

Digital M&A, R&D leapfrogging, and new quality productive forces: quasi-experimental evidence from China's listed firms

Jiawei Ma

p2626244@mpu.edu.mo

MPI GTR Center: Macao Polytechnic University Gaming Teaching and Research Center

<https://orcid.org/0009-0000-6423-3039>

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Abstract

Whether digital mergers and acquisitions (M&A) redirect firms' research and development (R&D) trajectories — and thereby enhance new quality productive forces (NQPF) — remains largely unexamined. Using 24,318 firm-year observations of Chinese listed firms from 2008 to 2023, we employ staggered difference-in-differences with heterogeneity-robust estimators and instrumental variables to estimate the effect of a firm's first digital-target acquisition on NQPF and on patent-based measures of technological-trajectory change. Digital M&A raises NQPF by 0.236 index points (4.9 per cent of the sample mean) and shifts 4.2 percentage points of patenting into previously unoccupied technological domains; R&D leapfrogging accounts for 27.4 per cent of the total effect. The gain follows an inverted-U in acquirer–target technological distance, turning negative beyond approximately 0.87 — evidence of an integration trap. Effects are strongest for traditional-sector and non-state-owned acquirers. The findings identify firm-level R&D leapfrogging as a micro-mechanism of growth-enhancing restructuring and imply that digital-deal screening should target moderate technological distance.

Keywords: Digital M&A; R&D leapfrogging; New quality productive forces; Technological trajectory; Economic restructuring; China

JEL Classification: G34; O33; O25; L25; P31

1. Introduction

Economic restructuring in transition and emerging economies turns, at its core, on whether firms can jump onto new technological trajectories rather than merely upgrading along existing ones. The structural-change literature has shown that aggregate productivity growth hinges on labour and capital moving toward higher-productivity, technology-intensive activities, and that this movement can stall — or even turn growth-reducing — when factors flow in the wrong

direction (McMillan and Rodrik 2011). Several emerging economies now face premature deindustrialization: they deindustrialize at lower income levels and smaller manufacturing shares than the early industrializers did, narrowing the window for conventional, rung-by-rung technological catch-up (Rodrik 2016). In this environment, digital technologies — artificial intelligence, big data, cloud computing, and the industrial internet — constitute the era’s general-purpose trajectory: digital knowledge is modular, recombinant, and transferable across industry boundaries, so that mastering it reconditions the productive structure of the whole economy rather than of a single sector (Hanelt et al. 2021). Whether and how incumbent firms relocate their research and development (R&D) onto this trajectory is therefore a first-order question for the micro-foundations of restructuring.

Mergers and acquisitions (M&A) are the market vehicle through which firms most plausibly make such jumps. Because the value of a technology is difficult to appropriate through licensing, and because commercializing it requires complementary capabilities that travel poorly across firm boundaries, acquisition is often the only feasible mode of transferring a functioning technological capability — people, code, data, and routines as an integrated bundle (Teece 1986; Ahuja and Katila 2001; Zhao 2009). In China, the largest transition economy, digital M&A — the acquisition of digital-technology targets by (often non-digital) incumbents — has grown into one of the world’s most active deal segments, propelled by the digital-transformation imperative that drives acquirers’ own strategies (Tu and He 2023; Zhang and Peng 2023). The policy backdrop sharpens the stakes: the Chinese leadership’s agenda of “new quality productive forces” (NQPF) reframes development as a qualitative, technology-driven upgrading of the three constituents of production — labourers, labour materials, and objects of labour — rather than extensive factor accumulation (Zhou and Xu 2023a; Xie et al. 2025). If digital M&A genuinely restructures firms’ productive forces, it is a candidate micro-mechanism of the restructuring that transition economies seek; if it merely relabels existing activities, it is not.

