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Digital M&A and Firm Innovation:
Evidence From China

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ABSTRACT

This study empirically examines how digital M&A affects firm innovation using data from Chinese listed companies from 2006 to 2019. The results show that digital M&A promotes firm innovation, and our findings also suggest that digital M&A enables firms to break away from technology path-dependence to achieve radical innovation and digital innovation. The analysis of different types of digital M&A shows that the innovation effect of vertical digital M&A is smaller than that of horizontal digital M&A. Vertical digital M&A significantly increases industry concentration and may change the competitive structure of the market; the innovation effect of cross-border digital M&A is smaller than that of domestic digital M&A, which may be related to the negative moderating effect of cultural and institutional distance between China and the host country, as well as the restriction of cross-border data flow.

KEYWORDS

digital innovation, digitalization, digital M&A

INTRODUCTION

With the application of digital technologies such as artificial intelligence, big data, cloud computing, and blockchain, new technologies, new products, new business, and new business models are emerging. Firms increasingly recognize that they must proactively to digital disruption. However, digital technologies are rapidly iterating, which means that new digital capabilities quickly go out of date, sometimes even before they are fully implemented. So if firms develop digital capabilities in-house, with relatively long R&D cycles and great uncertainty of R&D results, it is difficult for them to keep up with external technology updates. According to a survey conducted by Accenture Consulting in 2017 among 1,100 business executives from 13 industries in seven countries, "Acquisition of new digital capabilities" and "demand for new technologies" ranked alongside "expansion into new geographic markets" and "expansion into new industries" as the top drivers for M&A. The Boston

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Consulting Group (BCG) is a leading global provider of M&A services. According to the Boston Consulting Group (BCG), digital M&A has accelerated rapidly in recent years, with the global value of digital M&A deals reaching $658 billion in 2017 - more than double the value five years earlier-and digital deals represented 24% of the entire M&A market, with firms outside the tech sector seeking to acquire digital capabilities accounting for 2/3 of digital M&A deals[1]. Chinese firms are particularly active in digital M&A deals, leading the world in digital M&A deals according to international law firm *Freshfields Bruckhaus Deringer*, with Chinese listed companies included in S&P Global 1200 Index executed an average of 4.6 data or technology M&A, second only to Dutch companies (4.7 on average), with an average investment of US$1.47 billion per deal, up from US$1.26 billion for US companies, which is the highest in the world. And more than half (56%) of digital M&A executed by Chinese firms is cross-border[2].

Research on technology M&A and innovation focus on post-R&D investments (Zhao, Lin, & Hao, 2019), the integration capability or the degree of integration (Chen, Liu, & Ge, 2021a, 2021b), the knowledge base (Cloodt, Hagedoorn, & Van Kranenburg, 2006; Cassiman, Colombo, Garrone, & Veugelers, 2005, Hagedoorn & Duysters, 2002; Álvarez & Torrecillas, 2020), and proximity factors (such as geographical proximity, cognitive proximity and organizational proximity (Ensign, Lin, Chreim, & Persaud, 2014) of the M&A parties. And relevant studies focus less on digital M&A. Digital M&A means that the target companies are digital technology companies (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Huang, Henfridsson, Liu, & Newell, 2017; Tumbas, Berente, & vom Brocke, 2017) and it is different from other technology M&A. First, the inherent characteristics of digital technologies differ from other technologies, in terms of digital technology transactions, which are characterized by fast iterations, high external transaction costs, and high risks, and in terms of digital technology characteristics, which are characterized by *repro grammable functionality* and *data homogenization* (Yoo, Henfridsson, & Lyytinen, 2010; Ciriello, Richter, & Schwabe, 2018). Secondly, digital M&A is an important or even the only way for the digital transformation of firms (Catlin & May, 2020; Tang & Jiang, 2021). Digital M&A is different from general technology M&A in that digital M&A focuses more on the expansion of digital business and the building of digital capabilities by acquiring digital technology (Tang & Jiang, 2021). Current research related to digital M&A includes the following, Tang & Jiang (2021) summarize the connotations and characteristic facts of digital M&A. Jiang & Tang (2021) empirically examine the characteristics and drivers of cross-border digital M&A using industry-level data. Hanelt, Firk, Hildebrandt, & Kolbe (2021) suggest that digital M&A helps industrial-age firms in the automotive industry to build a digital knowledge base, which in turn enables them to drive digital innovation. However, the existing literature does not examine the impact of digital M&A on innovation for all micro-firms and lacks empirical evidence from China. Therefore, based on theoretical analysis, the authors empirically examine the impact of digital M&A on firm innovation using data from Chinese listed companies from 2006 to 2019, which enriches the research related to digital M&A.

The authors contribute to the literature as follows: First, this paper enriches the micro-firm-level evidence on the impact of digital M&A on firms' innovation behavior; Second, this paper constructs richer indicators of firms' digital innovation and examines the impact of digital M&A on firms' innovation behavior in terms of overall innovation, radical innovation, and digital innovation; Third, this paper classifies digital M&A events, explores the impact of vertical digital M&A and horizontal digital M&A, domestic digital M&A and cross-border digital M&A on the heterogeneity impact of innovation, and examines the possible consequences and causes of heterogeneity, which helps to understand digital M&A more comprehensively.

BACKGROUND AND HYPOTHESES

As a way of acquiring exogenous innovation resources, the resources acquired by digital M&A mainly include knowledge and technology resources and user resources. Knowledge and technology resources are the direct source of innovation for firms. By executing digital M&A, firms can quickly and directly acquire the knowledge and technology of the target firms, especially the tacit and complex knowledge and technology, as well as the intellectual capital that possesses the relevant knowledge and technology and has innovative ideas. In particular, digital technologies are characterized by rapid iterations, high external transaction costs, and high external transaction risks. Digital M&A not only allows for the full control of the digital technologies of the target firm (Datta & Roumani, 2015) but also effectively avoids the risk of digital technology leakage (Gao & Iyer, 2006). In addition, the *reprogrammable functionality* and *data homogenization* of digital technology (Yoo, Henfridsson, & Lyytinen, 2010; Ciriello, Richter, & Schwabe, 2018) can facilitate the integration. User resources are also an important intangible asset as innovation resources. User resources can be used to identify and satisfy customer needs. It is important to note that the *user base* in the digital economy (Oliva, Sterman, & Giese, 2003; Prasad, Venkatesh, & Mahajan, 2010; Sun, Xie, & Cao, 2004) is different from the *customer base* in that it does not need to be based on past purchase behavior (Schmittlein & Peterson, 1994). So user resources are also crucial for firms to gain a competitive advantage and expand their market size (E. Fang, Palmatier, & Grewal, 2011; Xu & Shan, 2019). Digital M&A (especially when the target company is a platform company) facilitates direct and rapid access to more user resources for the acquire firm. At the same time, the acquire can use digital technology to track and predict the dynamic needs of users in a timely, efficient and accurate manner, thus enabling deeper customer involvement in the R&D and innovation process.

Hypothesis 1: Digital M&A will promote firm innovation.

Digital M&A enables firms to apply digital technology to effectively tap into the implicit information deposited, and breakthrough the boundary constraints of traditional factors to explore the new value function of information data (Acemoglu, 2003; Qi & Xiao, 2020), and improve the efficiency of firms in processing large amounts of unstructured and non-standardized information, which helps them to identify optimal innovation paths and optimally reallocate innovation resources (Wu, Hu, & Ren, 2021). In addition, as firms tend to suffer from technological inertia, for example, because their technologies are relatively mature, new technologies tend to have similarities and evolutionary continuity with the original technologies while there are few technological mutations, which may result in their technologies being locked within a certain range of small changes (Li, 2019). While the convergence of digital innovation blurs industry boundaries, organizational boundaries, sector boundaries, and even product boundaries (Nambisan, Lyytinen, Majchrzak, & Song, 2017). Firms can cross boundaries to fully integrate internal and external resources and make efficient allocations of resources, thus breaking through the original technology track to achieve innovation.

Hypothesis 2: Digital M&A enables firms to break away from technology path-dependence to achieve radical innovation.

