a stacked propensity-score matched sample to explore whether the digitalization-involved commercial reform mitigates firms' stock price crash risk.[1] We find evidence to suggest that the commercial reform reduces crash risk. The finding is robust to firm-fixed-effects regression analyses, controls of region effects, tests of coefficient stability, placebo tests, and alternative measures of crash risk. Further, we provide evidence that improved information environments and monitoring are the underlying mechanisms through which the attenuating effect of digitalization-involved commercial reform on crash risk realizes. We also find that this mitigating effect is more evident for firms with higher levels of digitalization and innovation and those with weaker internal governance.

Our paper makes two main contributions. First, we extend existing studies on the effect of digitalization. Prior literature documents the economic consequences of corporate utilization of digital technologies (e.g., Ferreira et al., 2019; Blichfeldt and Faullant, 2021; Ciampi et al., 2021; Matarazzo et al., 2021; Chen et al., 2022; Xu et al., 2022), and have paid little attention on government application of digital technologies. Our paper is the first to show how governmental adoption of digital technologies in a regulatory reform would achieve the desired regulatory outcomes. By exploring the impact of digitalization-applied commercial reform on crash risk, our research enriches the understanding of the economic consequences of digitalization from a macro perspective. Second, we offer some insights into the policy implementation. By showing that digitalization-involved commercial reform reduces stock price crash risk via effectively improving information transparency and monitoring of firms' commercial activities, we highlight the benefits of applying digital technologies to achieve regulatory objectives, and the benefits of government digitalization to firms and other stock market participants.

The remainder of the paper is organized as follows. Section 2 introduces the institutional background, and proposes the research

[1] A difference-in-differences regression model applied on a stacked sample for staggered events is named stacked difference-in-difference regression design.

hypothesis from two aspects – the information channel and the monitoring channel. Section 3 describes the data and methodologies for our empirical analysis. Section 4 discusses empirical results. Section 5 concludes our study.

2. Institutional background and research hypothesis

2.1. The commercial reform in China

In 2013, the Chinese government held several national conferences on reforming the commercial registration system to simplify the registration processes, ease market access, and strengthen the supervision and management of commercial activities.[2] Following these conferences, in 2014, the Chinese government launched a commercial reform nationwide which emphasizes the application of digital technologies. Specifically, local governments in each city are required to provide online services regarding commercial activities for local firms, and use digital technologies to promote data processing as well as data sharing and integration across different departments.

In implementing this digital commercial reform, the Market Supervision Administration (MSA) is established in each city, and responsible for creating various online integrated data platforms, including the National Enterprise Credit Information Publicity Platform (NECIPP), to aggregate a broad spectrum of corporate commercial information and disclose it to the public, not least the media and stock market participants. The information covers financial records, credit ratings, business registration, licensing, regulatory compliance, administrative penalties, commercial transactions, labor relations, shareholder changes, and intellectual property, among other aspects. Data on this diverse information are consolidated and sent to the cloud server, allowing the governments to store and further process them in a big-data platform. Then, leveraging the cloud-based repository, the governments implement a data-sharing system across various departments by using blockchain technology. This ensures trackable data records, data privacy, and seamless data flows among departments. The application of blockchain technology focuses mainly on e-certificates, business registration, and e-invoices. Under the data-sharing system, the same type of credentials and information need to be submitted only once and can be used interchangeably across departments.

Meanwhile, big data analytics and cloud computing are employed to analyze and scrutinize the data. On the one hand, governments use these techniques to extract useful information from big databases and gain insights into industry trends, market demands, investment details, patents, bidding, etc. They then share this information with enterprises, assisting them in bolstering their competitive edge. On the other hand, big data analytics enable governments to swiftly pinpoint operational risks, detect potential frauds, issue risk alerts, and initiate appropriate regulatory actions. Furthermore, artificial intelligence (AI) is also incorporated into some government online services. Digital features like AI service expedite the governments' processing of firms' requests by quickly providing guidance and undertaking initial reviews, such as review of business registration, effectively lightening the workload for government employees.[3] All the foregoing information processed by digital technologies will be used for the governmental monitoring on the firms' commercial activities; some processed information, such as the one related to abnormal business operations, will be released publicly, improving the information environments of firms and facilitating public monitoring as well on their commercial activities.

This reform with emphasis on the application of digital technologies integrates government operations, enhances the information system, and elevates management standards for the government. To this end, the Market Supervision Administration (MSA) is established in a staggered way in each city at different years and takes the main responsibility of executing the local commercial reform. Decisions on the timing of the establishment of MSA are autonomously made by the local government in each city, and are orthogonal to firms' characteristics and events. As firms cannot anticipate the specific timing of establishing the local MSA, they are unlikely to respond to the reform in advance. Therefore, it facilitates us to examine its causal impact on stock price crash risk via a stacked difference-in-differences research design.

2.2. Hypothesis development

Stock price crash risk refers to the possibility of a sudden and significant decline in the stock price (Chen et al., 2001). It is primarily attributed to managers' opportunistic behaviors (e.g., withholding of bad news) leading to investors' overvaluation of stocks (Jin and Myers, 2006). The information asymmetry between investors and managers and the inadequate monitoring of the latter would make it difficult to detect managerial opportunism and potentially hidden corporate bad news, thereby increasing stock price crash risk (e.g., Hutton et al., 2009; Kim et al., 2011; He et al., 2019). Therefore, it is of great importance for regulators to reduce stock price crash risk by enhancing the information environment and monitoring in a commercial reform.

The utilization of digital technologies for commercial reform may enhance the government's ability to collect, process, and share

[2] On 28th February 2013, the Chinese government held the Second Plenary Session of the 18th Communist Party of China (CPC) Central Committee, where it decided to reform the commercial registration system, ease the market access, and strengthen the supervision and management of corporate commercial activities. Later, on 12th November of the same year, the Third Plenary Session of the 18th CPC Central Committee further called for promoting the commercial reform.

[3] More information about the application of digital technologies in the government works can be obtained from the "research report on the modernization of national governance in the digital age - experiences, challenges, and responses in using digital technologies for government governance" by the China Academy of Information and Communications Technology (CAICT). The Chinese version of this report can be accessed via the link http://www.caict.ac.cn/kxyj/qwfb/ztbg/202212/P020221207530304282075.pdf.

various corporate commercial information, thereby improving the quality and transparency of corporate information as well as external monitoring on firms. Regarding the information acquisition, a variety of digital government services provided during the commercial reform (e.g., online application systems, self-service terminals, and mobile terminals) help firms independently complete commercial registration procedures and swiftly publish commercial information related to their products, services, sales, business expansion, etc., and disclose additional details especially those concerning the creditworthiness of their commercial activities. In such a case, the government can promptly collect a wide range of up-to-date commercial information from different firms, even before its public announcements, and form a big database for comprehensive data analyses on a timely basis.

The application of digital technologies also contributes to effective and efficient information processing. On the one hand, by utilizing advanced big data analytics and cloud computing, the government can classify and group unstructured data from various sources across firms, such as images, news, videos, and audio. This facilitates the government to track and analyze commercial information through the process of a firm's commercial activities, from product design, quality monitoring, marketing, and sales to distribution. Some processed information especially related to abnormal business operations will be published on the government's online service platforms, increasing corporate information transparency. On the other hand, by analyzing the structured data, the government can perform dynamic, real-time, and intelligent monitoring on both the upstream and downstream firms in the supply chain (Gomber et al., 2018; Cong and He, 2019). For instance, using the technique of big data analytics, governments could foresee potential operational risks and generate risk alerts once identified by the digital risk-warning system. Other diversified monitoring through internet technologies, such as e-government platforms in real-time, allows the public to monitor and report in good time any violations of rules related to firms' commercial activities, internal controls, and financial reports. This prompt reporting by the public further facilitates regulators to detect firms' non-compliant activities so that penalties and corrections can be imposed in a timely manner.

Furthermore, using digital technologies such as blockchain significantly improves information sharing across different government sectors. The government can standardize and digitize numerous commercial information, timely transmit valuable commercial information across different departments, and then release it to the public for oversight. Consequently, commercial details concerned by market participants, such as regulatory non-compliance, unethical business practices, poor financial performance, legal complications, and corporate social irresponsibility, would become more transparent. Better information sharing would also eliminate the overlap of regulatory responsibilities among different governmental departments. This strengthens the accountability of each department and fosters better coordination across departments. As a result, the costs of monitoring decrease while the efficiency of monitoring improves.

In essence, the digitalization in commercial reform may help improve both the information environments and monitoring on the firms' commercial activities. The firms' information environments could be ameliorated via media coverage on commercial information processed and released by the government, as the media plays a crucial role in disseminating commercial news to a wide range of stakeholders. The improved information environment would in turn reduce stock price crash risk. For instance, high information quality and transparency enable managers, based on existing commercial information, to conduct more reliable assessments on future commercial investments. This improves firms' investment efficiency and prevent managers from investing in commercial projects that have negative present values (Biddle et al., 2009; Lai et al., 2014). Meanwhile, investors in the transparent environment will have better insight into government policies and firms' commercial investment activities, thus reducing their overvaluation of stocks (Drake et al., 2009; Lee and Lee, 2015). Moreover, information transparency raises the costs for managers to commit malpractice or malfeasance in commercial activities and to hide bad commercial news from investors. As a result, the stock price crash risk will diminish.

The improved monitoring due to digitalization-applied commercial reform further contributes to the reduction in stock price crash risk by mitigating firms' agency conflicts (Fan and Wong, 2005), reducing related-party transactions (Gallery et al., 2008), preventing firms from engaging in suboptimal, illegal, or value-destroying commercial activities, and prompting firms to disclose high-quality commercial information on a timely basis. In addition, digital monitoring in commercial reform can strengthen corporate credit education as well as credit monitoring of firms for their commercial activities. By using diverse digital information disclosure systems, governments can promptly analyze commercial credit information, release it online and issue early warnings when appropriate to relevant parties, thereby guiding and ensuring firms to adhere to laws, regulations, and ethical practices. This is instrumental in fostering the development of a robust commercial credit system and enhancing the standardization and credibility of firms' commercial activities to investors. As the information acquired and processed on a real time basis by the government via digital tools would also be released to the public for oversight, the reform would enhance not only the monitoring by the government but also by the stock market participants.

However, capitalizing on digital technologies in commercial reform does not necessarily increase the transparency of corporate commercial information or the external monitoring of firms' commercial activities. As such, it may not reduce stock price crash risk. This can be attributed to the potential risks and costs that are associated with technological obsolescence, privacy concerns, and cybersecurity risks, among others (Acemoglu, 2002; Dinev and Hart, 2006; Rosati et al., 2022). Technological obsolescence can lead to lower data quality and accuracy, posing challenges for the government to promptly capture the accurate commercial information of firms. Consequently, information opacity will rise (Acemoglu, 2002), impeding the effective monitoring and evaluation of firms' commercial activities and financial performance. Insufficient privacy protection could give rise to mistrust among firms and the public regarding the government's data collection and usage. As such, firms may be reluctant to disclose complete commercial information, hindering the external monitoring of their behaviors. Cybersecurity risks, such as cyber-attacks and data breaches, pose a threat of insecure data, information losses, or information tampering. These vulnerabilities will limit the government from obtaining accurate commercial information and reduce the monitoring effectiveness. Besides, the adoption of digital technologies brings additional expenses and uncertainties. Implementing new technologies properly requires ample time and substantial investments in hardware, software, and staff training. There are also learning costs associated with adopting new technologies and the costs of integrating with the existing government management systems. Considering the foregoing risks and costs associated with applying digital technologies in the commercial reform, it might not be effective in improving the information environment and monitoring on firms' commercial activities and thereby reducing stock price crash risk. Based on the above discussion, we propose the following null hypothesis for empirical tests:

H1. The digitalization-applied commercial reform is unrelated to firms' stock price crash risk.

3. Data and methodologies

3.1. Data sources and sample selection

We focus on listed companies in our study.[4] Data utilized for the empirical tests come mainly from two databases: China Stock Market & Accounting Research (CSMAR) and Chinese Research Data Services (CNRDS). Data on the stock trading, financial numbers, and governance structure of firms are taken from CSMAR. Data on media news about a firm are gathered from CNRDS. We hand-collected data on the timing of establishing the Market Supervision Administration in each city by searching the Chinese Industry and Commerce Administration Yearbook and/or the official websites of the municipal governments. Data on firm-level digitalization, which are used later for our moderation analysis, are obtained based on the approach proposed by Chen and Srinivasan (2023). This method employs the Python Crawler technique to search for and collate the digitalization-related keywords in firms' annual reports. Patent data used to construct the moderator variable regarding corporate innovation are collected from the website of the Chinese State Intellectual Property Office.

We focus on the policy implementation period of 2014–2019. Since 2014, the Chinese government across all administrative levels has implemented commercial reform, in which the Market Supervision Administration of each city introduced various digital technologies in a staggered manner. Therefore, we start our policy implementation period from 2014. Considering the confounding impact of COVID-19 on stock price crash risk, we end the policy implementation period in 2019. Meanwhile, we use a six-year period centered on the implementation year of the reform (i.e., a three-year pre-event period and a three-year post-event period) in our difference-in-differences research design. As a result, our treatment group only includes firms headquartered in cities that implemented commercial reform between 2014 and 2017. Therefore, our sample period starts from (ends in) 2011 (2019), three years before (since) 2014 (2017), while covering the period of the enactment of digitalization-involved commercial reform.

Our sample selection starts with the population of Chinese listed firms that have A shares traded on the Shenzhen and Shanghai Stock Exchanges for the period 2011–2019. This initial sample consists of 26,345 firm-year observations, corresponding to 4016 firms. Following prior studies, we exclude firms that receive Special Treatment (ST or *ST) or Particular Transfer (PT), as these firms are of high delisting risk. We then tease out firms in financial industries because the disclosure requirements and accounting rules for firms in financial industries differ significantly from those in the other industries. Firms cross-listed overseas are also deleted from our analysis, as their stock prices are influenced by foreign stock markets. We further eliminate observations with negative incomes. Finally, we remove firm-year observations that do not have the necessary data to construct the variables of interest for our regression analysis. We end up with 16,237 firm-year observations for 2577 listed firms. Appendix 1 expounds our sample selection procedure.

3.2. Measures of stock price crash risk

In line with previous research (e.g., Chen et al., 2001; Hutton et al., 2009; Kim et al., 2011; Chen et al., 2016), we measure stock price crash risk by the negative skewness of weekly stock returns (*NCSKEW*) and down-to-up volatility of weekly stock returns (*DUVOL*) over a fiscal year. For *NCSKEW*, we first calculate the firm-specific weekly raw returns by estimating the following equation:

$$r_{i,s} = \delta + \delta_{1,i} r_{m,s-2} + \delta_{2,i} r_{m,s-1} + \delta_{3,i} r_{m,s} + \delta_{4,i} r_{m,s+1} + \delta_{5,i} r_{m,s+2} + \varepsilon_{i,s} \tag{1}$$

where $r_{i,s}$ is the raw return of stock *i* in week *s*; $r_{m,s}$ is the value-weighted market rate of return of all stocks in week *s*. In particular, the lag terms (i.e., $r_{m,s\text{-}1}$, $r_{m,s\text{-}2}$) and lead terms (i.e., $r_{m,s+1}$, $r_{m,s+2}$) are also included to allow for the nonsynchronous stock trading (Dimson, 1979). $\varepsilon_{i,s}$ is the residual return from Eq. (1). The firm-specific weekly return of stock *i* in week *s*, $w_{i,s}$, is measured as the natural logarithm of one plus the residual return in Eq. (1), that is, $w_{i,s} = \ln(1+\varepsilon_{i,s})$ (e.g., Kim et al., 2011).

