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PROMOTING ECONOMIC RECOVERY: THE SILVER LINING OF DIGITAL TRANSFORMATION AND CORPORATE INNOVATION

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Abstract. With the unstable international environment, the global economy has experienced a slowcession. Previous research on digital innovation in firms has often neglected the impact of macroeconomic cycles. This paper examines the moderating effect of the economic slowcession in the digital transformation and corporate innovation nexus, by using the China's A-share listed companies'data during 2001 and 2021. The empirical results find that the positive impact of digitization on innovation is countercyclical. During recession, the positive impact of digital transformation on innovation is even greater compared to economic prosperity. Grouped regression results indicate that State-owned listed companies, Non-high tech companies, Large-scale companies, and Eastern companies are more affected by the positive moderating effect of the recession. This indicates that getting out of recession requires more aggressive support of these companies, which promotes innovation and economic recovery. This study provides a useful reference for countries in recession and provides an important complement to traditional economic cycle theory and innovation cycle theory.

Keywords: digital transformation, corporate innovation, recession, corporate heterogeneity.

JEL Classification: D22, O30, O32.

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1. Introduction

According to the Economic Situation Report released by the United Nations (2022), the global economic growth rate is expected to be 1.9% in 2023, which is one of the lowest growth rates in decades. This is mainly due to the interplay of multiple crises, including the COVID-19 pandemic, the Ukraine conflict and the resulting food and energy crises, inflationary pressures, and debt tightening (Fagoonee & Pellicano, 2020; Qureshi et al., 2022). The current global economy is in a sluggish state. In the latest outlook report, Mark Zandi, Chief Economist of Moody's, specifically proposed a new term for this long-term stagnant and barely avoiding a full-scale recession, namely "slowcession" (Moody's Analytics, 2022). China has maintained a high-speed growth of around 7% since the reform and opening up, but in recent years, the economic growth rate has slowed down, especially in 2020, with an annual average GDP growth rate of only 2.3% (National Bureau of Statistics, 2021), and it has only recovered to

3% in 2022 (National Bureau of Statistics, 2023). Although the economic development of different countries and regions varies, the trend of economic recession is universally present.

Innovation activities are closely related to economic development. According to the innovation cycle theory (Schumpeter, 1934; van Duijn, 1977), encouraging and supporting technological investment is an important means of achieving economic recovery and improving a country's international competitiveness. Especially during periods of recession, the importance of innovation is self-evident. Some studies discuss the relationship between economic cycles and innovation. Some scholars believe that during economic prosperity, companies have sufficient cash flow and improved market demand, leading to an increase in innovation activities (Rafferty & Funk, 2004). Other scholars argue that during periods of recession, the emergence of new technology drives economic recovery and prosperity (Aghion et al., 2010).

With the current global economic downturn, various companies are facing greater market and competitive pressure, and need to find new growth points and development opportunities. Digital transformation may become one of their important coping strategies. Since the concept of digitalization was proposed, it has quickly become the focus of academic attention (Khan & Tao, 2022; Scuotto et al., 2017). Existing studies focus on the value creation (Porter & Heppelmann, 2016), operations management (Mourtzis, 2020), and spawning new industries (Parida et al., 2019) of digital transformation. However, research on digitalization still focuses on the conventional context, focusing more on process optimization, cost reduction, efficiency enhancement, and model innovation brought about by digital transformation (Vial, 2019), the impact of digitalization on innovation in the economic shocks has not received sufficient attention. Regarding the impact of external environment on digital transformation, some studies have examined the acceleration effect of the COVID-19 on digital progress (Gavrila Gavrila & De Lucas Ancillo, 2022). During uncertain times such as the COVID-19 pandemic in 2019, service businesses can establish organizational resilience through digital transformation, enabling them to respond in creative, flexible, and resilient ways (He et al., 2022). Some studies also point out that after COVID-19, companies have seen an increase in digital product innovation (Soto-Acosta, 2020; P. Zheng et al., 2024). Digital transformation has become inevitable for corporate survival and overall economic recovery. Many countries promote digital economy and take it as an important strategic foundation for a new round of scientific and technological revolution. Therefore, the study on the moderating effect of recession in the digital transformation and innovation nexus and the heterogeneity among companies, no long enriches the research on innovation cycle theory but also provides evidence for policy makers and entrepreneur to recovery from recession.

Based on these considerations, the specific research objectives and research questions of this paper are as following: First, to investigate whether economic downturns can act as a catalyst for accelerating digital transformation across various industries, thereby enhancing companies' innovation efficiency and output. Second, this study aims to provide insights into how a country can effectively revitalize its innovation ecosystem during an economic downturn by implementing targeted support and guidance strategies tailored to companies of different ownership structures, technological capabilities, scales, and geographical locations. By addressing these research objectives, this paper seeks to contribute to the understanding of the relationship between economic downturns, digital transformation, corporate innovation, and the potential measures to foster innovation in different types of companies to promote recovery.

This study contributes to the extant literatures in two ways. First, this paper creatively explains the inherent mechanism of digital transformation driving innovation growth and the company's revitalization under recession. Existing literatures focus on the relationship of innovation and economic cycles (Minárik et al., 2018; Spescha & Woerter, 2019) or digital transformation (Gavrila Gavrila & De Lucas Ancillo, 2022; Niu et al., 2023; Parida et al., 2019), neglecting the role of economic cycles in the digital transformation and innovation nexus. This integration of macroeconomics and micro-strategy expands the theory of the economic cycle and innovation cycle in the digital economy era, making research conclusions more in line with reality, and providing reference for governments to formulate economic recovery policies and digital policies. Second, the discussion of heterogeneity has identified the types of companies on which economic recovery depends. By examining the different moderating effects of digital transformation on innovation in different companies during a recession, it reveals that to emerge from an recession, governments should rely more on state-owned listed companies, non-high tech companies, large-scale companies, and companies in eastern regions. This research result has made significant contributions to enterprises in formulating appropriate digital strategies to promote innovation, which is the micro foundation for the overall recovery of the national economy.

The remainder of this paper is organized as follows. Section 2 provides a literature review and articulates hypotheses, explaining the impact of digital transformation on innovation and the moderating effect of recession. Section 3 explains the methodology and data used in the study. This paper studies the influence channels of economics recession on the impact of digital transformation by constructing a moderating effect model. Section 4 presents the empirical results and discussion, and Section 5 concludes the paper.