Digital M&A not only contributes to building the digital knowledge base of firms but also enables them to continuously acquire digital knowledge. Digital M&A helps firms to build a digital knowledge base quickly and efficiently (Hanelt, Firk, Hildebrandt, & Kolbe, 2021), and produces positive synergy effects on innovation over the firms(Fomba Kamga, Talla Fokam, & Nchofoung, 2022), which enables firms to access all the digital knowledge and technologies of the target firm in a shorter period, consequently driving the potential for recombination and knowledge creation (Ahuja & Katila, 2001; Bos, Faems, & Noseleit, 2017;Dong & Yang, 2019). Digital M&A improves the ability of firms to acquire digital knowledge, digital knowledge is not only a direct source of innovation, but also the dynamic and extended nature of digital technology improves the ability of firms to acquire new digital knowledge, which is conducive to further absorption and utilization of digital knowledge, and this increases the potential of digital innovation (Yoo, Boland Jr, Lyytinen, & Majchrzak, 2012; Ciriello, Richter, & Schwabe, 2018).

Hypothesis 3: Digital M&A will enable firms to drive digital innovation.

DATA AND VARIABLES

Data

Chinese Listed Company data. This paper mainly uses Chinese A-share listed companies from 2006 to 2019 as the research sample and screens the sample according to the following principles: (1) exclude the financial sector samples; (2) exclude ST, PT, and insolvent samples; and (3) exclude samples with missing relevant variables. The final results involve 32,991 firm-annual observations from 2006 to 2019. Data at the firm level are obtained from the CSMAR Database (China Stock Market & Accounting Research Database) and the Chinese Research Data Services (CNRDS), with some data sourced from the annual reports of listed companies. And data at the regional level are obtained from the China City Statistical Yearbook.

Patent data. The patent data in this paper is mainly obtained from the China Patent Database maintained by the State Intellectual Property Office, the patent data from the CSMAR Database (China Stock Market & Accounting Research Database), and the innovation patent research and citation data from the Chinese Research Data Services (CNRDS). Patent data mainly includes patent abstract, patent name, patent type (invention, utility, and design), patent application number, patent number, application date, grant date, legal status, and patent cited information.

M&A data. The M&A data is sourced from the Thompson Financial Securities Data Company (SDC database). Referring to previous literature (Nguyen & Phan, 2017). The authors treat the data as follows: (1) Exclude LBOs, spin-offs, recapitalizations, self-tender offers, exchange offers, repurchases, and privatizations types of M&As. (2) Exclude M&A events in the highly regulated utility sector (SIC codes 4900-4999) and the financial sector (SIC codes 6000-6999). (3) Retain transactions where the acquirer owns less than 50% of the target firm before the acquisition but more than 50% of the shares after the acquisition.

Variables and Measurement

Digital M&A. Refer to Hanelt, Firk, Hildebrandt, & Kolbe (2021) for the definition of digital M&A as acquisitions of (or mergers with) digital target firms, specifically, M&A is defined as mergers and acquisitions by a firm that aims at acquiring (or merging with) firms that intensely leverage digital technologies as critical elements of their business models (Huang, Henfridsson, Liu, & Newell, 2017; Tumbas, Berente, & vom Brocke, 2017), which the authors classify as firms that intensely leverage digital technologies as critical elements of their business. Digital technologies are defined as combinations of information, computing, communication, and connectivity technologies and include instances such as cloud computing, mobile technology, social media, and big data analytics (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013). The authors manual evaluate whether an M&A matches the digital M&A definition based on the description of the industry business information of the M&A, which the description of the merger's business industry is provided in the SDC database. To determine whether a company is a digital enterprise, and to label M&A events in which the subject party is a digital enterprise as digital M&A events. The authors match the SDC database with the Chinese listed companies' database. A final total of 1256 digital M&A events are obtained. And if the firm executes a digital M&A event, the dummy variable that measures digital M&A (dmna) takes the value 1, otherwise, it takes the value 0. And the year of the digital M&A event is the policy year. In the policy year and the year after, the time dummy variable (post) takes 1, otherwise, it takes 0.

Vertical and horizontal M&A. The authors identify vertical and horizontal M&A and following the literature the authors use the input-output table to calculate a vertical relatedness coefficient between the primary industry of the acquirer and that of the target. But since the BEA (Bureau of Economic Analysis) input-output table is based on the NAICS (North American Industry Classification System) codes, the industry classification of firms in the SDC M&A database is based on the SIC (Standard Industry Classification) codes. So the authors first use the bridge table provided by the NAICS Association to convert the four-digit SIC codes to the corresponding six-digit NAICS codes. Secondly, refer to Fan & Goyal (2006), the authors construct the vertical relatedness coefficients using the BEA input-output table, and if the vertical relatedness coefficient for an M&A event is greater than 1%, it is considered a vertical M&A event. It should be noted that only the BEA input-output tables for 2007 and 2012 are available in the sample period. In this paper, the 2007 input-output tables are used for the 2006-2011 sample and the 2012 input-output tables are used for the 2012-2019 sample.

Patent application. Since there is a time lag between the application and granting of a patent, therefore, the authors use the number of patent applications as the benchmark dependent variable. To avoid the effect of zero values in the patent data, refer to Liu & Qiu (2016); Tan, Tian, Zhang, & Zhao (2014), the authors use the logarithm of the number of patents plus 1 value (*lnapply*).

Radical innovation is an innovation that is a breakthrough in a technical principle or idea that creates a disruptive change to an existing product or method (J. A. Schumpeter, 1939; J. Schumpeter & Backhaus, 2003; Christensen, 1997). According to the Chinese Patent Law, an invention is a new technical solution proposed for a product, method, or improvement thereof. The Patent Law conducts a rigorous examination of the novelty, inventiveness, practicability, and non-obviousness of an application for a patent for an invention, which is more innovative compared to a utility model patent and a design patent. Therefore, regarding the measurement of radical innovation, the authors refer to Zhang, Sun, & Xie (2020), and Liu, Lu, Lu, & Luong (2015) to identify invention patents as radical innovations. In this paper, the following methods are specifically used to measure radical innovation using invention patent information: one is to directly measure the number of invention patent applications (*lninvia*); the second is to use the ratio of the number of invention patent applications to the total number of patent applications (*inviar*); the third is to use the cited information of invention patents to construct indicators reflecting the firm's radical innovation, such as the average annual number of citations (*avcited*) of a firm's patents (Kogan, Papanikolaou, Seru, & Stoffman, 2017; Mann, 2018), which is only counted in this paper within five years after the patent application is granted, to avoid the problem of "broken tails" (Hall, Jaffe, & Trajtenberg, 2005). In addition, some studies suggest that patent generality measures the industry scope of an innovation's future influence (Hall, Jaffe, & Trajtenberg, 2005; Acharya & Xu, 2017), while Cai & Li (2019) argue that the importance of different industries' citation is further considered. This characteristic can be defined as the knowledge contribution degree of the invention patent, which is calculated as

$$knowldegree_i = \sum_j \left(\frac{c^{ji}}{\sum_k c^{jk}} \right) \tag{1}$$

where c^{ji} is the cited number of patents in industry *j* to patents in the industry *i*. And $\frac{c^{ji}}{\sum_k c^{jk}}$ is the fraction of citations made by *j* that is attributed to *i*.

In addition, the authors consider an indicator that captures the complexity of the patent (Akcigit, Baslandze, & Stantcheva, 2016), which is calculated according to

$$comp_{ipt} = 1 - \sum_{p \in i} (ratio_{ipt})^2 \tag{2}$$

where *ratio* is the ratio of each IPC classification *p* to the total number of classifications included in the invention patent.

Digital innovation. In this paper, the authors use the number of patents that intensely leverage digital technologies to measure the digital innovation of the firm. The authors can obtain the abstract information of the corresponding patents from the China Patent Database, and manual evaluation of whether the abstract matches the definition of digital innovations. And the authors can obtain the number of logarithmic digital patent applications (*lnapdigitl*), the number of logarithmic digital invention patent applications (*lninvdigitl*), the number of logarithmic digital utility patent applications (*lnutidigitl*), and the number of logarithmic digital design patent applications (*lndesdigitl*), as well as the number of digital patent applications as a percentage of total patent applications (*apdigitlr*).