A rapidly growing literature now evaluates digital M&A, and its verdict is broadly positive. Digital deals create market value for acquirers (Tang et al. 2022), raise the quantity and quality of acquirer innovation (Tang et al. 2024; Xu et al. 2025b), foster radical innovation that relaxes technology path dependence (Zhou et al. 2023b), and, most directly relevant here, raise firm-level NQPF through innovation and data-asset channels (Xu, Zhang and Li 2026a). Yet every

one of these studies estimates *level* gains along the acquirer’s *existing* technological trajectory — more patents, better patents, higher value, higher productivity — without asking whether the deal changes the *direction* of the firm’s trajectory. Three gaps follow. First, Xu, Zhang and Li (2026a) establish the NQPF effect but do not examine whether acquirers’ inventive activity enters technological domains they previously did not occupy, and they treat industrial structure only as a moderating condition rather than an outcome of the deal. Second, Zhou et al. (2023b) operationalize discontinuity as invention-patent radicalness, which measures breakthroughs *within* a path, not entry into new domains. Third, where new-domain entry has been measured — in firms’ internal artificial-intelligence innovation strategies (Li et al. 2026) or in diversified M&A portfolios (Xu, Yuan and Lei 2024) — it has not been linked to digital deals, post-deal integration, or the composition of productive forces. Whether digital M&A redirects the R&D trajectory — what we call R&D leapfrogging — whether that redirection transmits the NQPF gain, and under what conditions it fails, remain open questions.

This paper addresses these questions with quasi-experimental evidence from China’s A-share listed firms over 2008–2023. The sample comprises 24,318 firm-year observations on 2,847 unique firms, of which 386 completed their first digital-target acquisition during the window; deal records come from the China Stock Market and Accounting Research (CSMAR) database, and patent applications, International Patent Classification (IPC) codes, and citations from the China Research Data Services Platform (CNRDS) and IncoPat. We estimate the effect of digital M&A on an entropy-weighted, three-dimension firm-level NQPF index (Song et al. 2024; Xu et al. 2026b) using staggered difference-in-differences (DID), validated with heterogeneity-robust estimators — the interaction-weighted event study of Sun and Abraham (2021), the group-time average treatment effects of Callaway and Sant’Anna (2021), and the decomposition of Goodman-Bacon (2021) — and instrumented with two regionally predetermined sources of variation in digital-infrastructure cost (Huang et al. 2019). R&D leapfrogging is measured from patents: the share of filings in IPC subclasses new to the firm, the share of backward citations to previously uncited knowledge (Ahuja and Katila 2001), and the share of patents combining previously uncombined technology classes (Kaplan and Vakili 2015; Verhoeven et al. 2016).

Four results emerge. First, completing a first digital M&A raises acquirers' NQPF by 0.236 index points (s.e. 0.041), approximately 4.9 per cent of the sample mean; the estimate is stable across heterogeneity-robust estimators, survives matching, balancing, and placebo batteries, and is corroborated by instrumental-variable estimates. Second, the results are consistent with a leapfrogging mediation channel: digital M&A raises the share of patents in new-to-the-firm technology domains by 4.2 percentage points, and this domain-entry margin is consistent with mediating 27.4 per cent of the total NQPF effect (jointly with search scope, 33.1 per cent) — a directional change in the technological trajectory, not merely a level gain. Third, the gain is an inverted-U in acquirer–target technological distance, peaking at a distance of 0.553; beyond that turning point the marginal return declines, crossing zero at approximately 0.87, and in the high-distance upper tail (distance above 0.90, roughly 6 per cent of treated deals) digital M&A *reduces* NQPF by 0.089 points, an estimate significant only at the 10 per cent level — suggestive of an integration trap in which excessive distance overwhelms absorptive capacity. Fourth, the deals restructure the composition of productive forces, raising the R&D personnel share by 2.8 percentage points, the digital intangible assets share by 1.9 percentage points, and the new-business revenue share by 3.4 percentage points; the gains are significantly larger for non-state-owned acquirers and, strikingly, for traditional-sector acquirers, which leapfrog further than high-tech incumbents — a convergence pattern with direct implications for structural change.

The paper makes three contributions. First, it transplants the leapfrogging construct from latecomer theory (Lee and Lim 2001; Lee and Malerba 2017) to the M&A setting and provides its first firm-level operationalization for digital acquisitions, defining *R&D leapfrogging* as post-deal entry into previously unoccupied technological domains and linking domain entry to the composition of productive forces. This advances the digital-M&A literature (Tang et al. 2022, 2024; Xu et al. 2025b; Zhou et al. 2023b), which documents level gains and within-path radicalness but has not measured directional trajectory change, and complements the exploration–exploitation literature (March 1991; Benner and Tushman 2003) by showing that the market for corporate control can purchase the exploration that internal search fails to generate. Second, it makes restructuring an *outcome* rather than a moderator: by estimating digital M&A's effects on the three constituents of productive forces separately, the paper supplies firm-level micro evidence on growth-enhancing structural change in the largest transition economy, connecting the M&A–innovation literature to the structural-change and premature-