2. Literature review and hypotheses

2.1. Economic recession, digital transformation and innovation

Based on the importance of innovation for countries and companies, academia extensively discuss how digital transformation affects innovation. Existing research results show that digital transformation mainly promotes innovation by improving quality and efficiency, as well as reducing costs and risks. Firstly, digital transformation quickly and intelligently responds to market changes through automation and collaboration, reducing information asymmetry (Hughes et al., 2019; Canarella & Miller, 2018; Chen et al., 2022). Secondly, digital transformation captures precise data information and more accurately grasp market demand, providing direction for product innovation (Verhoef et al., 2021). Thirdly, digital transformation improves management efficiency, realizing real-time and comprehensive control over management or branch offices, thereby reducing regulatory and agency costs (Fernandez-Vidal et al., 2022; McGuire et al., 2012; Rachinger et al., 2019; Vaska et al., 2021). Through digital conferences, cloud computing, and other ways, companies reduce administrative and office costs (Warner & Wäger, 2019), and save warehousing costs by predicting and allocating production capacity through big data automatic pricing for online sales (Abe & Kamba, 2000; Østerlie & Monteiro, 2020). Cost reduction means that companies can provide more available funds for innovation. Based on this, this paper proposes the hypothesis:

H2: *Digital transformation has a positive impact on innovation.*

In times of recession, under the pressure of survival, digital transformation help companies stand out and become more efficient and innovative. Recession leads to problems such as reduced market demand, rising production costs, and increased difficulty in financing (Mann & Byun, 2017). Companies facing survival pressure accelerate their digital transformation to optimize processes, reduce costs, and find new market opportunities (Warner & Wäger, 2019), which facilitates innovation. The most obvious example is that during the COVID-19 pandemic, companies have rapidly increased their level of intelligence and digitization under survival pressure (Amankwah-Amoah et al., 2021; Gabryelczyk, 2020). A large number of users' demands have shifted from offline to online due to the epidemic, which has greatly tested the digital survival resilience of companies. Live broadcasting platforms, online sales, video conferences, and other new modes of production or office work have seen a surge in users (Hodder, 2020). With the continued global economic downturn after the epidemic, digital transformation gradually evolves from a short-term passive behavior into a long-term proactive choice.

In times of economic prosperity, companies usually operate in a better environment with more resources and opportunities for experimentation and exploration (Männasoo & Meriküll, 2020; Ortiz & Salas-Fumás, 2021). At this time, digital transformation also plays an important role in promoting innovation, but due to the lack of urgent survival pressure, the positive impact of digital transformation on innovation during economic prosperity is smaller than during recession. Based on this, the following hypothesis is proposed:

H3: *Digital transformation boosts innovation more in a recession than in a prosperity.*

2.2. Moderating effect of recession for different companies

As a hybrid of China's political economy, state-owned companies (SOEs) play an important role in the national political deployment (Lo, 1999), especially during the economic recession, to take on the responsibility of building digital infrastructure such as digital platforms and resisting digital risks. Compared with private companies (Non-SOEs), SOEs are less likely to go bankrupt (Borisova et al., 2015) and are often given preferential conditions such as resource tilt from local governments and state-owned banks, tax subsidies, etc. These help alleviate the funding pressure of SOEs, enabling them to maintain digital investment during recession and promote innovation. Based on this, the following hypothesis is proposed:

H4: *Compared with Non-SOEs, the digital transformation of SOEs boost innovation more during the recession.*

High-tech companies refer to companies that have independent intellectual property rights and core technologies. Most of these companies adopt a light-asset strategy (Yoo et al., 2010, 2012) and are often involved in fields related to science and high technology. Their level of digital transformation and innovation is generally higher than that of Low-tech companies. Low-tech companies have the late-mover advantage and learn from and absorb the experience of high-tech companies through imitation (Casadesus-Masanell & Zhu, 2013; Im & Shon, 2019), the cost of digital transformation is lower than that of high-tech companies. In terms of digital transformation, Low-tech companies are more focused on implementing industrial digitization by transforming their existing outdated production capacity through digital technology, bringing up new ideas. Especially during the recession, the digital transformation of the industry with more low-tech companies represents digitalization of traditional industries, which result in a huge capacity for innovation relative to the development of digital industry. In addition, the digital investment of high-tech companies also has a high adjustment cost during the recession, resulting in a loss of valuable knowledge and human capital which has high sunk costs (Dierickx & Cool, 1989; Knudsen, 2019). The digital projects of most Low-tech companies are simply imitative and involve fewer digital projects, so innovative activities can be continuous. Based on this, the following hypothesis is proposed:

H5: *Compared with high-tech companies, the digital transformation of low-tech companies boost innovation more during the recession.*

Due to severe information asymmetry, financing difficulties for small and medium-sized companies (SMEs) are a critical issue worldwide (Harrison et al., 2022), which is fatal for digital transformation projects with large capital requirements (Q. Wang & Du, 2022). During economic prosperity, the financial industry is highly competitive, and financial institutions have a stronger risk acceptance capacity, enabling SMEs to obtain financing for their digital projects. However, during economic recession, financial institutions such as banks tend to operate more cautiously, giving larger companies (Non-SMEs) an advantage in obtaining loans (Knudsen, 2019). In addition, non-SMEs also have the advantage of larger scale (Bumgardner et al., 2011).This means that non-SMEs have more financing support for their digital transformation and innovations than SMEs, especially in times of recession. Non-SMEs have greater role than SMEs in promoting digital transformation and innovation for economic recovery. Based on this, this paper proposes the hypothesis:

H6: *Compared with SMEs, the digital transformation of non-SMEs boost innovation more during the recession.*

China is a country with different natural resources in different regions and serious economic imbalance (Chan, 2021), which indicates the moderating effect of recession also has different manifestations. The operation of China's economic cycle has shown a significant differentiation trend. The economic growth rate in the developed eastern regions has slowed down after reaching a leading level, while the non-eastern regions are still enjoying the economic dividends brought by extensive growth, showing a high-speed development trend (D. Liu et al., 2020). This also means that the improvement space in the eastern regions is smaller than that in non-eastern regions, and the innovation effect brought by digital transformation in non-eastern regions is higher than that in the eastern regions. However, when considering economic shocks and recession, the ability to adjust industrial structure and seek technological transformation is still led by the eastern regions (Xiao et al., 2023), due to the fact that eastern companies have a better economic base, better talent pool (Jae-Hoon, 2018; Wang et al., 2022), more complete infrastructure (X. Zheng et al., 2013) and innovation climate (Xu et al., 2022). These advantages provide a better environment for digital transformation, making the eastern region have greater innovation potential during recession. Based on this, this paper proposes the hypothesis:

H7: *Compared with non-eastern companies, the digital transformation of eastern companies boost innovation more during the recession.*