Control variables used in this paper mainly include (1) firm age (*age)*, the logarithmic form of firm duration; (2) firm size (*size*), the logarithmic form of total assets; (3) a dummy variable for state-owned firms (*soe*), with state-owned firms taking 1 and non-state-owned firms taking 0; (4) firm financing constraints (*SA*): calculated by referring to Hadlock & Pierce (2010); (5) the asset-liability ratio (*daratio),* calculated as the ratio of total liabilities to total assets; (6) the industry competition (*hhi*): measured by using the Herfindahl index; (7) the level of the internet development (*inter*), measured by using the number of websites per 100 firms of the province where the firm is located; (8) level of economic development (*gdp),* the logarithm form of GDP of the city where the firm is located; (9) capital intensity (*klratio*), calculated as the ratio of total assets to operating revenue; (10) risk aversion degree (*risk*), calculated as the ratio of the firm's cash holding to total assets; (11) export (*exp*), the logarithmic form of the firm's export value.

EMPIRICAL TESTS

The authors are interested in the differences in innovation between firms that execute digital M&A compared to those that do not. The mean test results are reported in Table 1 and show that there are significant differences in the mean of the logarithmic form of patent applications, patent grants, and digital patent applications between the two groups of firms. And firms that execute digital M&A are more innovative. However, the results of the mean test are not sufficient to show that there is a causal relationship between digital M&A and firm innovation, and a more rigorous econometric analysis will be conducted to test the causal relationship further.

Empirical Method

The objective of this paper is to test whether there is an actual causal relationship between digital M&A and firm innovation, ideally by comparing the difference in innovation between the firm that executed digital M&A and the same firm that did not, and thus revealing the causal effect of digital M&A on firm innovation, however, the authors are unable to observe the innovation behavior of firms that executed digital M&A in the absence of digital M&A, which is the "counterfactual". The Propensity Score Matching Method (PSM), proposed by Heckman, Ichimura, & Todd (1997), can deal with the above problem more effectively. The basic idea is to construct a non-digital M&A firm (i.e. a control group) whose main characteristics are most similar to those of the firm executed digital M&A (i.e. the treatment group) before digital M&A, and then match the treatment group with the control group so that the matched control group can be approximated as a 'counterfactual' of the treatment group. Specifically for the problem under study in this paper, the authors proceed as follows.

First, the authors divide the sample into treatment group and control group, with one group being the treatment group of firms that execute digital M&A $i \in \Omega_1$ and the control group of firms that did not execute digital M&A $j \in \Omega_0$. If firm *i* executed a digital M&A in period *t*, $INNO_{i,t+s}^{1}$ denotes firm *i*'s innovation in period *t*+ *s*, and $INNO_{i,t+s}^{0}$ denotes firm *i*'s innovation in period *t*+*s* if firm *i*

Table 1.
Results of the mean test for differences in innovation

Variables	Explanations	Mean		Difference	t value
		Digital M&A	Non-digital M&A		
lnapply	patent applications	1.4740	1.1427	-0.3313	-7.7448
lninvia	invention patent applications	0.9891	0.7375	-0.2517	-7.7620
lnumia	utility patent applications	0.9225	0.6923	-0.2302	-6.8275
lndesia	design patent applications	0.3221	0.2375	-0.0845	-4.0702
lngrant	patents granted	1.3581	1.0516	-0.3066	-7.6264
lninvig	invention patents granted	0.6735	0.4801	-0.1934	-7.6520
lnumig	utility patents granted	0.9455	0.7212	-0.2243	-6.5421
lndesig	design patents granted	0.3483	0.2711	-0.0772	-3.3426
lnapdigitl	digital patent applications	0.2242	0.0615	-0.1628	-14.5048
lndigitl_invent	digital invention patent applications	0.1344	0.0322	-0.1022	-13.2450
lndigitl_utility	digital utility patent applications	0.1220	0.0400	-0.0821	-9.5197
lndigitl_design	digital design patent applications	0.1124	0.0362	-0.0762	-9.7337
apdigitlr	ratio of digital patent applications	0.0556	0.0153	0.0169	-13.0227

had not executed digital M&A, then the effect of a firm executing digital M&A on innovation, the average treatment effect (ATT), can be expressed as

$$' = \bullet\left(INNO^{1}_{i,t+s} - INNO^{0}_{i,t+s} \mid \Omega_{1}\right) = \bullet\left(INNO^{1}_{i,t+s} \mid \Omega_{1}\right) - \bullet\left(INNO^{0}_{i,t+s} \mid \Omega_{1}\right) \quad (3)$$

Where $\bullet\left(INNO^{0}_{i,t+s} \mid \Omega_{1}\right)$ is the innovation of firm *i* in the absence of digital M&A, which is an unobservable "counterfactual", and is treated by using the innovation of the control firm in period *t+s*, which is $\bullet\left(INNO^{0}_{i,t+s} \mid \Omega_{0}\right)$ as an approximate proxy for $\bullet\left(INNO^{0}_{i,t+s} \mid \Omega_{1}\right)$. However, the above treatment presupposes that the paths of innovation in time for the treatment and control group firms are parallel if the firm had not executed digital M&A. Existing studies have typically used some common influencing factors as covaiates to match the treatment group firms with the most similar firms from the control group for analysis.

Second, the authors calculate the probability of executing digital M&A for firms in the treatment and control groups $p = p\left(dmna = 1\right)$, based on existing studies, covaiates $X_{i,t-1}$ include firm age (*age*), firm size (*size*), nature of ownership (*soe*), financing constraints (*SA*), the asset-liability ratio (*daratio*), capital intensity (*klratio*), risk aversion degree (*risk*), and firm export (*exp*).

The authors estimate the following model using the logit method:

$$p = p\left(dmna = 1\right) = \Phi\left(X_{i,t-1}\right) \quad (4)$$

The probability prediction value obtained from the above equation $\hat{p}$ is the propensity score, and the PSM method is based on the $\hat{p}$ value to match the treatment and control group firms. Referring to Becker & Ichino (2002), the authors use one-to-one nearest neighbor matching in the benchmark regression analysis for matching.

As firms execute digital M&A in different years, the authors construct the following multiple difference in difference model based on propensity score matching.

$$inno_{ijrt} = \beta_0 + \beta_1 dmna_{ijrt} * post_i + \boldsymbol{Z}'_{ijrt} + \boldsymbol{Z}'_{jt} + \boldsymbol{Z}'_{rt} + \left\{\boldsymbol{F}\right\} + \varepsilon_{ijrt} \tag{5}$$

where the subscripts *i*, *j*, *r*, and *t* denote firm, industry, region, and year, respectively. $inno_{ijrt}$ are proxy variables for firms' innovation behavior. $dmna_{ijrt}$ denotes whether the firm *i* execute digital M&A, and $post_i$ is the time dummy variable, before the year firm *i* executed a digital M&A $post = 0$, and after the year firm *i* executed a digital M&A $post = 1$. So the coefficient of $dmna_{ijrt} * post_i$, which is β_1 measures the impact of digital M&A on innovation, and if β_1 is significantly greater than 0, it means that digital M&A significantly increases the innovation level of the firm, and vice versa. $\boldsymbol{Z}'_{ijrt}$, $\boldsymbol{Z}'_{jt}$ and $\boldsymbol{Z}'_{rt}$ denote firm-level, industry-level, and regional-level control variables respectively, where firm-level control variables include firm age (*age*), firm size (*size*), nature of ownership (*soe*), financing constraints (*SA*), and asset-liability ratio (*daratio*); industry-level control variable is the industry competition (*hhi*); regional-level control variables include the level of internet development (*inter*) and the level of economic development (*gdp*). In addition, the $\left\{\boldsymbol{F}\right\} = \left\{\varpi_i, \varphi_t, \zeta_j, \rho_r\right\}$ denote firm, year, industry and province fixed effects, respectively. As there are listed companies that have changed their main business or place of incorporation in the sample period, so the authors control the industry and province fixed effects. Random error term ε_{ijrt} clustered at the firm level.

