Biodiversity risk management: role of digital transformation

Zhang-hangjian CHEN[a,b,*], Jiali JIANG[a]

[a]*School of Economics, Anhui University, Hefei, Anhui 230601, China*

[b]*Institute of China Financial Research, Anhui University, Hefei, Anhui 230601, China*

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Abstract: This study examines the impact of corporate digital transformation on biodiversity risk using data from 4,932 listed Chinese firms between 2007 and 2023. Empirical results show that digital transformation significantly reduces biodiversity risk through mechanisms such as enhanced total factor productivity and dynamic capabilities. Heterogeneity analysis reveals stronger effects in high-pollution industries, low-carbon pilot cities, mature or regenerative resource-dependent cities, and the regions of the Yangtze River Economic Belt. Financial implications indicate that digital transformation improves the financial stability of firms with high biodiversity risk, although this effect diminishes over time. These results provide important insights for governments and firms on how to manage biodiversity risk effectively.

Keywords: digital transformation, biodiversity risk, total factor productivity, dynamic capabilities, financial stability

JEL codes: L2, D22, Q56, Q57, G3

First and Corresponding Author:

Zhang-Hangjian CHEN

School of Economics, Anhui University, Hefei 230601, China

111 Jiulong Road, P.O. Box 115, Hefei 230601, China.

hangjian@ahu.edu.cn

Second Author:

Jiali JIANG

School of Economics, Anhui University, Hefei 230601, China

111 Jiulong Road, Hefei 230601, China.

i125211039@stu.ahu.edu.cn

1. Introduction

Human activities, such as deforestation, the overexploitation of fisheries and industrial pollution, are widely recognized as a key cause of biodiversity loss (Forester et al., 1996). These activities have seriously damaged ecosystems, species and genetic diversity. China's rapid industrialization and urbanization over the past two decades have led to a severe decline in biodiversity. The 2020 Red List of China's Biodiversity reveals that a total of 4,088 species of higher plants are threatened, accounting for 10.39% of the total, while 1,050 species of vertebrates are also threatened, accounting for 22.02%. Severe biodiversity decline has left Chinese enterprises much more exposed to such risk than their counterparts in the United States (He et al., 2024). The disruption of raw material supplies, deterioration of production environments (Salmi et al., 2023), damage to market reputation (Bassen et al., 2024), weakened corporate liquidity (Liang et al., 2024), increased financing constraints (Becker et al., 2025), lower levels of dividend payments (Zhou et al., 2025a) and declining future profitability (Jiang et al., 2025) resulting from the decline in biodiversity are seriously hampering the sustainable development of corporate. How to reduce biodiversity risk exposure is starting to become a hot topic.

Technological progress is a key way of improving the productivity and dynamic capabilities of businesses. Digital transformation, in particular, has become a key driver of total factor productivity through the adoption of new digital technologies and applications (Xiong et al., 2025). This provides the technological basis for enhancing production efficiency and optimizing resource allocation (Salmi et al., 2023; Wang, 2023). In recent years, emerging technologies such as artificial intelligence and big data have continued to emerge, and the digital economy has overtaken the agricultural and industrial economies to become China's main economic form. On 12 January 2022, China's State Council issued the "14th Five-Year Plan for the Development of the Digital Economy," clearly stating that all-factor digital transformation is a key driver of new economic forms. On 17 May 2025, China's National Data Bureau issued the "Action Plan for the Construction of Digital China 2025". This plan explicitly states that we should embrace digitization to transform production, life, and social governance. Given the importance of digital transformation in human production and life, it is necessary to explore its potential to reduce corporate biodiversity risk exposure from this perspective.

According to the theory of technological innovation (Schumpeter, 1912), digital transformation can effectively reduce a firm's exposure to biodiversity risk by increasing its total factor productivity. An increase in total factor productivity means that firms can achieve greater output with fewer resources, reducing their dependence on natural resources and the potential negative impact on biodiversity (Ding et al., 2024). Specifically, digital transformation helps to optimize the allocation of resources and production efficiency. Using big data analysis and artificial intelligence, enterprises can predict market demand more accurately, optimize production plans and reduce inventory backlogs and waste. This reduces resource consumption (Wu et al., 2025).

Additionally, digital transformation can promote technological innovation and the upgrading of products and services. It can accelerate the research and development of new technologies and their application through digital platforms, which connect with external innovation resources. This enhances the added value of products and services, and reduces dependence on traditional, high-consumption, high-polluting production methods (Su et al., 2024). Ultimately, digital transformation can facilitate the development of intelligent production processes, automate and optimize production, and reduce costs and environmental impact while enhancing efficiency and product quality (Wang et al., 2023a; Wu et al., 2024).

Dynamic capabilities theory suggests that firms need to have the ability to integrate, construct and reconfigure internal and external resources and capabilities to adapt to change and create value in a changing environment (Pereira et al., 2024). Digital transformation reduces biodiversity risk exposure by enhancing the ability of organizations to sense, grasp and reshape the environment. Firstly, technologies such as the Internet of Things and big data analytics enable companies to access information on biodiversity, environmental change, policies and regulations more comprehensively and in a more timely manner (White, 2021). These technologies also allow companies to identify potential biodiversity risk (Yin et al., 2025). By analyzing social media data, companies can gain insight into public concerns about biodiversity conservation and adapt their business strategies accordingly (Yadegaridehkordi et al., 2021). This increased awareness of environmental issues enables firms to identify and assess biodiversity risk at an earlier stage, providing the basis for preventive measures.

Secondly, digital transformation provides companies with more efficient decision-support tools. For instance, AI algorithms enable companies to simulate the impact of various business scenarios on biodiversity, helping them to select the most effective solution (Truby, 2020). Digital platforms enable companies to communicate and collaborate more effectively with stakeholders in order to develop biodiversity conservation plans (Wei et al., 2021). This enhanced ability to capitalize on opportunities enables companies to make more informed decisions and act more efficiently in terms of biodiversity conservation.

Finally, in the face of increasingly stringent environmental regulations and higher consumer demand for sustainability, firms must continually adapt their business models and operations to this new environment. Digital transformation provides companies with the tools to reinvent their business. For instance, digital technologies can be used to optimize production processes, reducing resource consumption and pollution emissions (Song et al., 2024). By adopting a circular economy model, companies can transform waste into resources and lessen their reliance on natural resources (Wen et al., 2025). This enhanced capacity for reinvention enables companies to adapt more effectively to the requirements of sustainable development and reduce their exposure to biodiversity risk.

Based on the above theoretical analysis, this study empirically examines the impact of corporate digital transformation on biodiversity risk using a sample of 4,932 Chinese listed firms spanning 2007–2023. The core findings reveal that digital transformation significantly reduces firms' exposure to biodiversity risk, with robust results validated through multiple endogeneity tests and robustness checks. Mechanism analysis identifies two critical channels: Firstly, digital transformation enhances total factor productivity by optimizing resource allocation and operational efficiency, thereby reducing excessive resource consumption and pollution emissions that harm biodiversity. Secondly, it strengthens firms' dynamic capabilities, e.g., absorption, adaptation, and innovation capacities, enabling more effective environmental monitoring, risk management, and adaptive responses to ecological challenges.

The mitigating effect of digital transformation on biodiversity risk is particularly evident among firms from the East, Central and South China regions, high-polluting industries, low-carbon pilot cities, and mature or regenerative resource-dependent cities, reflecting the moderating role of ecological sensitivity, regulatory pressure, and urban development stages. Additionally, financial implications analysis shows that while high biodiversity risk undermines firms' financial stability, digital transformation alleviates this pressure for high-risk firms in the short term, though the effect diminishes over time. These findings collectively highlight the viability of digital transformation as a strategy for balancing corporate sustainability and biodiversity conservation.

This paper makes several contributions to the literature. Our study contributes to a growing body of research on the economic consequences of biodiversity risk. These consequences include asset returns (Giglio et al., 2023; He et al., 2024; Kalhoro et al., 2024; Chen et al., 2025; Xin et al., 2025), corporate bankruptcy risk (Adamolekun, 2024), spreads on credit default swaps (Giglio et al., 2024), environmental performance (Pi et al., 2025), corporate cash holdings (Ahmad et al., 2024), firm efficiency (Li et al., 2025). Extending these studies, our study focuses on the drivers of biodiversity risk at the micro-firm level. We document significant interactions between corporate digital transformation and biodiversity risk exposure.

Our research also contributes to the literature on the influence of digital transformation. Digital transformation has a positive role to play in optimizing resource use, reducing pollution emissions and promoting green innovation (Qiao et al., 2024; Yang et al., 2024; Gao et al., 2024), which in turn improves corporate environmental performance (Škare et al., 2024) and promotes corporate sustainability (Ilyas et al., 2022; Zhou et al., 2025b). We extend these studies to reveal how digital transformation can reduce corporate biodiversity risk and deepen the knowledge that technological change affects ecosystems.

Our study is also directly related to the research of Yin et al. (2025). They investigate whether biodiversity risk drives firms' digital transformation, and find that such risk positively influences digital efforts. Different from them, we focus more on the impact of digital transformation on corporate environmental performance from a biodiversity risk perspective. As a new type of environmental risk faced by firms, it is crucial to clarify the drivers of biodiversity risk. Additionally, they use the ratio of characters related to biodiversity in the annual report, which is essentially an indicator of attention. Based on the work of Giglio et al. (2023), we use the number of negative biodiversity-related sentences minus the number of positive sentences in the annual report as an indicator of biodiversity risk. This indicator identifies positive sentences that refer to actual action on biodiversity conservation, providing a more precise measure.

