Does Digital M&A Improve a Firm's Digital Innovation Performance? Evidence from Chinese A-Share Listed Companies

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Abstract:In the digital era, acquiring digital resources through M&A has become an important way for firms to carry out digital transformation. Using digital M&A events from Chinese A-share listed companies during 2010 to 2018, this paper studies how digital M&A relates to firm-level digital innovation performance. The results show that digital M&A increases the number of new digital patents filed by the acquirer in the years after the deal. Compared with exploitative digital innovation, the effect on exploratory digital innovation is much stronger and more persistent. Mechanism tests show that digital M&A works mainly through two channels. It expands the acquirer's digital knowledge base, and it makes up for limited digital knowledge absorption capacity. The effect is especially large for firms that start with a weak digital foundation. The findings give practical guidance for traditional firms that want to use M&A as a tool for digital transformation.

Keywords: Digital M&A; Digital Innovation Performance; Digital Transformation; Exploratory Innovation; Knowledge Base.

1. Introduction

Since the start of the 21st century, new digital technologies such as cloud computing, big data, artificial intelligence, and the Internet of Things have grown very fast. They have brought new opportunities for firm-level digital transformation and high-quality economic growth. China's 14th Five-Year Plan lists building new advantages in the digital economy and pushing deep integration between digital technology and the real economy as central tasks. As digital technology spreads into more products, services, and operations, it is reshaping the nature of innovation itself, and a new form called digital innovation has appeared.

Firms can build up digital knowledge in three main ways. The first way is internal R&D. This path takes a long time, has a high failure rate, and often suffers from path dependence. By the time the firm finishes a project, the underlying technology may already be out of date. The second way is to form a strategic alliance with another firm. Alliances depend on shared interests, so they are not always stable, and the supply of resources can be uneven. The third way is digital M&A, which is a deal in which the acquirer buys a target mainly to obtain digital technology, digital talent, or a digital platform. Digital M&A gives the acquirer ownership of the target's digital assets in a short period of time, and at the same time removes a possible competitor.

A 2019 BCG report shows that global digital M&A reached USD 258 billion in 2017, more than twice the level five years before. Roughly two-thirds of those deals were carried out by non-tech firms looking to gain digital capability. The Chinese market is also very active. According to a Freshfields study covering 2009 to 2017, China ranked first in the world for both average deal size and average number of deals per firm. Despite the size of the market, the academic literature on digital M&A is still thin. Most existing work studies general technology M&A, or focuses on a single industry. The link between digital M&A and digital innovation performance, especially for firms outside the pure tech sector, has not been examined in depth. This paper tries to fill that gap. Using digital M&A events from Chinese A-share listed firms during 2010 to 2018, we test whether digital M&A raises the number of digital patents filed by the acquirer, and whether the effect differs across two types of innovation activity. We also study two possible mechanisms, namely the digital knowledge base channel and the digital knowledge absorption capacity channel. The contributions of the paper are threefold. First, we narrow the focus from general technology M&A to digital M&A as a special form, which fits the current digital era better. Second, we propose digital innovation performance as a measurable concept and provide empirical evidence on what drives it. Third, we test the underlying mechanisms, which gives a clearer picture of why and when digital M&A actually pays off.

2. Theory and Hypotheses

2.1 Digital M&A and Digital Innovation Performance

The aim of digital M&A is to raise digital capability, and digital innovation sits at the core of that capability. Differences across firms in their digital knowledge base, in the structure of that knowledge, and in their ability to deploy it are what create differences in innovation outcomes.

There are several reasons to expect a positive effect. First, digital M&A brings in digital talent. People who think and work in a digital way are essential for digital innovation, and acquiring a target firm is a fast way to add such people to the team. Second, digital M&A expands the digital knowledge base. The acquirer gets ownership of new external knowledge in a short period of time, and that broadens the set of possible knowledge combinations for future innovation. Third, digital M&A often pushes the acquirer to flatten its organization and rebuild its routines, which makes the firm more responsive to market signals. Fourth, digital technology is programmable. The acquired technology can be adjusted and embedded into existing operations, which improves both efficiency and innovation output. Based on this reasoning we propose:

H1: Digital M&A increases the digital innovation performance of the acquirer.

2.2 The Effect on Two Types of Digital Innovation

Following the literature on ambidextrous innovation, we split digital innovation into two types. Exploratory digital innovation refers to the development of new digital products, services, or business lines based on new digital knowledge. Exploitative digital innovation refers to the use of digital technology to keep improving existing products, services, and processes.