Baseline Results

To test the reliability of the matching results, the authors conduct a propensity score matching balance test, the results of which are reported in Table 2. The table shows that the standard deviations of all variables are significantly reduced after matching and are less than 10%. The results of the t-test don't reject the original hypothesis that there is no systematic difference between the treatment and control groups, that is there is no significant difference between the matched variables in the treatment and control groups after matching. This paper also plots the distribution characteristics of the absolute values of the bias before and after matching (see Figure 1), which can be more intuitively seen that the standardized bias of all variables is significantly reduced after matching. The above tests indicate that the method of propensity score matching and the selection of matching variables in this paper are reasonable. The common support test as shown in figure 2.

Table 3 reports the impact of digital M&A on the number of firm patent applications, where the preliminary regression results in column (1), which control firm and year fixed effects only, indicate that digital M&A significantly increases the number of patent applications. Column (2) reports the results of the regression with the conclusion of control variables, and the coefficient on *dmna*post* remains significantly positive and larger than in column (1). Columns (3) and (4) further control industry and province fixed effects, respectively, and are generally consistent with the regression results in column (2), with the coefficient in column (4) being 1.4406 and significant at the 1% level of significance, indicating that digital M&A significantly increases the number of patent applications, validating hypothesis 1. The coefficients of the control variables are as expected in general. The coefficient of *soe* is significantly positive, indicating that the innovation effect of digital M&A is higher in state-owned firms. Referring to Beck, Levine, & Levkov(2010), the authors test the dynamic effect of digital M&A on innovation (see Figure 3), the authors consider a 12-year window, spanning from 6 years before digital M&A until 6 years after digital M&A. The dashed lines represent 95%

Table 2.
Propensity score matching balance test results

Variable	Unmatched Matched	Mean		%bias	%reduct |bias|	t-test	
		Treated	Control			t	p>|t|
age	U	13.789	15.453	-32.5		-8.32	0.000
	M	13.789	13.837	-0.9	97.1	-0.19	0.853
size	U	21.745	22.06	-29.3		-6.96	0.000
	M	21.745	21.734	1.1	96.4	0.23	0.815
soe	U	0.12903	0.38824	-62.0		-14.32	0.000
	M	0.12903	0.12231	1.6	97.4	0.39	0.696
SA	U	-3.6692	-3.7163	21.4		5.42	0.000
	M	-3.6692	-3.6716	1.1	94.8	0.22	0.826
daratio	U	0.37074	0.42826	-31.0		-7.77	0.000
	M	0.37074	0.3746	-2.1	93.3	-0.42	0.676
klratio	U	2.2797	2.0448	15.7		3.87	0.000
	M	2.2797	2.1532	8.5	46.2	1.44	0.149
risk	U	0.20106	0.18064	15.8		4.43	0.000
	M	0.20106	0.20433	-2.5	84.0	-0.45	0.650
exp	U	18.654	19.073	-19.8		-5.20	0.000
	M	18.654	18.723	-3.3	83.5	-0.65	0.515

Figure 1.
Distribution characteristics of the standardized %bias across covariates

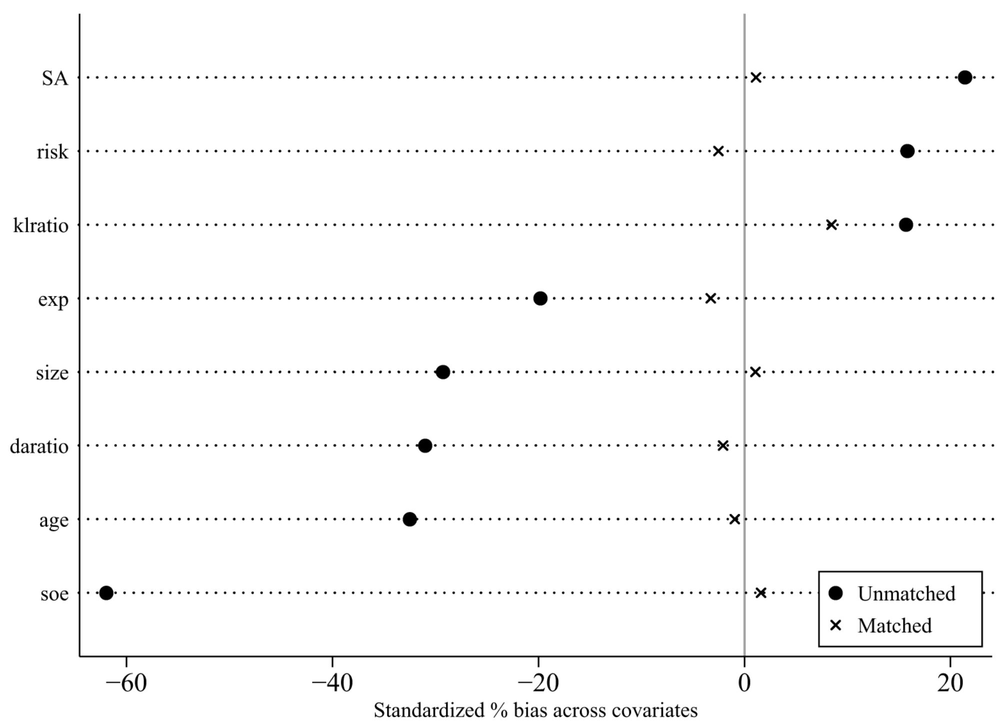
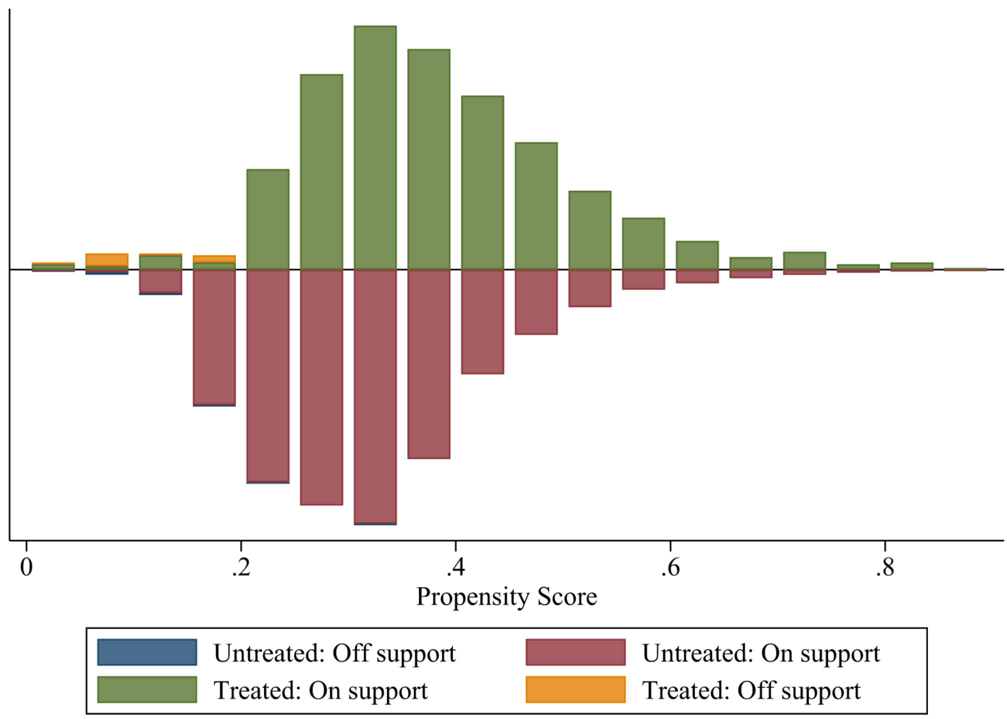


Figure 2.
The common support test



confidence intervals. From Figure 3, the authors can see that the assumption of parallel trend is satisfied. And executing digital M&A not only has a significant immediate effect of increasing firm innovation, but also a persistent one, but the innovation effect diminishes year by year.