The rest of this paper is structured as follows: Section 2 covers data selection and sources, variable definitions, and the construction of benchmark model. Section 3 presents the empirical findings and analysis. Section 4 discusses the financial implications. Section 5 concludes.

2. Data, variables and methodology

2.1 Data and samples

In this paper, we select all listed firms of the Chinese market from 2007 to 2023 as the research samples and perform the following sample screening: (1) we exclude the sampling firms in ST and PT categories that are performing poorly; (2) we exclude the sampling firms of the financial industry, due to their distinct regulatory environment; (3) we exclude the sampling firms that have serious missing data; and (4) to minimize the effect of outliers, we shrink all continuous variables by the 1st and 99th percentiles. Finally, 4,932 list firms are retained.

To measure the firm-level indicators of digital transformation and biodiversity risk, we collect the text of annual reports of all sampling firms from the Cninfo[1], which covers all listed firms in Shanghai and Shenzhen markets. Firms' financial and characteristic data used in this study are all obtained from the WIND and CSMAR databases.

2.2 Variables

2.2.1 Biodiversity risk

We use the biodiversity risk indicator constructed by Chen et al. (2025) to measure the level of biodiversity risk exposure of firms. They first construct a biodiversity lexicon containing 446 terms, based on keywords from 38,260 biodiversity-related studies on the China National Knowledge Infrastructure (CNKI).

They then then turn to measurement of biodiversity risk at the firm level. First, They count the number of sentences containing at least one biodiversity term in the text of each listed firm's annual report ($Frq_{Bio,it}^{AnuRep}$) as an indicator of biodiversity concern at the micro-firm level. And then, they develop a firm-level biodiversity risk exposure that is mindful of positive ($Frq_{Bio,it}^{Pos}$), neutral ($Frq_{Bio,it}^{Neu}$) and negative ($Frq_{Bio,it}^{Neg}$) information. An improved BERT model is applied to the classification of sentences (e.g., Cui et al., 2021). Finally, they further manually categorize positive biodiversity-related sentences in these reports. One category includes cases where firms explicitly mention taking

[1] http://www.cninfo.com.cn/new/index.

concrete actions for biodiversity conservation ($Frq_{Bio,it}^{Pos\_Action}$), such as implementing conservation projects or establishing clear biodiversity-related policies. The other category includes statements that lack evidence of actual action ($Frq_{Bio,it}^{Pos\_No\text{-}Action}$).

Following Giglio et al. (2023), we use the difference between $Frq_{Bio,it}^{Neg}$ and $Frq_{Bio,it}^{Pos\_Action}$ to measure the level of firm i's exposure to biodiversity risk ($BIO_{i,t}$). The higher the $BIO_{i,t}$, the higher the level of biodiversity risk exposure for firm i, which has more negative information and less actual action on biodiversity conservation.

2.2.2 Digital transformation

We use the indicator constructed by Li et al. (2023) to measure the degree of digital transformation of firms ($DCG_{i,t}$), who identify more than 80 keywords related to digital transformation in five categories, and then count the frequency of these keywords in the annual reports of listed firms , and the higher the frequency of occurrence, the higher the degree of digital transformation of the firms. Similar methods have been widely used in other studies (Liu et al., 2023; Ning et al., 2023; Chen et al., 2024).

2.2.3 Other variables

Following Bu et al. (2025) and Yin et al. (2025), we also control for other firm financial and characteristic variables as follows: management shareholding ($MAHARE_{i,t}$), firm age ($AGE_{i,t}$), firm size ($SIZE_{i,t}$), book-to-market ratio ($MBRATIO_{i,t}$), management expenses ratio ($MFEE_{i,t}$), whether the firm is state-owned enterprise ($SOE_{i,t}$), Tobin's Q ($TOBINQ_{i,t}$), total asset growth rate ($GROWTH_{i,t}$), and financial leverage ($LEV_{i,t}$). A detailed description of above variables is given in Table 1, and descriptive statistics for each variable are presented in Table 2.

[Insert Tables 1 and 2 Here]

2.3 Methodology

We use the follow model to explore the impact of corporate digital transformation on their biodiversity risk exposure:

$$BIO_{i,t} = \alpha + \beta_1 DCG_{i,t-1} + \sum \beta_k Controls_{k,t\text{-}1} + \gamma_t + \theta_f + \varepsilon_t, \tag{1}$$

where $BIO_{i,t}$ is the level of biodiversity risk exposure of firm i in year t, $DCG_{i,t-1}$ is the degree of digital transformation of firm i in year t-1. $Controls_{k,t\text{-}1}$ indicates control variables in year t-1, including management shareholding ($MAHARE_{i,t}$), firm age ($AGE_{i,t}$), firm size ($SIZE_{i,t}$), book-to-market ratio ($MBRATIO_{i,t}$), management expenses ratio ($MFEE_{i,t}$), whether the firm is state-owned enterprise ($SOE_{i,t}$), Tobin's Q

($TOBINQ_{i,t}$), total asset growth rate ($GROWTH_{i,t}$), and financial leverage ($LEV_{i,t}$). γ_t and θ_f denote the year and industry fixed effects, respectively. ε_t denotes the residual. Robust standard errors are clustered at the industry level.

3. Empirical results

3.1 Benchmark results

In this section, we first explore the influence of corporate digital transformation on biodiversity risk, results of the baseline regression are shown in Table 3. In columns (1) to (5), we control for different factors and find that the coefficients on $DCG_{i,t-1}$ are all significantly negative at the 1% level, i.e., digital transformation significantly reduces the level of biodiversity risk of firms.

[Insert Table 3 Here]

Digital transformation, on the one hand, can optimize the operational efficiency of corporates and enhance resource management, thereby reducing negative impacts on biodiversity (Yin et al., 2025). For example, by implementing digital technologies such as Artificial Intelligence, the Internet of Things, and Big Data analytics, corporates can more accurately monitor and assess their environmental impacts, leading to smarter decision-making and less overuse and destruction of natural resources. On the other hand, digital transformation encourages corporates to adopt more sustainable practices such as optimizing supply chain management and reducing waste, thus improving energy efficiency (Song et al., 2024). These practices not only reduce the operating costs, but also help to conserve biodiversity. Additionally, digital transformation provides an incentive for firms to engage in green innovation (Qian et al., 2024; Sun et al., 2024). Through technological innovation, firms can develop greener products and services that reduce negative impacts on the environment. These could be potentially important reasons why digital transformation reduces biodiversity risks.

3.2 Endogeneity tests

In this section, we perform a series of endogeneity tests on the above benchmark results. To mitigate endogeneity problems due to potential omitted variables, etc., following Bartik (2009), we construct an instrumental variable ($IV_{i,t}$) that is the interaction between the digital transformation index and its first-order difference. The digital transformation index in year *t* is measured using the mean of the degree of digital transformation of all firms in that year. Columns (1) and (2) of Table 4 reports the results of the two-stage least square regression (2SLS). The first stage of 2SLS shows a significantly positive coefficient on $IV_{i,t}$, and in the second stage regression, the coefficient on $DCG_{i,t\text{-}1}$ remains significantly negative at the 1% level, which is consistent with the results of Table 3. In addition, the instrumental variable $IV_{i,t}$ pass the identifiability test at the 1% level, and the value of Cragg-Donald Wald F-statistic is 3458.194, suggesting that there is no problem of weak instrumental variable.

[Insert Table 4 Here]

Since we screen the sample firms in the Section 2.1, this may introduce endogeneity issues due to sample selection bias. Therefore, we employ a Heckman approach to mitigate this problem, as shown in column (3) of Table 4. The coefficient on IMR is significantly positive at the 5% level, indicating some degree of sample selection bias problem. However, the coefficient on $DCG_{i,t\text{-}1}$ remains significantly negative at the 1% level, again indicating that the benchmark results are reliable.

Although the core explanatory variables are lagged in all regressions to diminish the effects of bidirectional causality, there may still be omitted variable bias. We therefore construct a multi-period double difference model to further overcome the endogeneity problem:

$$BIO_{i,t} = \alpha + \beta_1 Du_{i,t} \times Dt_{i,t} + \sum \beta_k Controls_{k,t\text{-}1} + \gamma_t + \theta_f + \varepsilon_t, \tag{2}$$

where $Du_{i,t}$ is an individual dummy variable, with $Du_{i,t}$=1 indicating the group of firms that performed digital transformation during the sample period, and $Du_{i,t}$=0 indicating the group of firms that have not been digitally transformed. $Dt_{i,t}$ is a period dummy variable that assigns a value of 1 to $Dt_{i,t}$ if firm i performs digital transformation in the current year and the following years, and 0 otherwise. Column (4) of Table 4 shows the regression results of Eq.(2), one can see that the coefficient on $Du_{i,t} \times Dt_{i,t}$ is still significantly negative at the 1% level, which once again validates the above results.

The DID method is prone to selectivity bias; that is to say, it does not ensure that the experimental and control groups have the same characteristics at the outset. To eliminate this bias, we conduct the PSM-DID test. First, we use the 1:1 nearest neighbour matching method to match firms in the treatment group year by year. The DID results after sample screening are shown in the column (5) of Table 4 and are essentially consistent with the benchmark regression results. In addition, the entropy balanced matching is also used to reduce the effect of sample loss from strict PSM matching, and the regression results after matching are shown in the column (6) of Table

4, and the results are still robust.