NCSKEW for a firm *i* in a fiscal year *t* is measured by taking the negative of the third moment of firm-specific weekly returns for each sample firm-year and dividing it by the standard deviation of firm-specific weekly returns raised to the third power:

[4] There are four reasons for focusing on listed firms for the empirical analysis of the effectiveness of digitalization-applied commercial reform. First, the commercial activities of listed firms involve a myriad of stakeholders and concern public interest, investor protection as well as the stability of capital market, among others. Their commercial information accessible via reputable government websites is trusted and sought highly by the stakeholders. Second, the government's digital platforms form an important channel through which listed firms release value-relevant information to investors. Hence, the commercial reform would affect these firms significantly. Third, listed firms often have greater influence and visibility in the market, so their commercial activities can act as a model for reference by other enterprises. Fourth, from the methodological point of view, a signficantly more comprehensive set of publicly available data from Chinese listed firms, relative to those from non-listed firms, enable us to perform a more rigorous empirical analysis to assure the internal validity of results.

$$NCSKEW_{i,t} = -\left[n(n-1)^{\frac{3}{2}}\sum w_{i,s}^{3}\right] \Big/ \left[(n-1)(n-2)\left(\sum w_{i,s}^{2}\right)^{\frac{3}{2}}\right] \tag{2}$$

where n is the number of trading weeks for stock i in year t.

DUVOL captures asymmetric volatilities between the negative and positive firm-specific weekly returns and is calculated as follows:

$$DUVOL_{i,t} = ln\left[(n_u-1)\sum\nolimits_{down} w_{i,s}^{2}\right] \Big/ \left[(n_d-1)\sum\nolimits_{up} w_{i,s}^{2}\right] \tag{3}$$

where n_u (n_d) is the number of weeks in which the firm-specific weekly returns of stock i are higher (lower) than the annual average return. The larger the negative skewness of weekly stock returns (*NCSKEW*) or the down-to-up volatility of weekly stock returns (*DUVOL*), the greater the probability of stock price crashes for the firm.

3.3. Difference-in-differences research design

Given that the municipal MSA is the primary responsible authority for commercial reform in each city, we utilize the timing of establishing municipal MSA to reflect the timing of implementing the commercial reform. MSA is established in different cities at different years, so we adopt a stacked difference-in-differences (DID) approach to evaluate the economic effect of commercial reform on firms' stock price crash risk. The DID research design requires identifying a treatment (control) group, of which firms are (not) subject to the exogenous regulatory event. Accordingly, our treatment group comprises firms headquartered in cities that established MSA from 2014 to 2017. To maintain a clean identification of the control groups for matching with treatment firms for a year t (Baker et al., 2022; Roth et al., 2023), we classify firms, headquartered in cities that did not establish MSA during the six-year period from year t-3 to $t+2$ nor before year t-3, into our control group. For example, if a firm is based in the city where an MSA was established in 2014, the control firms used to match these treatment firms in 2014 are firms with headquarters in cities that did not have an MSA at or before 2016.

The stacked DID regression model is specified as follows:

$$\begin{aligned} &NCSKEW_{i,t} \text{ or } DUVOL_{i,t} = \\ &\alpha_0 + \alpha_1 Treat_t \times Post_i + \alpha_2 Treat_t + \alpha_3 size_{i,t} + \alpha_4 soe_{i,t} + \alpha_5 roe_{i,t} + \alpha_6 lev_{i,t} \\ &+ \alpha_7 salesgrowth_{i,t} + \alpha_8 cashholdings_{i,t} + \alpha_9 duality_{i,t} + \alpha_{10} boardsize_{i,t} \\ &+ \alpha_{11} topshareholdings_{i,t} + \alpha_{12} hhi_{i,t} + \alpha_{13} ceoshare_{i,t} + \alpha_{14} ret_{i,t} + \alpha_{15} sigma_{i,t} \\ &+ \alpha_{16} share\_turnover_{i,t} + \alpha_{17} roa\_volatility_{i,t} + year\_dummies \\ &+ industry\_dummies + city\_dummies + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where the dependent variable is stock price crash risk (i.e., *NCSKEW* or *DUVOL*). $Treat_t$ is an indicator for the treatment and equals 1 (0) if a firm is in the treatment (control) group at year t. $Post_i$ is the time indicator which equals 1 (0) if a firm is in the three-year post- (pre-) event period that is from year t (year t-3) to year $t+2$ (year t-1). The coefficient on interaction term, $Treat_t \times Post_i$, captures changes in the stock price crash risk of treatment firms, relative to those of control firms, from the pre-event period to the post-event period. $Post_i$ is not included in the regression as this variable is potentially multicollinear with the year dummies.

Consistent with previous research (e.g., Kim et al., 2011; Chen et al., 2016; Jin et al., 2022), we control for a bunch of variables that may affect stock price crash risk, i.e., firm size (*size*), state ownership (*soe*), return on equity (*roe*), financial leverage (*lev*), sales growth (*salesgrowth*), financial health (*cashholdings*), CEO-chair(*wo*)man duality (*duality*), board size (*boardsize*), the largest shareholder's stock holdings (*top_shareholdings*), industrial concentration (*hhi*), CEOs' stock holdings (*ceoshare*), the average weekly stock returns (*ret*), the volatility of weekly stock returns (*sigma*), share turnover (*share_turnover*), and the volatility of returns on assets (*roa_volatility*). We also include year dummies, industry dummies, and city dummies (*year_dummies*, *industry_dummies*, and *city_dummies*) in our regressions. All variables are winsorized at the 1st and 99th percentiles to avoid the impact of outliers on our results, and are defined in Appendix 2. The standard errors of coefficients in the regressions are clustered at the firm level to control for potential heteroscedasticity and autocorrelation.

3.4. Propensity score matching

The potential systematic differences in firm characteristics between the treated firms and controlled firms may bias our analysis. To mitigate this concern, we perform the propensity score matching (PSM) and use the post-matched sample to run our DID regression. We do the matching year by year to ensure that our DID design based on the matched sample will compare the outcome of the treatment for the same treated firm, relative to that of its matched control firm, for the same year of interest. We match each treatment firm, with replacement, with a control firm by the year of establishing MSA in the city where the treatment firm is headquartered. A vector of matching covariates are selected as independent variables to run the following logit regression for the binary variable, *Treat*, to obtain the closest propensity score within a caliper of 1 % in each year:

$$
\begin{aligned}
Treat_t = \\
&\beta_0 + \beta_1 size_{i,t} + \beta_2 roe_{i,t} + \beta_3 lev_{i,t} + \beta_4 salesgrowth_{i,t} + \beta_6 cashholdings_{i,t} \\
&+ \beta_6 boardsize_{i,t} + \beta_7 roa\_volatility_{i,t} + industry\_dummies + city\_dummies + \varepsilon_{i,t}
\end{aligned} \tag{5}
$$

The matching covariates include firm size (*size*), return on equity (*roe*), financial leverage (*lev*), sales growth (*salesgrowth*), financial health (*cashholdings*), board size (*boardsize*), the volatility of returns on assets (*roa_volatility*), as well as the industry dummies and city dummies. After the matching, we obtain the final sample, which comprises 7072 firm-year observations corresponding to 1156 unique firms, for our DID regression analysis.

To check the effectiveness of our matching, we perform a test of the common support in propensity-score matching. The result of the test is displayed in Fig. 1. As shown in Fig. 1-a, a certain difference exists in propensity scores between the treatment group and the control group prior to the matching. Fig. 1-b reveals that after the matching, the distribution trends of the treatment group and the control group become similar. These results indicate that our matching substantively reduces the differences between the treated firms and the non-treated control firms.

To further check the covariate balance, we run the preceding logit regression, Model (5), by year based on the pre-matched and post-matched samples, respectively. Panel A (Panel B) of Table 1 reports the results for the pre-matched (post-matched) sample. While some covariates have statistically significant coefficients for the pre-matched sample, the coefficients for all covariates become statistically nonsignificant after the matching. These results further support the effectiveness of our propensity-score matching.

3.5. Descriptive statistics

Panel A of Table 2 reports the summary statistics of all variables, which are based on the sample after PSM and used in our regression analysis. The mean value of *NCSKEW* (*DUVOL*) is −0.243 (−0.195), with a standard deviation of 0.737 (0.506). The mean value of *Treat* is 0.511, indicating that approximately 51.1 % of our sample firms are subject to digitalization-applied commercial reform and are classified into the treatment group, while the remaining 48.9 % of firms do not experience such a reform and are classified into the control group. Panel B of Table 2 shows the Spearman correlation matrix of variables. *NCSKEW* and *DUVOL* are highly correlated, with the statistically significant correlation coefficient of 0.879, suggesting that these two variables capture the underlying same construct for stock price crash risk. The values of all other correlation coefficients are below 0.6, assuring that multicollinearity is of less concern in our regression analyses.

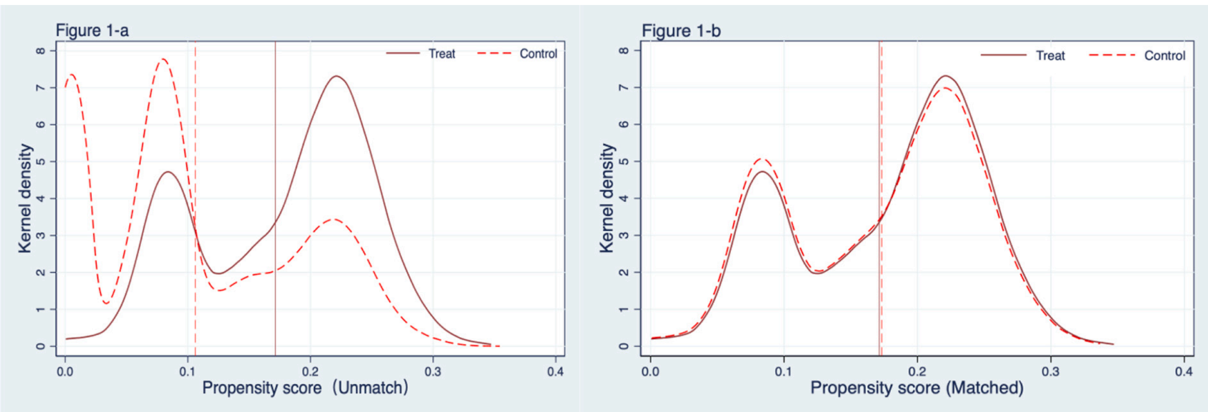

Fig. 1. Kernel density distribution of propensity matching.
Notes: Fig. 1 shows the distribution, in the form of kernel density curve, of propensity scores for the treatment group and control group before and after the matching. The horizontal axis represents the propensity scores; the vertical axis represents the probability density. The left (right) figure shows the distribution of propensity scores before (after) the matching. The sample period ranges from 2011 to 2019. The treatment indicator variable, *Treat*, equals 1 (0) for a treatment (control) firm. The treatment firm is defined as subject to the digitalization-involved commercial reform in which the Market Supervision Administration was established to introduce digital commercial registration system for improving information environments and monitoring on commercial activities of firms. The control firm is not subject to the digitalization-involved commercial reform in the six-year period centered at the beginning of the year of the reform for the treatment firm, nor before the period. The solid (dashed) curves represent the distribution of propensity scores for the treatment (control) firms. We follow Leuven and Sianesi (2018) to match each treatment firm, with replacement, with a control firm by using the closest propensity score within a caliper of 1 % for each year.

Table 1
Propensity-score matching between the treatment and control firms.

Panel A: Logit regressions run by year for estimating propensity scores based on the pre-matched sample

Variables	(1) 2014	(2) 2015	(3) 2016	(4) 2017
$size_t$	−0.1531***	−0.0831***	−0.0912*	−0.0426
	(−2.7627)	(−4.4918)	(−1.6741)	(−0.5204)
roe_t	1.8439***	−0.0548	0.4761	0.4937***
	(3.0658)	(−0.1033)	(0.6149)	(3.4030)
lev_t	0.4215	−0.0789	−0.1989	−0.1372
	(1.2213)	(−0.2174)	(−0.5679)	(−0.2663)
$salesgrowth_t$	−0.0281	−0.0068	0.0072***	0.0007
	(−0.7767)	(−0.7332)	(3.0177)	(0.0658)
$cashholdings_t$	−4.6840	−1.3945	4.3861*	7.0830***
	(−1.3649)	(−0.4237)	(1.6510)	(4.5412)
$boardsize_t$	−0.0558	−0.0547	0.2190***	0.1685
	(−0.1877)	(−0.1928)	(7.7989)	(0.4102)
$roa\_volatility_t$	4.3793	3.0264	−1.3763	−6.5241
	(1.5004)	(1.0426)	(−0.6181)	(−1.6002)
Observations	2022	2125	2306	2137
Pseudo R^2	0.010	0.009	0.013	0.007
Industry-fixed effects	included	included	included	included
City-fixed effects	included	included	included	included

Panel B: Tests of covariate balance for the post-matched sample

Variables	(1) 2014	(2) 2015	(3) 2016	(4) 2017
$size_t$	0.0154	−0.0461	−0.0507	−0.0357
	(0.2269)	(−0.7385)	(−0.8618)	(−0.3790)
roe_t	0.4841	0.1686	0.2704	−0.0250
	(0.6626)	(0.3175)	(0.3626)	(−0.0194)
lev_t	−0.2889	0.2375	0.2313	0.3527
	(−0.7415)	(0.6256)	(0.6219)	(0.5529)
$salesgrowth_t$	0.0357	0.0038	−0.0003	0.0907
	(0.9044)	(0.6704)	(−0.0645)	(1.3699)
$cashholdings_t$	0.6760	0.2070	0.9401	−0.8769
	(0.6642)	(0.2117)	(1.0147)	(−0.5123)
$boardsize_t$	0.1398	0.0814	0.1754	−0.3518
	(0.3888)	(0.2485)	(0.5541)	(−0.6909)
$roa\_volatility_t$	0.3230	−0.6001	−0.1815	0.8991
	(0.4462)	(−0.8156)	(−0.1275)	(0.4323)
Observations	1032	1246	1122	1024
Pseudo R^2	0.004	0.006	0.004	0.022
Industry-fixed effects	included	included	included	included
City-fixed effects	included	included	included	included

Notes: Panel A of Table 1 reports the results of the logit regression, which is run by year for estimating propensity scores based on the pre-matched sample. The sample period ranges from 2011 to 2019. We use seven covariates - *size*, *roe*, *lev*, *salesgrowth*, *cashholdings*, *boardsize*, and *roa_volatility*. The definitions of all variables are provided in Appendix 2. The treatment indicator variable, *Treat*, equals 1 (0) for a treatment (control) firm. The treatment firm is defined as subject to the digitalization-involved commercial reform in which the Market Supervision Administration was established to introduce digital commercial registration system for improving information environments and monitoring on commercial activities of firms. The control firm is not subject to the digitalization-involved commercial reform in the six-year period centered on the beginning of the year of reform for the treatment firm, nor before the period. Industry-fixed effects and city-fixed effects are controlled in each regression, but their results are not reported for simplicity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Notes: Panel B of Table 1 reports the results from testing the covariate balance for the matched sample used in the difference-in-differences regression of stock price crash risk. We use seven covariates - *size*, *roe*, *lev*, *salesgrowth*, *cashholdings*, *boardsize*, and *roa_volatility*. The definitions of all variables are provided in Appendix 2. The treatment indicator variable, *Treat*, equals 1 (0) for a treatment (control) firm. The treatment firm is defined as subject to the digitalization-involved commercial reform in which the Market Supervision Administration was established to introduce digital commercial registration system for improving information environments and monitoring on commercial activities of firms. The control firm is not subject to the digitalization-involved commercial reform in the six-year period centered at the beginning of the year of the reform for the treatment firm, nor before the period. We follow Leuven and Sianesi (2018) to match each treatment firm, with replacement, with a control firm by using the closest propensity score within a caliper of 1 % for each year. Industry-fixed effects and city-fixed effects are controlled in each regression, but their results are not reported for simplicity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 2
Univariate statistics.