The Impact of Digital M&A on Radical Innovation

The literature review section explains that executing digital M&A helps firms to optimize their innovation paths and drives them to radical innovation. This section examines the impact of digital M&A on firms' radical innovation. Table 4 reports the regression results. Column (1) reports the regression results of digital M&A on the number of invention patent applications (*lninvia*), and the regression coefficients show that digital M&A significantly increases the number of invention patent applications. Columns (2)-(4) report the regression results of digital M&A on the share of invention patents (*inviar*), the average annual number of invention patents cited (*avcited*), the *knowledge* contribution of invention patents (*knowldegree*), and the technical complexity of invention patents (*comp)* respectively. The regression results in column (2) indicate that digital M&A significantly increases the share of invention patents. The regression results in column (3) shows that digital M&A significantly increases the number of citations of invention patents, and the regression results in columns (4) and (5) show that digital M&A significantly increases the knowledge contribution of invention patents to cities and the technical complexity of patents. Therefore, the authors can conclude that digital M&A significantly drives the firm to radical innovation, which verifies hypothesis 2 proposed in this paper.

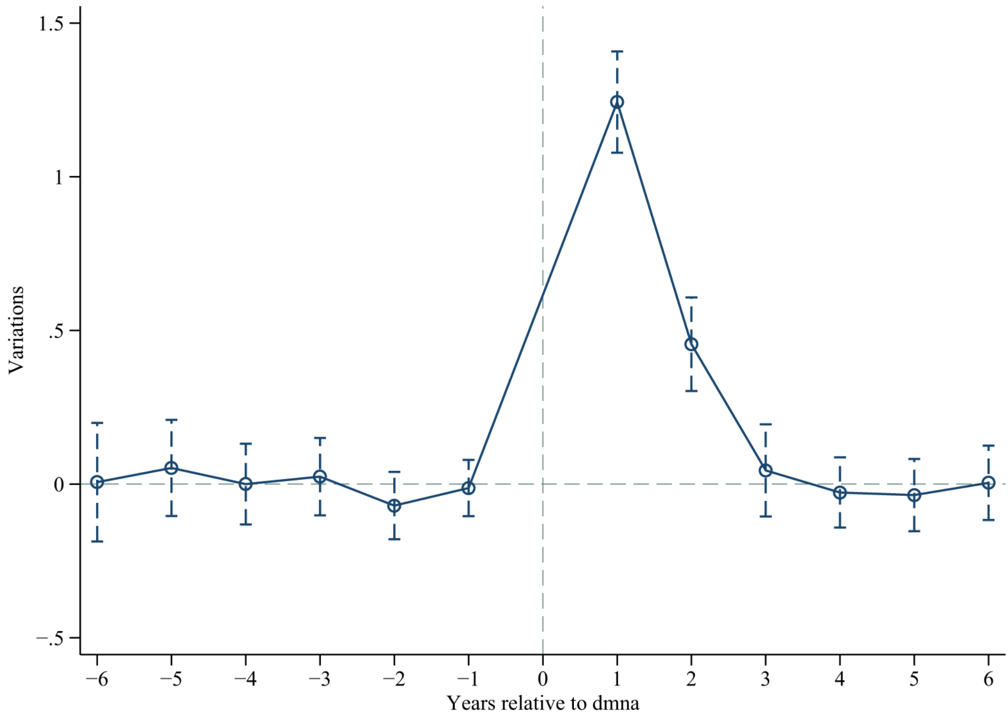
Table 3.
Impact of digital M&A on patent applications (Benchmark regression)

variables	(1)	(2)	(3)	(4)
	lnapply	lnapply	lnapply	lnapply
dmna*post	0.3970***	1.4339***	1.4263***	1.4406***
	(11.00)	(19.54)	(19.42)	(17.64)
age		-0.5328***	-0.5373***	-0.5405***
		(-22.47)	(-22.82)	(-22.05)
size		-0.0119	0.0086	0.0091
		(-0.53)	(0.38)	(0.40)
soe		0.0900*	0.1029**	0.1192**
		(1.68)	(2.00)	(2.31)
SA		0.2728	0.2046	0.2231
		(1.54)	(1.17)	(1.27)
daratio		0.1284*	0.1071	0.1178
		(1.66)	(1.42)	(1.55)
hhi		-0.2970*	-0.0729	-0.0590
		(-1.89)	(-0.37)	(-0.30)
inter		-0.1650	-0.1655	-0.1338
		(-1.03)	(-1.04)	(-0.78)
gdp		0.0797	0.1012	0.1515
		(1.20)	(1.49)	(1.33)
_cons	9.2970***	1.1212***	1.1214***	1.1206***
	(32.50)	(386.83)	(386.34)	(322.57)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
Province FE	No	No	No	Yes
N	29233	28226	28226	28226
Within R^2	0.0579	0.0597	0.0602	0.0608

The Impact of Digital M&A on Digital Innovation

In this section, the authors examine whether digital M&A affects digital innovation and leans firms toward digital innovation. Columns (1)-(4) of Table 5 show the regressions of digital M&A on the logarithm form of the total number of digital patent applications (*lnapdigitl*) and the number of three types of digital patent applications, namely the logarithm form of the number of digital invention patent applications (*lninvdigitl*), the logarithm form of the number of digital utility patent applications (*lnutidigitl*) and the logarithm form of the number of digital design patent applications (lndesdigitl), respectively. The regression results of the digital patent applications (*lndesdigitl)* show that, overall, digital M&A contributed to an increase in the total number of digital patent applications as well as the number of digital invention and utility patent applications. But the effect of digital M&A on the number of digital design patent applications is not

Figure 3.
The dynamic effect of digital M&A on innovation



significant. The regression results in column (5) analyze the effect of digital M&A on the ratio of digital patent applications (*apdigitlr*), the regression coefficient is significantly positive, indicating that digital M&A leans firms toward digital innovation. Therefore, digital M&A in general improves the level of digital innovation of firms, which verifies hypothesis 3 proposed in this paper.

Endogeneity Processing

PSM-DID can partially address the endogeneity problem, further endogeneity processing is still required. To solve the endogeneity problems such as reverse causality, the authors use the integration policy of informatization and industrialization as a quasi-natural experiment for endogeneity processing. China to promote informatization and industrialization depth fusion, comprehensively improve the quality and efficiency of industrial development, in August 2013, the ministry issued the "*Informatization and industrialization depth fusion special action plan (2013-2018)* ", for the next five years the key work of informatization and industrialization depth fusion comprehensive deployment. In September 2013, Standardization Administration issued the "*Standards for the Evaluation of Integration of Informatization and Industrialization of Industrial Enterprises*" (hereinafter referred to as the "Standards"). Digital construction runs through all links of enterprise design, production, sales, and management, and has become the national standard to promote the digital transformation of firms. In May 2014, the Ministry of Industry and Information Technology (MIIT) issued the Notice of the General Office of the Ministry of Industry and Information Technology on printing and issuing the 2014 Work Plan for the "*Standardization of the Integration Management System and the List of Pilot Enterprises for the Standardization of the Integration Management System*" (hereinafter referred to as the "List"). And in the following years have released the industrialization and information integration management system standard implementation work plan and standard implementation

Table 4.
The impact of digital M&A on radical innovation

variables	(1)	(2)	(3)	(4)	(5)
	lninvia	inviar	avcited	knowldegree	comp
dmna*post	0.7610***	0.5085***	0.1973***	1.7440***	0.1551***
	(11.47)	(14.53)	(16.23)	(5.70)	(5.13)
age	-0.2884***	-0.2017***	-0.0758***	-0.7700***	-0.0550***
	(-14.41)	(-18.38)	(-23.14)	(-9.38)	(-5.86)
size	0.0156	-0.0042	-0.0016	-0.3474***	0.0185**
	(0.89)	(-0.45)	(-0.39)	(-3.73)	(2.46)
soe	0.1013***	0.0138	0.0049	-0.3034	0.0646**
	(2.61)	(0.56)	(0.37)	(-1.17)	(2.21)
SA	0.0407	-0.0977	-0.1635***	-2.3591***	0.0143
	(0.28)	(-1.34)	(-5.36)	(-2.83)	(0.23)
daratio	0.1382**	-0.0085	0.0350**	0.2870	-0.0332
	(2.40)	(-0.26)	(2.16)	(0.89)	(-1.17)
hhi	0.0293	-0.0397	-0.0200	0.6184	0.0674
	(0.19)	(-0.48)	(-0.41)	(0.52)	(0.80)
inter	-0.2560*	0.0091	-0.0159	-1.9660***	-0.0979*
	(-1.81)	(0.14)	(-0.60)	(-3.33)	(-1.83)
gdp	0.1589*	-0.0826*	0.0136	0.1171	0.0734*
	(1.67)	(-1.87)	(0.66)	(0.22)	(1.86)
_cons	0.7292***	-0.7304***	0.0385***	5.3922***	0.2624***
	(262.53)	(-45.64)	(18.38)	(89.31)	(19.97)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
N	28155	13515	19300	17231	12553
Within R^2	0.0526	0.0818	0.0813	0.1930	0.0341