3.3 Robustness checks

We next conduct a series of robustness tests to re-validate the above conclusions. Enterprises with lower biodiversity risk tend to perform better on environmental protection. Therefore, we first replace the explained variable with the environmental score ($Escore_{i,t}$) from the CSI ESG index system. Column (1) of Table 5 reports the results after replacing the explained variable, the coefficient of $DCG_{i,t\text{-}1}$ on $Escore_{i,t}$ is significantly positive at the 1% level, suggesting that digital transformation helps to improve firms' environmental performance.

[Insert Table 5 Here]

Because both the digital transformation and biodiversity risk indicators are constructed based on the text of corporate annual reports, there may still be endogeneity issues, despite our discussion in section 3.2. Therefore, we replace the measurement of digital transformation. Following Bu et al. (2025), we develop a new digital transformation indicator ($DCG1_{ic,t}$) through the entropy method, incorporating five dimensions reflecting the digital landscape of the city where firm *i* is located. Column (2) of Table 5 give the results of the new digital transformation indicator on biodiversity risk, $DCG1_{ic,t\text{-}1}$ remains significantly negative at the 1% level, consistent with the effect of $DCG_{i,t\text{-}1}$.

Considering the impact of the COVID-19 outbreak on corporate business activities, we also exclude data for 2020 to mitigate the impact of external shocks on the results. Column (3) of Table 5 shows the results excluding the outlier year, and the significant negative effect of $DCG_{i,t\text{-}1}$ remains. We also exclude sampling firms located in municipal and provincial capital cities, as firms in these areas may have received special consideration during the development process. Results in the column (4) of Table 5 verify that our main findings are not affected by these factors. Finally, we also include the province fixed effect in the baseline regression model, as biodiversity risk may also be influenced by geographic location and resource endowment (Wu et al., 2025), as shown in the column (5) of Table 5, and the main conclusions remain robust.

3.4 Potential mechanisms

In this section, we will discuss how digital transformation can mitigate biodiversity risk from two perspectives on enterprise total factor productivity and dynamic capability.

In terms of total factor productivity ($TFP_{i,t}$), since the traditional Olley-Pakes method of measuring firms' total factor productivity assumes that investment is always monotonically related to total output, which makes the sample with zero investment not be estimated. Therefore, we use the Levinsohn-Petrin method (Levinsohn et al., 2003) to calculate firms' total factor productivity. Dynamic capability is the ability of a firm to integrate, structure and reconfigure internal and external resources in a rapidly changing environment in order to gain a competitive advantage (Zhang et al., 2023). Following Xie et al. (2025), we also calculate dynamic capabilities of enterprises ($DynCap_{i,t}$) based on the dimensions of absorption, adaptive and innovation capabilities using a panel data framework.

Columns (1) and (2) of Table 6 report the results of the significantly positive impact of digital transformation (*Coef.*=0.020, *p*-value<0.01) on total factor productivity, and the coefficient of $TFP_{i,t}$ on $BIO_{i,t}$ is significantly negative at the 10% level. These results suggest that digital transformation can help to increase the total factor productivity of enterprises, which in turn reduces their biodiversity risk exposure. Digital transformation helps to enhance enterprise efficiency improvement and resource optimization, helping enterprises to achieve higher productivity, thus decreasing resource consumption (Ding et al., 2024) and pollution emissions (Wang et al., 2023b), and ultimately reducing the negative impact of their business activities on the ecological environment.

We next examine the role of firms' dynamic capabilities, and the regression results are presented in columns (3) and (4) of Table 6. In column (3), firms' digital transformation significantly increases their dynamic capabilities (*Coef.*=0.013, *p*-value<0.01), and higher dynamic capabilities help to reduce firms' exposure to biodiversity risk (*Coef.*=-0.047, *p*-value<0.01). The digital transformation of enterprises can facilitate the more effective management and mitigation of biodiversity risks by enhancing organisations' dynamic capabilities. Digital transformation provides the technology and data analytics tools to help companies monitor environmental impacts more effectively, optimise resource use and implement more effective risk management measures (Wang et al., 2023c). These capabilities allow enterprises to adapt quickly to changing environments, identify opportunities and gain a competitive advantage in sustainable development.

[Insert Table 6 Here]

3.5 Heterogeneity analysis

To deepen our understanding of the relationship between digital transformation and biodiversity risk, we conduct a series of heterogeneity analyses from the following perspectives: geographic differences, cities' natural resource dependence, the degree of industry pollution, and policy-driven factors.

As there are significant differences in biodiversity and ecosystem vulnerability across regions (Adamolekun, 2024), this may lead to significant regional differences in the inhibiting effect of digital transformation on biodiversity risk. We therefore divide all samples into seven groups based on the location of listed firms, which are samples from North (NC), Northeast (NE), East (EC), Central (CC), South (SC), Southwest (SW), and Northwest (NW) regions of China, and perform group tests. Table 7 gives the results of group tests, one can see that the coefficient on $DCG_{i,t\text{-}1}$ is significantly negative only in the East, Central and South China regions. The common characteristic of these regions is that they are located on the Yangtze River Economic Belt of China. The ecological environment of the Yangtze River Basin used to be seriously damaged due to the discharge of industrial wastewater and other pollutants. In recent years, however, the Chinese government has placed great importance on protecting the area's ecology, introducing policies such as the Law of the People's Republic of China on the Protection of the Yangtze River. The digital transformation of these regions may have contributed greatly to the restoration of the ecological environment, which in turn has significantly reduced the biodiversity risk of enterprises in these regions.

[Insert Table 7 Here]

We next examine the effect of a city's natural resource dependence on the benchmark results, as cities that are highly dependent on natural resources may face situations such as weak growth and difficulties in digital transformation at a later stage. We categorize cities of all listed firms into two groups, natural resource-dependent and non-dependent, based on the National Sustainable Development Plan for Resource-Based Cities 2013-2020 issued by the China's State Council in 2013. Columns (1) and (2) of Table 8 report the grouping test, and we find that the coefficients on $DCG_{i,t\text{-}1}$ are both significantly negative in natural resource-dependent and non-dependent groups, with no significant difference. Therefore, we further group the natural resource-dependent cities into four groups: growing, mature, declining and regenerative based on the above Plan. The coefficients on $DCG_{i,t\text{-}1}$ are significantly negative only in the groups of mature and regenerative cities. Mature cities have stable economic and service systems and tend to invest more in transformation strategies and green practices. Regenerative cities have a more prioritized philosophy, are more in pursuit of harmonizing environment and innovation, and have a higher willingness of companies to digitally transform and protect the environment (Pedersen et al., 2022). These may be important reasons for the above results.

[Insert Table 8 Here]

Pollution emission from enterprises is a direct factor affecting biodiversity, and we thus categorize all sampling enterprises into two groups of low- and high- polluting based on the pollution level of the industry. Results in columns (1) and (2) of Table 9 show that digital transformation has a more significant dampening effect on biodiversity risk in the group of high-polluting firms. The Chinese government's strict environmental regulatory policies in recent years have pushed high- polluting firms to invest more in R&D for technological innovation to reduce pollution emissions, which helps to reduce biodiversity risks. To further test this conjecture, we examine the effect of environmental policies on the results by examining whether the city where the listed firm is located is a low-carbon pilot city. Results in columns (1) and (2) of Table 9 suggest that the coefficient on $DCG_{i,t\text{-}1}$ is significantly negative only in the group of low-carbon pilot cities. These results suggest that environmental policies can drive technological innovation, accelerating the digital transformation of firms, particularly highly polluting firms, and ultimately reducing biodiversity risk.

[Insert Table 9 Here]

4. Financial implications

In this section, we further discuss whether the digital transformation of enterprises is driving the health development while reducing the risk of biodiversity exposure from the perspective of financial stability?

Financial stability refers to the state in which an enterprise maintains capital liquidity and solvency in long-term operations, is able to effectively deal with external shocks and maintains sustainable growth. It is the cornerstone of enterprises' development and helps to balance short-term survival and long-term competitiveness. The financial risks associated with biodiversity loss affect overall corporate financing and expenditure (Hadji-Lazaro et al., 2024). This is mainly due to the financial system's ability to tighten credit, which exacerbates corporate financing constraints and squeezes the liquidity of companies with high ecological footprints. This has a consequent impact on their financial stability (Davis et al., 2004). While corporate digital transformation can reduce resource mismatches by lowering operating costs and overcoming financing constraints (Wu et al., 2024). It can also effectively improve productivity, achieve corporate environmental responsibility, and reduce pollution (Zhao et al., 2023; Wang et al., 2023c). This may in turn mitigate the impacts of biodiversity risks on the financial stability of firms. However, digital transformation is a high-investment, high-difficulty, and high-risk long-term process, and Chinese firms have yet to improve their technological, resource, and capability bases, which may lead to unstable operations and increased performance volatility (Liu et al., 2024). Therefore, it is necessary to further discuss the economic consequences of digital transformation and biodiversity risk from the perspective of financial stability.

Following Altman (1968), we use the Z-Score indicator to measure the financial stability of firms ($ZScore_{i,t}$). A higher value of $ZScore_{i,t}$ indicates that the firm is more financially stable. Columns (1) to (4) of Table 10 give the results of the impact of digital transformation and biodiversity risk, and their interaction terms, on financial stability in the current period as well as in the following three years, respectively. One can see that the coefficients on $BIO_{i,t}$ are all significantly negative, i.e., higher exposure to biodiversity risk exacerbates firms' financial instability, which is consistent with intuition. The coefficients on $DCG_{i,t}$ are also significantly negative, indicating that digital transformation is detrimental to firms' financial stability, possibly due to excessive investment in transformation. Interestingly, there is a significant positive effect of the interaction term between $BIO_{i,t}$ and $DCG_{i,t}$ on financial stability in the current period, and this effect diminishes over time, almost disappearing in the third year. These results suggest that, in the short term, digital transformation can significantly enhance the financial stability of firms with high biodiversity risk. However, this positive effect appears to fade in the long term, possibly due to other external pressures or declining internal adaptive capacity (Zhou et al., 2025c).