Panel A: Summary statistics of variables

Variables	N	Mean	Min.	10%	25%	Median	75%	90%	Max.	Std. Dev.
NCSKEW	7,072	-0.243	-2.788	-1.150	-0.643	-0.212	0.189	0.597	2.267	0.737
DUVOL	7,072	-0.195	-1.686	-0.790	-0.486	-0.162	0.165	0.474	1.429	0.506
*CRASH*1	7,072	0.481	0.000	0.000	0.000	0.000	1.000	1.000	1.000	0.500
*CRASH*2	7,072	0.552	0.000	0.000	0.000	0.000	0.423	2.156	4.587	0.429
Treat	7,072	0.511	0.000	0.000	0.000	1.000	1.000	1.000	1.000	0.334
Ab_accrual	7,072	-0.017	-0.326	-0.096	-0.045	-0.006	0.030	0.053	0.066	0.062
Media_coverage	7,072	4.279	0.693	3.132	3.555	4.246	4.344	5.123	8.344	1.047
Related_transaction	7,072	6.159	0.000	0.000	0.000	0.000	18.000	25.279	28.788	10.782
Other_receivable	7,072	0.347	0.000	0.096	0.201	0.345	0.490	0.599	0.806	0.187
Digit	7,072	1.028	0.000	0.000	0.000	0.693	1.792	2.996	6.252	1.278
*Digit*1	7,072	0.003	0.000	0.000	0.000	0.001	0.003	0.007	0.045	0.007
Innovation	7,072	0.040	0.000	0.002	0.012	0.032	0.049	0.082	1.259	0.049
*Innovation*1	7,072	0.652	0.000	0.000	0.000	0.000	1.099	2.079	8.034	1.007
CG	7,072	0.405	0.000	0.073	0.216	0.413	0.587	0.711	0.890	0.232
CG1	7,072	0.076	0.000	0.000	0.013	0.054	0.091	0.133	0.652	0.125
size	7,072	22.275	18.964	20.775	21.336	22.082	23.017	24.044	26.297	1.281
soe	7,072	0.411	0.000	0.000	0.000	0.000	1.000	1.000	1.000	0.492
roe	7,072	0.058	-1.595	0.005	0.031	0.070	0.113	0.164	0.377	0.151
lev	7,072	0.412	0.044	0.156	0.277	0.454	0.565	0.665	0.901	0.189
salesgrowth	7,072	0.395	-0.772	-0.181	-0.030	0.135	0.424	0.992	12.455	1.131
cashholdings	7,072	0.044	-0.208	-0.037	0.006	0.043	0.084	0.126	0.256	0.068
duality	7,072	0.248	0.000	0.000	0.000	0.000	0.000	1.000	1.000	0.432
boardsize	7,072	2.152	1.609	1.946	2.079	2.197	2.197	2.398	2.708	0.198
top_shareholdings	7,072	36.186	8.260	17.710	24.195	34.650	46.435	56.850	75.790	14.978
hhi	7,072	0.054	0.001	0.007	0.018	0.038	0.073	0.122	0.304	0.053
ceoshare	7,072	0.003	0.000	0.000	0.001	0.002	0.004	0.007	0.017	0.041
ret	7,072	0.001	-0.034	-0.010	-0.006	-0.001	0.006	0.014	0.081	0.011
sigma	7,072	0.062	0.018	0.038	0.045	0.056	0.071	0.097	0.243	0.026
share_turnover	7,072	-0.019	-0.251	-0.079	-0.033	-0.009	0.006	0.026	0.152	0.049
roa_volatility	7,072	0.041	0.001	0.006	0.010	0.019	0.037	0.078	0.748	0.073

Panel B: Correlation matrix

Variables	*NCSKEW*	*DUVOL*	*Treat×Post*	*size*	*soe*	*roe*	*lev*	*salesgrowth*	*cashholdings*	*duality*	*boardsize*	*top_shareholdings*	*hhi*	*ceoshare*	*ret*	*sigma*	*share_turnover*	*roa_volatility*
NCSKEW	1.000																	
DUVOL	0.879***	1.000																
Treat×Post	0.005	0.003	1.000															
size	0.097***	0.121***	-0.043***	1.000														
soe	0.111***	0.115***	-0.100***	0.410***	1.000													
roe	0.103	0.111***	-0.047***	0.590***	0.350***	1.000												
lev	-0.011	-0.001	0.008	0.086***	-0.008	-0.101***	1.000											
salesgrowth	-0.004	-0.003	-0.004	0.027***	0.013	0.092***	0.040***	1.000										
cashholdings	-0.006	-0.003	0.030***	0.052***	0.029***	-0.148***	0.283***	-0.097***	1.000									
duality	-0.049***	-0.053***	0.050***	-0.209***	-0.292***	-0.166***	-0.008	-0.020**	-0.024***	1.000								
boardsize	0.051***	0.053***	-0.033***	0.277***	0.294***	0.175***	0.039***	-0.028***	0.054***	-0.182***	1.000							
top_shareholdings	0.067***	0.061***	-0.012	0.225***	0.208***	0.106***	0.096***	0.014*	0.076***	-0.043***	0.028***	1.000						
hhi	-0.010	-0.008	0.005	-0.034***	-0.055***	0.080***	-0.042***	0.132***	-0.259***	0.022***	-0.059***	-0.028***	1.000					
ceoshare	-0.050	-0.052***	0.042***	0.023***	-0.144***	-0.067***	0.003	-0.015*	0.001	0.069***	-0.013	0.000	0.088***	1.000				
ret	0.122***	0.124***	0.134***	-0.043***	-0.058***	-0.035***	0.070***	0.041***	0.086***	0.022***	-0.058***	-0.005	-0.008	0.004	1.000			
sigma	0.094***	0.093***	0.100***	-0.212***	-0.161***	-0.082***	-0.109***	0.058***	-0.045***	0.082***	-0.143***	-0.089***	0.057***	0.013	0.593***	1.000		
share_turnover	0.060***	0.063***	0.023***	0.225***	0.167***	0.171***	-0.057***	0.024***	0.073***	-0.105***	0.058***	-0.031***	-0.030***	0.028***	0.383***	0.243***	1.000	
roa_volatility	-0.006	0.000	0.006	-0.090***	-0.037***	-0.073***	-0.104***	-0.012	-0.008	0.012	-0.039***	-0.034***	0.061***	0.046***	0.057***	0.081***	0.047***	1.000

Notes: Panel A of Table 2 reports the descriptive statistics of all variables used in the multivariate tests of the association between the digitalization-involved commercial reform and stock price crash risk. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2. The sample period ranges from 2011 to 2019. Observations that have missing values in any of the regressors are excluded from the samples used for the multivariate tests.

Notes: Panel B of Table 2 provides the Spearman correlation coefficients for all variables involved in the baseline regression regarding the relationship between digitalization-involved commercial reform and stock price crash risk. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

4. Empirical analysis of the effect of digitalization-applied commercial reform on stock price crash risk

4.1. Tests of parallel trends assumption

The validity of difference-in-differences research design relies crucially on the parallel trends assumption, which requires similar trends of the outcome variable (i.e., stock price crash risk) for both the treatment and control groups in the pre-event period (i.e., before the implementation of digitalization-involved commercial reform) (e.g., Beck et al., 2010; Roberts and Whited, 2013). To test this assumption, we first construct the following model to compare the stock price crash risk of treatment firms with that of control firms for our pre- versus post-event periods:

$$
\begin{aligned}
& NCSKEW_{i,t} \text{ or } DUVOL_{i,t} = \\
& \beta_0 + \beta_1 Treat_t \times Pre3 + \beta_2 Treated_t \times Pre2 + \beta_3 Treated_t \times Pre1 \\
& + \beta_4 Treated_t \times Post1 + \beta_5 Treated_t \times Post2 + \beta_6 Treated_t \times Post3 + \beta_7 size_{i,t} \\
& + \beta_8 soe_{i,t} + \beta_9 roe_{i,t} + \beta_{10} lev_{i,t} + \beta_{11} salesgrowth_{i,t} + \beta_{12} cashholdings_{i,t} \\
& + \beta_{13} duality_{i,t} + \beta_{14} boardsize_{i,t} + \beta_{15} top\_shareholdings_{i,t} + \beta_{16} hhi_{i,t} \\
& + \beta_{17} ceoshare_{i,t} + \beta_{18} ret_{i,t} + \beta_{19} sigma_{i,t} + \beta_{20} share\_turnover_{i,t} + \beta_{21} roa\_volatility_{i,t} \\
& + year\_dummies + industry\_dummies + city\_dummies + \varepsilon_{i,t}
\end{aligned} \tag{6}
$$

where *Pre*3, *Pre*2, *Pre*1, *Post*1, *Post*2, and *Post*3 are the year dummies for the 6-year periods.

Panel A of Table 3 presents the results of running Model (6). The coefficients on interaction terms, *Treat*×*Pre*3, *Treat*×*Pre*2, and *Treat*×*Pre*1, are not statistically significant, supporting the parallel trends assumption for our DID research design. The coefficients on interaction terms, *Treat*×*Post*3, *Treat*×*Post*2, and *Treat*×*Post*1, are all negative and statistically significant. These results indicate that the commercial reform with the application of digitalization affects stock price crash risk in each year of our post-event sample period. From the magnitude of their coefficients, we may infer that the effect of digitalization-applied commercial reform is amplified over the post-event sample years.

We also show in Fig. 2 the dynamic economic effects of digitalization-applied commercial reform in different years. It reveals that before the implementation of commercial reform, the estimated coefficient is close to 0, with no obvious difference over the years. However, after the implementation of reform, the policy effect becomes prominent. This finding lends further support to the parallel trends assumption and suggests that the reduced risk of stock price crashes is attributed to the commercial reform other than potential omitted time-series factors.

4.2. Empirical results of the difference-in-differences regression

Table B of Table 3 reports the results of our stacked difference-in-differences regression (i.e., Model (4)). The coefficients on *Treat*×*Post* are negative and statistically significant at the 1 % level for both *NCSKEW* and *DUVOL*. The point estimate on *Treat*×*Post* is −0.161 (−0.159), which accounts for 21.85 % (31.42 %) of one standard deviation of *NCSKEW* (*DUVOL*) for the matched sample and is economically significant. These results reject the null hypothesis H1 and suggest that firms subject to the digitalization-applied commercial reform experience a decrease in stock price crash risk relative to those unaffected by the reform. In addition, the regression results for control variables are in line with those reported in prior studies (e.g., Kim et al., 2014; Piotroski et al., 2015; Chen et al., 2016).

4.3. Robustness tests

4.3.1. Control for firm-fixed effects and within-city correlations of residuals

There might be some unobserved firm-specific characteristics that affect firms' stock price crash risk. To allay this concern, we include firm-fixed effects and run both the univariate and multivariate regressions on *Treat*×*Post* for *NCSKEW* and *DUVOL*. Panel A of Table 4 presents the results. All the coefficients on *Treat*×*Post* are negative with the statistical significance level of 1 %. The point estimate on *Treat*×*Post* in our multivariate regression for *NCSKEW* (*DUVOL*) is −0.145 (−0.117), which accounts for 19.67 % (23.12 %) of one standard deviation of *NCSKEW* (*DUVOL*) for the matched sample and is economically significant. These results substantiate that our baseline DID regression results are immune to the bias associated with potential omitted time-invariant factors.

The residuals of observations might be correlated across firms and years within each city. Thus, in addition to the control of city-fixed effects, we also cluster the standard errors of coefficients by city. Panel B reports the results, which appear qualitatively identical to our baseline results.

Table 3
Baseline regression.

Panel A: Multivariate test of the parallel trends assumption

Variables	(1) Dependent variable = $NCSKEW_t$	(2) Dependent variable = $DUVOL_t$
*Treat×Pre*3	0.022	0.040
	(0.447)	(1.220)
*Treat×Pre*2	0.037	0.034
	(0.762)	(0.984)
*Treat×Pre*1	0.045	0.031
	(0.982)	(0.943)
*Treat×Post*1	−0.085**	−0.065**
	(−2.278)	(−2.549)
*Treat×Post*2	−0.100**	−0.076**
	(−2.133)	(−2.364)
*Treat×Post*3	−0.111**	−0.085***
	(−2.321)	(−2.605)
$size_t$	0.045***	0.043***
	(5.426)	(7.369)
soe_t	0.087***	0.055***
	(5.382)	(4.845)
roe_t	0.054	0.029
	(1.181)	(0.967)
lev_t	−0.142**	−0.082*
	(−1.964)	(−1.649)
$salesgrowth_t$	−0.019***	−0.013***
	(−2.655)	(−2.914)
$cashholdings_t$	−0.122	−0.096
	(−1.200)	(−1.327)
$duality_t$	−0.020	−0.014
	(−1.304)	(−1.299)
$boardsize_t$	0.058*	0.032
	(1.713)	(1.331)
$top\_shareholdings_t$	0.001***	0.001**
	(3.006)	(2.074)
hhi_t	−0.192	−0.134
	(−1.616)	(−1.615)
$ceoshare_t$	−0.121	−0.077
	(−0.637)	(−1.206)
ret_t	10.719***	8.970***
	(10.401)	(11.665)
$sigma_t$	5.559***	3.106***
	(11.402)	(9.029)
$share\_turnover_t$	−0.001	0.007
	(−0.009)	(0.070)
$roa\_volatility_t$	−0.053	0.024
	(−0.494)	(0.350)
Constant	−1.191***	−1.009***
	(−6.077)	(−7.336)
Observations	7072	7072
Adj. R^2	0.098	0.100
Year-fixed effects	included	included
Industry-fixed effects	included	included
City-fixed effects	included	included

Panel B: Difference-in-differences (DID) regression as to the association between digitalization-involved commercial reform and stock price crash risk

Variables	(1) Dependent variable = $NCSKEW_t$	(2) Dependent variable = $DUVOL_t$
Treat×Post	−0.161***	−0.159***
	(−12.579)	(−20.129)
Treat	0.639***	0.692***
	(10.961)	(19.039)
$size_t$	0.046***	0.043***
	(5.513)	(7.470)
soe_t	0.087***	0.055***
	(5.378)	(4.834)
roe_t	0.051	0.027
	(1.122)	(0.894)
lev_t	−0.145	−0.084
	(−1.005)	(−1.102)

(*continued on next page*)

Table 3 (*continued*)

Panel B: Difference-in-differences (DID) regression as to the association between digitalization-involved commercial reform and stock price crash risk

Variables	(1) Dependent variable = $NCSKEW_t$	(2) Dependent variable = $DUVOL_t$
$salesgrowth_t$	−0.019***	−0.013***
	(−2.665)	(−2.917)
$cashholdings_t$	−0.123	−0.097
	(−1.209)	(−1.335)
$duality_t$	−0.019	−0.013
	(−1.270)	(−1.249)
$boardsize_t$	0.058*	0.031
	(1.693)	(1.309)
$top\_shareholdings_t$	0.001***	0.001**
	(3.040)	(2.115)
hhi_t	−0.196	−0.137*
	(−1.644)	(−1.655)
$ceoshare_t$	−0.122***	−0.078***
	(−4.697)	(−4.268)
ret_t	10.735***	8.974***
	(10.451)	(11.701)
$sigma_t$	5.553***	3.106***
	(11.385)	(9.031)
$share\_turnover_t$	−0.004	0.005
	(−0.028)	(0.051)
$roa\_volatility_t$	−0.051	0.026
	(−0.473)	(0.371)
Constant	−1.304***	−1.097***
	(−6.865)	(−8.192)
Observations	7072	7072
Adj. R^2	0.119	0.120
Year-fixed effects	included	included
Industry-fixed effects	included	included
City-fixed effects	included	included

Notes: Table A of Table 3 presents the results of the multivariate test of the parallel trends assumption for the difference-in-differences regression of the association between digitalization-involved commercial reform (*Treat*×*Post*) and stock price crash risk (*NCSKEW* and *DUVOL*). The treatment indicator variable, *Treat*, equals 1 (0) for a treatment (control) firm. The treatment firm is defined as subject to the digitalization-involved commercial reform in which the Market Supervision Administration was established to introduce digital commercial registration system for improving information environments and monitoring on commercial activities of firms. The control firm is not subject to the digitalization-involved commercial reform in the six-year period centered at the beginning of the year of the reform for the treatment firm, nor before the period. *Pre*3, *Pre*2, *Pre*1, *Post*1, *Post*2, and *Post*3 are the year dummies for the 6-year periods. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. Year dummies, industry dummies, and city dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2.