deindustrialization debate (McMillan and Rodrik 2011; Rodrik 2016) and extending the NQPF literature (Song et al. 2024; Xu et al. 2026b; Xu, Zhang and Li 2026a), which has linked NQPF to financial-statement drivers but not to technological-trajectory change. Third, it exports an established boundary condition to a new setting and quantifies its negative region. The inverted-U in acquirer–target technological relatedness is established for M&A innovation performance (Ahuja and Katila 2001; Cloudt et al. 2006); this paper’s contribution is to carry it into digital M&A with NQPF as the outcome and to document the previously unquantified negative (‘integration-trap’) region in which excessive technological distance reduces productive forces, refining absorptive-capacity logic on optimal cognitive distance for digital acquisitions and yielding an operational screening criterion for deal evaluation and competition policy. The quasi-experimental battery that supports these claims — staggered DID with heterogeneity-robust estimators, matched and balanced samples, placebo randomization, and two instrumental variables — is a safeguard for credible inference, not a contribution in itself.

The remainder of the paper proceeds as follows. Section 2 reviews the institutional background and the digital-M&A, NQPF, and restructuring literatures, locating the paper against the closest works. Section 3 develops the theoretical framework and three hypotheses. Section 4 describes the sample, variables, and econometric models. Section 5 reports baseline estimates, identification diagnostics, robustness checks, and instrumental-variable results. Section 6 examines the R&D leapfrogging mechanism and its mediation of the NQPF effect. Section 7 analyses the technological-distance inverted-U and integration trap, the restructuring margins, and heterogeneity across ownership, industry, and regional factor-market development. Section 8 concludes with theoretical and policy implications.

2. Institutional background and literature review

2.1 Digital transformation and M&A in China’s economic restructuring

China’s economic restructuring has entered a phase in which growth increasingly depends on upgrading the composition of productive forces rather than on factor accumulation alone. The policy concept of “new quality productive forces”, introduced in late 2023, crystallizes this shift: it denotes productivity gains driven by technological innovation, the reallocation of labour and capital toward knowledge-intensive activities, and the emergence of new industries, as distinct

from the traditional extensive growth model (Zhou and Xu 2023a). Xie et al. (2025) clarify that NQPF is a Marxian political-economy construct in which the three constituents of production — labourers, labour materials (means of labour), and objects of labour — are each upgraded to a “new quality” through scientific and technological progress. At the macro level, this agenda responds to a well-documented challenge for transition and emerging economies: structural change has often been growth-reducing where labour moves toward low-productivity services, and several economies face premature deindustrialization (McMillan and Rodrik 2011; Rodrik 2016). China, the largest transition economy, thus provides a setting in which the micro-foundations of structural transformation can be observed with unusual clarity.

Digital technologies occupy a central place in this restructuring because of their general-purpose character: digital knowledge is modular, recombinant, and readily transferable across industry boundaries, so that its diffusion reshapes the factor composition of firms throughout the economy. Consistent with this view, the digital economy has been shown to raise total factor productivity (TFP) in China (Pan et al. 2022), and digital technology innovation proxied by firms’ digital patents is associated with high-quality enterprise development (Huang et al. 2023). Yet internal digital transformation is slow and path-dependent. M&A offers an alternative route: by acquiring digital-technology firms outright, incumbents can import whole bundles of digital knowledge, personnel, and data assets, effectively buying a position on a new technological trajectory rather than building one incrementally (Teece 1986). Acquirers’ own digital transformation stimulates subsequent M&A activity (Tu and He 2023; Zhang and Peng 2023) and raises acquirer TFP through M&A channels (Li, Wang and Zhang 2025). Cross-country evidence similarly frames Industry 4.0-related M&A as an instrument of industrial transformation (Schwan et al. 2026). China’s market for such deals is among the most active worldwide, and it offers an unusually clean empirical setting: a large, institutionally unified transition economy undergoing deliberate digital restructuring, with rich deal-level and patent-level data that permit the technological consequences of digital M&A to be measured directly.