Digital M&A can support both types. For exploratory innovation, the deal expands the pool of innovation participants. Customers, suppliers, and other stakeholders linked to the target firm can now feed into the acquirer's innovation process, and high-end digital talent acquired from the target raises the technical ceiling of the R&D team. For exploitative innovation, the new digital technology can be used to upgrade existing products, and customer feedback collected through new digital channels guides further iteration. So we propose:

H2a: Digital M&A promotes exploratory digital innovation.

H2b: Digital M&A promotes exploitative digital innovation.

However, the two effects are unlikely to be equal in size. Innovation resources within a firm are limited, and the two activities compete for the same pool of money and people. Exploratory innovation gives a larger long-term payoff and is more central to building real digital capability, so firms that pursue digital M&A tend to allocate the marginal resource toward exploration. In addition, the typical target in a digital M&A is a young digital startup, and startups are usually better at exploration than at incremental improvement. The acquirer therefore inherits exploration capability at a relatively low price. We propose:

H2c: Compared with exploitative digital innovation, the effect of digital M&A on exploratory digital innovation is stronger.

3. Research Design

3.1 Sample and Data

We use Chinese A-share listed firms during 2010 to 2018 as the sample. We drop ST and ST* firms, failed M&A deals, and observations missing key financial data. After cleaning, we have 13,371 M&A events at the deal level and 7,572 firm-year observations at the panel level. Among the firm-year observations, 2,255 contain at least one digital M&A. Continuous variables are winsorized at the 1% and 99% levels. The data come from CSMAR and from a hand-coded classification of M&A deals based on the deal description.

3.2 Identifying Digital M&A

We classify a deal as a digital M&A when its target name, business scope, or transaction summary contains at least one keyword from a digital technology dictionary. The dictionary covers six broad areas, namely general digitalization terms, intelligent technology, information technology and the Internet, cloud computing, AI-related technology such as machine learning and computer vision, and frontier technology such as blockchain and 3D printing. The variable DMA equals one if firm i carries out at least one digital M&A in year t, and zero otherwise.

3.3 Variables

The dependent variable is digital innovation performance Dipe, defined as the natural log of one plus the number of digital patents filed by the firm in year t plus k, where k equals 1, 2, or 3. A patent is treated as a digital patent when its title or abstract contains a digital keyword. Exploratory digital innovation Inv equals one if the firm files a digital invention patent in t plus k, and zero otherwise. Exploitative digital innovation Exp equals one if the firm files a digital utility model or design patent in t plus k, and zero otherwise. The controls are firm size (Size), leverage (Lev), return on assets (Roa), listing age (Age), state ownership (Property), independent director ratio (Indep), and R&D spending (RD). We also include year and industry fixed effects.

3.4 Empirical Model

The main equations are as follows. Equation (1) is estimated with a negative binomial model since the dependent variable is a count. Equations (2) and (3) are estimated with logit models.

$$Dipe(i,t+k)=\beta 0+\beta 1\cdot DMA(i,t)+\beta 2\cdot Controls(i,t)+YearFE+IndustryFE+\varepsilon \quad (1)$$

$$Inv(i,t+k)=\beta 0+\beta 1\cdot DMA(i,t)+\beta 2\cdot Controls(i,t)+YearFE+IndustryFE+\varepsilon \quad (2)$$

$$Exp(i,t+k)=\beta 0+\beta 1\cdot DMA(i,t)+\beta 2\cdot Controls(i,t)+YearFE+IndustryFE+\varepsilon \quad (3)$$

4. Empirical Results

4.1Descriptive Statistics

Table 1 reports descriptive statistics for the main variables. The mean of DMA is 0.298, which means that about 30 percent of firm-year observations contain at least one digital M&A. The mean of Dipe rises from 0.080 in t plus 1 to 0.194 in t plus 3, suggesting that digital innovation output grows over time. Figure 1 shows how digital M&A activity has evolved during the sample period. Both the absolute number of digital deals and the share of digital deals in total M&A activity rose sharply between 2012 and 2015, then leveled off.

Figure 1. Trend of Digital M&A in Chinese A-Share Listed Firms (2010-2018)

Table 1. Descriptive Statistics

Variable	N	Mean	SD	Min	Median	Max
Dipe_1	7572	0.080	0.257	0.000	0.000	2.833
Dipe_2	7572	0.142	0.334	0.000	0.000	2.833
Dipe_3	7572	0.194	0.383	0.000	0.000	2.833
DMA	7572	0.298	0.457	0.000	0.000	1.000
Roa	7572	0.037	0.061	-0.187	0.038	0.190
Age	7572	8.468	2.911	0.000	8.000	21.000
Lev	7572	0.404	0.158	0.059	0.394	0.868
Size	7572	22.041	1.216	19.500	22.029	26.500
RD	7572	17.674	1.475	13.200	17.697	21.500
Property	7572	0.258	0.437	0.000	0.000	1.000
Indep	7572	0.382	0.045	0.330	0.377	0.570