Notes: Table B of Table 3 reports the OLS regression results for the association between digitalization-involved commercial reform (*Treat*×*Post*) and stock price crash risk (*NCSKEW* and *DUVOL*). *Treat* equals 1 (0) for a treatment (control) firm. The treatment firm is defined as subject to the digitalization-involved commercial reform in which the Market Supervision Administration was established to introduce digital commercial registration system for improving information environments and monitoring on commercial activities of firms. The control firm is not subject to the digitalization-involved commercial reform in the six-year period centered at the beginning of the year of the reform for the treatment firm, nor before the period. *Post* is the time indicator variable that equals 1 (0) if a treatment firm is in the three-year period since (before) the digitalization-involved commercial reform took place. The interaction term, *Treat*×*Post*, captures the impact of digitalization-involved commercial reform on stock price crash risk. The sample period ranges from 2011 to 2019. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2. Year dummies, industry dummies, and city dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

4.3.2. Test of coefficient stability

Following Altonji et al. (2005), we analyze coefficient stability to evaluate whether potential omitted factors would have driven our baseline regression results. The econometric rationale behind this analysis is that if the regression model adequately controls for the main determinants of dependent variable, any newly added control variable should exhibit a minimal correlation with the already included explanatory variables, and the additional control should not significantly alter the stability of coefficient estimates for those existing explanatory variables. In this context, the higher the stability of coefficients for the explanatory variables following an addition of control variables, the lower the likelihood that the regression model omits any key variable. Based on this reasoning, we

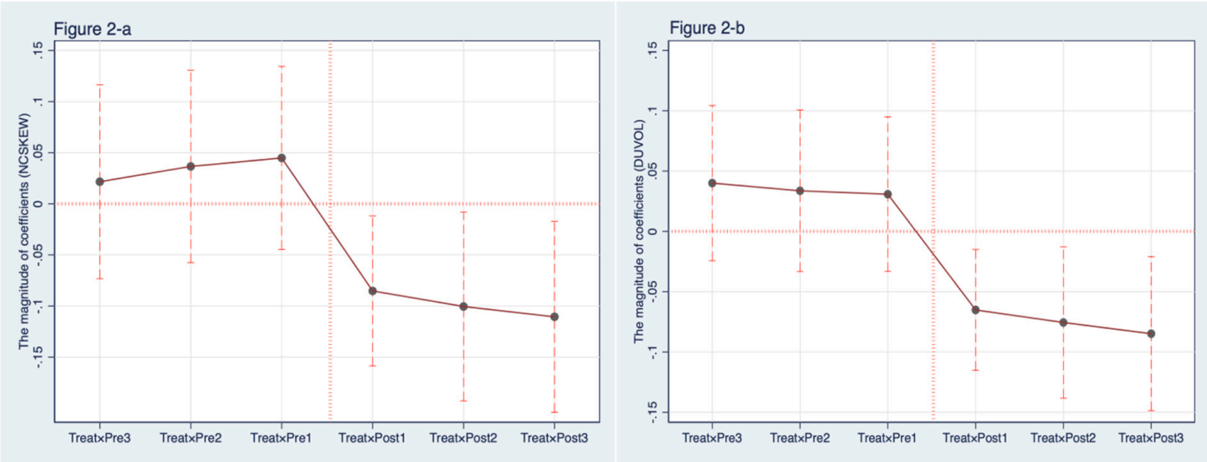

Fig. 2. Parallel trend test.
Notes: Fig. 2 presents the results of the coefficient test of the parallel trends assumption for the difference-in-differences (DID) regression estimation. Specifically, Fig. 2-a (2-b) shows the graphical diagnostic of parallel trend assumption for the DID regression where *NCSKEW* (*DUVOL*) is the dependent variable. The horizontal axis represents the interaction terms between *Treat* and *Pre** (*Post**); the vertical axis represents the magnitude of the coefficient of *Treat*×*Pre** (*Treat*×*Post**). The short dashed lines, which are perpendicular to the horizontal axis, are the corresponding 95 % confidence interval for each coefficient. We consider a 6-year period and report the coefficients of *Treat*×*Pre** (*Treat*×*Post**), which are estimated from the regression model (6). *Pre** and *Post** include *Pre*3, *Pre*2, *Pre*1, *Post*1, *Post*2, and *Post*3, which are the year dummies for the 6-year period. The standard errors of the coefficients are adjusted for heteroskedasticity and clustered by firm. All the continuous variables are winsorized at 1 and 99 percentage points, respectively, and are defined in Appendix 2.

test the coefficient stabililty in the following ways. First, we rank the 15 control variables based on the economic magnitude of their coefficients in the baseline regression analysis,[5] and take the top 60 % as the main control variables and the rest as the additional control variables. Second, we run a DID regression with the 9 main control variables, and progressively introduce each of the additional control variables into this regression.

The results are reported in Panel C of Table 4. The progressive addition of control variables has no substantial effect on the significance levels of the DID coefficient, substantiating its stability and insensitivity to additional controls. Meanwhile, the absolute values of the ratios of the standardized selection on "unobservables" to the standardized selection on "observables", reported in the Columns (3) and (6) of Panel C, are all well below 1 %.[6] From these results, it could be inferred that any plausibly omitted variables in our baseline regression, including those determining the timing of the reform implemented by local MSAs, are likely to be weakly correlated with explanatory variables and thus should not bias our DID estimator substantively.

4.3.3. Placebo test

As with previous studies (e.g., Ferrara et al., 2012; Alder et al., 2016), we conduct a placebo test to check whether our baseline regression results are free from the potential confounding effect of random factors or omitted variables. To this end, we first randomly assign our control firms into the treatment and control groups to generate a fake treatment group, $Treat^{fake}$, and associated fake commercial reform time, $Post^{fake}$, for each year. We repeat this trial for 1000 times to enhance the efficacy of our placebo test. Fig. 3 displays the distribution and *p* values of estimated coefficients on the interaction term, $Treat^{fake} \times Post^{fake}$. The placebo DID estimators for both *NCSKEW* and *DUVOL* are normally distributed and centered around 0. Almost all the placebo DID coefficients are positioned to the right of the baseline DID coefficient (as depicted by the vertical dotted line) and have p values higher than 0.1. In our one-sample *t*-test, the mean value of the placebo DID estimators shows no statistically significant difference from 0 ($p = 0.234$ and 0.211). It can be inferred from these results that the reduction in stock price crash risk is not accidental or driven by omitted factors; rather, it is attributed to the effectiveness of commercial reform.

[5] The economic magnitude of the coefficient is estimated by the percentage change in the sample mean of the dependent variable in response to a one-standard-deviation change in the control variable.

[6] The ratio is calculated as: $\left|\frac{\beta^F - \beta^R}{\beta^F}\right|$, where β^F is the estimated coefficient of the core explanatory variable (i.e., *Treat*×*Post* in our case) in the regression that includes a selected number of main control variables, and β^R is the estimated coefficient of the core explanatory variable in the regression that includes the selected main control variables as well as the progressively added control variables. The lower the ratio, the stronger the explanatory power of the main control variables, and thus the lesser extent to which any omitted variable would bias the results for the core explanatory variable. The ratio less than 1 % implies that omitted variables are unlikely to overturn the results and inferences for the core regressor.

Table 4
Robustness tests of baseline results.

Panel A: Inclusion of firm-fixed effects in the DID regression

Variables	(1) Dependent variable = $NCSKEW_t$	(2) Dependent variable = $DUVOL_t$	(3) Dependent variable = $NCSKEW_t$	(4) Dependent variable = $DUVOL_t$
Treat×Post	−0.174***	−0.147***	−0.145***	−0.117***
	(−22.781)	(−33.297)	(−22.579)	(−26.476)
$size_t$			0.709***	0.576***
			(22.177)	(29.019)
soe_t			−0.008	0.030**
			(−0.357)	(2.088)
roe_t			0.074	0.041
			(0.691)	(0.806)
lev_t			0.126*	0.060
			(1.722)	(1.042)
$salesgrowth_t$			−0.053	−0.040
			(−0.654)	(−0.744)
$cashholdings_t$			−0.025***	−0.015***
			(−2.745)	(−2.841)
$duality_t$			−0.202*	−0.076
			(−1.817)	(−0.932)
$boardsize_t$			0.006	0.005
			(0.199)	(0.224)
$top\_shareholdings_t$			0.003	−0.014
			(0.040)	(−0.285)
hhi_t			0.005***	0.002***
			(3.614)	(2.750)
$ceoshare_t$			−0.085	−0.062
			(−0.645)	(−0.804)
ret_t			0.058	0.041*
			(1.527)	(1.678)
$sigma_t$			10.659***	9.020***
			(8.953)	(10.032)
$share\_turnover_t$			5.681***	3.072***
			(9.464)	(6.808)
$roa\_volatility_t$			−0.078	−0.047
			(−0.438)	(−0.410)
Constant	0.228***	0.148***	−0.205	−0.820**
	(58.269)	(54.314)	(−0.390)	(−2.467)
Observations	7072	7072	7072	7072
Adj. R^2	0.067	0.255	0.113	0.121
Year-fixed effects	included	included	included	included
Firm-fixed effects	included	included	included	included
City-fixed effects	included	included	included	included

Panel B: Clustering the standard errors of coefficients by city in the DID regression

Variables	(1) Dependent variable = $NCSKEW_t$	(2) Dependent variable = $DUVOL_t$	(3) Dependent variable = $NCSKEW_t$	(4) Dependent variable = $DUVOL_t$
Treat×Post	−0.174***	−0.147***	−0.161***	−0.159***
	(−24.511)	(−33.297)	(−16.597)	(−37.783)
$Treat_t$			0.639***	0.692***
			(10.824)	(16.386)
$size_t$			0.046***	0.043***
			(4.771)	(6.716)
soe_t			0.087***	0.055***
			(4.917)	(4.378)
roe_t			0.051	0.027
			(1.267)	(0.993)
lev_t			−0.145**	−0.084*
			(−2.019)	(−1.828)
$salesgrowth_t$			−0.019**	−0.013***
			(−2.444)	(−2.918)
$cashholdings_t$			−0.123	−0.097
			(−1.176)	(−1.327)
$duality_t$			−0.019	−0.013
			(−1.080)	(−1.002)
$boardsize_t$			0.058*	0.031
			(1.892)	(1.537)

(*continued on next page*)

Table 4 (*continued*)

Panel B: Clustering the standard errors of coefficients by city in the DID regression

Variables	(1) Dependent variable = $NCSKEW_t$	(2) Dependent variable = $DUVOL_t$	(3) Dependent variable = $NCSKEW_t$	(4) Dependent variable = $DUVOL_t$
$top\_shareholdings_t$			0.001***	0.001**
			(3.224)	(2.094)
hhi_t			−0.196*	−0.137**
			(−1.899)	(−1.989)
$ceoshare_t$			−0.122***	−0.078***
			(−4.307)	(−4.097)
ret_t			10.735***	8.974***
			(9.183)	(10.077)
$sigma_t$			5.553***	3.106***
			(11.466)	(9.159)
$share\_turnover_t$			−0.004	0.005
			(−0.031)	(0.062)
$roa\_volatility_t$			−0.051	0.026
			(−0.520)	(0.373)
Constant	0.230***	0.148***	−1.304***	−1.097***
	(88.381)	(54.314)	(−5.883)	(−7.039)
Observations	7072	7072	7072	7072
Adj. R^2	0.067	0.256	0.119	0.120
Year-fixed effects	included	included	included	included
Industry-fixed effects	included	included	included	included
City-fixed effects	included	included	included	included

Panel C: Test of coefficient stability

	Dependent variable = $NCSKEW_t$				Dependent variable = $DUVOL_t$		
Variables	(1) DID Coefficients	(2) t-stat.	(3) Selection ratio	Variables	(4) DID coefficients	(5) t-stat.	(6) Selection ratio
Main control variables	−0.167***	−5.960		*main control variables*	−0.160***	−8.296	
$+roa\_volatility_t$	−0.168***	−5.971	0.0085	$+size_t$	−0.172***	−8.734	0.0019
$+size_t$	−0.159***	−6.061	0.0021	$+duality_t$	−0.172***	−8.731	0.0019
$+salesgrowth_t$	−0.151***	−5.973	0.0017	$+boardsize_t$	−0.168***	−8.768	0.0052
$+duality_t$	−0.161***	−5.924	0.0043	$+salesgrowth_t$	−0.162***	−8.811	0.0033
$+share\_turnover_t$	−0.159***	−10.058	0.0009	$+lev_t$	−0.173***	−8.753	0.0017
$+top\_shareholdings_t$	−0.161***	−10.102	0.0006	$+top\_shareholdings_t$	−0.159***	−8.551	0.0010

Panel D: Alternative measures of stock price crash risk

Variables	(1) Dependent variable = $CRASH1_t$	(2) Dependent variable = $CRASH1_t$	(3) Dependent variable = $CRASH2_t$	(4) Dependent variable = $CRASH2_t$
Treat×Pre3	−0.006		0.000	
	(−0.169)		(0.215)	
Treat×Pre2	0.001		−0.001	
	(0.034)		(−0.639)	
Treat×Pre1	0.011		−0.001	
	(0.317)		(−0.835)	
Treat×Post1	−0.068***		−0.005**	
	(−2.629)		(−2.289)	
Treat×Post2	−0.079**		−0.008***	
	(−2.379)		(−2.634)	
Treat×Post3	−0.094***		−0.011***	
	(−2.781)		(−3.079)	
Treat×Post		−0.160***		−0.104**
		(−24.904)		(−2.278)
Treat		0.555***		0.005**
		(27.580)		(2.367)
$size_t$	0.023***	0.028***	0.006***	0.006***
	(3.890)	(4.824)	(5.990)	(5.764)
soe_t	0.050***	0.053***	0.009***	0.008***
	(4.086)	(4.467)	(4.164)	(4.032)
roe_t	0.064**	0.069**	0.996***	0.995***
	(1.977)	(2.174)	(225.676)	(216.508)
lev_t	−0.132***	−0.155***	0.017*	0.018*

(*continued on next page*)

Table 4 (*continued*)

Panel D: Alternative measures of stock price crash risk				
Variables	(1) Dependent variable = $CRASH1_t$	(2) Dependent variable = $CRASH1_t$	(3) Dependent variable = $CRASH2_t$	(4) Dependent variable = $CRASH2_t$
	(−2.598)	(−3.040)	(1.877)	(1.959)
$salesgrowth_t$	−0.012***	−0.011**	0.000	0.001
	(−2.750)	(−2.539)	(0.636)	(0.906)
$cashholdings_t$	−0.152*	−0.146*	−0.001	−0.004
	(−1.927)	(−1.899)	(−0.093)	(−0.422)
$duality_t$	−0.020*	−0.022**	−0.002*	−0.003**
	(−1.750)	(−1.967)	(−1.909)	(−2.100)
$boardsize_t$	0.031	0.038	−0.006	−0.005
	(1.199)	(1.481)	(−1.581)	(−1.322)
$top\_shareholdings_t$	0.001***	0.001***	−0.000*	−0.000**
	(2.788)	(2.999)	(−1.890)	(−2.050)
hhi_t	−0.254***	−0.241***	−0.021**	−0.020**
	(−2.737)	(−2.618)	(−2.405)	(−2.106)
$ceoshare_t$	−0.068***	−0.077***	−0.007***	−0.008***
	(−3.605)	(−4.057)	(−3.100)	(−3.084)
ret_t	5.358***	5.327***	−0.056	−0.082
	(7.487)	(7.463)	(−1.029)	(−1.443)
$sigma_t$	3.019***	3.113***	0.067**	0.094***
	(10.155)	(10.606)	(2.244)	(2.978)
$share\_turnover_t$	0.068	0.067	0.040***	0.037***
	(0.607)	(0.604)	(4.801)	(4.374)
$roa\_volatility_t$	−0.003	−0.019	0.013*	0.016**
	(−0.045)	(−0.267)	(1.752)	(1.995)
Constant	−0.229	−0.442***	−1.084***	−1.095***
	(−1.625)	(−3.357)	(−50.929)	(−49.335)
Observations	7072	7072	7072	7072
Adj. R^2	0.062	0.054	0.168	0.167
Year-fixed effects	included	included	included	included
Industry-fixed effects	included	included	included	included
City-fixed effects	included	included	included	included