[Insert Table 10 Here]

5. Conclusions

This study investigates the impact of corporate digital transformation on biodiversity risk using data from 4,932 Chinese listed firms over 2007–2023. Empirical results show that digital transformation can significantly reduce corporate biodiversity risk. This negative effect is particularly evident among firms from the East, Central and

South China regions, highly polluting industries, low-carbon pilot cities, and mature or regenerative resource-dependent cities, reflecting the moderating role of ecological sensitivity, regulatory pressure, and urban development stages. Mechanism analysis reveals that digital transformation mitigates biodiversity risk by enhancing total factor productivity and strengthening dynamic capabilities. Finally, financial implications indicate that digital transformation enhances financial stability for firms with high biodiversity risk in the short term, though this effect diminishes over time. Our main conclusions remain robust after a series of robustness and endogeneity tests.

Our study provides valuable insights for governments and firms. Firstly, promote digital transformation in ecologically sensitive areas and high-pollution industries. Governments should provide subsidies or tax incentives for digital investments of firms from the Yangtze River Economic Belt and high-polluting sectors to align digitalization with biodiversity conservation. Secondly, strengthen the synergies between digital policies and environmental regulations. For example, incorporating digital transformation requirements into low-carbon pilot programs could enhance the reduction of pollution. Thirdly, support cities that depend on resources by helping them to upgrade digitally, particularly mature and regenerative cities, by improving their digital infrastructure to facilitate green transformation. Finally, guide firms in leveraging digital technologies to improve productivity and dynamic capabilities. For example, provide training programs on data analytics for environmental risk management to help reduce the impact on biodiversity in a sustainable way.

There are some limitations to our study. Our samples are restricted to listed firms, excluding unlisted enterprises, limiting generalizability. Biodiversity risk and digital transformation are measured via annual report text analysis, which may overlook non-textual information, e.g., actual project data. Additionally, the long-term financial effects of digital transformation on biodiversity risk remain underexplored, with the fading short-term effect requiring further investigation. Future research could expand the sample size to include non-listed firms and cross-country data, in order to test whether the findings are universal. We can improve the measurement process by incorporating objective indicators. For example, we could use satellite data to measure the impact of biodiversity. We could also explore the heterogeneous effects of specific digital technologies, such as AI or blockchain, on biodiversity risk. In addition, the long-term effects of digital transformation can be discussed further.

References

Adamolekun, G. (2024). Firm biodiversity risk, climate vulnerabilities, and bankruptcy risk. Journal of International Financial Markets, Institutions and Money, 97, 102075.

Ahmad, M. F., & Karpuz, A. (2024). Beyond climate change risk: Biodiversity and corporate cash holdings. Economics Letters, 236, 111608.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance, 23(4), 589-609.

Bartik, T. J. (2009). How do the effects of local growth on employment rates vary with initial labor market conditions? (No. 09-148). Upjohn Institute Working Paper.

Bassen, A., Buchholz, D., Lopatta, K., & Rudolf, A. R. (2024). Biodiversity management and stock price crash risk. Business Strategy and the Environment.

Becker, A., Di Girolamo, F. E., & Rho, C. (2025). Loan pricing and biodiversity exposure: Nature - related spillovers to the financial sector. Research in International Business and Finance, 75, 102724.

Bu, W., Yan, Z., & Yang, S. (2025). Digital economy and corporate sustainability: Mediating roles of green innovation and risk-taking. Finance Research Letters, 78, 107200.

Chen, L., Tu, R., Huang, B., Zhou, H., & Wu, Y. (2024). Digital transformation's impact on innovation in private enterprises: Evidence from China. Journal of Innovation & Knowledge, 9(2), 100491.

Chen, Z, J Derwall, X Gao and K Koedijk (2025). Does Biodiversity Risk Matter to Capital Markets? New Evidence from China. CEPR Discussion Paper No. 20066. CEPR Press, Paris & London. https://cepr.org/publications/dp20066.

Cui Y, Che W, Liu T, et al. Pre-training with whole word masking for Chinese BERT[J]. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2021, 29: 3504–3514.

Davis, E. P., & Stone, M. R. (2004). Corporate financial structure and financial stability. Journal of Financial Stability, 1(1), 65-91.

de Paula Pereira, G., de Medeiros, J. F., Kolling, C., Ribeiro, J. L. D., Morea, D., & Iazzolino, G. (2024). Using dynamic capabilities to cope with digital transformation and boost innovation in traditional banks. Business Horizons, 67(4), 317–330.

Ding, X., Sheng, Z., Appolloni, A., Shahzad, M., & Han, S. (2024). Digital transformation, ESG practice, and total factor productivity. Business Strategy and the Environment, 33(5), 4547–4561.

Forester, D. J., & Machlist, G. E. (1996). Modeling human factors that affect the loss of biodiversity. Conservation Biology, 10(4), 1253-1263.

Gao, L., & Huang, R. (2024). Digital transformation and green total factor productivity in the semiconductor industry: The role of supply chain integration and economic policy uncertainty. International Journal of Production Economics, 274, 109313.

Giglio, S., Kuchler, T., Stroebel, J., & Wang, O. (2024). The economics of biodiversity loss (No. w32678). National Bureau of Economic Research.

Giglio, S., Kuchler, T., Stroebel, J., & Zeng, X. (2023). Biodiversity risk. Working Paper Available at National Bureau of Economic Research (No. w31137).

Hadji-Lazaro, P., Salin, M., Svartzman, R., Espagne, E., Gauthey, J., Berger, J., & Vallier, A. (2024). Biodiversity loss and financial stability as a new frontier for central banks: An exploration for France. Ecological Economics, 223, 108246.

He, F., Chen, L., & Lucey, B. M. (2024). Chinese corporate biodiversity exposure. Finance Research Letters, 70, 106275.

Ilyas, I. M., & Osiyevskyy, O. (2022). Exploring the impact of sustainable value proposition on firm performance. European Management Journal, 40(5), 729–740.

Jiang, C., Li, Y., Zhang, X., & Zhao, Y. (2025). Climate risk and corporate debt decision. Journal of International Money and Finance, 151, 103261.

Kalhoro, M. R., & Kyaw, K. (2024). Manage biodiversity risk exposure? Finance Research Letters, 61, 104989.

Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Review of Economic Studies. 70, 317–341.

Li, C., Huo, P., Wang, Z., Zhang, W., Liang, F., & Mardani, A. (2023). Digitalization generates equality? Enterprises' digital transformation, financing constraints, and labor share in China. Journal of Business Research, 163, 113924.

Li, Y., Liu, X., Canil, J., & Cheong, C. S. (2025). Biodiversity risk and firm efficiency. Finance Research Letters, 71, 106414.

Liang, C., Yang, J., Shen, L., & Dong, D. (2024). The role of biodiversity risk in stock price crashes. Finance Research Letters, Article 105856.

Liu, F., & Liu, X. (2024). Digital transformation is not a painless change: Evidence from corporate risk. Pacific-Basin Finance Journal, 86, 102427.

Liu, M., Li, C., Wang, S., & Li, Q. (2023). Digital transformation, risk-taking, and innovation: Evidence from data on listed enterprises in China. Journal of Innovation & Knowledge, 8(1), 100332.

Ning, J., Jiang, X., & Luo, J. (2023). Relationship between enterprise digitalization and green innovation: A mediated moderation model. Journal of Innovation & Knowledge, 8(1), 100326.

Pedersen Zari, M., MacKinnon, M., Varshney, K., & Bakshi, N. (2022). Regenerative living cities and the urban climate–biodiversity–wellbeing nexus. Nature Climate Change, 12(7), 601-604.

Pi, T., Jiao, L., Zhou, Y., & Shi, J. (2025). Can biodiversity risk improve firm ESG performance? Empirical evidence from China. Finance Research Letters, 76, 106931.

Qian, Y., & Chen, J. (2024). The green innovation effect of digital transformation — evidence from the Chinese experience. Environment, Development and Sustainability.

Qiao, P., Liu, S., Fung, H.-G., & Wang, C. (2024). Corporate green innovation in a digital economy. International Review of Economics & Finance, 92, 870–883.

Salmi, A., Quarshie, A. M., Scott-Kennel, J., & Kähkönen, A. K. (2023). Biodiversity management: A supply chain practice view. Journal of Purchasing and Supply Management, 29(4), 100865.

Schumpeter, J. A. (1912). The Theory of Economic Development. Cambridge, MA: Harvard University Press.

Škare, M., Gavurova, B., & Porada-Rochon, M. (2024). Digitalization and carbon footprint: Building a path to a sustainable economic growth. Technological Forecasting and Social Change, 199, 123045.

Song, Y., Du, C., Du, P., Liu, R., & Lu, Z. (2024). Digital transformation and corporate environmental performance: Evidence from Chinese listed companies. Technological Forecasting and Social Change, 201, 123159.

Su, J., liu, J., & Wang, S. (2024). A study on the action mechanism of digital transformation on the output quality of technological innovation. Total Quality Management & Business Excellence, 35(3–4), 321–340.

Sun, Z., Zhao, L., Mehrotra, A., Salam, M. A., & Yaqub, M. Z. (2024). Digital transformation and corporate green innovation: An affordance theory perspective. Business Strategy and the Environment, 34(1), 433–449.