pilot enterprises list. The integration of informatization and industrialization has become an important policy for the government to carry out the digital transformation of enterprises, and digital M&A is an important way for enterprises to carry out the digital transformation. Therefore, this policy is an excellent quasi-natural experiment for examining the economic consequences of digital M&A. This paper constructs the DID model based on the List of informatization and industrialization pilot firms from 2014 to 2018 and investigates its impact on innovation. During the sample period, the pilot firm is set as the treatment group (*treat=1*), and the control group is set as the control group (*treat=0*) if the firm has not been the pilot enterprise during the sample period. *post=1* is set in the year when the firm is selected as the pilot firm and in subsequent years, otherwise *post=0*. Columns (1) to (4) of the regression results in Table 6 shows that the coefficient of *treat*post* is significantly positive, which verifies the research conclusion that digitalization promotes innovation. Column (5)

Table 5.
The impact of digital M&A on digital innovation

variables	(1)	(2)	(3)	(4)	(5)
	lnapdigitl	**lninvdigitl**	**lnutidigitl**	**lndesdigitl**	**apdigitlr**
dmna*post	0.0729***	0.0379**	0.0489**	0.0272	0.1103***
	(3.09)	(2.43)	(2.55)	(1.43)	(8.37)
age	-0.0085	-0.0003	-0.0103*	-0.0032	0.0014
	(-1.32)	(-0.07)	(-1.81)	(-0.59)	(0.52)
size	0.0004	-0.0006	-0.0005	-0.0027	0.0003
	(0.06)	(-0.15)	(-0.13)	(-0.75)	(0.17)
soe	-0.0333***	-0.0250**	-0.0119	-0.0188**	-0.0088**
	(-2.92)	(-2.47)	(-1.01)	(-2.17)	(-2.04)
SA	0.1841***	0.1054***	0.1085***	0.1064***	0.0546***
	(4.28)	(3.60)	(3.76)	(3.94)	(3.68)
daratio	-0.0765***	-0.0548***	-0.0404**	-0.0311**	-0.0255***
	(-3.67)	(-3.79)	(-2.33)	(-2.12)	(-3.87)
hhi	-0.0933*	-0.0201	-0.0860***	-0.0880***	-0.0107
	(-1.81)	(-0.53)	(-2.63)	(-2.80)	(-0.75)
inter	-0.1099**	-0.0359	-0.0687	-0.0524	-0.0109
	(-2.00)	(-0.87)	(-1.56)	(-1.38)	(-0.63)
gdp	0.0036	-0.0028	0.0356	0.0062	0.0015
	(0.13)	(-0.17)	(1.40)	(0.36)	(0.33)
_cons	0.0656***	0.0348***	0.0418***	0.0387***	0.0258***
	(67.28)	(54.00)	(52.30)	(52.27)	(49.51)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
N	28226	28226	28226	28226	28226
Within R^2	0.0106	0.0083	0.0069	0.0062	0.0370

is the dynamic effect test. It can be seen from the regression results that the regression coefficient before being selected as the pilot firm is not significant, while the regression coefficient of the first four periods after being selected as the pilot firm is significantly positive, which tests the promotion effect of this policy on firm innovation. Digital M&A is an important way for firm digitalization. The innovation effect of this policy can explain the innovation effect of M&A to a certain extent.

Robustness Checks

Placebo Test

The authors do the placebo test and the result is shown in figure 4. To do the placebo test, the authors first group firms according to their province, and then the authors randomly select a year as a firm's

Table 6.
The quasi-natural experiment

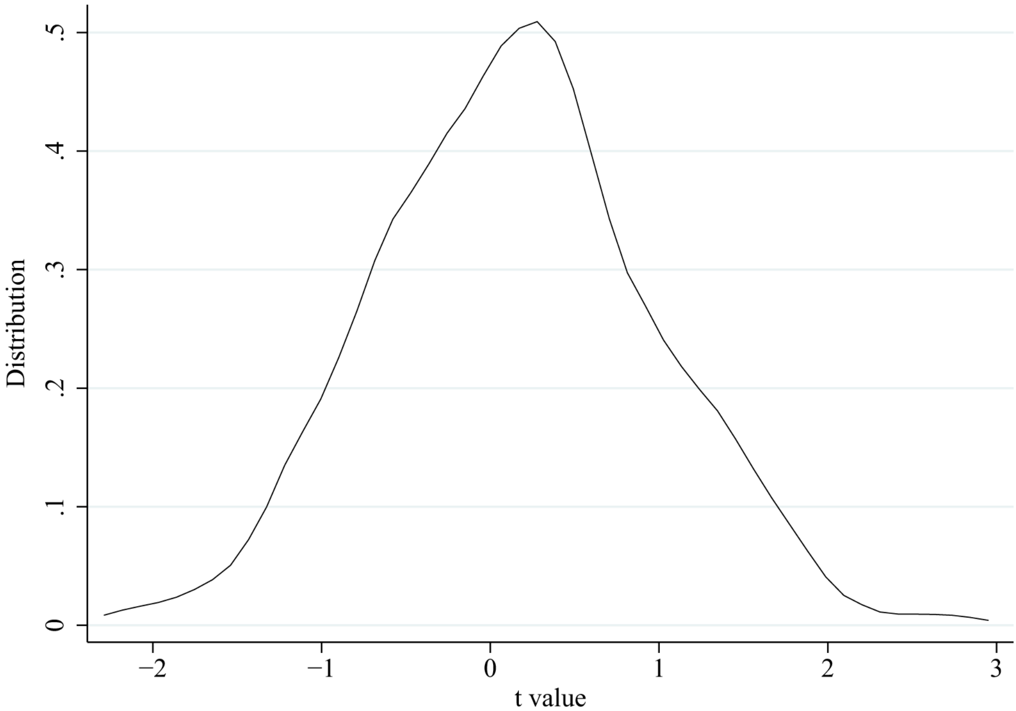
variables	(1)	(2)	(3)	(4)	(5)
	lnapply	lnapply	lnapply	lnapply	lnapply
treat*post	0.2057***	0.1761***	0.1690***	0.1668***	
	(4.20)	(3.49)	(3.35)	(3.30)	
d_5					-0.0163
					(-0.17)
d_4					0.0991
					(1.07)
d_3					0.0720
					(0.72)
d_2					-0.0981
					(-0.97)
d_1					0.0008
					(0.01)
d1					0.9660***
					(13.24)
d2					0.7587***
					(8.78)
d3					2.3770***
					(17.66)
d4					0.2883**
					(2.22)
d5					0.0032
					(0.02)
Controls	No	Yes	Yes	Yes	
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes
Province FE	No	No	No	Yes	Yes
N	31934	28128	28128	28128	29057
Within R^2	0.0574	0.0613	0.0616	0.0622	0.0628

policy dummy variables to perform a placebo test, and repeat the preceding operation 500 times. The kernel density distribution of the t-value of the results is reported in Figure 4. In general, the t-values are much smaller than the t-value of the benchmark regression, and most of the coefficients are not significant, which is in line with the expectations of the placebo test.

Replacement of Proxy Variables

In this section, robustness tests are conducted by replacing the digital M&A and innovation proxy variables. In the baseline regression, the authors use a digital M&A dummy to analyze. In column (1) of Table 7, the authors use the number of annual digital M&A events (*sumdmna*) of a firm to measure the digital M&A, and the regression results show that digital M&A increases the number of

Figure 4.
The placebo test



patent applications. Columns (2)-(4) of Table 7 replace the innovation proxy variables for testing, in order, the logarithm form of patents granted (*lngrant*), the logarithm form of patents cited (*lncited*), and the logarithm form of joint patent applications by listed companies in conjunction with other subsidiaries (*lnapplyja)*. In all three columns of the regression results, the coefficient of *dmna*post* is significantly positive, indicating that the baseline regression result is robust.