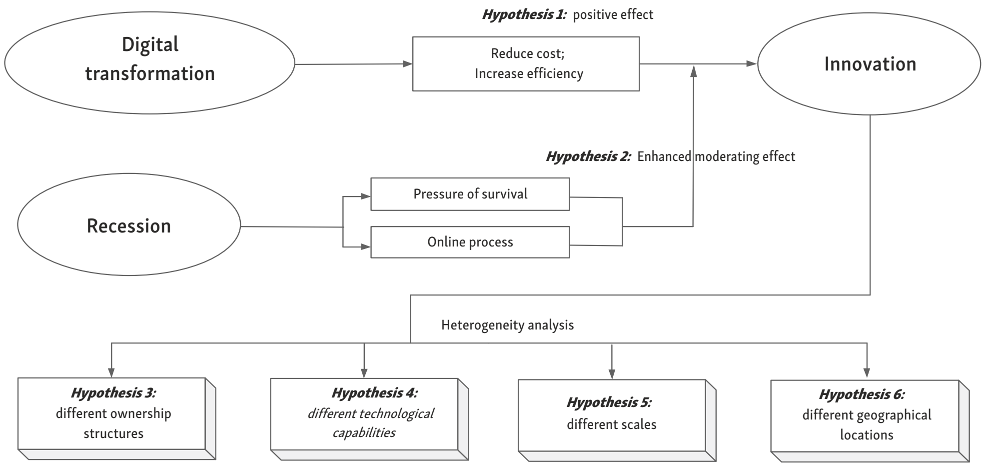

Figure 1. The study framework and relationship of the hypotheses (source: the author compiled the information based on the logical relationships of hypotheses)

The six hypotheses provide a framework for understanding the relationship between digital transformation and innovation, and how this relationship is affected by economic conditions and different types of companies. The study framework and relationship of the hypotheses in this paper are shown in Figure 1.

3. Methodology

3.1. Model specification

This paper uses Eq. (1) to measure the impact of digital transformation on innovation:

$$PG_{it} = \alpha + \delta_1 DT_{it} + \delta_2 Control_{it} + \varepsilon_{it}. \quad (1)$$

When the relationship between the independent variable and the dependent variable is influenced by a third variable, this third variable is referred to as a moderator. A moderator can affect both the direction and strength of the relationship between the independent variable and the dependent variable (Baron & Kenny, 1986). Since Aiken and West (1991) provided a detailed explanation of the analytical mechanism of moderation effects, moderating effects have become one of the most commonly used methods of analysis in social science research.

To test the impact of digital transformation on corporate innovation under different economic cycles, the interaction variable of digital transformation and economic cycle are introduced on the basis of Eq. (1), and the moderating effect model is as follows:

$$PG_{it} = \alpha + \beta_1 DT_{it} + \beta_2 ECO_{it} + \beta_3 DT_{it} \times ECO_{it} + \beta_4 Control_{it} + \varepsilon_{it}, \quad (2)$$

where PG_{it} is the corporate innovation, represented by the logarithm of the total number of patents granted by the *i*-th company in year *t*. DT_{it} is the digital transformation, measured by the frequency ratio of digitized related words in the annual reports of *i*-th company in year *t*. ECO_{it} is the economic cycle, which is 1 when the economy is in recession and 0 otherwise.

$DT_{it} \times ECO_{it}$ represents the interaction variable of digital transformation and economic cycle. $Control_{it}$ represents the control variable, ε_{it} is the residual. When interpreting the moderating effect of a categorical variable, it is important to consider how the relationship between the independent and dependent variables may differ across the different categories of the moderator. Interaction effects occur when the effect of the independent variable on the dependent variable varies depending on the levels of the categorical moderator. If the interaction term is significant, it indicates that the categorical variable moderates the relationship between the independent and dependent variables. When the economy is in a downturn, $ECO_{it} = 0$, $PG_{it} = \alpha + \beta_1 DT_{it} + \beta_4 Control_{it} + \varepsilon_{it}$, the impact of digital transformation on innovation is measured by β_1. In other words, β_1 measures the influence of digital transformation on innovation during the boom period. Similarly, $\beta_1 + \beta_3$ evaluates the impact of digital transformation on innovation during the recession.

3.2. Variable selection

3.2.1. Dependent variable

Most of the current literature uses the number of patents to represent a corporate innovation capability (Acharya & Xu, 2017; Luo et al., 2022). This paper uses the logarithm of the number of patent authorizations as a representative variable for corporate innovation, because the number of patent authorizations is better than the number of patent applications in reflecting the quality of innovation (Graham et al., 2015).

3.2.2. Independent variable

At present, annual reports of listed companies in China do not include the degree of digital transformation, which leads some scholars to take the proportion of network technology and software assets in intangible assets as the degree of digital transformation of companies (Jiang et al., 2022). There are also literatures that use the number of robots as a measurement index of corporate digital transformation (Babina et al., 2020; Q. Wang & Du, 2022), but digitalization is a complex system, and artificial intelligence only represents one aspect.

Text analysis has been widely used in top financial, accounting and management journals (Caserio et al., 2019; Ertugrul et al., 2017; Loughran & McDonald, 2020). The words used by managers convey decision-making information. By analyzing the documents issued by the company, it can be inferred whether the company is in the process of digital transformation. Based on the text analysis method, this study calculated the digitization degree (*DIG*) of the listed company by dividing the total frequency of digital-related words by the length of the MD&A paragraph in the annual report of the listed company. The specific calculation method is:

The first step is to build a digital glossary. By searching the websites of the Central People's Government of China and the Ministry of Industry and Information Technology, 31 important national digital economy-related policy documents released during 2012–2020 are manually screened to extract keywords related to company digitalization. After Python word segmentation and manual recognition, words related to company digitalization whose frequency is greater than or equal to 5 times are selected. Based on these words, supplemented by the word frequency of digital transformation in Liu et al. (2022), a total of 239 keywords of digital transformation are obtained, which constitute the dictionary of digital terms in this paper. The second step is to import the digital dictionary into Wingo database for word frequency statistics.[1] After extracting the word frequency of digitalization related keywords, we get the index of digital transformation by adding them up and dividing it by the text length of MD&A part of the corporate annual report (excluding numbers). The index is multiplied by 100 as the proxy variable of the corporate digital transformation.

3.2.3. Mediator

Academia mainly use three methods to measure the economic cycle. The first method is to determine whether the GDP growth rate is greater than 0 based on the growth rate, but it cannot eliminate the impact of long-term trends. The second method is filtering method, including BP filtering method and HP filtering method. Its essence is spectral analysis method, which can eliminate the impact of long-term trends in time series (Hamilton, 2018). The third method is the Markov regime transformation model, where the smoothing probability of the regime divides the economic situation at various time points into different regimes (Hamilton, 1989). This paper uses the HP filter commonly used in academia to determine whether the economy is in a recession, and uses the Markov system transformation to conduct the robustness test.