2.2 Digital M&A and firm outcomes: the level-gain consensus

A rapidly growing literature examines the consequences of digital M&A — acquisitions whose targets possess digital technologies such as artificial intelligence, big data, and cloud computing (Hanelt et al. 2021) — for acquiring firms, and converges on a broadly positive

verdict. On market outcomes, Tang et al. (2022) show, using propensity score matching combined with DID, that digital M&A announcements create market value for Chinese acquirers, and Huang and Shen (2024) confirm positive shareholder wealth effects while identifying the deal and firm conditions under which value creation is strongest. On innovation, Tang et al. (2024) find with staggered DID that digital M&A increases both the quantity and quality of acquirer innovation; Xu et al. (2025b) reach a similar conclusion using stacked DID; Liang et al. (2025) document gains along the scale, efficiency, and quality dimensions of technological innovation; and Xu and Deng (2024) report innovation-quality improvements that operate through R&D investment and overseas subsidiaries. Zhou et al. (2023b) push furthest toward discontinuity, arguing that digital M&A helps firms “break away from technology path-dependence” and achieve radical innovation. Beyond innovation, Liang et al. (2024) show that digital-oriented M&A reshapes enterprise labour demand, and Xu et al. (2025a) caution that such deals can also coincide with greenwashing behaviour. Most directly relevant to this paper, Xu, Zhang and Li (2026a) demonstrate with multi-period DID that digital M&A raises firm-level NQPF among Chinese listed firms, operating through innovation and data-asset channels, with industrial structure, urban human capital, and policy uncertainty as moderators.

This digital-M&A strand builds on canonical results in the general M&A–innovation literature. Technological acquisitions enhance acquirer innovation performance when the acquired knowledge base is related but not redundant (Ahuja and Katila 2001); firms with complementary technological capabilities are more likely to combine, and their post-merger innovation output rises (Bena and Li 2014); Zhao (2009) shows that acquisitions allow firms to access external technologies to offset internal innovation shortfalls; and in high-tech industries the innovation effect of M&A depends on the technological relatedness between partners (Cloudt et al. 2006).

Taken together, however, this body of work estimates *level* gains — more patents, better patents, higher market value, higher productivity — along the acquirer’s *existing* technological trajectory. Even the three closest studies stop short of measuring directional change. Xu, Zhang and Li (2026a) establish that digital M&A raises NQPF but do not examine whether the acquirer’s inventive activity enters technological domains it previously did not occupy, and they treat industrial structure only as a moderating condition rather than an outcome. Zhou et

al. (2023b) operationalize radical innovation through invention-patent counts, which capture breakthroughs *within* a path rather than entry into new domains. Li et al. (2026) do measure discontinuous jumps into new technological domains, but as an outcome of firms’ internal artificial intelligence innovation strategies, not of acquiring another firm. Relatedly, Xu, Yuan and Lei (2024) study diversified M&A portfolios and breakthrough technologies without isolating digital deals. The one prior study that does connect M&A to technological trajectories, Cretini, Robert and Vázquez (2025), traces qualitatively how acquisitions reshape knowledge bases and redirect search in a single sector (wind energy); the present study complements it with quantitative, firm-level evidence on trajectory-direction change for digital M&A. What remains unexamined, therefore, is whether digital M&A changes the *direction* of the acquirer’s technological trajectory — entry into previously unoccupied technological domains — and whether such directional change underlies the documented level gains.

2.3 New quality productive forces: concept and measurement

The NQPF concept originates in Chinese policy discourse and has been given analytical content by Zhou and Xu (2023a), who define its connotative characteristics around technological innovation-led productivity, and by Xie et al. (2025), who provide an English-language conceptualization emphasizing the qualitative upgrading of the three factors of production. Measurement has proceeded at two levels. At the provincial level, Han et al. (2024) construct a comprehensive index of new quality productivity and link it to China’s new growth drivers. At the firm level — the level relevant to this paper — an entropy-weighted indicator system organized around the three Marxian constituents — new-quality labourers, labour materials, and objects of labour — has become the *de facto* standard. Song et al. (2024) pioneer this firm-level approach for Chinese A-share companies, and Xu et al. (2026b) refine it into a twelve-indicator, three-dimension entropy index; the framework has since been applied widely, for instance to study how media attention shapes corporate NQPF (Chen et al. 2025). A parallel, more parsimonious measurement tradition proxies NQPF with TFP estimated from production functions, on the argument that the essence of NQPF is a substantial increase in TFP (Shi and Sun 2024), and machine-learning methods have been used to evaluate NQPF at scale (Cao and Dai 2026). These firm-level measures have been linked to a growing list of drivers, including

environmental, social, and governance performance (Song et al. 2024) and digital transformation broadly defined (Liu and He 2024).