Notes: Table A of Table 4 reports the firm-fixed-effects difference-in-differences regression results for the association between digitalization-involved commercial reform (*Treat*×*Post*) and stock price crash risk (*NCSKEW* and *DUVOL*). Columns (1) and (2) report the results of the univariate regression that includes *Treat*×*Post* and excludes the control variables. Columns (3) and (4) report the results of the multivariate regression that includes *Treat*×*Post* and the control variables. The sample period ranges from 2011 to 2019. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2. Year dummies, firm dummies, and city dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Notes: Table B of Table 4 reports the OLS regression results for the association between digitalization-involved commercial reform (*Treat*×*Post*) and stock price crash risk (*NCSKEW* and *DUVOL*). Columns (1) and (2) report the results of the univariate regression that includes *Treat*×*Post* and excludes the control variables. Columns (3) and (4) report the results of the multivariate regression that includes *Treat*×*Post* and the control variables. The sample period ranges from 2011 to 2019. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2. Year dummies, industry dummies, and city dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by city. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Notes: Table C of Table 4 reports the results from testing the stability of the coefficient of *Treat*×*Post* in the difference-in-differences regression of stock price crash risk (*NCSKEW* and *DUVOL*). Column (1) and (2) (Column (4) and (5)) present the coefficients and t value of *Treat*×*Post* in the regression of *NCSKEW* (*DUVOL*), after controlling for the 9 main control variables (i.e., the control variables ranked in the top 60 % based on the economic magnitude of their coefficients in the baseline regression analysis), and progressively introduce each of the other 6 control variables into the regression (i.e., the control variables ranked in the bottom 40 % based on the economic magnitude of their coefficients in the baseline regression). For instance, in the first (second) row of Column (1), the coefficient of *Treat*×*Post* in the regression of *NCSKEW* is −0.167 (−0.168) when *roa_volatility* (both *roa_volatility and size*) is (are) included in the regression along with the 9 main control variables (i.e., *ret*, *sigma*, *hhi*, *lev*, *cashholdings*, *ceoshare*, *soe*, *boardsize*, and *roe*). In the first (second) row of Column (4), the coefficient of *Treat*×*Post* in the regression of *DUVOL* is −0.160 (−0.172) when *size* (both *size and duality*) is (are) included in the regression along with the 9 main control variables (i.e., *sigma*, *cashholdings*, *ret*, *roe*, *roa_volatility*, *share_turnover*, *ceoshare*, *soe*, and *hhi*). In Column (3) (Column (6)), the selection ratio (i.e., the absolute value of the ratio of the standardized selection on "unobservables" to the standardized selection on "observables") is calculated as the absolute value of the difference in the estimated coefficients *Treat*×*Post* between the *NCSKEW* (*DUVOL*) regression with the 9 main control variables and the *NCSKEW* (*DUVOL*) regression with all controls that include the progressively added control variable(s), divided by the coefficient *Treat*×*Post* estimated from the regression with the 9 main control variables. For instance, in the first (second) row of Column (3), the selection ratio for *Treat*×*Post* in the regression of *NCSKEW* is 0.0085 (0.0021) when *roa_volatility* (both *roa_volatility and size*) is (are) included along with the 9 main control variables in the regression. In the first (second) row of Column (6), the selection ratio for *Treat*×*Post* in the regression of *DUVOL* is 0.0019 (0.0019) when *size* (both *size and duality*) is (are) included along with the 9 main control variables in the regression.

Notes: Table Dof Table 4 reports the results of the test that uses alternative measures of stock price crash risk (i.e., *CRASH*1 and *CRASH*2). Columns (1) and (3) report the results of the parallel trends assumption test using alternative measures as to *CRASH*1 and *CRASH*2, respectively. Columns (2) and

(4) report the results of baseline regression using alternative measures as to *CRASH*1 and *CRASH*2, respectively. The sample period ranges from 2011 to 2019. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2. Year dummies, industry dummies, and city dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

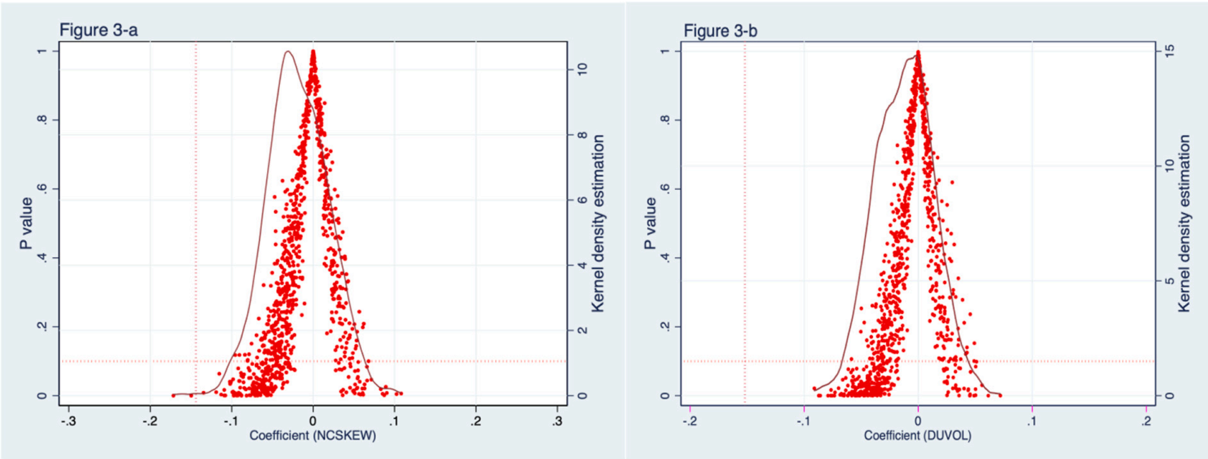

Fig. 3. Placebo test.
Notes: Fig. 3 plots the cumulative distribution density of the 1000 coefficient estimates in a placebo test. We randomly assign observations, which are not subject to the digitalization-involved commercial reform, to generate a fake treatment group $Treat^{fake}$ and associated fake reform time $Post^{fake}$ for each year and repeat this trial for 1000 times to obtain 1000 DID estimators for the interaction term $Treat^{fake} \times Post^{fake}$. The horizontal axis represents the magnitude of the estimated coefficients of the interaction term $Treat^{fake} \times Post^{fake}$; the vertical axis represents its corresponding *p* values on statistical significance and kernel density estimates, respectively. The dots (solid curve) represent (s) the distribution of kernel density (p values) of the estimated coefficients in the placebo test; the left (right) figure shows such results for *NCSKEW* (*DUVOL*). The dotted vertical line represents the estimated coefficient on *Treat*×*Post* for the baseline regression of *NCSKEW* (*DUVOL*), corresponding with the result of Column (1) (Column (2)), under Table B of Table 3.

4.3.4. Alternative measures of stock price crash risk

Following previous research (e.g., Hutton et al., 2009; Kim et al., 2011), we generate two alternative measures of stock price crash risk, *CRASH*1 and *CRASH*2, to re-test our main hypothesis. *CRASH*1 equals 1 if a firm experiences at least one crash week in the fiscal year, and 0 otherwise. *CRASH*2 equals the natural logarithm of 1 plus the frequency of crash weeks of the firm during a fiscal year. We report the results for this robustness check in Panel D of Table 4. Column (1) (Column (3)) shows the results from using *CRASH*1 (*CRASH*2) to test the parallel trends assumption. The coefficients on *Treat*×*Pre*3, *Treat*×*Pre*2, and *Treat*×*Pre*1 are statistically nonsignificant, indicating that the parallel trend assumption is satisfied for the DID regression analysis. Column (2) (Column (4)) reports the results from using *CRASH*1 (*CRASH*2) to run the DID regression. *Treat*×*Post* takes on significantly negative coefficients, reinforcing the notion that firms subject to the digitalization-involved commercial reform enjoy lower stock price crash risk.

4.4. Mechanism tests for the association between digitalization-involved commercial reform and stock price crash risk

As discussed in Section 2.2, the digitalization-applied commercial reform might enhance the information transparency and monitoring of corporate commercial activities, leading to the decrease in firms' stock price crash risk. Therefore, information transparency and monitoring are arguably two channels through which the digitalization-involved commercial reform reduces stock price crash risk. To lend credence to these mechanisms, we conduct two tests.

We first test the mediating role of information transparency, which is measured by media news (*Media_coverage*). *Media_coverage* is computed as the natural logarithm of a firm's total number of media news in a fiscal year. A higher value of *Media_coverage* indicates higher information transparency.

We next test whether the enhanced monitoring of firms' commercial activities is another mechanism. Given the difficulty of directly measuring the monitoring level, we use three outcome-based measures, that is, related party transactions (*Related_transaction*), abnormal accruals (*Ab_accrual*) and other accounts receivable (*Other_receivable*), to capture the strength of monitoring on firms' commercial activities. These measurements are in line with previous research (e.g., Dechow et al., 1995; Jiang et al., 2010; Kohlbeck and Mayhew, 2017; Brockman et al., 2019). *Related_transaction* is computed as the natural logarithm of 1 plus the non-market-price transactions of commodities and services between a firm and its closely related business parties (i.e., its parent company or subsidiaries) during a fiscal year. *Ab_accrual* is the abnormal accruals of a firm for a fiscal year, which is estimated using the modified Jones model (Dechow et al., 1995). Firms could inflate accruals to hoard bad news arising from commercial activities (e.g., He and Ren, 2023). Thus, the stronger the monitoring, the lower the abnormal accruals which are likely associated with opportunistic bad news hoarding by the firms. *Other_receivable* is calculated as the amount of other accounts receivable, divided by the total assets of the firm, at the end of a fiscal year. A higher balance of other accounts receivable is likely associated with a greater likelihood of asset losses that result from corporate malpractices or malfeasances (e.g., Jiang et al., 2010; Brockman et al., 2019). In short, a higher value of *Related_transaction, Ab_accrual* or *Other_receivable* implies a lower degree of the monitoring strength that a firm confronts. We perform the mediation analysis by running the following regressions:

$$\begin{aligned}
&Media_coverage, Relate_transaction, Ab_accrual, \text{or } Other_receivable_{i,t} = \\
&\beta_0 + \beta_1 Treat_t \times Post_i + \beta_2 Treated_t + \beta_3 size_{i,t} + \beta_4 soe_{i,t} + \beta_5 roe_{i,t} + \beta_6 lev_{i,t} \\
&+ \beta_7 salesgrowth_{i,t} + \beta_8 cashholdings_{i,t} + \beta_9 duality_{i,t} + \beta_{10} boardsize_{i,t} \\
&+ \beta_{11} top_sharesholdings_{i,t} + \beta_{12} hhi_{i,t} + \beta_{13} ceoshare_{i,t} + \beta_{14} ret_{i,t} + \beta_{15} sigma_{i,t} \\
&+ \beta_{16} share_turnover_{i,t} + \beta_{17} roa_volatility_{i,t} + year_dummies \\
&+ industry_dummies + city_dummies + \varepsilon_{i,t}
\end{aligned} \tag{7}$$

$$\begin{aligned}
&NCSKEW \text{ or } DUVOL_{i,t} = \\
&\beta_0 + \beta_1 Media_coverage, Related_transaction, Ab_accrual, \text{or } Other_receivable_{i,t} \\
&+ \beta_2 size_{i,t} + \beta_3 soe_{i,t} + \beta_4 roe_{i,t} + \beta_5 lev_{i,t} + \beta_6 salesgrowth_{i,t} + \beta_7 cashholdings_{i,t} \\
&+ \beta_8 duality_{i,t} + \beta_9 boardsize_{i,t} + \beta_{10} top_shareholdings_{i,t} + \beta_{11} hhi_{i,t} + \beta_{12} ceoshare_{i,t} \\
&+ \beta_{13} ret_{i,t} + \beta_{14} sigma_{i,t} + \beta_{15} share_turnover_{i,t} + \beta_{16} roa_volatility_{i,t} \\
&+ year_dummies + industry_dummies + city_dummies + \varepsilon_{i,t}
\end{aligned} \tag{8}$$

where the mediator variables are *Media_coverage*, *Related_transaction*, *Ab_accrual*, and *Other_receivable*, which are defined in Appendix 2. If the mediating effect exists, the coefficients of *Treat*×*Post* for *Media_coverage* (*Related_transaction*, *Ab_accrual*, and *Other_receivable*) in Eq. (7) should be positive (negative) and statistically significant at conventional levels, while their coefficients in Eq. (8) should be significantly negative (positive).

Panel A of Table 5 reports the results of the mechanism tests for the information channel. Both the coefficients of *Treat*×*Post* for the first-stage regressions (reported in Columns (1)) and the mediator (*Media_coverage*) for the second-stage regression (reported in Columns (2), (3)) are statistically significant at the 1 % level with the predicted signs. These results support the conjecture that the digitalization-involved commercial reform lowers stock price crash risk by enhancing information transparency. Panel B shows the results of the mechanism test for the monitoring channel. The coefficients on *Treat*×*Post* in Columns (1), (4), and (7) for the first-stage regressions are negative and statistically significant. The coefficients for the mediators (*Related_transaction*, *Ab_accrual*, and *Other_receivable*) in Columns (2), (3), (5), (6), (8), and (9) for the second-stage regressions are positive and statistically significant at the 1 % level. Combined, these results corroborate that the increased strength of monitoring is another channel through which the digitalization-involved commercial reform reduces stock price crash risk.[7]

4.5. Cross-sectional analyses of the association between digitalization-applied commercial reform and stock price crash risk

We also explore how our baseline results vary under different circumstances. Apart from the government, firms might reshape their commercial processes and models by utilizing digital technologies such as artificial intelligence, blockchain, cloud computing, or big data analytics. Adopting digital technologies enables firms to better transmit their internal information to the government authorities in real time. This enhanced transmission enables the government to efficiently access more comprehensive and accurate information about different aspects of the firm, such as internal operations, production, and sales, thereby facilitating the digitalization-involved commercial reform to take even stronger attenuating effect on stock price crash risk. In this regard, the favorable impact of the commercial reform on reducing crash risk is expected to be more pronounced for firms with a higher level of digitalization.

Innovation plays a crucial role in maintaining competitive advantages, achieving commercial success, and ensuring sustainable development (Le et al., 2006; Jiménez-Jiménez and Sanz-Valle, 2011). Yet, pursuing innovation not only requires long-term substantial investments but also involves significant uncertainty as the innovation outcomes are often unpredictable inter alia for reasons

[7] Including the interaction term *Treat*×*Post* in the second-stage regression, the estimations in both mechanism tests yield similar results: the coefficients of *Treat*×*Post* and those of the mediators (i.e., *Media_coverage*, *Related_transaction*, *Ab_accrual*, and *Other_receivable*) remain statistically significant with the predicted signs.

Table 5
Tests of the mechanisms through which the digitalization-involved commercial reform reduces stock price crash risk.