This paper uses the *GDP* deflator of 31 provinces to process the nominal *GDP* data from 2001 to 2021 to obtain the corresponding annual actual *GDP*, and takes the natural logarithm to obtain the time series GDP_t. Using the HP filtering algorithm to minimize Eq. (3), we obtain the long-term trend portion GDP_t^l, and then the short-term volatility portion $GDP_t^c = GDP_t - GDP_t^l$. If $\Delta GDP_t^c < 0$, year *t* is the recession period, with a value of 1 assigned, if $\Delta GDP_t^c > 0$, the year *t* is the economic prosperity period, with a value of 0 assigned.

$$\min \sum_{t=1}^{T}(GDP_t - GDP_t^l)^2 + \lambda \sum_{t=1}^{T}[(GDP_t^l - GDP_{t-1}^l) - (GDP_{t-1}^l - GDP_{t-2}^l)]^2. \quad (3)$$

3.2.4. Control variables for innovation

To estimate the impact of economic digitization on innovation, the other driving factors for innovation are controlled. (1) Capital structure: Asset-liability ratio can be used as one of the indicators to measure whether a company has the ability to innovate and the possibility to take action (Myers & Majluf, 1984). In this paper, the Asset-liability ratio is used to represent the capital structure of the company. (2) Asset Structure: Brouwer and Kleinknecht (1997) believes that fixed assets investment is a very important non R&D investment in the innovation process, especially for the service industry. Therefore, this paper adds fixed asset ratio to control the corporate asset structure. (3) Profitability capability: Profitability are positively related to corporate future innovation potential (Pham et al., 2021). This paper uses rate of return on total assets to represent the corporate profitability. (4) Developing Capacity: capital preservation and appreciation rate is an important indicator to evaluate the corporate efficiency and development capability, this paper uses capital preservation and appreciation

[1] Wingo database provides analysis of exact word frequency, extended word frequency, exact sentence frequency and extended sentence frequency, as well as the total word count and total word count of the segment text of "Management Discussion and Analysis" (MD&A) in annual reports of listed companies.

rate to represent the development capability of a company. (5) Big4: If the audit institution is one of the four major accounting firms, take 1, otherwise take 0.

The variables in this paper are shown in Table 1.

Table 1. Variables description and selection (source: the author compiled the information based on the database)

Variable Type	Variable Name	Symbol	Variable Description	Indicator unit
Explained variable	Innovation Output	PG	Ln (the number of patents granted+1)	–
Independent variable	Digital transformation	DT	Digital related word frequency in annual reports of listed companies	%
Moderating variables	Economic cycle	EC	Economic contraction or expansion period	0 or 1
Control variables	Capital structure	ALR	Asset-liability ratio	%
	Fixed asset ratio	FAR	Fixed assets / total assets	%
	Profitability capability	PC	Net profit/total assets	%
	Developing capacity	DC	Ending owner's equity / Beginning owner's equity	%
	Big4	Big4	audit institution is one of the four major accounting firms	0 or 1

3.3. Research sample

The research samples in this paper are all the A-share listed companies in Shanghai and Shenzhen from 2001 to 2021, excluding the delisted companies, excluding the data before listing, excluding the samples of the financial industry, excluding the samples of ST, *ST or PT listed companies. The corporate patent data are from the Chinese Research Data Services (CNRDS) database, and the digital word frequency data are from the WinGo database. Macroeconomic indicators are obtained from China's National Bureau of Statistics and the CEInet statistics database. The remaining data come from China Stock Market & Accounting Research Database (CSMAR). All analyses of these data in this paper are conducted using the Stata and Eviews software.

3.4. Descriptive statistics

The correlation coefficients between the variables are shown in Table 2. There is a positive correlation between innovation output and digital transformation, and a negative correlation between innovation and economic cycle. There is a negative correlation between digital transformation and economic cycle. According to the descriptive statistics of the variables in Table 3, non-SOEs, High-tech, SMEs and eastern companies have higher innovation output and higher level of digital transformation.

Table 2. Correlation coefficient between variables (source: the author compiled the table based on Stata regression results)

	PG	DT	EC	ALR	FAR	PC	DC	Big4
PG	1.000							
DT	0.281^{***}	1.000						
EC	-0.058^{***}	-0.055^{***}	1.000					
ALR	0.023^{***}	-0.138^{***}	0.019^{***}	1.000				
FAR	-0.121^{***}	-0.285^{***}	0.046^{***}	0.104^{***}	1.000			
PC	0.055^{***}	0.003	-0.019^{***}	-0.283^{***}	-0.059^{***}	1.000		
DC	-0.008^{*}	0.012^{**}	-0.009^{*}	-0.091^{***}	-0.064^{***}	0.109^{***}	1.000	
Big4	0.100^{***}	-0.028^{***}	0.000	0.088^{***}	0.049^{***}	0.030^{***}	0.012^{**}	1.000

Table 3. Descriptive statistics of variables (source: the author compiled the table based on Stata results)

	Mean									S.D.	Min	Max
	National	SOEs	Non-SOEs	High-tech	Low-tech	SMEs	Non-SMEs	Eastern	Non-eastern			
PG	2.1401	1.9763	2.2468	2.8513	1.6833	2.5440	1.9033	2.2513	1.8908	1.7711	0.0000	9.6321
DT	0.8120	0.5821	0.9617	1.0892	0.6338	1.1119	0.6362	0.9031	0.6076	1.0452	0.0000	16.8478
EC	0.4551	0.4917	0.4312	0.4183	0.4786	0.4262	0.4720	0.4308	0.5093	0.4980	0.0000	1.0000
ALR	0.4256	0.4970	0.3791	0.3629	0.4660	0.3486	0.4708	0.4143	0.4511	0.2029	0.0274	0.9911
FAR	0.2263	0.2722	0.1964	0.1955	0.2461	0.1862	0.2498	0.2062	0.2713	0.1686	0.0015	0.8064
PC	0.0369	0.0311	0.0407	0.0441	0.0324	0.0410	0.0346	0.0391	0.0320	0.0934	–8.7534	0.7859
DC	1.2720	1.1420	1.3568	1.2988	1.2548	1.3614	1.2197	1.2951	1.2204	1.9960	–28.1842	366.0535
Big4	0.0577	0.0899	0.0368	0.0299	0.0756	0.0208	0.0794	0.0665	0.0380	0.2332	0.0000	1.0000

4. Results

4.1. The estimated results of moderating effect

To reduce multicollinearity and enhance the interpretability of variable coefficients (Hayes, 2013), this paper centralizes the independent variables *DT*in Eq. (2). The moderating variable (*EC*) is a dummy variable, which is not centralized. Based on the results of the Hausman test, this paper chooses to use the fixed effects model, and the results are shown in Table 4.

Model (1) measures the impact of digital transformation on innovation without adding control variables, while model (2) captures this relationship by controlling other influential factors. The coefficients of *DT* are significant at the 1% level of significance in both Model (1) and Model (2), indicating that digital transformation can effectively enhance innovation output, hypothesis 1 is confirmed. In the boom period, the impact of digital transformation on innovation is β_1 in Eq. (2). The estimated coefficient of *DT* shows that, during economic prosperity, every one-unit increase in digital transformation leads to a increase in innovation output by 0.5394 units. During recession, the effect of digital transformation on innovation is described by the combined coefficients $\beta_1 + \beta_3$. More specifically, during recession, every one-unit increase in digital transformation leads to an increase in innovation output by 0.6465[0.5394+0.1071] units. 0.1071 is the difference in the impact of digital transformation between recession and booms, which indicates the innovation output during recession is 0.1071 units higher than during economic prosperity, thereby confirming Hypothesis 2. During recessions, when market demand is weak, companies tend to accelerate their digital research and engage in more innovative activities to enhance market demand under survival pressure. Hence, during recessions, the impact of digital transformation on innovation is even stronger than during economic prosperity.