Two observations motivate this paper’s use of the construct. First, the three-factor entropy index is well established, so the measurement choice is deliberate replication of a validated standard rather than a novel contribution. Second, and more importantly, NQPF has so far been connected almost exclusively to financial-statement indicators — R&D intensity, personnel structure, and asset composition — and not yet linked to change in the firm’s *technological trajectory* as revealed by patenting behaviour. Because digital M&A imports recombinant, general-purpose digital knowledge, it is precisely the kind of event that could redirect inventive search toward unoccupied domains; if NQPF gains arise through such redirection, the trajectory mechanism is the missing micro-foundation linking the digital-M&A and NQPF literatures.

This paper therefore departs from the three closest works along three dimensions. Relative to Xu, Zhang and Li (2026a), it differs in *mechanism*: rather than treating innovation input and data assets as mediating channels, it asks whether digital M&A changes the direction of R&D — entry into previously unoccupied technological domains — and whether this R&D leapfrogging transmits the NQPF gain. Relative to both Xu, Zhang and Li (2026a) and the broader digital-M&A literature, it differs in *outcome framing*: restructuring of the composition of productive forces is modelled as a result of digital M&A, not as a contextual moderator. Relative to Zhou et al. (2023b) and Li et al. (2026), it differs in *construct and boundary condition*: it measures new-domain entry directly from patent classifications in an M&A setting, and it theorizes an inverted-U in acquirer–target technological distance, beyond which excessive distance produces an integration trap rather than a successful jump. Section 3 develops the theoretical framework and hypotheses underlying these claims.

3. Theoretical framework and hypotheses

Fig. 1 summarizes the conceptual framework developed in this section. Digital M&A is hypothesized to upgrade new quality productive forces and their three constituents (H1); the effect is transmitted by R&D leapfrogging — new-domain entry, wider knowledge-search scope, and recombinant novelty (H2); and acquirer–target technological distance moderates the M&A–

leapfrogging link as an inverted-U spanning a redundancy trap, an optimal window, and an integration trap (H3).

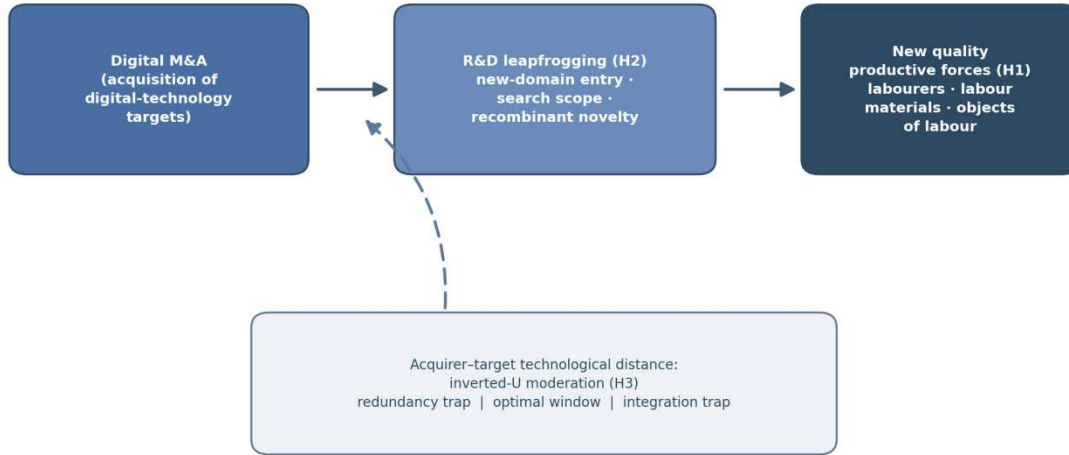


Fig. 1 Conceptual framework: digital M&A, R&D leapfrogging, and the moderation of technological distance. The diagram summarizes the paper’s hypotheses: digital M&A (acquisition of digital-technology targets) upgrades new quality productive forces and the composition of their three constituents — labourers, labour materials, and objects of labour (H1); the effect is transmitted by R&D leapfrogging, operationalized as entry into previously unoccupied technology domains, a widening of knowledge-search scope, and novel knowledge recombination (H2); and acquirer–target technological distance moderates the M&A–leapfrogging link as an inverted-U (H3), with a redundancy trap at near-zero distance, an optimal moderate-distance window, and an integration trap at excessive distance (Section 3.3).