Truby, J. (2020). Governing Artificial Intelligence to benefit the UN Sustainable Development Goals. Sustainable Development, 28(4), 946–959.

Wang, H., Jiao, S., Bu, K., Wang, Y., & Wang, Y. (2023a). Digital transformation and manufacturing companies' ESG responsibility performance. Finance Research Letters, 58, 104370.

Wang, J., Wang, W., Wu, H., & Liu, Y. (2023b). Exploring the effects of manufacturing servitization on enterprise energy conservation and emissions reduction moderated by digital transformation. Energy Economics, 122, 106706.

Wang, Y., Jiang, Z., Li, X., Chen, Y., Cui, X., & Wang, S. (2023c). Research on antecedent configurations of enterprise digital transformation and enterprise performance from the perspective of dynamic capability. Finance Research Letters, 57, 104170.

Wei, J., Wang, Y., & Lu, J. (2021). Information sharing and sales patterns choice in a supply chain with product's greening improvement. Journal of Cleaner Production, 278, 123704.

Wen, J., Hai, H., Zhang, Y., Chen, Z., & Li, L. (2025). Does digital transformation impact green total factor productivity? Evidence from national big data comprehensive pilot zones in China. Economic Analysis and Policy, 86, 2207–2221.

White, T. B., Viana, L. R., Campbell, G., Elverum, C., & Bennun, L. A. (2021). Using technology to improve the management of development impacts on biodiversity. Business Strategy and the Environment, 30(8), 3502–3516.

Wu, J., Wang, X., & Wood, J. (2025). Can digital transformation enhance total factor productivity? Evidence from Chinese listed manufacturing firms. Journal of Productivity Analysis.

Wu, K., Liu, S., Zhu, M., & Qu, Y. (2024). The impact of digital transformation on resource mismatch of Chinese listed companies. Scientific Reports, 14(1), 9011.

Xie, Q., & Li, S. (2025). Business model innovation, dynamic capabilities, and enterprise development. International Review of Economics & Finance, 104149.

Xin, W., Grant, L., Groom, B., & Zhang, C. (2025). Noisy biodiversity: The impact of ESG biodiversity ratings on asset prices. Ecological Economics, 236, 108662.

Xiong, Q., Yang, J., Zhang, X., Deng, Y., Gui, Y., & Guo, X. (2025). The influence of digital transformation on the total factor productivity of enterprises: the intermediate role of human-machine cooperation. Journal of Innovation & Knowledge, 10(4), 100736.

Yadegaridehkordi, E., Nilashi, M., Nizam Bin Md Nasir, M. H., Momtazi, S., Samad, S., Supriyanto, E., & Ghabban, F. (2021). Customers segmentation in eco-friendly hotels using multi-criteria and machine learning techniques. Technology in Society, 65, 101528.

Yang, A., Yang, M., Zhang, F., Kassim, A. A. M., & Wang, P. (2024). Has Digital Financial Inclusion Curbed Carbon Emissions Intensity? Considering Technological Innovation and Green Consumption in China. Journal of the Knowledge Economy, 15(4), 19127–19156.

Yin, L., Zhu, X., & Li, J. (2025). Does exposure to biodiversity risk drive firms' digital transformation? Finance Research Letters, 82, 107489.

Zhang, J., Chen, Y., Li, Q., & Li, Y. (2023). A review of dynamic capabilities evolution—based on organisational routines, entrepreneurship and improvisational capabilities perspectives. Journal of Business Research, 168, 114214.

Zhao, X., Lu, S., & Yuan, S. (2023). How does the digitization of government environmental governance affect environmental pollution? spatial and threshold effects. Journal of Cleaner Production, 415, 137670.

Zhou, Y., Lucey, B. M., & He, F. (2025a). Dividend payouts and biodiversity risk-Chinese evidence. Research in International Business and Finance, 102792.

Zhou, Z., Yuan, Z., & He, C. (2025b). Can digital transformation promote firms' sustainable development? Evidence based on ESG performance. International Review of Financial Analysis, 105, 104434.

Zhou, Z., & Zhang, J. (2025c). Manufacturing enterprise digital transformation, financial flexibility, and financial risk—Evidence from China. International Review of Financial Analysis, 104, 104279.

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Authors' contributions

All authors contributed equally to idea conceptualization, investigations, and writing the manuscript.

Table 1. Description of the main variables.

Variable	Definition	Measurement
$BIO_{i,t}$	Biodiversity risk	Measure by the difference between the number of negative sentences and the number of positive sentences indicating actual actions.
$DCG_{i,t}$	Digital transformation	Using text mining technology, it performs frequency-weighted summation on feature words and then applies logarithmic processing.
$MAHARE_{i,t}$	Management shareholding ratio	The proportion of shares held by directors, supervisors and senior executives to the total share capital.
$AGE_{i,t}$	Firm age	The logarithm of the company's listing years plus one.
$SIZE_{i,t}$	Firm size	Natural logarithm of total assets.
$MBRATIO_{i,t}$	Book-to-market ratio	Ratio of book equity to market capitalization.
$MFEE_{i,t}$	Management expenses ratio	Ratio of management expenses to total assets
$SOE_{i,t}$	Whether the firm is a state-owned enterprise	It takes the value of 1 if the enterprise is a state-owned enterprise, and 0 otherwise.
$TOBINQ_{i,t}$	Tobin's Q	Market value of equity plus book value of liabilities divided by book value of assets.
$GROWTH_{i,t}$	Total asset growth rate	Percentage change in total assets.
$LEV_{i,t}$	Financial leverage	Total assets divided by total liabilities.

Table 2. Summary statistics of main variables.

Variable	Obs.	Mean	Std	Median	Min	Max
$BIO_{i,t}$	15,530	0.049	0.331	0.000	-1.000	2.000
$DCG_{i,t}$	53,569	1.118	1.366	0.693	0.000	5.352
$MAHARE_{i,t}$	38,761	15.14	20.14	2.202	0.000	70.50
$AGE_{i,t}$	59,950	1.978	0.916	2.197	0.000	3.434
$SIZE_{i,t}$	63,173	21.18	1.546	21.07	15.84	25.89
$MBRATIO_{i,t}$	58,621	0.643	0.243	0.651	0.057	1.258
$MFEE_{i,t}$	39,833	0.086	0.071	0.068	0.007	0.641
$SOE_{i,t}$	41,521	0.329	0.470	0.000	0.000	1.000
$TOBINQ_{i,t}$	58,621	1.945	1.309	1.536	0.795	17.680
$GROWTH_{i,t}$	39,817	0.143	0.382	0.088	-0.653	3.808
$LEV_{i,t}$	76,432	0.445	0.236	0.433	0.031	3.678

Table 3. Results of the baseline regression model.

Notes: This table reports the results of the impact of digital transformation on biodiversity risk, the baseline regression is: $BIO_{i,t} = \alpha + \beta_1 DCG_{i,t-1} + \sum \beta_k Controls_{k,t\text{-}1} + \gamma_t + \theta_f + \varepsilon_t$, where $BIO_{i,t}$ is the level of biodiversity risk exposure of firm *i* in year *t*, $DCG_{i,t-1}$ is the degree of digital transformation of firm *i* in year *t*-1. $Controls_{k,t\text{-}1}$ indicates control variables in year *t*-1, including management shareholding ($MAHARE_{i,t-1}$), firm age ($AGE_{i,t-1}$), firm size ($SIZE_{i,t-1}$), book-to-market ratio ($MBRATIO_{i,t-1}$), management expenses ratio ($MFEE_{i,t-1}$), whether the firm is state-owned enterprise ($SOE_{i,t-1}$), Tobin's Q ($TOBINQ_{i,t-1}$), total asset growth rate ($GROWTH_{i,t-1}$), and financial leverage ($LEV_{i,t-1}$). γ_t and θ_f denote the year and industry fixed effects, respectively. ε_t denotes the residual. Robust standard errors are clustered at the industry level. The *t*-values of coefficients are given in parentheses. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	(1)	(2)	(3)	(4)	(5)
$DCG_{i,t\text{-}1}$	-0.019***	-0.018***	-0.019***	-0.016***	-0.017***
	(-5.484)	(-8.281)	(-9.014)	(-4.104)	(-4.512)
$MAHARE_{i,t\text{-}1}$		-0.001***	-0.001***	-0.001***	-0.001***
		(-5.308)	(-5.453)	(-5.010)	(-5.141)
$AGE_{i,t\text{-}1}$		-0.002	-0.002	0.0005	0.001
		(-0.768)	(-0.558)	(0.160)	(0.305)
$SIZE_{i,t\text{-}1}$		-0.014***	-0.016***	-0.015***	-0.017***
		(-4.324)	(-5.233)	(-5.347)	(-7.020)
$MBRATIO_{i,t\text{-}1}$		0.018	0.043*	0.021	0.049**
		(0.709)	(1.987)	(0.958)	(2.638)
$MFEE_{i,t\text{-}1}$		-0.218***	-0.254***	-0.244***	-0.288***
		(-3.043)	(-3.119)	(-3.741)	(-4.209)
$SOE_{i,t\text{-}1}$		-0.026***	-0.028***	-0.026***	-0.028***
		(-5.857)	(-5.971)	(-7.368)	(-7.658)
$TOBINQ_{i,t\text{-}1}$		0.001	0.001	0.002	0.003
		(0.173)	(0.277)	(0.313)	(0.453)
$GROWTH_{i,t\text{-}1}$		0.019***	0.017***	0.018***	0.016***
		(5.353)	(4.571)	(5.679)	(4.787)
$LEV_{i,t\text{-}1}$		-0.018	-0.019	-0.019	-0.019
		(-0.679)	(-0.689)	(-1.111)	(-1.044)
_CONS	0.071***	0.411***	0.454***	0.414***	0.457***
	(15.999)	(7.197)	(7.939)	(7.579)	(8.702)
Year FE	Yes	No	Yes	No	Yes
Industry FE	Yes	No	No	Yes	Yes
Adj. R^2	0.012	0.010	0.013	0.014	0.016
N	14,169	11,783	11,783	11,783	11,783

Table 4. Results of endogeneity tests.