Table 4. The regression results of moderating effects (source: the author compiled the table based on Stata regression results)

Variables	(1)	(2)	(3)
	PG	PG	PG
DT	0.6270*** (68.3227)	0.5726*** (62.5822)	0.5394*** (55.4819)
EC			–0.0643*** (–5.7795)
DT×EC			0.1071*** (9.2571)
ALR		1.4698*** (29.8254)	1.4649*** (29.7723)
FAR		–1.2764*** (–20.2712)	–1.2292*** (–19.5068)
PC		0.1196* (1.7794)	0.1018 (1.5161)
DC		–0.0112*** (–3.9113)	–0.0114*** (–4.0174)
Big4		0.2467*** (5.5130)	0.2436*** (5.4527)
Constant	1.6310*** (177.1864)	1.3339*** (47.4242)	1.3858*** (48.4458)
Hausman test (P value)	355.68 (0.0000)	993.83 (0.0000)	1057.10 (0.0000)
Observations	41,267	41,267	41,267
Number of id	4,373	4,373	4,373
R-squared	0.112	0.144	0.147

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The value in the parentheses is *t* test.

4.2. Heterogeneity analysis

4.2.1. Heterogeneity of SOEs and non-SOEs

The sample is divided into state owned companies (SOEs) and non-state owned companies (Non-SOEs) based on the equity nature of the company. The regression results are showed in Table 5. First, compare with Non-SOEs, SOEs' digital transformation has a greater positive impact on innovation. According to Model (4), each additional unit of digital transformation leads to an increase of 0.7612 units in SOEs' innovation, while Model (6) shows that Non-SOEs' innovation l only increase by 0.4614 units. Second, the recession has a more significant positive moderating effect on SOEs' digital transformation. According to Model (5), the *DT×EC* coefficient is 0.1171, indicating that the recession strengthen the positive impact of SOEs' digital transformation on innovation, which is greater than the 0.0625 in Model (7). This also implies that during the recession, greater reliance should be placed on the digital drive of SOEs to promote innovation, hypothesis 3 is confirmed.

Table 5. Regression results of the SOEs and non-SOEs (source: the author compiled the table based on Stata regression results)

Variables	SOEs		Non-SOEs	
	(4)	(5)	(6)	(7)
	PG	PG	PG	PG
DT	0.7612*** (42.4921)	0.7175*** (36.9436)	0.4614*** (45.6525)	0.4443*** (41.6877)
EC		–0.1549*** (–8.4125)		–0.0117 (–0.8922)
DT×EC		0.1171*** (5.0770)		0.0625*** (4.9324)
ALR	1.1253*** (12.6479)	1.0738*** (12.0865)	1.4441*** (24.1038)	1.4447*** (24.1272)
FAR	–1.7961*** (–18.0693)	–1.7258*** (–17.3720)	–0.6267*** (–7.3284)	–0.6066*** (–7.0849)
PC	–0.3850** (–2.0778)	–0.4894*** (–2.6453)	0.1539** (2.3003)	0.1487** (2.2234)
DC	–0.0667*** (–4.7977)	–0.0659*** (–4.7482)	–0.0081*** (–3.0838)	–0.0083*** (–3.1451)
Big4	0.1313** (2.0501)	0.1239* (1.9402)	0.2677*** (3.9847)	0.2687*** (4.0017)
Constant	1.5393*** (25.5297)	1.6526*** (27.0091)	1.3735*** (44.7788)	1.3928*** (44.5788)
Hausman test (P value)	471.51*** (0.0000)	75.44*** (0.0000)	716.22*** (0.0000)	532.73*** (0.0000)
Observations	16,281	16,281	24,986	24,986
Number of id	1,442	1,442	3,870	3,870
R-squared	0.154	0.160	0.135	0.136

4.2.2. Heterogeneity of high-tech and low-tech companies

The sample is divided into high-tech companies (High-tech) and non-high-tech companies (Low-tech) based on the qualification list of Chinese high-tech companies. The regression results are showed in Table 6. First, compared to High-tech companies, Low Tech companies' digital transformation has a greater positive impact on innovation. According to Model (8), each additional unit of digital transformation leads to an increase of 0.3609 units in innovation for High-tech companies, while Model (10) shows an increase of 0.6759 units in innovation for Low-tech companies. Descriptive statistics presented in Table 3 show that Low-tech companies have a lower level of digital transformation than High-tech companies, which gives them a catch-up advantage in digital transformation. They can absorb and learn from the technical experience of original High-tech companies, and has a greater positive impact on innovation. Second, the recession has a more significant positive moderating effect on the digital transformation of Low-tech companies. According to Model (11), the $DT \times EC$ coefficient is 0.1286, proving that the economic downturn strengthens the positive impact of Low-tech companies' digital transformation on innovation. This coefficient is greater than 0.0307 in model (9). During the recession, the promoting effects of digital transformation on innovation is greater than during the economic prosperity, and the effects is higher in the Low-tech companies than in the high-tech companies, hypothesis 4 is confirmed. High-tech companies mostly focus on big data, artificial intelligence etc, which represent digital industrialization. Low-tech companies are mostly in manufacturing industries, whose digital transformation represents digitization of traditional industries. This also indicates that during the recession, China relies more on innovation induced by the digitalization of traditional industries to get out of the economic quagmire.

Table 6. Regression results of the high-tech and low-tech companies (source: the author compiled the table based on Stata regression results)

Variables	high-tech		low-tech	
	(8)	(9)	(10)	(11)
	PG	PG	PG	PG
DT	0.3609*** (33.0769)	0.3537*** (31.0236)	0.6759*** (49.0883)	0.6318*** (42.2542)
EC		0.0118 (0.8191)		–0.0912*** (–6.1561)
DT×EC		0.0307** (2.3642)		0.1286*** (6.9073)
ALR	1.7971*** (22.7581)	1.7963*** (22.7510)	1.1979*** (19.2441)	1.1904*** (19.1622)
FAR	–0.6617*** (–5.7218)	–0.6599*** (–5.6994)	–1.3520*** (–17.9565)	–1.2980*** (–17.2269)
PC	–0.3073** (–2.5447)	–0.3152*** (–2.6086)	0.1817** (2.3018)	0.1577** (2.0014)
DC	–0.1114*** (–11.1993)	–0.1114*** (–11.2038)	–0.0017 (–0.5739)	–0.0020 (–0.6598)
Big4	0.3210*** (3.4333)	0.3199*** (3.4226)	0.1043** (1.9849)	0.1013* (1.9313)
Constant	2.0839*** (46.4527)	2.0877*** (46.0178)	1.0178*** (26.6693)	1.0846*** (27.9406)
Hausman test (P value)	310.55*** (0.0000)	322.19*** (0.0000)	230.58*** (0.0000)	664.72*** (0.0000)
Observations	16,140	16,140	25,127	25,127
Number of id	2,301	2,301	3,144	3,144
R-squared	0.161	0.161	0.140	0.144