3.1 Digital M&A and new quality productive forces

Mergers and acquisitions are, at their core, a market-based mechanism for reallocating the factors of production across firm boundaries. Where internal contracting is costly or infeasible, the market for corporate control transfers productive assets — technology, human capital, and organizational routines — to the owner who can deploy them at highest value (Coase 1937). For technology assets in particular, acquisition is often the only feasible transfer mode: because the value of an innovation is difficult to appropriate through licensing, and because complementary

capabilities are needed to commercialize it, integration within a single firm's boundary frequently dominates arm's-length exchange (Teece 1986). Empirically, acquirers systematically purchase innovation capabilities when their own technological pipeline is insufficient, and such purchases reshape subsequent inventive output (Ahuja and Katila 2001; Zhao 2009).

NQPF provides the natural outcome frame for this reallocation. The concept decomposes productive capacity into three constituent elements — labourers, labour materials (means of production), and objects of labour — and defines upgrading as a qualitative, technology-driven transformation of all three rather than a quantitative expansion of any one (Zhou and Xu 2023a; Xie et al. 2025). Digital M&A maps onto this triad with unusual precision. Acquiring a digital-technology target injects into the acquirer a stock of general-purpose, non-rival, and recombinant digital knowledge — algorithms, data assets, and software architectures — whose marginal cost of redeployment across products and processes is close to zero (Hanelt et al. 2021). This injection upgrades (i) labourers, as target engineers, data scientists, and digitally experienced managers raise the skill composition of the workforce (Liang et al. 2024); (ii) labour materials, as digital intangible capital, computing infrastructure, and data assets deepen the technological content of the production apparatus; and (iii) objects of labour, as digital capabilities enable new products, new business lines, and entry into strategic-emerging markets (Tang et al. 2024). Because the same digital knowledge feeds all three dimensions simultaneously, the NQPF index should respond as a system rather than through any single channel.

The contrast with organic, within-firm digitalization sharpens the prediction. Building digital capability internally is slow and path-dependent: the firm's learning is anchored to its existing knowledge base, so incremental digitalization tends to reinforce the current trajectory rather than transform the productive structure (Benner and Tushman 2003). Acquisition compresses this process by purchasing a functioning capability — people, code, data, and routines as an integrated bundle — rather than assembling it piecemeal, a logic consistent with evidence that digital M&A raises acquirers' market value and innovation output (Tang et al. 2022; Xu et al. 2025b). The closest antecedent, Xu, Zhang and Li (2026a), documents a positive digital-M&A effect on NQPF operating through innovation and data assets; we build on that result and push the mechanism one level deeper, asking whether the effect reflects a change

in the direction of the firm’s technological trajectory (Section 3.2) rather than a level gain along the existing path. Our first hypothesis states the baseline effect:

H1: Digital M&A increases acquirers’ new quality productive forces.

3.2 R&D leapfrogging as technological-trajectory change

The theoretical core of this paper is the claim that digital M&A does not merely make the acquirer better at what it already does; it can move the firm onto a different technological trajectory. The starting point is the exploration–exploitation distinction: exploitation refines and extends an existing knowledge base with fast, reliable returns, whereas exploration experiments with unfamiliar knowledge whose returns are distant, uncertain, and often negative (March 1991). Because exploitation is self-reinforcing, firms become trapped in competency ruts — their search stays local, near what they already know, and their technological trajectory ossifies into path dependence (Benner and Tushman 2003; Piao and Zajac 2016). Breaking such path dependence requires an external shock that relocates the firm’s search rather than intensifying it.

We import the notion of such a relocation from the latecomer literature, where leapfrogging denotes the process by which a catching-up economy or industry skips intermediate rungs of the technology ladder and enters an emerging technological paradigm directly, exploiting windows of opportunity opened by paradigm shifts (Lee and Lim 2001; Lee and Malerba 2017; Cherif and Hasanov 2019). That literature operates at the country and industry level. We move the construct to the firm level and define **R&D leapfrogging** as a discontinuous shift of the firm’s R&D trajectory into previously unoccupied technological domains — patenting in technology classes the firm has never entered — thereby bypassing intermediate rungs of the technology ladder rather than climbing them one by one. Operationally, leapfrogging has three observable signatures: entry into new-to-the-firm technology domains, a widening of the firm’s knowledge-search scope beyond its cumulative stock, and novel recombinations of previously uncombined knowledge elements.