Panel A: The information channel			
Variables	(1) Dependent variable = $Media\_coverage_t$	(2) Dependent variable = $NCSKEW_t$	(3) Dependent variable = $DUVOL_t$
Treat×Post	0.263***		
	(9.248)		
Treat	−0.252***		
	(−9.073)		
Media_coverage		−0.188***	−0.142***
		(−5.808)	(−6.442)
$size_t$	0.033***	0.052***	0.048***
	(7.461)	(6.249)	(8.284)
soe_t	−0.090***	0.070***	0.042***
	(−8.835)	(4.340)	(3.717)
roe_t	−0.206***	0.012	−0.002
	(−8.882)	(0.273)	(−0.079)
lev_t	0.105***	−0.125*	−0.069
	(3.988)	(−1.732)	(−1.400)
$salesgrowth_t$	0.005**	−0.018**	−0.012***
	(2.106)	(−2.551)	(−2.786)
$cashholdings_t$	0.030	−0.117	−0.092
	(0.726)	(−1.161)	(−1.286)
$duality_t$	0.002	−0.019	−0.013
	(0.297)	(−1.248)	(−1.228)
$boardsize_t$	0.041**	0.065*	0.037
	(2.211)	(1.927)	(1.571)
$top\_shareholdings_t$	0.011***	0.004***	0.002***
	(40.158)	(6.028)	(5.714)
hhi_t	0.094**	−0.178	−0.124
	(2.040)	(−1.498)	(−1.499)
$ceoshare_t$	0.065***	−0.110***	−0.069***
	(5.376)	(−4.216)	(−3.765)
ret_t	1.877***	11.087***	9.241***
	(7.785)	(10.786)	(12.034)
$sigma_t$	0.825***	5.708***	3.223***
	(5.843)	(11.714)	(9.390)
$share\_turnover_t$	−0.960***	−0.184	−0.131
	(−21.677)	(−1.251)	(−1.222)
$roa\_volatility_t$	−0.072*	−0.064	0.015
	(−1.943)	(−0.603)	(0.224)
Constant	2.844***	−0.770***	−0.691***
	(29.404)	(−3.629)	(−4.692)
Observations	7072	7072	7072
Adj. R^2	0.473	0.101	0.103
Year-fixed effects	included	included	included
Industry-fixed effects	included	included	included
City-fixed effects	included	included	included

(*continued on next page*)

Table 5 (*continued*)

Panel B: The monitoring channel									
Variables	(1) Dependent variable = *Related_transaction$_t$*	(2) Dependent variable = *NCSKEW$_t$*	(3) Dependent variable = *DUVOL$_t$*	(4) Dependent variable = *Ab_accrual$_t$*	(5) Dependent variable = *NCSKEW$_t$*	(6) Dependent variable = *DUVOL$_t$*	(7) Dependent variable = *Other_receivable$_t$*	(8) Dependent variable = *NCSKEW$_t$*	(9) Dependent variable = *DUVOL$_t$*
Treat×Post	−0.153***			−0.003***			−0.0760***		
	(−5.345)			(−4.563)			(−5.543)		
Treat	0.123***			0.002***			−0.0830***		
	(5.243)			(3.897)			(−4.591)		
Related_transaction		0.018**	0.012**						
		(2.182)	(2.034)						
Ab_accrual					12.294***	11.011***			
					(5.230)	(6.925)			
Other_receivable								0.244***	0.197***
								(5.195)	(5.989)
size$_t$	0.957***	0.028**	0.032***	−0.006***	0.123***	0.112***	0.010***	0.043***	0.041***
	(56.503)	(2.468)	(3.912)	(−155.824)	(7.707)	(10.068)	(6.681)	(5.242)	(7.171)
soe$_t$	0.024	0.087***	0.054***	0.000	0.086***	0.054***	0.028***	0.080***	0.049***
	(0.637)	(5.352)	(4.809)	(1.030)	(5.276)	(4.743)	(9.221)	(4.974)	(4.352)
roe$_t$	0.372***	0.044	0.022	0.028***	−0.292***	−0.280***	−0.012	0.054	0.029
	(4.039)	(0.971)	(0.739)	(134.692)	(−3.770)	(−5.252)	(−1.433)	(1.184)	(0.964)
lev$_t$	−1.170***	−0.126*	−0.071	−0.001***	−0.137*	−0.077	−0.031**	−0.137*	−0.078
	(−9.203)	(−1.734)	(−1.429)	(−2.797)	(−1.878)	(−1.540)	(−2.345)	(−1.914)	(−1.583)
salesgrowth$_t$	−0.079***	−0.017**	−0.012***	0.000	−0.019***	−0.013***	−0.003**	−0.018***	−0.013***
	(−5.921)	(−2.464)	(−2.702)	(0.436)	(−2.679)	(−2.954)	(−2.236)	(−2.578)	(−2.812)
cashholdings$_t$	1.957***	−0.158	−0.120*	0.002***	−0.146	−0.115	−0.049**	−0.111	−0.087
	(10.121)	(−1.547)	(−1.652)	(3.474)	(−1.429)	(−1.587)	(−2.461)	(−1.097)	(−1.208)
duality$_t$	−0.029	−0.018	−0.013	0.000	−0.020	−0.014	−0.002	−0.019	−0.013
	(−1.024)	(−1.223)	(−1.212)	(1.076)	(−1.316)	(−1.308)	(−0.769)	(−1.248)	(−1.224)
boardsize$_t$	0.295***	0.053	0.028	−0.000	0.058*	0.031	0.004	0.057*	0.031
	(3.741)	(1.547)	(1.172)	(−0.673)	(1.709)	(1.298)	(0.663)	(1.677)	(1.287)
top_shareholdings$_t$	0.003***	0.001***	0.001**	−0.000	0.001***	0.001**	−0.000***	0.002***	0.001**
	(2.746)	(2.936)	(2.016)	(−1.496)	(3.095)	(2.169)	(−3.913)	(3.223)	(2.329)
hhi$_t$	−1.685***	−0.162	−0.114	−0.000	−0.187	−0.129	−0.136***	−0.160	−0.107
	(−8.291)	(−1.349)	(−1.359)	(−0.748)	(−1.566)	(−1.563)	(−5.653)	(−1.347)	(−1.301)
ceoshare$_t$	−0.217***	−0.118***	−0.076***	0.000	−0.124***	−0.079***	−0.017***	−0.118***	−0.075***
	(−4.525)	(−4.560)	(−4.142)	(0.479)	(−4.775)	(−4.368)	(−3.184)	(−4.552)	(−4.103)
ret$_t$	3.148***	10.686***	8.943***	−0.026***	11.019***	9.222***	−4.964***	11.950***	9.959***
	(2.842)	(10.406)	(11.650)	(−6.313)	(10.715)	(12.013)	(−26.487)	(11.157)	(12.541)
sigma$_t$	−3.321***	5.610***	3.143***	−0.006***	5.620***	3.171***	−1.633***	5.951***	3.427***
	(−5.420)	(11.468)	(9.108)	(−3.404)	(11.534)	(9.221)	(−20.181)	(12.165)	(9.978)
share_turnover$_t$	0.592***	−0.015	−0.002	−0.004***	0.040	0.046	−0.124***	0.026	0.030
	(3.432)	(−0.102)	(−0.015)	(−5.754)	(0.274)	(0.435)	(−4.265)	(0.182)	(0.284)
roa_volatility$_t$	0.050	−0.050	0.026	0.001**	−0.068	0.011	−0.022	−0.045	0.030
	(0.368)	(−0.470)	(0.375)	(2.475)	(−0.649)	(0.161)	(−1.219)	(−0.424)	(0.438)
Constant	−1.426***	−1.278***	−1.080***	0.131***	−2.913***	−2.533***	0.258***	−1.368***	−1.148***
	(−3.882)	(−6.723)	(−8.059)	(147.677)	(−8.537)	(−10.543)	(7.646)	(−7.244)	(−8.661)
Observations	7072	7072	7072	7072	7072	7072	7072	7072	7072

(*continued on next page*)

Table 5 (*continued*)

Panel B: The monitoring channel

Variables	(1) Dependent variable = $Related\_transaction_t$	(2) Dependent variable = $NCSKEW_t$	(3) Dependent variable = $DUVOL_t$	(4) Dependent variable = $Ab\_accrual_t$	(5) Dependent variable = $NCSKEW_t$	(6) Dependent variable = $DUVOL_t$	(7) Dependent variable = $Other\_receivable_t$	(8) Dependent variable = $NCSKEW_t$	(9) Dependent variable = $DUVOL_t$
Adj. R^2	0.798	0.098	0.100	0.859	0.100	0.103	0.435	0.100	0.103
Year-fixed effects	included	included	included	included	included	included	included	included	included
Industry-fixed effects	included	included	included	included	included	included	included	included	included
City-fixed effects	included	included	included	included	included	included	included	included	included

Notes: Panel A of Table 5 reports the results as to the test of the information channel through which the digitalization-involved commercial reform reduces stock price crash risk. Column (1) reports the results of the regression of media news (*Media_coverage*) on digitalization-involved commercial reform (*Treat*×*Post*). Columns (2) and (3) report the results of the baseline regression that is augmented by *Media_coverage* but excludes *Treat*×*Post* and *Treat.* The sample period ranges from 2011 to 2019. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2. Year dummies, industry dummies, and city dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Notes: Panel B of Table 5 reports the results of the test of the monitoring channel through which the digitalization-involved commercial reform reduces stock price crash risk. Column (1) reports the results of the regression of related party transactions (*Related_transaction*) on digitalization-involved commercial reform (*Treat*×*Post*). Columns (2) and (3) report the results of the baseline regression that is augmented by *Related_transaction* but excludes *Treat*×*Post* and *Treat*. Column (4) reports the results of the regression of abnormal accruals (*Ab_accrual*) on digitalization-involved commercial reform (*Treat*×*Post*). Columns (5) and (6) report the results of the baseline regression that is augmented by *Ab_accrual* but excludes *Treat*×*Post* and *Treat*. Column (7) reports the results of the regression of other accounts receivable (*Other_receivable*) on digitalization-involved commercial reform (*Treat*×*Post*). Columns (8) and (9) report the results of the baseline regression that is augmented by *Other_receivable* but excludes *Treat*×*Post* and *Treat*. The sample period ranges from 2011 to 2019. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2. Year dummies, industry dummies, and city dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

the rapid developments of technologies by competitors and the unforeseeable changes in market demands. Hence, monitoring firms that invest largely in innovation becomes challenging. Meanwhile, managers who are more familiar with their firms enjoy the information advantages in the productivity and value of innovation projects, not least compared to external investors (Aboody and Lev, 2000). This information asymmetry makes it even more difficult to monitor these firms. Consequently, the crash risk of such firms is plausibly higher. Given that the application of digital technologies for commercial reform reduces the crash risk by enhancing information transparency and external monitoring, we expect this impact to be particularly stronger for firms with a high level of innovation. Accordingly, the negative association between digitalization-involved commercial reform and stock price crash risk should be more prominent for firms with intensive innovation activities.

Firms with strong internal governance have effective internal control mechanisms to handle diverse risks, improve the quality of information disclosures, and avoid information distortion. Moreover, strong corporate governance facilitates more effective monitoring of managers, which helps deter managers' self-serving behaviors and decreases the likelihood of them concealing negative news (e.g., Jin et al., 2022). In contrast, weak internal governance implies an opaque information environment and weak monitoring. Hence, we expect that the digitalization-applied commercial reform has a more pronounced mitigating effect on stock price crash risk for firms with weaker internal governance, as the application of digital technologies helps improve information transparency and strengthen external monitoring mechanisms for these firms.

To test the moderating effects, we create binary variables based on the full-sample medians of corporate digitalization (*Digit* and *Digit*1), corporate innovation (*Innovation* and *Innovation*1), and internal governance (*CG* and *CG*1), respectively. *Digit* equals the natural logarithm of the total number of words related to digital technologies in the annual report of a firm during a fiscal year[8]; *Digit*1 equals the digital-technology-related intangible assets disclosed in a firm's annual report, divided by the total intangible assets of the firm during a fiscal year.[9] *Innovation* is computed by the research and development (R&D) expenditures of a firm, divided by its total sales during a fiscal year; *Innovation*1 is calculated by the natural logarithm of the number of invention patents that are applied by a firm in a year and subsequently granted by the China National Intellectual Property Administration (CNIPA). *CG* is calculated as the number of independent directors, divided by the total number of directors of a firm, at the end of a fiscal year; *CG*1 is calculated as the number of shares held by the board members of a firm, divided by the number of its total shares outstanding, at the end of a fiscal year. The moderator variables (*Dum_Digit*, *Dum_Digit*1, *Dum_Innovation*, *Dum_Innovation*1, *Dum_CG*, and *Dum_CG*1) equal 1 if the values of *Digit, Digit*1, *Innovation*, *Innovation*1, *CG*, and *CG*1 are higher than their sample medians, respectively, and 0 otherwise. We then augment the baseline model (4) by including the moderator variable and its interaction with *Treat*×*Post*.

Table 6 shows the results of the moderation analysis. Panel A, Panel B, and Panel C report the moderating effects of firm-level digitalization, corporate innovation, and internal governance, respectively, when using *NCSKEW* and *DUVOL* as the proxies for stock price crash risk. The coefficients on ternary interaction terms are all statistically significant with the expected signs, indicating that the digitalization-involved commercial reform has a more prominent attenuating effect on stock price crash risk for firms with higher levels of digitalization and innovation and for those with weaker internal governance.

We further visualize the moderating effects of the three moderators in Fig. 4, Fig. 5, and Fig. 6, respectively. The moderation effect is captured by the interaction terms between the moderator and the interaction term, *Treat*×*Post*. As depicted in Figs. 4–6, the digitalization-involved commercial reform has a restraining effect on firms' stock price crash risk, regardless of the level of moderators. However, for firms with greater digitalization, higher innovation, and weaker internal governance, the mitigating effect of commercial reform on stock price crash risk is more evident. These results are thus consistent with our predictions.[10]

5. Conclusion

In recent years, the Chinese government has applied digital technologies in commercial reform that is aimed at optimizing commercial environments for sustainable economic growth. To assess the effectiveness of this digitalization-involved commercial reform, we examine its impact on firms' stock price crash risk. We provide robust evidence of a causal link between digitalization-involved commercial reform and a reduction in firms' stock price crash risk. Our mediating analyses reveal that the reform improves commercial information transparency as well as monitoring of corporate commercial activities and thereby lowers the stock price crash

[8] We take the following steps to construct the variable for corporate digitalization. First, we sort out the annual reports of listed companies and extract all the text content by virtue of Python Crawler technologies. Second, we use python open source with "Jiaba" participle features to extract the text content, which involves the keywords of digital technologies based on the semantic system of national-level digital economy-related policy documents in China. The text content on digital technologies is shown in Appendix 3, which include artificial intelligence, blockchain, cloud computing, and big data analytics. Finally, we count the frequency of keywords on the digital technologies and take the natural logarithm of it as the indicator for corporate digitalization (*Digit*).

[9] Pursuant to the Chinese accounting standards for enterprises, investments in digital technologies are recorded as intangible assets. These assets are named with keywords that are related to digital technologies, such as "digital platforms", "digital management system", "intelligent automation", or associated patents. We classify these asset items as "digital-technology-related intangible assets".

[10] In addition, we test whether our baseline results differ between state-owned firms and non-state-owned firms. To this end, we generate a moderator variable (*soe*) that indicates whether a firm is state-owned, augment Model (4) with the moderator variable (*soe*) and its interaction with *Treat*×*Post*, and run the augmented regression model. In results not tabulated, the coefficients on the ternary interaction term *Treat*×*Post*×*soe* are statistically nonsignificant, while those on the interaction term *Treat*×*Post* remain negative and statistically significant at the 1 % level. This suggests that there is no statistically significant difference in the negative coefficients of *Treat*×*Post* between the state-owned and non-state-owned firms, and thus that the attenuating effect of commercial reform on crash risk does not vary with the firms' state ownership.

Table 6
The moderation analysis of the association between digitalization-applied commercial reform and stock price crash risk.