4.2.3. Heterogeneity of SMEs and non-SMEs

The sample is divided into small and medium-sized companies (SMEs) and large companies (Non-SMEs) based on their listing locations. Companies listed on the Science and Technology Innovation Board, the Growth Enterprise Board, and the Small and Medium Sized Board are classified as SMEs, while the rest are Non-SMEs. The regression results are showed in Table 7. First, compared to SMEs, Non-SMEs' digital transformation has a greater positive impact on innovation. According to Model (12), each additional unit of digital transformation leads to an increase of 0.3811 units in innovation in SMEs, while Model (14) shows that innovation in Non-SMEs is increased by 0.6865 units. The digital transformation of large companies has a longer production and sales chain, and the butterfly effect brought by digital transformation is far greater than that of small companies. Second, the recession has a more significant positive moderating effect on the digital transformation of Non-SMEs, and there is no moderating effect on SMEs. According to Model (13), the $DT \times EC$ coefficient is not significant, whereas the $DT \times EC$ coefficient in Model (15) is 0.1674, proving that the recession strengthens the positive impact of Non-SMEs' digital transformation on innovation. This indicates that during the recession, China needs to rely on the digital power of large listed companies to promote innovation and drive economic recovery, hypothesis 5 is confirmed.

Table 7. Regression results of the SMEs and non-SMEs (source: the author compiled the table based on Stata regression results)

Variables	SMEs		Non-SMEs	
	(12)	(13)	(14)	(15)
	PG	PG	PG	PG
DT	0.3811*** (31.8055)	0.3787*** (30.0486)	0.6865*** (52.6233)	0.6313*** (44.8158)
EC		0.0177 (1.1216)		–0.1077*** (–7.2492)
DT×EC		0.0109 (0.7528)		0.1674*** (9.2866)
ALR	2.0413*** (26.2392)	2.0422*** (26.2447)	1.1728*** (18.5188)	1.1654*** (18.4589)
FAR	–0.6860*** (–5.9289)	–0.6914*** (–5.9634)	–1.4546*** (–19.0341)	–1.3854*** (–18.1350)
PC	0.0128 (0.1158)	0.0060 (0.0537)	0.1921** (2.2930)	0.1624* (1.9434)
DC	–0.1127*** (–12.3706)	–0.1125*** (–12.3382)	–0.0022 (–0.6879)	–0.0025 (–0.7957)
Big4	0.4752*** (4.9782)	0.4772*** (4.9987)	0.1859*** (3.5716)	0.1803*** (3.4755)
Constant	1.6794*** (38.6081)	1.6753*** (37.8901)	1.2591*** (32.2731)	1.3384*** (33.7999)
Hausman test (P value)	305.18*** (0.0000)	304.38*** (0.0000)	5676.82*** (0.0000)	465.48*** (0.0000)
Observations	15,249	15,249	26,018	26,018
Number of id	1,771	1,771	2,602	2,602
R-squared	0.182	0.183	0.146	0.151

4.2.4. Heterogeneity of eastern and non-eastern regions

The sample is divided into Eastern companies and Non-Eastern companies according to the registered address of the company. The regression results are showed in Table 8. First, compared to Eastern companies, the digital transformation of Non-Eastern companies has a greater positive impact on innovation. According to Model (16), each additional unit of digital transformation leads to an increase of 0.5318 units in Eastern innovation, while Model (18) shows an increase of 0.7105 units in Non-Eastern innovation. The economic development speed of the eastern region is faster than that of the non-eastern region. For the Non-Eastern region, digital transformation can not only achieve intelligent transformation of backward production capacity (Caggiano & Teti, 2018), but also facilitate standardization of management and reduce management manipulation (Fernandez-Vidal et al., 2022; Rachinger et al., 2019; Vaska et al., 2021), which is more evident than in the Eastern region, non-Eastern regions have a late-development advantage. Therefore, when companies in the Eastern and Non-Eastern regions simultaneously conduct digital transformation, Non-Eastern companies play a greater role in promoting innovation. Second, the recession has a more significant

Table 8. Regression results of the eastern and non-eastern regions (source: the author compiled the table based on Stata regression results)

Variables	Eastern		Non-eastern	
	(16)	(17)	(18)	(19)
	PG	PG	PG	PG
DT	0.5318*** (52.6338)	0.5050*** (48.2848)	0.7105*** (34.7351)	0.6783*** (26.1171)
EC		–0.0805*** (–6.1140)		–0.0419** (–2.0205)
DT×EC		0.1059*** (8.0607)		0.0569** (2.1349)
ALR	1.4559*** (24.3063)	1.4440*** (24.1502)	1.4418*** (16.5571)	1.4431*** (16.5750)
FAR	–1.2719*** (–16.4663)	–1.2050*** (–15.5786)	–1.3121*** (–12.0040)	–1.3005*** (–11.8907)
PC	–0.0673 (–0.7594)	–0.0842 (–0.9520)	0.4906*** (4.4755)	0.4832*** (4.4065)
DC	–0.0076*** (–2.6465)	–0.0079*** (–2.7596)	–0.0771*** (–6.2266)	–0.0771*** (–6.2185)
Big4	0.2151*** (4.3109)	0.2112*** (4.2419)	0.3321*** (3.4495)	0.3324*** (3.4529)
Constant	1.4283*** (43.1647)	1.4841*** (44.1372)	1.2304*** (21.8478)	1.2668*** (21.9880)
Hausman test (P value)	777.46*** (0.0000)	870.58*** (0.0000)	625.03*** (0.0000)	502.76*** (0.0000)
Observations	28,535	28,535	12,732	12,732
Number of id	3,235	3,235	1,138	1,138
R-squared	0.148	0.152	0.144	0.144

positive moderating effect on the digital transformation of Eastern companies. According to Model (17), the $DT \times EC$ coefficient is 0.1059, while the $DT \times EC$ coefficient in Model (19) is 0.0569, proving that the recession strengthens the positive impact of Eastern companies' digital transformation on innovation. Even though the performance of digital transformation in the non-eastern region is stronger, when considering economic shocks and during recession, the ability to adjust industrial structure and seek technological transformation is still led by the eastern region, hypothesis 6 is confirmed.