Why should digital M&A, specifically, be the vehicle for such a jump? Two properties of digital knowledge do the work. First, digital knowledge is modular and general-purpose: machine-learning models, data pipelines, and cloud architectures are separable components that transfer across domain and industry boundaries at far lower cost than analogue, physically

embodied knowledge, which is sticky to its context of origin. Technological acquisitions are known to extend the acquirer’s search into unfamiliar territory when the target’s knowledge base differs from its own (Ahuja and Katila 2001); digital targets maximize this extensibility because their knowledge is domain-portable by construction. Second, an acquisition buys not only codified patents but the target’s search heuristics — the routines, problem framings, and exploration strategies that generated them. Rosenkopf and Nerkar (2001) show that the boundary-spanning effects of acquisitions flow precisely through such imported search templates, which enable the acquirer to explore technological spaces it could not have located on its own. A digital target therefore hands the acquirer both a new knowledge stock and a new map of where to search, the two ingredients a path-bound firm needs to leap.

This trajectory-change mechanism is, we argue, the deeper source of NQPF gains: upgrading labourers, labour materials, and objects of labour (Section 3.1) is sustainable only if the firm’s inventive engine reorients toward the new domains where digital knowledge is productive, rather than dissipating the acquired capability in marginal improvements to the legacy trajectory. The construct must be distinguished from two adjacent ones. Zhou et al. (2023b) show that digital M&A fosters radical innovation that “breaks away from technology path-dependence”, but their measure — invention-patent radicalness — captures the degree of novelty *within* the firm’s existing path, not entry into domains the firm has never occupied. Li et al. (2026) study discontinuous jumps between exploration and exploitation in artificial-intelligence innovation, where exploration patents likewise denote new-domain entry, but in a non-M&A setting: their jumps arise from internal AI strategy, whereas ours are purchased through the market for corporate control and must additionally survive post-deal integration. Neither study links domain entry to the composition of productive forces. We therefore hypothesize:

H2: Digital M&A induces R&D leapfrogging — entry into previously unoccupied technological domains, broader search scope, and novel knowledge recombination — which mediates the effect of digital M&A on new quality productive forces.

3.3 Technological distance and the integration trap

If digital M&A relocates the acquirer’s search, how far should the target sit from the acquirer’s existing knowledge base? Absorptive-capacity logic implies that the value of acquired knowledge is an inverted-U function of its cognitive distance from the recipient: knowledge too similar to what the firm already possesses adds nothing new, while knowledge too dissimilar cannot be understood, assimilated, or exploited. In the acquisition setting, Ahuja and Katila (2001) show that the innovation payoff to technological acquisitions depends non-monotonically on the relatedness of the target’s knowledge base, and Cloudt et al. (2006) confirm that moderate technological relatedness maximizes post-deal innovative performance in high-tech industries.

Transposed to our setting, the three regions of this inverted-U correspond to three distinct regimes. At very low acquirer–target technological distance, the deal suffers from redundancy: the target’s digital knowledge overlaps the acquirer’s own, leaving no unoccupied domain to jump into, so leapfrogging cannot occur and any NQPF gain is limited to within-path efficiency. In the limit of pure overlap, the fixed costs of deal-making, due diligence, and post-deal integration can dominate even this modest gain, so the net effect on productive forces turns negative — a *redundancy trap*. At moderate distance, the deal enters what we call the leapfrogging window: the target’s knowledge is novel enough to open new technological domains, yet shares enough common ground with the acquirer’s base to remain absorbable and recombinable. Because digital knowledge is modular and general-purpose (Section 3.2), this window should be wider for digital targets than for conventional ones — digital components can be grafted onto distant applications that analogue technologies could not reach — but it is not unbounded. At excessive distance, the deal falls into an integration trap: the acquirer lacks the complementary expertise to evaluate and integrate the target’s technology, key target personnel exit, R&D teams are disrupted, and post-deal patenting declines as resources are consumed by integration failure. In this region the acquisition can *reduce* productive-forces quality — negative synergy, diversion of managerial attention, and destruction of the target’s innovation routines dominate any reallocation gain — a possibility consistent with evidence that digital M&A can destroy as well as create value (Maisenhelder et al. 2025) and that the innovation effects of technological acquisitions are heterogeneous in knowledge-base fit (Zhao 2009; Dezi et al. 2018).