Panel A: The moderating effect of corporate digitalization

Variables	(1) Dependent variable = $NCSKEW_t$	(2) Dependent variable = $DUVOL_t$	(3) Dependent variable = $NCSKEW_t$	(4) Dependent variable = $DUVOL_t$
Treat×Post×Dum_Digit	−0.088**	−0.052**		
	(−2.449)	(−2.131)		
*Treat×Post×Dum_Digit*1			−0.071**	−0.053**
			(−2.136)	(−2.049)
Dum_Digit	−0.026***	−0.022**		
	(−2.764)	(−1.996)		
*Dum_Digit*1			−0.039***	−0.036***
			(−2.582)	(−3.417)
Treat×Post	−0.071***	−0.046***	−0.203***	−0.111***
	(−11.363)	(−18.575)	(−10.654)	(−17.060)
Treat	0.721***	0.739***	0.709***	0.728***
	(12.355)	(20.031)	(12.136)	(19.564)
$size_t$	0.053***	0.048***	0.051***	0.046***
	(6.016)	(7.716)	(5.825)	(7.519)
soe_t	0.084***	0.052***	0.084***	0.052***
	(5.193)	(4.594)	(5.246)	(4.650)
roe_t	0.074	0.041	0.079	0.044
	(1.352)	(1.121)	(1.428)	(1.213)
lev_t	−0.542***	−0.275***	−0.552***	−0.281***
	(−4.117)	(−2.910)	(−4.192)	(−2.981)
$salesgrowth_t$	−0.025***	−0.017***	−0.025***	−0.017***
	(−2.989)	(−3.214)	(−3.015)	(−3.255)
$cashholdings_t$	0.243*	0.082	0.265*	0.099
	(1.692)	(0.818)	(1.849)	(0.987)
$duality_t$	−0.018	−0.013	−0.018	−0.012
	(−1.193)	(−1.196)	(−1.190)	(−1.178)
$boardsize_t$	0.091*	0.061	0.091*	0.061
	(1.685)	(1.620)	(1.679)	(1.634)
$top\_shareholdings_t$	0.002***	0.001**	0.002***	0.001***
	(3.252)	(2.568)	(3.349)	(2.712)
hhi_t	−0.023	−0.036	−0.042	−0.052
	(−0.186)	(−0.414)	(−0.330)	(−0.588)
$ceoshare_t$	−0.122***	−0.078***	−0.121***	−0.078***
	(−4.398)	(−4.030)	(−4.392)	(−4.019)
ret_t	4.871***	5.474***	4.815***	5.435***
	(4.193)	(6.534)	(4.132)	(6.465)
$sigma_t$	6.871***	3.699***	6.835***	3.675***
	(11.961)	(9.425)	(11.864)	(9.328)
$share\_turnover_t$	1.147***	0.957***	1.163***	0.971***
	(3.434)	(3.959)	(3.479)	(4.016)
$roa\_volatility_t$	−0.117	−0.023	−0.110	−0.018
	(−1.049)	(−0.305)	(−0.986)	(−0.235)
Constant	−1.655***	−1.315***	−1.589***	−1.263***
	(−7.695)	(−8.656)	(−7.446)	(−8.381)
Observations	7072	7072	7072	7072
Adj. R^2	0.100	0.103	0.101	0.100
Year-fixed effects	included	included	included	included
Industry-fixed effects	included	included	included	included
City-fixed effects	included	included	included	included

Panel B: The moderating effect of corporate innovation

Variables	(1) Dependent variable = $NCSKEW_t$	(2) Dependent variable = $DUVOL_t$	(3) Dependent variable = $NCSKEW_t$	(4) Dependent variable = $DUVOL_t$
Treat×Post×Dum_Innovation	−0.089**	−0.079***		
	(−2.367)	(−3.018)		
*Treat×Post×Dum_Innovation*1			−0.148**	−0.097**
			(−2.260)	(−1.999)
Dum_Innovation	−0.025	−0.015		
	(−1.453)	(−1.270)		
*Dum_Innovation*1			−0.017	0.008
			(−0.658)	(0.434)
Treat×Post	−0.078***	−0.040***	−0.091***	−0.105***
	(−9.592)	(−16.803)	(−10.868)	(−18.670)

(*continued on next page*)

Table 6 (*continued*)

Panel B: The moderating effect of corporate innovation

Variables	(1) Dependent variable = $NCSKEW_t$	(2) Dependent variable = $DUVOL_t$	(3) Dependent variable = $NCSKEW_t$	(4) Dependent variable = $DUVOL_t$
Treat	0.629***	0.686***	0.638***	0.693***
	(10.658)	(18.592)	(10.905)	(18.958)
$size_t$	0.044***	0.042***	0.045***	0.042***
	(5.370)	(7.335)	(5.398)	(7.178)
soe_t	0.084***	0.053***	0.088***	0.055***
	(5.223)	(4.671)	(5.425)	(4.857)
roe_t	0.039	0.019	0.049	0.027
	(0.839)	(0.612)	(1.084)	(0.894)
lev_t	−0.145**	−0.084*	−0.148**	−0.087*
	(−1.999)	(−1.685)	(−2.047)	(−1.758)
$salesgrowth_t$	−0.018***	−0.013***	−0.019***	−0.013***
	(−2.603)	(−2.851)	(−2.640)	(−2.900)
$cashholdings_t$	−0.127	−0.099	−0.121	−0.097
	(−1.248)	(−1.374)	(−1.190)	(−1.334)
$duality_t$	−0.017	−0.012	−0.019	−0.013
	(−1.134)	(−1.096)	(−1.292)	(−1.276)
$boardsize_t$	0.059*	0.032	0.059*	0.032
	(1.728)	(1.334)	(1.720)	(1.316)
$top\_shareholdings_t$	0.001***	0.001**	0.001***	0.001**
	(3.021)	(2.098)	(3.047)	(2.127)
hhi_t	−0.203*	−0.142*	−0.199*	−0.138*
	(−1.703)	(−1.713)	(−1.672)	(−1.672)
$ceoshare_t$	−0.117***	−0.074***	−0.123***	−0.078***
	(−4.511)	(−4.077)	(−4.747)	(−4.299)
ret_t	10.706***	8.955***	10.760***	8.981***
	(10.416)	(11.679)	(10.472)	(11.714)
$sigma_t$	5.570***	3.118***	5.554***	3.116***
	(11.389)	(9.044)	(11.389)	(9.070)
$share\_turnover_t$	−0.012	−0.000	−0.009	0.001
	(−0.084)	(−0.001)	(−0.062)	(0.005)
$roa\_volatility_t$	−0.048	0.028	−0.052	0.025
	(−0.449)	(0.407)	(−0.482)	(0.361)
Constant	−1.266***	−1.071***	−1.303***	−1.077***
	(−6.643)	(−7.988)	(−6.747)	(−7.923)
Observations	7072	7072	7072	7072
Adj. R^2	0.099	0.101	0.098	0.100
Year-fixed effects	included	included	included	included
Industry-fixed effects	included	included	included	included
City-fixed effects	included	included	included	included

Panel C: The moderating effect of corporate governance

Variables	(1) Dependent variable = $NCSKEW_t$	(2) Dependent variable = $DUVOL_t$	(3) Dependent variable = $NCSKEW_t$	(4) Dependent variable = $DUVOL_t$
Treat×Post×Dum_CG	0.082**	0.053**		
	(2.205)	(2.031)		
*Treat×Post×Dum_CG*1			0.123***	0.063**
			(3.293)	(2.393)
Dum_CG	−0.006	−0.004		
	(−0.339)	(−0.335)		
*Dum_CG*1			0.019	0.012
			(1.228)	(1.052)
Treat×Post	−0.183***	−0.121***	−0.181***	−0.114***
	(−11.066)	(−18.520)	(−10.754)	(−17.942)
Treat	0.634***	0.689***	0.630***	0.686***
	(10.747)	(18.735)	(10.704)	(18.719)
$size_t$	0.045***	0.043***	0.046***	0.043***
	(5.057)	(6.958)	(5.585)	(7.526)
soe_t	0.087***	0.055***	0.086***	0.054***
	(5.387)	(4.846)	(5.352)	(4.814)
roe_t	0.048	0.025	0.045	0.023
	(1.043)	(0.818)	(0.983)	(0.765)
lev_t	−0.145**	−0.084*	−0.132*	−0.077
	(−2.000)	(−1.695)	(−1.829)	(−1.557)
$salesgrowth_t$	−0.019***	−0.013***	−0.019***	−0.013***

(*continued on next page*)

Table 6 (*continued*)

Panel C: The moderating effect of corporate governance

Variables	(1) Dependent variable = $NCSKEW_t$	(2) Dependent variable = $DUVOL_t$	(3) Dependent variable = $NCSKEW_t$	(4) Dependent variable = $DUVOL_t$
	(−2.687)	(−2.936)	(−2.682)	(−2.931)
$cashholdings_t$	−0.124	−0.097	−0.148	−0.111
	(−1.215)	(−1.343)	(−1.449)	(−1.528)
$duality_t$	−0.019	−0.013	−0.018	−0.013
	(−1.241)	(−1.222)	(−1.218)	(−1.210)
$boardsize_t$	0.058*	0.032	0.057*	0.031
	(1.704)	(1.321)	(1.687)	(1.300)
$top\_shareholdings_t$	0.001***	0.001**	0.001***	0.001**
	(3.048)	(2.125)	(3.012)	(2.093)
hhi_t	−0.198*	−0.138*	−0.181	−0.129
	(−1.664)	(−1.674)	(−1.519)	(−1.556)
$ceoshare_t$	−0.122***	−0.078***	−0.122***	−0.078***
	(−4.695)	(−4.263)	(−4.730)	(−4.285)
ret_t	10.774***	8.999***	10.701***	8.953***
	(10.487)	(11.734)	(10.429)	(11.672)
$sigma_t$	5.546***	3.101***	5.574***	3.117***
	(11.376)	(9.018)	(11.445)	(9.075)
$share\_turnover_t$	−0.008	0.003	−0.003	0.006
	(−0.057)	(0.026)	(−0.024)	(0.052)
$roa\_volatility_t$	−0.051	0.025	−0.054	0.023
	(−0.477)	(0.367)	(−0.509)	(0.341)
Constant	−1.285***	−1.085***	−1.322***	−1.107***
	(−6.380)	(−7.697)	(−6.946)	(−8.255)
Observations	7072	7072	7072	7072
Adj. R^2	0.098	0.100	0.099	0.100
Year-fixed effects	included	included	included	included
Industry-fixed effects	included	included	included	included
City-fixed effects	included	included	included	included

Notes: Panel A of Table 6 reports the results for the moderating effect of corporate digitalization (*Digit* and *Digit*1) on the association between digitalization-involved commercial reform and stock price crash risk (*NCSKEW* and *DUVOL*). The moderating effect is captured by the interaction term between the indicator for corporate digitalization (i.e., *Dum_Digit* and *Dum_Digit*1) and *Treat*×*Post*. *Dum_Digit* (*Dum_Digit*1) equals 1 if the value of *Digit* (*Digit*1) is higher than its full-sample median, and 0 otherwise. Columns (1) and (2) report the moderating effect of *Dum_Digit*. Columns (3) and (4) report the moderating effect of *Dum_Digit*1. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2. Year dummies, industry dummies, and city dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Notes: Panel B of Table 6 reports the results for the moderating effect of corporate innovation (*Innovation* and *Innovation*1) on the association between digitalization-involved commercial reform and stock price crash risk (*NCSKEW* and *DUVOL*). The moderating effect is captured by the interaction term between the indicator for corporate innovation (i.e., *Dum_Innovation* and *Dum_Innovation*1) and *Treat*×*Post*. *Dum_Innovation* (*Dum_Innovation*1) equals 1 if the value of *Innovation* (*Innovation*1) is higher than its full-sample median, and 0 otherwise. Columns (1) and (2) report the moderating effect of *Dum_Innovation*. Columns (3) and (4) report the moderating effect of *Dum_Innovation*1. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2. Year dummies, industry dummies, and city dummies are included in each regression, but their results are not reported for the sake of brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Notes: Panel C of Table 6 reports the results for the moderating effect of corporate governance (*CG* and *CG*1) on the association between digitalization-involved commercial reform and stock price crash risk (*NCSKEW* and *DUVOL*). The moderating effect is captured by the interaction term between the indicator for corporate governance (i.e., *Dum_CG* and *Dum_CG*1) and *Treat*×*Post*. *Dum_CG* (*Dum_CG*1) equals 1 if the value of *CG* (*CG*1) is higher than its full-sample median, and 0 otherwise. Columns (1) and (2) report the moderating effect of *Dum_CG*. Columns (3) and (4) report the moderating effect of *Dum_CG*1. The sample period ranges from 2011 to 2019. All the continuous variables are winsorized at the 1 and 99 percentage points, respectively, and are defined in Appendix 2. Year dummies, industry dummies, and city dummies are included in each regression, but their results are not reported for brevity. The t-statistics are based on robust standard errors adjusted for heteroskedasticity and clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

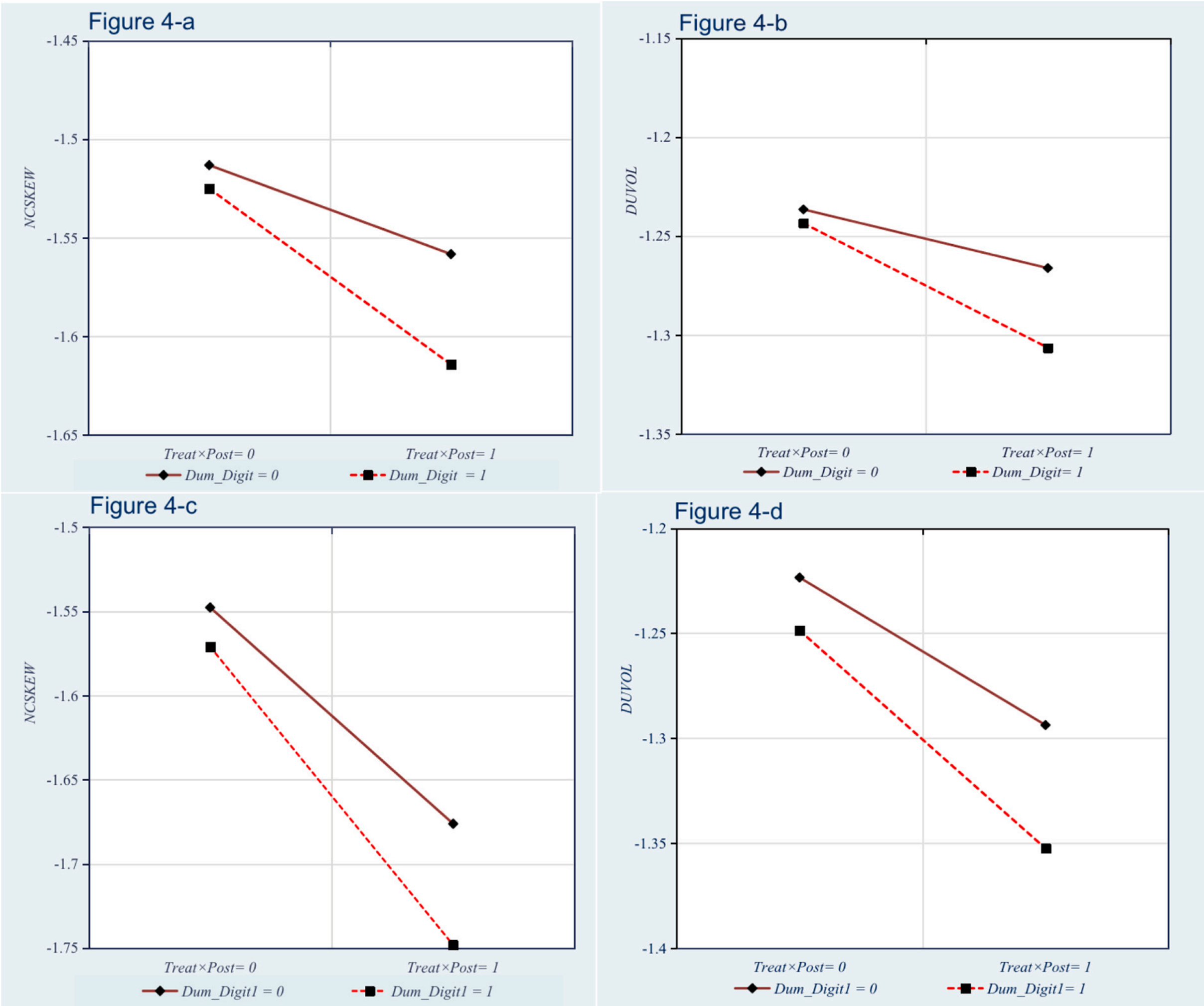

Fig. 4. The moderating effect of corporate digitalization.