Replacement of Matching Method

This section replaces the PSM matching method for robustness testing. In the baseline regression, the authors use the nearest neighbor matching method for propensity score matching and illustrate the rationality of this matching method and the selection of matching variables through the propensity score matching equilibrium test. In this section, the authors use kernel matching to re-match similar control group firms to the treatment group firms and on this basis, the authors perform DID estimations and the regression results are shown in Table 8. The results all suggest that digital M&A has a significant positive innovation effect and the innovation effect is comparable to the results of the benchmark regression. So the authors validate the robustness of the benchmark regression results.

Replacement of Econometric Model

The existing econometric models for empirical studies using patent data are mainly divided into log-linear models (Liu & Qiu, 2016; Liu & Ma, 2020; Kou & Liu, 2020) and count models (J. Fang, Gao, & Lai, 2020; Zhang & Nie, 2021). In this paper, a log-linear model is used in the baseline model, and in this part, a count model is used to test the impact of digital M&A on the number of patent applications, and due to the "over-discrete" nature of patent data, a panel fixed effects negative

Table 7.
Replacement of proxy variables

variables	(1)	(2)	(3)	(4)
	lnapply	lngrant	lncited	lnapplyja
sumdmna	0.3413***			
	(15.50)			
dmna*post		0.1612***	2.7531***	0.3127***
		(3.38)	(29.10)	(5.79)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
N	28226	28225	19495	28226
Within R^2	0.0595	0.0579	0.3987	0.0372

Table 8.
Replacement of matching method

variables	(1)	(2)	(3)	(4)
	lnapply	lninvia	lnumia	lndesia
dmna*post	1.5049***	0.7812***	1.7132***	0.3500***
	(16.87)	(10.70)	(22.43)	(7.63)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
Province FE	No	No	No	Yes
N	24805	24740	24805	24692
Within R^2	0.0629	0.0522	0.0835	0.0093

binomial model is used to test the results. The coefficients of *dmna*post* are significantly positive, which is consistent with the findings of the log-linear model (table 9).

The Sub-Samples

In this section, the authors perform robustness tests using sub-samples. There are firms in our sample that have executed M&As but the M&As are not digital M&As, to exclude such M&A events from interfering with the empirical results of this paper, the authors exclude such firms from the PSM matching and regressions, and the regression results are reported in column (1) of Table 10. The coefficient of *dmna*post* is significantly positive and larger than that in the baseline regressions, indicating that the innovation effect of digital M&A is larger than that of firms that execute non-digital M&A. Then by dividing the acquire firm according to whether they intensely leverage digital

Table 9.
Replacement of econometric model

variables	(1)	(2)	(3)	(4)
	apply	**invia**	**umia**	**desia**
dmna*post	0.1380***	0.1445***	0.1508***	0.3144***
	(3.67)	(3.53)	(3.40)	(4.57)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
N	19948	18839	17299	10061
Log likelihood	-40838.345	-29032.043	-26936.93	-11249.332

technologies as critical elements of their business, our sample can be divided into M&A events between digital firms and M&A events in which non-digital firms acquire digital firms. The regression results are reported in columns (2) and (3) of Table 10, respectively. The regression results show that the innovation effect of M&As between digital firms in column (2) is larger than that of M&As non-digital firms acquire digital firms in column (3), which may be because when the acquirer is also a digital firm, its digital knowledge base and its similarity to the target firm facilitates better integration (Zhang Chi and Yu Pengyi, 2017; Cloodt, Hagedoorn, & Van Kranenburg, 2006), and thus the innovation effect of digital M&A is greater when both firms are digital firms.

HETEROGENEITY

Heterogeneity Effects of M&A Types

Vertical Versus Horizontal M&As

Inter-firm M&A may change the competitive structure of the market (Ye Guangliang and Chenglong, 2019), and the "winner-takes-all" of the digital economy has exacerbated a market structure with just a small number of large, powerful firms that can effectively manage vast resources to gain an

Table 10.
The sub-samples

variables	(1)	(2)	(3)
	lnapply	**lnapply**	**lnapply**
dmna*post	1.5033***	1.5406***	1.3726***
	(17.33)	(15.58)	(17.01)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
N	24165	27581	27711
Within R^2	0.0598	0.0616	0.0611

advantage over local competitors and capture a large market share in almost every segment they enter. At the same time, the monopoly of soft resources, such as traffic and data, by the top companies has further exacerbated that trend of the economy. Especially those with strong capital to achieve "technology-takes-all" and "business model-takes-all" through M&As. This will lead to a high degree of concentration in the industry. The authors identify horizontal digital M&A and vertical digital M&A and examine the differences in innovation effects between the two types of M&A. And analyses the possible industrial concentration effects of M&A. The regression results are shown in Table 11, where columns (1) and (2) denote the regressions of vertical digital M&A and horizontal digital M&A on the number of patent applications respectively, with the regression coefficients of *dmna*post* both positively significant, and the value of the regression coefficient of horizontal digital M&A is greater than that of vertical M&A, indicating that the innovation effect of horizontal digital M&A is greater than that of vertical digital M&A, possibly since such firms completing vertical M&As experience witness an increase in systemic innovation but a drop in autonomous innovation (Zhang and Tong,2021). Columns (3)-(6) of Table 11 examine the effects of vertical and horizontal M&As on firms' market share (*marketshare*) and industry concentration (*hhi*), respectively. The results show that both types of M&As significantly increase the market share of firms, but horizontal M&As have a more significant effect on the market share of firms, probably since most firms execute horizontal M&As mainly to expand their market size. The regression results in columns (5) and (6) show that an increase in the number of vertical M&A events in the industry significantly increases the industry concentration, while the effect of increasing the number of horizontal M&A events on industry concentration is not significant. This suggests that firms achieve control and synergy in the

Table 11.
Vertical versus horizontal M&As

variables	(1)	(2)	(3)	(4)	(5)	(6)
	lnapply	lnapply	marketshare	marketshare	hhi	hhi
	Vertical	Horizontal	Vertical	Horizontal	Vertical	Horizontal
dmna*post	1.3696***	1.6884***				
	(16.83)	(16.74)				
vertical			0.5734*			
			(1.80)			
horizontal				0.7342***		
				(6.43)		
vertical_ind					0.0171***	
					(6.10)	
horizontal_ind						0.0031
						(0.55)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
N	27954	27188	27512	26282	27954	27188
Within R^2	0.0610	0.0615	0.0218	0.0773	0.1066	0.1053

industry chain through upstream and downstream M&A, and may lead to a high degree of industry concentration through network effect in the digital era.

Domestic Versus Cross-Border M&As

According to the international law firm *Freshfields Bruckhaus Deringer*, Chinese companies lead the world in digital M&A deals, with more than half (56%) of digital M&A by Chinese companies from 2009 to 2017 being cross-border M&A[3]. Chinese companies have strong technology-seeking motives for cross-border digital M&A, with the core driver for initiating digital M&A being the search for advanced digital technologies and abundant R&D resources in the host country (Jiang & Tang, 2021). Then the M&A events were divided into domestic digital M&A events and cross-border digital M&A events according to whether the target firm is a foreign firm. Columns (1) and (2) of Table 12 indicate the regressions results of domestic digital M&A and cross-border digital M&A on the number of patent applications, respectively, and suggest that the innovation effect of cross-border digital M&A is smaller than that of domestic digital M&A, which may be related to the greater integration difficulty of cross-border M&A due to institutional and cultural distance. (Yan, 2009; Tian, Huang, & Sun, 2015), and may also weaken the innovation effect of digital M&A due to cross-border data flow restrictions (Zhou, & Yao, 2021). Columns (3) and (4) of Table 12 test the moderating effects of cultural distance (*cdist*) and institutional distance (*idist*) on cross-border digital M&A, respectively, and the coefficients of *dmna*post*cdist* and *dmna*post*idist* are significantly negative, indicating that cultural and institutional distance between China and the host country weakens the innovation effect of cross-border digital M&A. In addition, many countries have introduced a series of data flow restriction policies due to national security, personal privacy or commercial confidentiality concerns, and data flow restrictions may also significantly reduce the innovation effect of cross-border digital M&A. However, there are few studies on the quantitative assessment of cross-border data flow restrictions, and the ECIPE's Digital Trade Restrictiveness Index Report (DTRI) only publishes the data flow restriction index for 2017. The authors use policy information on data regulation from the ECIPE-DTE database and quantitative methods from the DTRI Index report to account for the data flow restriction index for 64 countries from 2000 to 2018. Referring to Ferracane, Lee-Makiyama, & Van Der Marel (2018); Ferracane, Kren, & Van Der Marel (2020), dividing the policies into two categories, one is the policies related to the direct impact on the cross-border transfer of data, which mainly involves all the measures adopted to force companies to keep data within a certain boundary or to impose additional requirements on the transfer of data abroad, whereby the country's data flow restrictiveness index across borders can be calculated (*restrcb*); the other category is related to domestic restrictive policies that indirectly affect data flows and uses, mainly all measures that impose certain requirements on companies to access, store, process or make any commercial use of data within a jurisdiction, from which the country's domestic data flow restrictiveness index (*restrde)* can be calculated, adding up to the country's overall data flow restrictiveness index (*restr*). Columns (5)-(7) of Table 12 examine the impact of the host country data flow restriction index (*restr*), the host country data flow restrictiveness index (*restrcb*), and the host country domestic data flow restrictiveness index (*restrde*) on the innovation effect of cross-border digital M&A. The coefficients of the triple interaction term are all significantly negative, indicating that data flow restrictions significantly weaken the innovation effect of cross-border digital M&A.