Notes: This table presents the results of a series of endogeneity tests. The first stage regression model of 2SLS is: $DCG_{i,t} = \alpha + \beta_1 IV_{i,t} + \sum \beta_k Controls_{k,t\text{-}1} + \gamma_t + \theta_f + \varepsilon_t$, the second stage regression model of 2SLS is: $BIO_{i,t} = \alpha + \beta_1 \widehat{DCG_{i,t-1}} + \sum \beta_k Controls_{k,t\text{-}1} + \gamma_t + \theta_f + \varepsilon_t$, where $IV_{i,t}$ is the instrumental variable, $BIO_{i,t}$ is the level of biodiversity risk exposure of firm *i* in year *t*, $DCG_{i,t-1}$ is the degree of digital transformation of firm *i* in year *t*-1. $Controls_{k,t\text{-}1}$ indicates control variables in year *t*-1, including management shareholding ($MAHARE_{i,t-1}$), firm age ($AGE_{i,t-1}$), firm size ($SIZE_{i,t-1}$), book-to-market ratio ($MBRATIO_{i,t-1}$), management expenses ratio ($MFEE_{i,t-1}$), whether the firm is state-owned enterprise ($SOE_{i,t-1}$), Tobin's Q ($TOBINQ_{i,t-1}$), total asset growth rate ($GROWTH_{i,t-1}$), and financial leverage ($LEV_{i,t-1}$). γ_t and θ_f denote the year and industry fixed effects, respectively. ε_t denotes the residual. Robust standard errors are clustered at the industry level. The *t*-values of coefficients are given in parentheses. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	2SLS		Heckman	DID		
	(1)	(2)	(3)	(4)	(5)	(6)
	$DCG_{i,t}$	$BIO_{i,t}$	$BIO_{i,t}$	$BIO_{i,t}$	$BIO_{i,t}$	$BIO_{i,t}$
$DCG_{i,t\text{-}1}$		-0.029***	-0.016***		-0.014**	-0.017***
		(0.009)	(-4.598)		(-2.669)	(-3.357)
$IV_{i,t}$	4.922***					
	(0.210)					
IMR			0.031**			
			(2.225)			
$Du_{i,t} \times Dt_{i,t}$				-0.051***		
				(-3.367)		
$MAHARE_{i,t\text{-}1}$	0.002	-0.001**	-0.001**	-0.001***	-0.001***	-0.001**
	(0.002)	(0.0004)	(-2.630)	(-5.101)	(-4.106)	(-2.639)
$AGE_{i,t\text{-}1}$	-0.012	0.002	0.002	0.002	-0.002	-0.004
	(0.028)	(0.019)	(0.128)	(0.507)	(-0.604)	(-1.443)
$SIZE_{i,t\text{-}1}$	0.104***	-0.017**	-0.016***	-0.016***	-0.007*	-0.011***
	(0.022)	(0.007)	(-5.882)	(-6.563)	(-1.868)	(-4.505)
$MBRATIO_{i,t\text{-}1}$	-0.369**	0.032	0.035	0.042*	0.082***	0.033**
	(0.178)	(0.045)	(1.289)	(2.109)	(3.670)	(2.781)
$MFEE_{i,t\text{-}1}$	0.799	-0.221**	-0.216**	-0.270***	-0.055*	-0.000***
	(0.529)	(0.093)	(-2.881)	(-3.430)	(-2.018)	(-8.121)
$SOE_{i,t\text{-}1}$	-0.124**	-0.0427**	-0.043***	-0.031***	-0.038***	-0.023***
	(0.061)	(0.020)	(-5.038)	(-8.087)	(-4.432)	(-3.986)
$TOBINQ_{i,t\text{-}1}$	-0.060**	0.004	0.005	0.002	0.005	-0.001
	(0.029)	(0.008)	(0.446)	(0.343)	(1.202)	(-0.320)
$GROWTH_{i,t\text{-}1}$	-0.007	0.009	0.009	0.015***	0.002	-0.000***
	(0.042)	(0.010)	(1.710)	(4.344)	(1.562)	(-8.879)
$LEV_{i,t\text{-}1}$	0.079	0.007	0.006	-0.015	-0.066*	-0.029
	(0.134)	(0.045)	(0.207)	(-0.702)	(-1.734)	(-1.244)
_CONS			0.418***	0.462***	0.237***	0.331***
			(6.950)	(9.312)	(3.187)	(6.694)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2		0.013	0.030	0.016	0.011	0.014
N	6,439	6,439	6,439	9,311	4,585	11,783

Table 5. Results of Robustness checks.

Notes: This table reports the results of robustness checks, the regression model is: $Y_{i,t} = \alpha + \beta_1 X_{i,t\text{-}1} + \sum \beta_k Controls_{k,t\text{-}1} + \gamma_t + \theta_f + \varepsilon_t$, where in the column (1), $Y_{i,t}$ denotes the environmental score, $Escore_{i,t}$; in columns (2)-(5), $Y_{i,t}$ denotes the biodiversity risk, $BIO_{i,t}$. $X_{i,t\text{-}1}$ denotes the indicators of digital transformation, $DCG_{i,t\text{-}1}$ or $DCG1_{ic,t\text{-}1}$. $Controls_{k,t\text{-}1}$ indicates control variables in year t-1, including management shareholding ($MAHARE_{i,t-1}$), firm age ($AGE_{i,t-1}$), firm size ($SIZE_{i,t-1}$), book-to-market ratio ($MBRATIO_{i,t-1}$), management expenses ratio ($MFEE_{i,t-1}$), whether the firm is state-owned enterprise ($SOE_{i,t-1}$), Tobin's Q ($TOBINQ_{i,t-1}$), total asset growth rate ($GROWTH_{i,t-1}$), and financial leverage ($LEV_{i,t-1}$). γ_t and θ_f denote the year and industry fixed effects, respectively. ε_t denotes the residual. Robust standard errors are clustered at the industry level. The t-values of coefficients are given in parentheses. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	(1)	(2)	(3)	(4)	(5)
	$Escore_{i,t}$	$BIO_{i,t}$	$BIO_{i,t}$	$BIO_{i,t}$	$BIO_{i,t}$
$DCG_{i,t\text{-}1}$	0.019***		-0.015***	-0.021***	-0.016***
	(4.500)		(-3.626)	(-7.831)	(-5.626)
$DCG1_{ic,t\text{-}1}$		-0.017***			
		(-4.161)			
$MAHARE_{i,t\text{-}1}$	0.0004	-0.001***	-0.001***	-0.001***	-0.001***
	(0.104)	(-4.689)	(-4.647)	(-5.755)	(-4.524)
$AGE_{i,t\text{-}1}$	-0.010	0.001	0.001	-0.005	0.001
	(-1.443)	(0.211)	(0.290)	(-1.328)	(0.270)
$SIZE_{i,t\text{-}1}$	0.071***	-0.017***	-0.017***	-0.019***	-0.017***
	(9.838)	(-7.489)	(-8.112)	(-8.719)	(-6.716)
$MBRATIO_{i,t\text{-}1}$	0.013	0.051**	0.049**	0.039*	0.046**
	(0.962)	(2.730)	(2.253)	(2.104)	(2.195)
$MFEE_{i,t\text{-}1}$	0.020	-0.284***	-0.306***	-0.252*	-0.256***
	(0.186)	(-4.177)	(-4.131)	(-1.940)	(-4.081)
$SOE_{i,t\text{-}1}$	0.023	-0.027***	-0.025***	-0.034***	-0.026***
	(1.379)	(-7.446)	(-4.483)	(-4.507)	(-4.839)
$TOBINQ_{i,t\text{-}1}$	0.001	0.003	0.005	-0.006***	0.002
	(0.414)	(0.456)	(0.580)	(-2.972)	(0.256)
$GROWTH_{i,t\text{-}1}$	-0.022***	0.017***	0.018***	0.027***	0.016***
	(-3.298)	(4.763)	(3.945)	(3.800)	(3.834)
$LEV_{i,t\text{-}1}$	-0.042**	-0.016	-0.018	-0.050***	-0.016
	(-2.409)	(-0.901)	(-1.102)	(-5.169)	(-0.812)
_CONS	-0.498***	0.475***	0.444***	0.565***	0.456***
	(-3.759)	(8.701)	(7.950)	(8.823)	(8.713)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.117	0.015	0.014	0.022	0.021
N	33,216	11,783	10,185	6,969	11,782