4.2Effect of Digital M&A on Digital Innovation Performance

Table 2 reports the effect of digital M&A on digital innovation performance. Columns 1 to 3 show the results without controls. Columns 4 to 6 show the results after adding firm-level controls. The coefficient on DMA is positive and significant at the 1 percent level in every column, no matter whether we look at t plus 1, t plus 2, or t plus 3. With controls included, the coefficients are 0.130, 0.238, and 0.332. So during the three years following the deal, digital M&A clearly raises the number of new digital patents filed by the acquirer. The size of the effect grows over time, which suggests that the benefits of digital M&A take a few years to fully appear. Hypothesis H1 is supported.

Table 2. Effect of Digital M&A on Digital Innovation Performance

	Without controls	Without controls	Without controls	With controls	With controls	With controls
Variable	Dipe_1 (1)	Dipe_2 (2)	Dipe_3 (3)	Dipe_1 (4)	Dipe_2 (5)	Dipe_3 (6)
DMA	0.130***	0.238***	0.333***	0.130***	0.238***	0.332***
	(0.008)	(0.011)	(0.012)	(0.008)	(0.011)	(0.012)
Roa				0.184	0.301**	0.342**
				(0.118)	(0.149)	(0.169)
Age				-0.001	-0.002	-0.003*
				(0.001)	(0.002)	(0.002)
Lev				-0.078**	-0.121**	-0.143**
				(0.034)	(0.048)	(0.057)
Size				0.011**	0.018**	0.022**
				(0.005)	(0.007)	(0.008)
RD				0.005	0.008	0.009
				(0.004)	(0.005)	(0.006)
Property				0.003	0.005	0.006
				(0.013)	(0.017)	(0.020)
Indep				0.085	0.118	0.144
				(0.121)	(0.155)	(0.176)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7572	7572	7572	7572	7572	7572
R^2	0.058	0.101	0.140	0.060	0.104	0.145

Note: Robust standard errors in parentheses. ***, **, * indicate significance at the 1%, 5%, 10% levels.

4.3Two Types of Digital Innovation

Table 3 reports the logit results for the two types of digital innovation. For exploratory innovation Inv, the DMA coefficient is 1.368, 0.887, and 1.090 at t plus 1, t plus 2, and t plus 3, all significant at the 1 percent level. For exploitative innovation Exp, the corresponding coefficients are 0.608, 0.489, and 0.320, also significant at the 1 percent level but smaller in size. Figure 2 plots the comparison directly. The effect on exploration is roughly twice as strong as the effect on exploitation, and the gap shows up in every horizon. So digital M&A pushes both types of innovation, but it pushes exploration much harder. Hypotheses H2a, H2b, and H2c are all supported. The result fits the idea that firms use digital M&A to break into new digital territory, not just to polish what they already do.

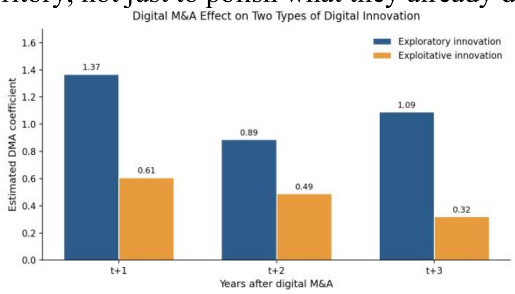

Figure 2. Estimated DMA Coefficient for Exploratory and Exploitative Innovation

Table 3. Effect of Digital M&A on the Two Types of Digital Innovation

	Exploratory innovation	Exploratory innovation	Exploratory innovation	Exploitative innovation	Exploitative innovation	Exploitative innovation
Variable	Inv_1 (1)	Inv_2 (2)	Inv_3 (3)	Exp_1 (4)	Exp_2 (5)	Exp_3 (6)
DMA	1.368***	0.887***	1.090***	0.608***	0.489***	0.320***
	(0.084)	(0.078)	(0.079)	(0.089)	(0.081)	(0.077)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7572	7572	7572	7572	7572	7572
Pseudo R^2	0.065	0.032	0.044	0.018	0.014	0.014

Note: Logit estimation. Robust standard errors in parentheses. ***, **, * indicate significance at the 1%, 5%, 10% levels.

5. Mechanism Tests

5.1 The Digital Knowledge Base Channel

We argue that digital M&A works in part by expanding the acquirer's digital knowledge base. To test this, we measure the prior knowledge base by counting the digital patents filed by the firm in the three years before the M&A event. We then split the sample at the yearly median and rerun the main regression on each subsample. If the channel is real, the DMA coefficient should be larger and more significant in the low-knowledge-base group, since these firms gain the most from a sudden jump in their knowledge base.