4.3. Robustness test

4.3.1. Robustness test of moderating effect

To test the robustness of the model results, this study replaced the explained variables, mediator, and the model. The logarithm of the total number of patent authorizations is replaced by the logarithm of invention patent authorizations, and the MSVAR is used to calculate the economic cycle. This model is simple and accurate, and when the smoothing probability of a certain regime is above 0.5, the economic cycle is considered to be in that regime. China's total import and export growth rate (*TIE*) represents the level of foreign trade, while consumer confidence index (*CCI*) represents the judgment of current and future employment conditions, income levels, and durable consumer goods purchase timing (Batchelor & Dua, 1998), these pieces of information are emotional signals that evaluate changes in economic activity (Kim, 2016), and have a close relationship with variables such as industrial production, personal consumption expenditures, and housing market variables (Kilic & Cankaya, 2016). Using monthly data on China's total import and export growth rate (*TIE*) and consumer confidence index (*CCI*) from January 2001 to December 2021, we can identify the duration of economic recessions in the same regional system by dividing it accordingly.

First, a stationary test is performed. As shown in Table A1 and Table A2 in the Appendix, *CCI* is a non-stationary series that becomes stable after the first-order difference, and Table A3 shows that the *TIE* series is stable. Second, the lagging period is selected according to the information criteria such as AIC, SC in Table A4. The MSVAR model in this paper selects a lag period. Third, the regime conversion probability is shown in Table A5 and the regime probabilities is shown in Figure 2. The recession and boom periods of China are shown in Table 9. Using the time and individual dual fixed effect model, the results obtained are shown in Table 10. The results show that digital transformation has a positive impact on innovation, and economic recession enhances the positive impact of digital transformation on innovation. Hence, the research conclusions of this paper are robust.

Table 9. Years of China's economic status (source: smoothed trend results from Figure 1)

Period	Year
Recession period	2009, 2012–2016, 2019–2020
Economic prosperity period	2001–2008, 2010–2011, 2017–2018, 2021

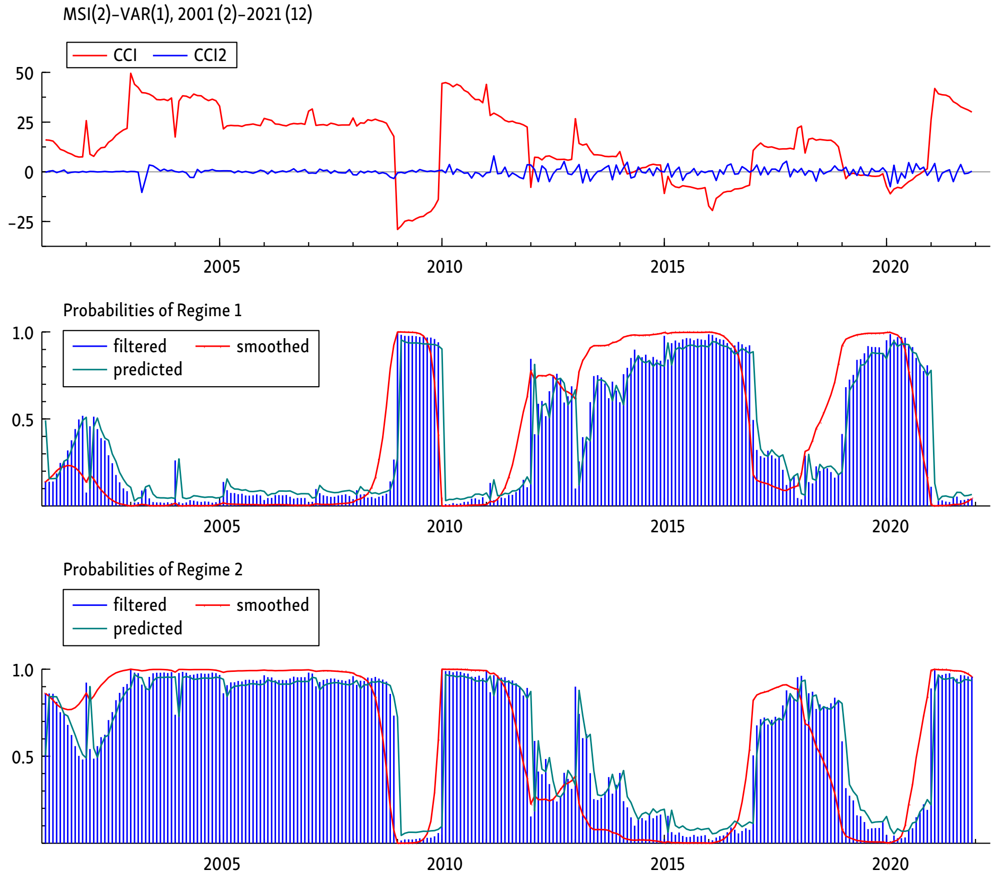

Figure 2. China's economic cycle (2001.01–2021.12)
(source: smoothed probabilities calculated and presented by using Eviews)

Table 10. Regression results of the eastern and non-eastern regions (source: the author compiled the table based on Stata regression results)

Variables	(20)	(21)	(22)
	PG	PG	PG
DT	0.1552^{***} (21.8519)	0.1556^{***} (21.9341)	0.1444^{***} (19.5560)
EC			1.3052^{***} (43.4260)
DT×EC			0.0456^{***} (5.4851)
ALR		0.3792^{***} (11.3526)	0.3794^{***} (11.3616)
FAR		0.2897^{***} (6.6681)	0.2926^{***} (6.7371)

End of Table 10

Variables	(20) PG	(21) PG	(22) PG
PC		0.0169 (0.3769)	0.0110 (0.2456)
DC		–0.0012 (–0.6550)	–0.0012 (–0.6478)
Big4		0.0094 (0.3140)	0.0102 (0.3405)
Constant	0.0021 (0.0801)	–0.2037*** (–6.4700)	–0.2032*** (–6.4569)
Year	YES	YES	YES
Id	YES	YES	YES
Observations	41,267	41,267	41,267
Number of id	4,373	4,373	4,373
R-squared	0.297	0.301	0.302

4.3.2. Endogenous test

In order to solve the possible reverse causality between economic recession, digital transformation and innovation, this study uses the lag of independent variable as instrumental variable for endogenous test. The results in Table 11 show that instrumental variables (*IVDT*) and independent variables (*DT*) are significantly positively correlated. The second stage regression results show that the coefficient of the interaction variables ($IVDT \times FD_b$ and $IVDT \times FD_c$) are positive and significant at the 1% level. The *p*-value of the *LM* statistic and the *Wald-F* statistic pass the test. This shows that digital transformation has a positive effect on innovation, banking and capital market enhance the positive impact of digital transformation on innovation.