Other Heterogeneity Effects

The innovation effects of digital M&A can be heterogeneous, and this section analyses possible heterogeneity factors. Firms' *absorptive capacity*, such as the ability to acquire, digest, transform and apply knowledge, plays a crucial role in the innovation effect of M&A. Firms with higher absorptive capacity can benefit more from M&A and thus have a stronger innovation effect. The authors use the ratio of R&D investment to operating revenue to measure firms' absorptive capacity (*abs*). The regression results are reported in column (1) of Table 13, where the coefficient of *dmna*post*abs* is significantly

Table 12.
Domestic versus cross-border M&As

variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnapply	**lnapply**	**lnapply**	**lnapply**	**lnapply**	**lnapply**	**lnapply**
dmna*post	1.4430***	1.3393***	1.5119***	1.4995***	-0.2959***	-0.2824***	-0.3094***
	(17.73)	(10.31)	(10.79)	(10.75)	(-2.61)	(-2.62)	(-2.61)
dmna*post*cdist			-0.0445*				
			(-1.96)				
dmna*post*idist				-0.0159*			
				(-1.81)			
dmna*post*restr					-3.0722***		
					(-7.80)		
dmna*post*restrcb						-3.8968***	
						(-6.71)	
dmna*post*restrde							-5.9321***
							(-7.18)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28102	27189	27189	27189	27189	27189	27189
Within R^2	0.0607	0.0623	0.0625	0.0625	0.0623	0.0623	0.0623

positive, indicating that the stronger the firm's absorptive capacity, the greater the innovation effect of digital M&A. Then the authors test the effect of heterogeneity in the management efficiency of firms, which is measured by referring to Yu (2022), $lnadcost_{it} = \alpha_1 l_{it} + \alpha_2 exp_{it} + \alpha_3 markup_{it} + \varepsilon_i + \varepsilon_t + \mu_{it}$, where $lnadcost_{it}$ is the logarithm form of the firm's management costs, and l_{it} is the logarithm form of the number of employees, and exp_{it} is the logarithm form of the firm's export value, and $markup_{it}$ is the price mark-up of the firm, and the authors use the ratio of the firm's revenue to the difference between the firm's revenue and profit to measure. ε_i and ε_t denote firm fixed effects and year fixed effects respectively, and the residual obtained μ_{it} is the management efficiency of the firm (logarithmic value)[4], the larger the value the lower the management efficiency of the firm. For convenience, the inverse of the above values is used as a measure of management efficiency (*mangeff*) in the regression model. The regression results are presented in column (2) of Table 13, where the coefficient of *dmna*pos*mangeff* is significantly positive, so management efficiency has a positive moderating effect on the innovation effect of digital M&A. Columns (3) and (4) of Table 13 examine the moderating effect of the political affiliation of listed companies. Referring to Faccio (2006); Yu & Pan (2008), use a dummy variable to measure political affiliation (*political*) if the chairman or general manager of a listed company has been or is currently serving in a government department, or has been or is currently elected as a deputy to the National People's Congress or a member of the Chinese People's Political Consultative Conference, it is considered that the company is politically connected, then *political* takes

1, otherwise, it takes 0. The coefficient of *dmna*post* in column (3) is significantly larger than that in column (4), indicating that having political affiliation has a positive moderating effect on the innovation effect of digital M&A. In addition, the authors refer to Zhao, Zhang & Liang (2020) who use principal component analysis to measure the level of digital economy development (*cditl*) in the city level. The authors examine the impact of the level of digital economy development in the cities where listed companies are located on the innovation effect of digital M&A in column (5), the coefficient of *dmna*post*cditl* is significantly positive, indicating that the stronger the level of digital economic development of the region where the acquirer firm is located, the greater the innovation effect of the digital M&A.

CONCLUSION

This study empirically examines how digital M&A affects firm innovation using data from Chinese listed companies from 2006 to 2019. The authors find that digital M&A promotes firm innovation, and our findings also suggest that digital M&A enables firms to break away from technology path-dependence to achieve radical innovation and digital innovation. The analysis of different types of digital M&A shows that the innovation effect of vertical digital M&A is smaller than that of horizontal digital M&A. Vertical digital M&A significantly increases industry concentration and may change the competitive structure of the market; The innovation effect of cross-border digital M&A is smaller than that of domestic digital M&A, which may be related to the negative moderating effect of cultural and institutional distance between China and the host country, as well as the restriction of cross-border data flow. Further analysis shows that the innovation effect of digital M&A is stronger if the company is politically connected, if the firm's absorptive capacity is stronger, if the firm's

Table 13.
Other heterogeneity analysis

variables	(1)	(2)	(3)	(4)	(5)
	lnapply	lnapply	lnapply	lnapply	lnapply
dmna*post	-0.0907*	-1.4680	1.8753***	1.3448***	0.1197
	(-1.71)	(-1.46)	(8.66)	(15.04)	(0.41)
dmna*post*abs	0.1154***				
	(13.69)				
dmna*post*mangeff		0.0530***			
		(2.84)			
dmna*post*cditl					0.1110***
					(3.99)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
N	17532	15072	5559	22400	20433
Within R^2	0.0703	0.0732	0.0740	0.0588	0.0530

management efficiency is higher, or if the level of digital economy development in the region where the firm located is higher.

In general, digital M&A is conducive to promoting innovation and can drive firms to change their technological paths to radical innovation, firms should seize opportunities for breakthrough and digital innovation through digital M&A to move away from technology dependency and achieve innovative growth, however, it is also important to be wary of economic monopolies resulting from M&A in the digital era. Firms should further focus on the sustainable effects of innovation from digital M&A, for example by enhancing the absorptive capacity and management efficiency of the company, or by using digital technology to acquire deeper and more heterogeneous digital knowledge to further enhance the innovation effects of digital M&A. In the cross-border digital M&A market, firms need to address the impact of non-economic factors such as host country censorship and data flow restrictions on M&A, especially in the data or technology sectors, as well as the cultural and institutional distance between China and the host country. In addition, it is necessary for China to actively provide guidance and policy support to encourage corporate digital investment, digital transformation, and digital innovation while further promoting new infrastructure development strategies and the digital economy.

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ENDNOTES

1. Source: Boston Consulting Group: Cracking the Code of Digital M& A, 2019.
2. Source: Freshfields Bruckhaus Deringer: The World of Digital M&A, 2018. where the statistics are for listed companies included in the S&P Global 1200 Index.
3. Source: Freshfields Bruckhaus Deringer: The World of Digital M&A, 2018. where the statistics are for listed companies included in the S&P Global 1200 Index.
4. Referring to Sun, Hou, & Sheng. (2018), the residuals were taken as exp to eliminate the effect of inconsistent positive and negative signs of the residuals in order to measure the level of enterprise management efficiency more easily.

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