Table 4 reports the results. In the low-knowledge-base group, the DMA coefficient ranges from 0.183 at t plus 1 to 0.451 at t plus 3, all significant at the 1 percent level. In the high-knowledge-base group, the coefficient is much smaller, between 0.055 and 0.165. The gap is large, especially at longer horizons, which supports the knowledge base channel. Figure 3a shows the comparison.

Table 4. Mechanism: Digital Knowledge Base

	High knowledge base	High knowledge base	High knowledge base	Low knowledge base	Low knowledge base	Low knowledge base
Variable	Dipe_1 (1)	Dipe_2 (2)	Dipe_3 (3)	Dipe_1 (4)	Dipe_2 (5)	Dipe_3 (6)
DMA	0.055***	0.111***	0.165***	0.183***	0.328***	0.451***
	(0.010)	(0.013)	(0.016)	(0.012)	(0.015)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3136	3136	3136	4436	4436	4436
R^2	0.021	0.041	0.059	0.101	0.165	0.224

Note: Robust standard errors in parentheses. ***, **, * indicate significance at the 1%, 5%, 10% levels.

5.2 The Absorptive Capacity Channel

Absorptive capacity is the firm's ability to recognize, take in, and use external knowledge. We measure it as the ratio of cumulative R&D spending to granted patents in the three years before the deal. Again we split the sample at the yearly median. There are two competing predictions. Under a reinforcement view, firms with high absorptive capacity should benefit more, because they can convert new knowledge into output more easily. Under an incremental view, firms with low absorptive capacity should benefit more, because digital M&A delivers ready-to-use digital resources that compensate for their weak conversion ability.

Table 5 supports the incremental view. In the low-absorptive-capacity group the DMA coefficient is 0.198, 0.353, and 0.494 at the three horizons, all significant at the 1 percent level. In the high-absorptive-capacity group the coefficient is much smaller, between 0.062 and 0.170. So the incremental effect of digital M&A is largest exactly when the firm cannot easily build digital capability on its own. Figure 3b shows the same pattern.

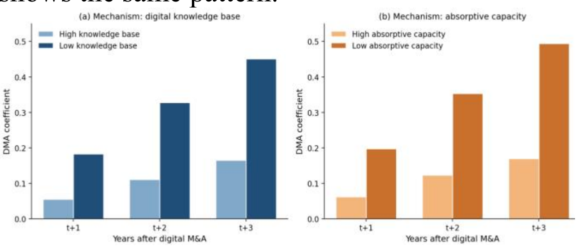

Figure 3. Mechanism Tests for Digital Knowledge Base (a) and Absorptive Capacity (b)

Table 5. Mechanism: Absorptive Capacity

	High absorptive capacity	High absorptive capacity	High absorptive capacity	Low absorptive capacity	Low absorptive capacity	Low absorptive capacity
Variable	Dipe_1 (1)	Dipe_2 (2)	Dipe_3 (3)	Dipe_1 (4)	Dipe_2 (5)	Dipe_3 (6)
DMA	0.062***	0.123***	0.170***	0.198***	0.353***	0.494***
	(0.009)	(0.012)	(0.014)	(0.013)	(0.017)	(0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3786	3786	3786	3786	3786	3786
R^2	0.023	0.046	0.063	0.107	0.175	0.243

Note: Robust standard errors in parentheses. ***, **, * indicate significance at the 1%, 5%, 10% levels.

6.Conclusions and Implications

Using digital M&A events from Chinese A-share listed firms during 2010 to 2018, this paper finds that digital M&A raises digital innovation performance. The acquirer files more new digital patents in the years after the deal, and the effect grows from t plus 1 to t plus 3. The effect on exploratory digital innovation is roughly twice as strong as the effect on exploitative digital innovation, which suggests that firms use M&A mainly to enter new digital territory rather than to refine existing offerings. The benefit is concentrated in firms with a weak prior digital knowledge base and limited absorptive capacity, which means digital M&A is most useful when the firm cannot quickly build digital capability on its own.

Several practical lessons follow. First, for traditional firms that are still early in digital transformation, M&A can be a clear and concrete path to building digital knowledge. Second, regulators should keep working on digital infrastructure, open data sharing, and standards that lower the cost of building digital capability. Third, since exploratory digital innovation is what creates real long-term value, supporting policies such as tax breaks, talent subsidies, and joint training programs with universities deserve priority. The findings are also subject to limits. The sample only covers listed firms in one country, and we cannot fully separate the effect of digital M&A from other simultaneous transformation efforts. Future work could extend the sample to cross-border settings, and could exploit deal-level details such as target characteristics and integration depth to refine the analysis.

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