Table 6. Results of the potential mechanism analysis

Notes: This table reports the results of the analysis of potential mechanisms by which digital transformation affects biodiversity risk. The first stage of the regression model is: $M_{i,t} = \alpha + \beta_1 DCG_{i,t-1} + \sum \beta_k Controls_{k,t\text{-}1} + \gamma_t + \theta_f + \varepsilon_t$, and the second stage of the model is: $BIO_{i,t} = \alpha + \beta_1 DCG_{i,t\text{-}1} + \beta_2 M_{i,t} + \sum \beta_k Controls_{k,t\text{-}1} + \gamma_t + \theta_f + \varepsilon_t$, where $M_{i,t}$ is the mediating variable, including the total factor productivity ($TFP_{i,t}$) and the dynamic capacity ($DynCap_{i,t}$). $BIO_{i,t}$ is the level of biodiversity risk exposure of firm *i* in year *t*, $DCG_{i,t\text{-}1}$ is the degree of digital transformation of firm *i* in year *t*-1. $Controls_{k,t\text{-}1}$ indicates control variables in year *t*-1, including management shareholding ($MAHARE_{i,t-1}$), firm age ($AGE_{i,t-1}$), firm size ($SIZE_{i,t-1}$), book-to-market ratio ($MBRATIO_{i,t-1}$), management expenses ratio ($MFEE_{i,t-1}$), whether the firm is state-owned enterprise ($SOE_{i,t-1}$), Tobin's Q ($TOBINQ_{i,t-1}$), total asset growth rate ($GROWTH_{i,t-1}$), and financial leverage ($LEV_{i,t-1}$). γ_t and θ_f denote the year and industry fixed effects, respectively. ε_t denotes the residual. Robust standard errors are clustered at the industry level. The *t*-values of coefficients are given in parentheses. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	(1)	(2)	(3)	(4)
	$TFP_{i,t}$	$BIO_{i,t}$	$DynCap_{i,t}$	$BIO_{i,t}$
$DCG_{i,t\text{-}1}$	0.020***	-0.016***	0.013***	-0.019***
	(3.441)	(-4.266)	(8.335)	(-6.807)
$TFP_{i,t\text{-}1}$		-0.023*		
		(-1.818)		
$DynCap_{i,t\text{-}1}$				-0.047***
				(-4.613)
$MAHARE_{i,t\text{-}1}$	0.001***	-0.001***	0.0004***	-0.0004***
	(5.278)	(-5.371)	(4.255)	(-2.968)
$AGE_{i,t\text{-}1}$	-0.036***	0.001	0.015***	0.002
	(-9.580)	(0.310)	(10.013)	(0.365)
$SIZE_{i,t\text{-}1}$	0.673***	-0.001	0.017***	-0.018***
	(69.491)	(-0.101)	(4.136)	(-4.220)
$MBRATIO_{i,t\text{-}1}$	-0.124***	0.040**	-0.047***	0.041***
	(-5.062)	(2.486)	(-4.219)	(2.951)
$MFEE_{i,t\text{-}1}$	-0.734***	-0.316***	0.261***	-0.226***
	(-6.402)	(-5.352)	(4.422)	(-3.757)
$SOE_{i,t\text{-}1}$	-0.002	-0.032***	-0.001	-0.029***
	(-0.158)	(-6.874)	(-0.234)	(-3.868)
$TOBINQ_{i,t\text{-}1}$	0.031***	0.003	-0.005***	0.004
	(4.921)	(0.434)	(-4.077)	(0.689)
$GROWTH_{i,t\text{-}1}$	0.102***	0.013***	-0.034***	0.010*
	(7.987)	(3.940)	(-4.493)	(1.925)
$LEV_{i,t\text{-}1}$	0.053	-0.015	-0.126***	0.002
	(1.134)	(-0.791)	(-14.074)	(0.061)
_CONS	-5.711***	0.311**	-0.284**	0.459***
	(-30.638)	(2.766)	(-2.856)	(6.723)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.885	0.016	0.122	0.025
N	32,668	11,601	19,273	7,122

Table 7. Results of heterogeneity analysis based on the geographical location.

Notes: This table reports the results of heterogeneity analysis based on the geographical location, NC, NE, EC, CC, SC, SW and NW represent the regions of North, Northeast, East, Central, South, Southwest and Northwest of China respectively. The baseline regression is: $BIO_{i,t} = \alpha + \beta_1 DCG_{i,t-1} + \sum\beta_k Controls_{k,t\text{-}1} + \gamma_t + \theta_f + \varepsilon_t$, where $BIO_{i,t}$ is the level of biodiversity risk exposure of firm i in year t, $DCG_{i,t-1}$ is the degree of digital transformation of firm i in year t-1. $Controls_{k,t\text{-}1}$ indicates control variables in year t-1, including management shareholding ($MAHARE_{i,t-1}$), firm age ($AGE_{i,t-1}$), firm size ($SIZE_{i,t-1}$), book-to-market ratio ($MBRATIO_{i,t-1}$), management expenses ratio ($MFEE_{i,t-1}$), whether the firm is state-owned enterprise ($SOE_{i,t-1}$), Tobin's Q ($TOBINQ_{i,t-1}$), total asset growth rate ($GROWTH_{i,t-1}$), and financial leverage ($LEV_{i,t-1}$). γ_t and θ_f denote the year and industry fixed effects, respectively. ε_t denotes the residual. Robust standard errors are clustered at the industry level. The t-values of coefficients are given in parentheses. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	NC	NE	EC	CC	SC	SW	NW
$DCG_{i,t\text{-}1}$	0.0002	-0.018	-0.021**	-0.038***	0.002	-0.036**	-0.024
	(0.002)	(-1.371)	(-2.346)	(-6.886)	(0.703)	(-2.927)	(-1.636)
$MAHARE_{i,t\text{-}1}$	0.001	-0.0001	-0.001*	0.0001	-0.001*	-0.002**	-0.001
	(0.995)	(-1.233)	(-1.936)	(0.006)	(-1.951)	(-2.670)	(-0.768)
$AGE_{i,t\text{-}1}$	0.018*	-0.035**	0.001	0.048***	-0.007	-0.017	-0.011
	(1.759)	(-2.690)	(0.137)	(8.517)	(-0.878)	(-0.506)	(-1.167)
$SIZE_{i,t\text{-}1}$	-0.001	0.001	-0.016*	-0.025**	-0.022***	0.005	-0.013**
	(-0.181)	(0.101)	(-1.850)	(-2.245)	(-3.493)	(0.152)	(-2.944)
$MBRATIO_{i,t\text{-}1}$	0.002	-0.217***	-0.016	0.202**	0.126**	0.161	0.108
	(0.039)	(-4.163)	(-0.355)	(2.928)	(2.138)	(1.495)	(1.428)
$MFEE_{i,t\text{-}1}$	-0.179*	-0.003	-0.221*	-0.533***	-0.366**	0.441	-0.282**
	(-1.838)	(-0.016)	(-1.987)	(-3.375)	(-2.285)	(0.594)	(-2.435)
$SOE_{i,t\text{-}1}$	-0.050**	0.022	-0.038	-0.063	0.006	-0.042	-0.061***
	(-2.652)	(1.388)	(-1.319)	(-1.619)	(0.189)	(-1.394)	(-5.179)
$TOBINQ_{i,t\text{-}1}$	-0.005	-0.001	0.0001	-0.002	0.012	-0.009	0.027***
	(-0.903)	(-0.271)	(0.013)	(-0.196)	(1.046)	(-0.462)	(4.437)
$GROWTH_{i,t\text{-}1}$	-0.000	0.008	0.019	-0.011	-0.003	0.045	0.016
	(-0.044)	(0.384)	(1.499)	(-1.139)	(-0.248)	(1.442)	(0.292)
$LEV_{i,t\text{-}1}$	-0.014	-0.016	0.011	-0.187**	-0.064	-0.076	0.010
	(-0.443)	(-0.124)	(0.405)	(-2.462)	(-1.656)	(-0.660)	(0.249)
_CONS	0.055	0.255**	0.491***	0.584**	0.462***	-0.015	0.269*
	(0.490)	(2.906)	(3.281)	(2.674)	(3.782)	(-0.026)	(2.222)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.009	0.037	0.026	0.024	0.038	0.052	0.024
N	1,442	333	4,395	805	2,082	850	427

Table 8. Results of heterogeneity analysis based on the degree of urban development.