Table 11. Endogenous test (source: the author compiled the table based on Stata regression results)

Variables	(23) First stage DIG	(24) Second stage PG	(25) First stage DIG	(26) Second stage PG
DT	1.0545*** (301.3003)	0.5641*** (52.6729)	1.1162*** (249.2321)	0.5128*** (39.6535)
EC			0.0541*** (–7.4947)	–0.2917*** (–11.9962)
DT×EC			–0.1472*** (22.1708)	0.1220*** (5.8963)
ALR	–0.0871*** (–5.9607)	0.6874*** (14.5280)	–0.0876*** (–6.0381)	0.6910*** (14.6447)
FAR	–0.2244*** (–13.0774)	–0.3436*** (–6.1244)	–0.2288*** (–13.4236)	–0.3087*** (–5.5075)
PC	–0.0000 (–0.0015)	1.3702*** (14.0775)	0.0137 (0.4585)	1.3370*** (13.7704)

End of Table 11

Variables	(23) First stage	(24) Second stage	(25) First stage	(26) Second stage
	DIG	PG	DIG	PG
DC	0.0019 (1.3534)	–0.0071 (–1.5882)	0.0022 (1.6081)	–0.0072 (–1.6285)
Big4	0.0210* (1.7771)	0.7542*** (19.7419)	0.0190 (1.6207)	0.7512*** (19.7183)
Constant	0.1560*** (16.7244)	1.4297*** (46.1837)	0.1334*** (13.6229)	1.5573*** (47.9473)
F Value	17513.46	649.17***	13414.21***	509.37***
Anderson canon. corr. LM statistic		26000***		26000***
Cragg-Donald Wald F statistic		91000		46000
Observations	35,919	35,919	35,919	35,919
R-squared	0.745	0.099	0.749	0.104

5. Conclusions

The current literature on innovation primarily focuses on its relationship with economic cycles and the driving factors, while neglecting the asymmetric impact of economic cycles on corporate innovation. Considering many countries implement digital strategies to promote a new round of scientific and technological revolution. The purpose of this study is to identify evidence of how digital technology can break through limitations and drive innovation during economic downturns after COVID-19 and international conflicts. Therefore, a moderation effects model is constructed using Stata software, with economic recession as the moderator, to investigate whether and how digital strategies can be used to help the global economy recover from its sluggish state. Understanding the impact of digital transformation on innovation during the recession helps to provide feasible policy suggestions for the realization of corporate innovation and development and solving the economic difficulties, thus providing decision-making basis and policy reference.

This study provides important insights into the relationship between economic cycles, digital transformation, and corporate innovation. Using the panel data from China's A-share listed companies during the period of 2001–2021, this paper draws the following conclusions: First, this paper verifies the positive impact of digital transformation on innovation disregarding economic conditions. The benchmark regression results evaluate the direct effect of digital transformation on innovation, independent of the influence of economic recession or recovery. It helps in comparing the moderating effect of economic recession indicators on innovation to better understand the greater contribution of digital transformation to innovation during economic downturns. Second, digital transformation has a countercyclical effect on innovation, with its positive impact being even greater during recession than during periods of prosperity. When facing a decrease in market demand and survival pressure, companies accelerate digital transformation, which leads to more innovation output. This empirical finding provides evidence for the main argument and hypothesis of this paper, achieving the core objective of filling the research gap between macroeconomic cycles and micro-level digital innovation in companies, contributing to a comprehensive understanding of the impact of digitalization on innovation. Third, this study extends the inferred implications of the results, aiming to provide reference for the government and companies' next strategic orientation. The investigation highlights that state-owned listed companies, non-high tech companies, large-scale companies, and eastern companies are more susceptible to the positive moderating effect of the recession. This underscores that if the government and companies intend to sustain their innovative capacity during economic downturns, they should rely more on the digitalization of these companies to promote economic recovery.

Based on the above findings, the following policy recommendations are proposed: First, based on the important role of digitization, countries should take active measures to continuously break through the forefront of digital technology and improve the efficiency of digitization in transforming into real productivity, which help achieve innovative development strategies and occupy the high ground of digitalization. Second, according to the endogenous laws of technological innovation, market mechanisms should be used to encourage companies to actively undergo digital transformation. During recession, the government should focus on increasing funding subsidies and tax incentives for enterprises' digital transformation, breaking market monopolies, and enabling companies to form their own unique market competitiveness under survival pressure, thereby achieving a rapid economic recovery. Third, there are significant differences in the effect of digital transformation on companies with different attributes. Therefore, the government can formulate differentiated support policies, especially by increasing support for state-owned listed companies, non-high tech companies, large-scale companies, and eastern companies' digital transformation. The excellent performance of these companies during the recession help the overall Chinese economy emerge from the quagmire.

Despite the valuable insights provided by this study, there are still some limitations and areas for further exploration. First, this study only focuses on A-share listed companies in China. If data are available, future research should include a broader sample of companies, such as unlisted micro companies, which are the majority in China. Second, the findings of this study have certain reference significance for understanding the relationship between recession, digital transformation, and corporate innovation. However, there are limitations to using only historical data for empirical verification. Future research can be done by taking incorporate digitization as a key input into innovation or economic growth theoretical models to further explore the impact of digitization on innovation and economic growth, in order to obtain more universally applicable theoretical deductions.

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Conflicts of interest

The authors declare no conflict of interest.

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APPENDIX

Table A1. Unit root test of Consumer Confidence Index (source: the author compiled the table based on Eviews regression results)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		–2.549035	0.3044
Test critical values:	1% level	–3.994891	
	5% level	–3.427758	
	10% level	–3.137225	

Table A2. Unit root test of Consumer Confidence Index after first order difference (source: the author compiled the table based on Eviews regression results)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		–17.75489	0.0000
Test critical values:	1% level	–3.995040	
	5% level	–3.427830	
	10% level	–3.137268	

Table A3. Unit root test of the growth rate of total import and export (source: the author compiled the table based on Eviews regression results)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		–3.510601	0.0404
Test critical values:	1% level	–3.995040	
	5% level	–3.427830	
	10% level	–3.137268	

Table A4. VAR Lag order selection criteria (source: the author compiled the table based on Eviews regression results)

Lag	LogL	LR	FPE	AIC	SC	HQ
0	–1583.859	NA	1514.878	12.99884	13.02751	13.01039
1	–1355.575	450.9536*	240.9773*	11.16045*	11.24645*	11.19509*
2	–1354.586	1.938758	246.9996	11.18513	11.32846	11.24285
3	–1351.270	6.440420	248.3946	11.19074	11.39140	11.27155
4	–1350.494	1.494974	255.0551	11.21717	11.47515	11.32107
5	–1347.105	6.473144	256.3490	11.22217	11.53749	11.34916
6	–1344.594	4.754051	259.5180	11.23438	11.60703	11.38446
7	–1342.590	3.762440	263.8265	11.25074	11.68072	11.42391
8	–1339.790	5.209794	266.4721	11.26057	11.74788	11.45683

Note: * indicates lag order selected by the criterion.

Table A5. Matrix of transition probabilities (source: the author compiled the table based on Eviews and Stata regression results)

	Regime1	Regime2
Regime1	0.9576	0.0424
Regime2	0.0277	0.9723