Notes: Fig. 4 shows the diagram as to the linear interaction effect of corporate digitalization (*Digit* and *Digit*1) on the association between digitalization-involved commercial reform and stock price crash risk. The interaction effect is captured by the ternary interaction term between the indicator variable for corporate digitalization *Dum_Digit* (*Dum_Digit*1) and the DID interaction term *Treat*×*Post*. *Dum_Digit* (*Dum_Digit*1) equals 1 if the value of *Digit* (*Digit*1) is higher than its full-sample median, and 0 otherwise. The horizontal axis represents the value of the interaction term *Treat*×*Post*. The vertical axis represents the levels of stock price crash risk (i.e., *NCSKEW* and *DUVOL* for the left figure and right figure, respectively).

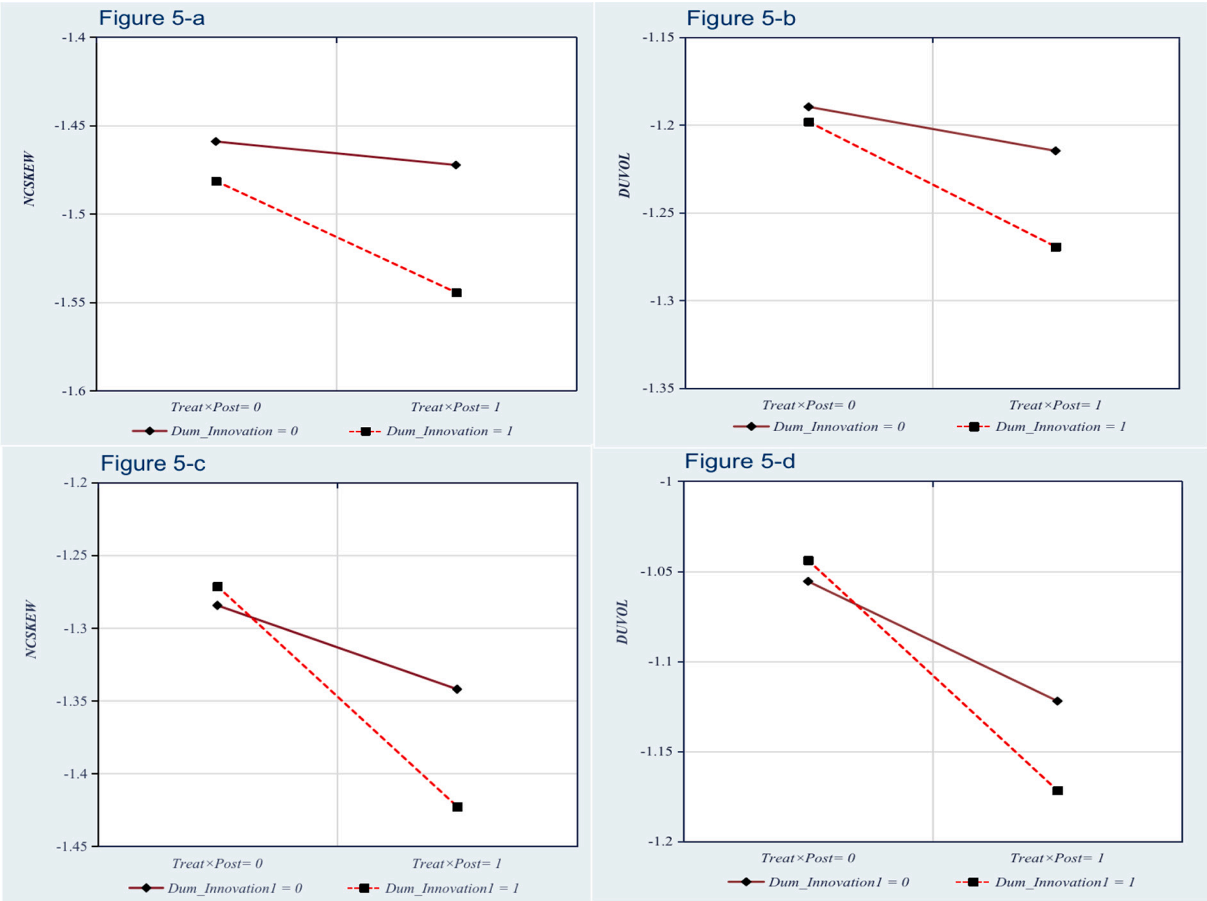

Fig. 5. The moderation effect of corporate innovation.

Notes: Fig. 5 shows the diagram as to the linear interaction effect of corporate innovation (*Innovation* and *Innovation*1) on the association between digitalization-involved commercial reform and stock price crash risk. The interaction effect is captured by the interaction term between the indicator variable for corporate innovation *Dum_Innovation* (*Dum_Innovation*1) and the DID interaction term *Treat*×*Post*. *Dum_Innovation* (*Dum_Innovation*1) equals 1 if the value of *Innovation* (*Innovation*1) is higher than its full-sample median, and 0 otherwise. The horizontal axis represents the value of the interaction term *Treat*×*Post*. The vertical axis represents the levels of stock price crash risk (i.e., *NCSKEW* and *DUVOL* for the left figure and right figure, respectively).

risk of firms. We also find that higher levels of corporate digitalization and innovation and weaker internal governance amplify the mitigating effect of digitalization-involved commercial reform on crash risk.

Our findings underline the positive impact of digitalization-involved commercial reform on information environments and emphasize its potential in facilitating well-organized commercial activities and mitigating risks. In this regard, the government should make good use of digital technologies, ideally in a way that minimizes their associated risks and costs, in order to improve firms' commercial information transparency and effectively monitor their commercial activities. In addition, our finding as to the strengthening moderating effect of firm-level digitalization also offers valuable implications for the government. To better realize the economic benefits of digitalization-involved commercial reform, the government may encourage firms to actively integrate digital technologies into corporate business structures and activities.

CRediT authorship contribution statement

Guanming He: Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Zhichao Li:** Writing – original draft, Investigation, Formal analysis, Conceptualization. **Ling Yu:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Zhanqiang Zhou:** Validation, Supervision, Investigation, Formal analysis.

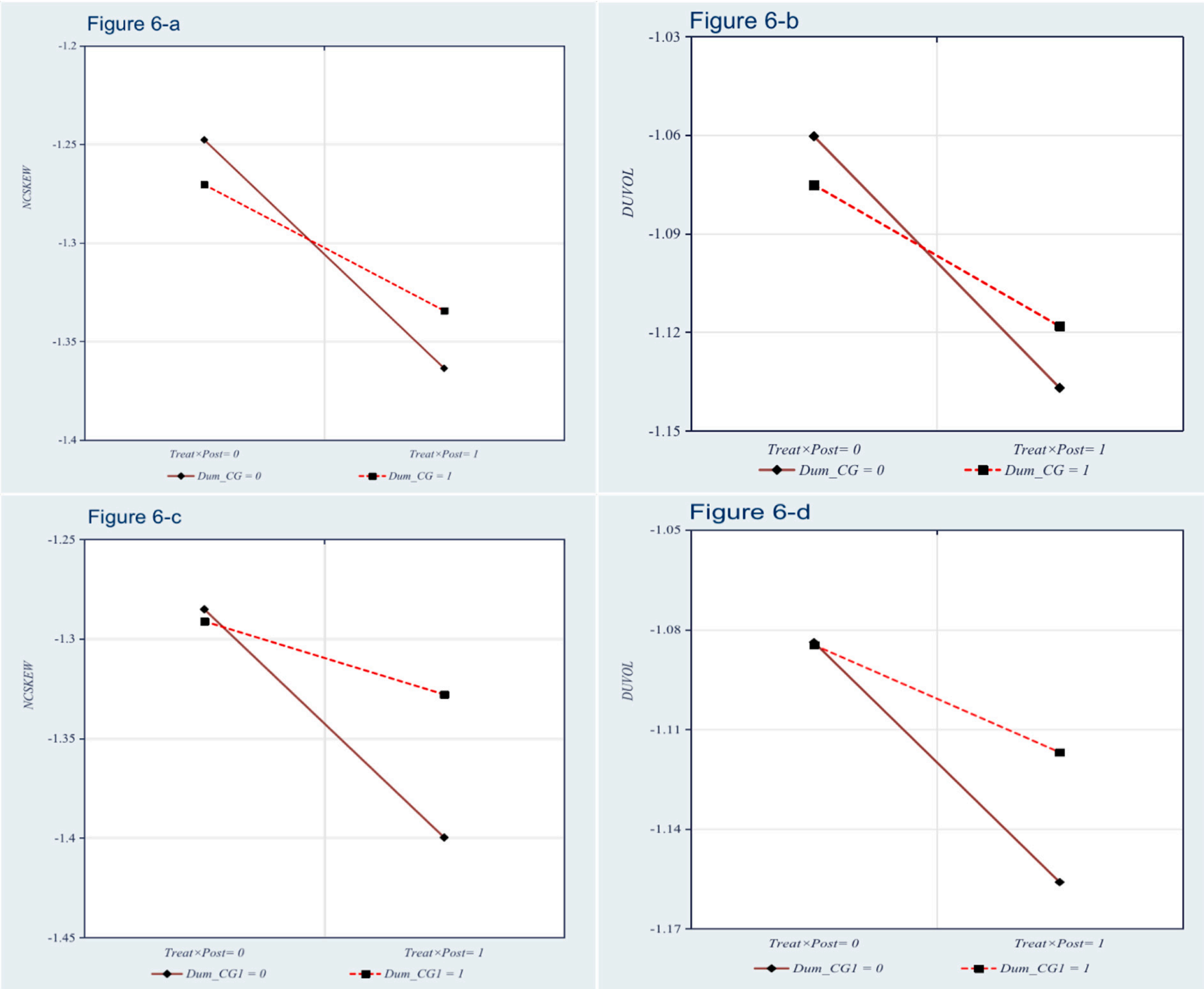

Fig. 6. The moderating effect of corporate governance.
Notes: Fig. 6 shows the diagram as to the linear interaction effect of corporate governance (*CG* and *CG*1) on the association between digitalization-involved commercial reform and stock price crash risk. The interaction effect is captured by the interaction term between the indicator variable for corporate governance *Dum_CG* (*Dum_CG*1) and the DID interaction term *Treat*×*Post*. *Dum_CG* (*Dum_CG*1) equals 1 if the value of *CG* (*CG*1) is higher than its full-sample median, and 0 otherwise. The horizontal axis represents the value of the interaction term *Treat*×*Post*, and the vertical axis represents the levels of the stock price crash risk (i.e., *NCSKEW* and *DUVOL* for the left figure and right figure, respectively).

Appendix

Appendix 1
Sample selection.

The sample selection procedure	No. of observations	No. of firms
Observations of the population of companies listed on the Shenzhen or Shanghai Stock Exchanges for the period 2011–2019	26,345	4016
Less: observations of firms labeled with ST, ST *, or PT	(1935)	(234)
Less: observations of firms in the financial industry	(512)	(89)
Less: observations of firms cross-listed overseas	(35)	(9)
Less: observations of loss firms	(58)	(18)
Less: observations with missing values in regressors	(7568)	(1089)
Sample before propensity-score matching	16,237	2577
Final sample after propensity-score matching	7072	1156

Appendix 2
Summary of variable definitions.

Variables	Definitions
NCSKEW	A measure of stock price crash risk that captures the negative skewness of firm-specific weekly stock returns over a fiscal year. See Eq. (2) for detail.
DUVOL	The down-to-up volatility measure of stock price crash risk, calculated as the natural logarithm of the ratio of the standard deviation of firm-specific weekly stock returns in the "down" weeks to that in the "up" weeks. See Eq. (3) for detail.
*CRASH*1	1 if a firm has at least one crash week in a fiscal year, and 0 otherwise. The crash week is defined as a week when the firm-specific weekly stock return falls by 3.2 standard deviations of the weekly returns for the year.
*CRASH*2	The natural logarithm of 1 plus the frequency of crash weeks of a firm during a fiscal year.
Treat	1 (0) for a treatment (control) firm. The treatment firm is defined as subject to the digitalization-involved commercial reform in which the Market Supervision Administration was established to introduce digital commercial registration system for improving information environments and monitoring on commercial activities of firms. The control firm is defined as not subject to the digitalization-involved commercial reform in the six-year period centered at the beginning of the year of the reform for the treatment firm, nor before the period.
Post	1 (0) if a treatment firm is in the three-year period since (before) the digitalization-involved commercial reform took place.
Related_transaction	The natural logarithm of 1 plus the non-market-price transactions of commodities and services between a firm and its closely related business parties (i.e., its parent company or subsidiaries) during a fiscal year.
Other_receivable	The amount of other accounts receivable of a firm, divided by the total assets of the firm, at the end of a fiscal year.
Media_coverage	The natural logarithm of the total number of media news about a firm in a fiscal year.
Ab_accrual	The abnormal accruals of a firm for a fiscal year, which are estimated by using the modified Jones model (Dechow et al., 1995).
Digit	The natural logarithm of the total number of words related to digital technologies in the annual report of a firm during a fiscal year, and 0 if there is no such word in the annual report.
*Digit*1	The digital-technology-related intangible assets, divided by the total intangible assets of a firm, during a fiscal year.
Innovation	The R&D expenditures by a firm, divided by the total sales of the firm, during a fiscal year.
*Innovation*1	The natural logarithm of the number of invention patents that are applied by a firm in a year and subsequently granted by the China National Intellectual Property Administration.
CG	The number of independent directors, divided by the total number of directors on the board of a firm, at the end of a fiscal year.
*CG*1	The number of shares held by the board members of a firm, divided by the number of its total shares outstanding, at the end of a fiscal year.
size	The natural logarithm of the total assets of a firm at the end of a fiscal year.
soe	1 if a firm is a state-owned enterprise (i.e., the firm of which the largest ultimate shareholder pertains to a government entity), and 0 otherwise.
roe	Return on equity, calculated as the net profit of a firm for a fiscal year, divided by the total assets of the firm at the end of the fiscal year.
lev	The total debt of a firm, divided by the total assets of the firm, at the end of a fiscal year.
salesgrowth	The difference between the firm's sales for the current fiscal year and the sales for the previous year, divided by the sales for the previous year.
cashholdings	The cash flows of a firm, divided by the total assets of the firm, at the end of a fiscal year.
duality	1 if the CEO of a firm and the chairman/chairwoman of the board are the same person for a fiscal year.
boardsize	The natural logarithm of the total number of board members of a firm at the end of a fiscal year.
top_shareholdings	The number of shares held by the largest shareholder of a firm, divided by the number of its total shares outstanding, at the end of a fiscal year.
hhi	The Herfindahl-Hirschman Index computed on firms' sales for each industry in a fiscal year; industries are classified based on the industrial classification guidance released by the China Securities Regulatory Commission in 2012.
ceoshare	The percentage of outstanding shares owned by a firm's CEO at the end of a fiscal year.
ret	The mean of firm-specific weekly stock returns in a fiscal year.
sigma	The standard deviation of firm-specific weekly stock returns in a fiscal year.
share_turnover	The detrended stock trading volume, calculated as the average monthly share turnover for the current fiscal year minus the average monthly share turnover for the previous fiscal year. The monthly share turnover is the monthly trading volume divided by the number of the total floating shares in the month.
roa_volatility	The standard deviation of a firm's returns on assets for the recent five fiscal years.

Appendix 3
Glossary of corporate digitalization.

Digitalization	Specific digital technologies
Artificial intelligence technology	Artificial intelligence, business intelligence, image understanding, investment decision support system, intelligent data analysis, machine learning, deep leaning, intelligent robotics, semantic search, biometric technology, face recognition, voice recognition, identity verification, autonomous diving, and natural language processing
Blockchain technology	Blockchain, digital currency, distributed computing, differential privacy technology, and smart financial contract
Cloud computing technology	Cloud computing, stream computing, graph computing, in-memory computing, multi-party security computing, brain-like computing, green computing, cognitive computing, fusion architecture, billion level concurrency, exabyte storage, Internet of things, and information physics system
Big data technology	Big data, data mining, text mining, data visualization, heterogeneous data, credit reporting, augmented reality, mixed reality, and virtual reality

Data availability

Data will be made available on request.

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