Notes: This table reports the results of heterogeneity analysis based on the degree of urban development, we categorize cities in which firms are located into two types of natural resource-dependent and non-dependent. We also categorize cities of natural resource-dependent into four types: growing, mature, declining and regenerative. The baseline regression is: $BIO_{i,t} = \alpha + \beta_1 DCG_{i,t-1} + \sum \beta_k Controls_{k,t\text{-}1} + \gamma_t + \theta_f + \varepsilon_t$, where $BIO_{i,t}$ is the level of biodiversity risk exposure of firm *i* in year *t*, $DCG_{i,t-1}$ is the degree of digital transformation of firm *i* in year *t*-1. $Controls_{k,t\text{-}1}$ indicates control variables in year *t*-1, including management shareholding ($MAHARE_{i,t-1}$), firm age ($AGE_{i,t-1}$), firm size ($SIZE_{i,t-1}$), book-to-market ratio ($MBRATIO_{i,t-1}$), management expenses ratio ($MFEE_{i,t-1}$), whether the firm is state-owned enterprise ($SOE_{i,t-1}$), Tobin's Q ($TOBINQ_{i,t-1}$), total asset growth rate ($GROWTH_{i,t-1}$), and financial leverage ($LEV_{i,t-1}$). γ_t and θ_f denote the year and industry fixed effects, respectively. ε_t denotes the residual. Robust standard errors are clustered at the industry level. The *t*-values of coefficients are given in parentheses. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-dependent	Dependent	Growing	Mature	Declining	Regenerating
$DCG_{i,t\text{-}1}$	-0.015***	-0.037***	0.007	-0.023**	-0.015	-0.062***
	(-2.990)	(-5.630)	(0.078)	(-2.800)	(-0.696)	(-12.076)
$MAHARE_{i,t\text{-}1}$	-0.0001*	-0.003***	0.003	-0.005***	0.001	-0.002***
	(-1.780)	(-5.230)	(1.466)	(-3.277)	(0.499)	(-22.797)
$AGE_{i,t\text{-}1}$	0.002	-0.022	0.057	-0.018	0.052***	-0.091***
	(0.490)	(-1.460)	(0.663)	(-1.427)	(14.898)	(-4.293)
$SIZE_{i,t\text{-}1}$	-0.014***	-0.014	-0.229*	-0.058	0.005	0.037**
	(-6.450)	(-0.610)	(-4.186)	(-1.799)	(0.410)	(2.881)
$MBRATIO_{i,t\text{-}1}$	0.037	0.007	0.126	0.130	-0.089***	-0.133**
	(1.640)	(0.130)	(0.347)	(1.720)	(-21.935)	(-2.982)
$MFEE_{i,t\text{-}1}$	-0.257***	-0.077	-11.916**	-0.365	0.032	0.772
	(-3.330)	(-0.360)	(-5.100)	(-1.339)	(0.021)	(0.759)
$SOE_{i,t\text{-}1}$	-0.017	-0.119***	0.031	-0.096*	-0.236***	-0.124***
	(-1.380)	(-5.600)	(0.224)	(-2.003)	(-6.788)	(-7.176)
$TOBINQ_{i,t\text{-}1}$	0.004	-0.021***	0.030	-0.016**	-0.042*	0.003
	(0.550)	(-5.240)	(0.410)	(-2.985)	(-2.687)	(0.289)
$GROWTH_{i,t\text{-}1}$	0.015**	-0.002	-0.476	0.024	-0.008	-0.042***
	(2.540)	(-0.150)	(-2.078)	(0.555)	(-0.093)	(-4.932)
$LEV_{i,t\text{-}1}$	-0.012	-0.105	1.377**	-0.215***	0.017	-0.125
	(-0.440)	(-1.610)	(6.143)	(-3.777)	(0.129)	(-0.912)
_CONS	0.376***	0.642	5.293*	1.541**	0.075	-0.324
	(8.360)	(1.470)	(3.183)	(2.310)	(0.296)	(-1.160)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.013	0.051	0.092	0.092	0.036	0.089
N	9,140	1,198	57	556	249	334

Table 9. Results of heterogeneity analysis based on the degree of industry pollution and policy-driven.

Notes: This table reports the results of heterogeneity analysis based on the degree of industry pollution and policy-driven. The baseline regression is: $BIO_{i,t} = \alpha + \beta_1 DCG_{i,t-1} + \sum \beta_k Controls_{k,t\text{-}1} + \gamma_t + \theta_f + \varepsilon_t$, where $BIO_{i,t}$ is the level of biodiversity risk exposure of firm i in year t, $DCG_{i,t-1}$ is the degree of digital transformation of firm i in year t-1. $Controls_{k,t\text{-}1}$ indicates control variables in year t-1, including management shareholding ($MAHARE_{i,t-1}$), firm age ($AGE_{i,t-1}$), firm size ($SIZE_{i,t-1}$), book-to-market ratio ($MBRATIO_{i,t-1}$), management expenses ratio ($MFEE_{i,t-1}$), whether the firm is state-owned enterprise ($SOE_{i,t-1}$), Tobin's Q ($TOBINQ_{i,t-1}$), total asset growth rate ($GROWTH_{i,t-1}$), and financial leverage ($LEV_{i,t-1}$). γ_t and θ_f denote the year and industry fixed effects, respectively. ε_t denotes the residual. Robust standard errors are clustered at the industry level. The t-values of coefficients are given in parentheses. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	(1)	(2)	(3)	(4)
	Low- polluting	High- polluting	Low carbon	Non-low carbon
$DCG_{i,t\text{-}1}$	-0.013	-0.017***	-0.031***	-0.001
	(-1.687)	(-4.996)	(-5.606)	(-0.199)
$MAHARE_{i,t\text{-}1}$	-0.001***	-0.001***	-0.002***	-0.001
	(-7.715)	(-4.941)	(-4.192)	(-1.019)
$AGE_{i,t\text{-}1}$	0.0003	0.002	0.005	-0.022*
	(0.037)	(0.791)	(0.341)	(-1.961)
$SIZE_{i,t\text{-}1}$	-0.017**	-0.017***	-0.027***	-0.019***
	(-2.648)	(-8.012)	(-3.534)	(-3.378)
$MBRATIO_{i,t\text{-}1}$	0.145***	0.026**	0.042	0.070*
	(3.385)	(2.151)	(1.229)	(2.012)
$MFEE_{i,t\text{-}1}$	-0.323	-0.269**	-0.385*	-0.197*
	(-1.349)	(-2.587)	(-1.934)	(-1.813)
$SOE_{i,t\text{-}1}$	-0.007	-0.035***	-0.055***	-0.006
	(-0.581)	(-9.987)	(-7.033)	(-0.298)
$TOBINQ_{i,t\text{-}1}$	0.014	-0.001	0.002	0.006
	(0.837)	(-0.358)	(0.220)	(0.543)
$GROWTH_{i,t\text{-}1}$	0.014	0.018**	0.024	0.023***
	(0.946)	(2.458)	(1.457)	(3.157)
$LEV_{i,t\text{-}1}$	-0.051*	-0.018	-0.029	0.006
	(-2.005)	(-1.092)	(-0.976)	(0.179)
_CONS	0.381**	0.466***	0.715***	0.472***
	(2.650)	(9.278)	(5.218)	(3.996)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.014	0.017	0.022	0.021
N	2,744	9,039	3,718	3,478

Table 10. Results of economic consequences from the perspective of financial stability.

Notes: This table reports the results of the analysis of economic consequences from the perspective of financial stability, and the regression model is: $BIO_{i,t}$=α+$\beta_1 DCG_{i,t}$+$\beta_2 ZSCORE_{i,t}$+$\beta_3 DCG_{i,t}$×$ZSCORE_{i,t}$+ $\sum\beta_k$ $Controls_{k,t}$+γ_t+θ_f+ε_t, where $BIO_{i,t}$ is the level of biodiversity risk exposure of firm i in year t, $DCG_{i,t}$ is the degree of digital transformation of firm i in year t. $ZSCORE_{i,t}$ represents the financial stability of firm i in year t. $Controls_{k,t\text{-}1}$ indicates control variables in year t-1, including management shareholding ($MAHARE_{i,t-1}$), firm age ($AGE_{i,t-1}$), firm size ($SIZE_{i,t-1}$), book-to-market ratio ($MBRATIO_{i,t-1}$), management expenses ratio ($MFEE_{i,t-1}$), whether the firm is state-owned enterprise ($SOE_{i,t-1}$), Tobin's Q ($TOBINQ_{i,t-1}$), total asset growth rate ($GROWTH_{i,t-1}$), and financial leverage ($LEV_{i,t-1}$). γ_t and θ_f denote the year and industry fixed effects, respectively. ε_t denotes the residual. Robust standard errors are clustered at the industry level. The t-values of coefficients are given in parentheses. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01, respectively.

	(1)	(2)	(3)	(4)
	$ZSCORE_{i,t}$	$ZSCORE_{i,t+1}$	$ZSCORE_{i,t+2}$	$ZSCORE_{i,t+3}$
$BIO_{i,t} \times DCG_{i,t}$	0.191***	0.148**	0.146*	0.031
	(4.24)	(2.77)	(1.94)	(0.33)
$BIO_{i,t}$	-0.291***	-0.264***	-0.461***	-0.346**
	(-3.85)	(-3.12)	(-4.62)	(-2.32)
$DCG_{i,t}$	-0.062***	-0.029**	-0.066***	-0.125***
	(-5.32)	(-2.61)	(-4.00)	(-4.47)
$MAHARE_{i,t\text{-}1}$	-0.005***	-0.010***	-0.013***	-0.013***
	(-3.39)	(-6.87)	(-6.65)	(-5.04)
$AGE_{i,t\text{-}1}$	0.175***	0.008	-0.001	-0.365***
	(5.67)	(0.25)	(-0.02)	(-4.35)
$SIZE_{i,t\text{-}1}$	0.269***	0.091**	0.017	0.009
	(7.52)	(2.25)	(0.24)	(0.12)
$MBRATIO_{i,t\text{-}1}$	1.324***	-0.593	-2.488***	-2.796***
	(4.12)	(-1.34)	(-7.19)	(-7.36)
$MFEE_{i,t\text{-}1}$	-2.946***	-0.069	1.376	0.451
	(-4.53)	(-0.16)	(0.91)	(0.30)
$SOE_{i,t\text{-}1}$	0.281***	0.345***	0.247**	0.331
	(3.92)	(3.92)	(2.20)	(1.73)
$TOBINQ_{i,t\text{-}1}$	2.732***	1.718***	1.021***	0.704***
	(39.83)	(26.82)	(14.22)	(4.76)
$GROWTH_{i,t\text{-}1}$	-0.066	0.056	0.045	-0.184
	(-1.53)	(0.93)	(0.47)	(-1.22)
$LEV_{i,t\text{-}1}$	-13.951***	-13.122***	-11.961***	-10.903***
	(-18.96)	(-14.92)	(-11.68)	(-10.91)
_CONS	-1.712**	5.063***	8.725***	10.200***
	(-2.49)	(6.08)	(5.77)	(6.12)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.722	0.504	0.391	0.328
N	10,975	10,775	8,549	6,670