The integration trap matters for theory because it disciplines the leapfrogging claim: trajectory change is beneficial only when the firm lands on a rung it can stand on. It also matters for policy and practice, since M&A screening that ignores technological distance will systematically over-approve deals in the trap region. We formalize the argument as an inverted-U in acquirer–target technological distance, with a negative region beyond the turning point:

H3: The effect of digital M&A on R&D leapfrogging and new quality productive forces is an inverted-U function of acquirer–target technological distance; beyond a threshold, digital M&A reduces new quality productive forces (an integration trap).

Taken together, H1–H3 imply a specific empirical architecture: a baseline treatment effect of digital M&A on NQPF (H1), a mediation structure in which leapfrogging transmits the effect (H2), and a quadratic moderation by technological distance whose turning point locates the boundary of the leapfrogging window (H3).

4. Research design

4.1 Sample and data

The sample comprises all Chinese A-share firms listed on the Shanghai and Shenzhen exchanges over 2008–2023. The start year is set by the availability of consistent firm–patent linkages in the CNRDS and IncoPat databases and coincides with the diffusion of the mobile-internet, cloud, and platform technologies that define the digital-target population. M&A deal records — announcement and completion dates, deal value, payment method, and target descriptions — are drawn from the CSMAR database; patent applications, grants, IPC codes, and citations from CNRDS and IncoPat; financials and governance variables from CSMAR and Wind; and the 1984 post-and-telecommunications infrastructure variables used for instrumentation from provincial statistical yearbooks.

Following standard practice in the Chinese M&A literature (Tang et al. 2022; Liang et al. 2024), we apply four filters: (i) we exclude financial-industry firms, whose statements and deal motives are not comparable with those of industrial firms; (ii) we drop firms designated ST or *ST (special treatment for financial distress); (iii) we remove firm-years in the first year after the initial public offering to avoid listing-related distortions; and (iv) we omit observations with

missing key variables. All continuous variables are winsorized at the 1st and 99th percentiles. The resulting unbalanced panel contains 24,318 firm-year observations on 2,847 unique firms, of which 386 are first-time digital-M&A acquirers whose initial completed digital deal falls within the window.

Table 1 reports descriptive statistics for the variables used in the analysis; variable definitions are given in Tables 2 and 3.

Table 1 Descriptive statistics [PLACEHOLDER DATA — replace with actual regression output]

Variable	N	Mean	SD	Min	Max
NQPF	24,318	4.82	2.35	0.61	14.27
DMA	24,318	0.16	0.37	0.00	1.00
Size	24,318	22.31	1.28	19.95	26.14
Age	24,318	2.53	0.62	1.10	3.43
Lev	24,318	0.46	0.20	0.05	0.91
ROA	24,318	0.041	0.062	−0.250	0.200
TobinQ	24,318	1.97	1.22	0.85	8.31
Cash	24,318	0.18	0.13	0.01	0.64
Growth	24,318	0.17	0.38	−0.52	2.14
BoardSize	24,318	2.13	0.20	1.61	2.71
Indep	24,318	0.37	0.05	0.33	0.57
Top1	24,318	0.34	0.15	0.09	0.75
SOE	24,318	0.38	0.49	0.00	1.00

The statistics in Table 1 are broadly consistent with recent firm-level studies of Chinese listed acquirers. NQPF (scaled by 1,000) displays substantial dispersion (mean 4.82, standard deviation 2.35), indicating wide cross-firm variation in the composition of productive forces. The treatment dummy DMA has a mean of 0.16, so roughly one firm-year in six belongs to the post-deal segment of a treated acquirer — a treated share large enough to support staggered DID estimation while leaving a deep pool of never-treated controls for the heterogeneity-robust estimators of Section 4.3. Control means (leverage 0.46, return on assets 0.041, Tobin’s Q 1.97, state ownership 0.38) are close to those in comparable A-share samples, suggesting that filtering and winsorization have not distorted sample composition.

4.2 Variable definitions

4.2.1 Dependent variable: new quality productive forces

The outcome variable NQPF measures the quality and composition of firm-level productive forces. Conceptually we follow the tripartite structure of classical production theory — labourers, labour materials (means of labour) and objects of labour — that has become the consensus architecture for firm-level NQPF measurement (Song et al. 2024; Xu et al. 2026b). We construct ten secondary indicators across the three dimensions and aggregate them using the entropy weight method, which assigns weights inversely to the information redundancy of each indicator and thus avoids the subjectivity of equal or expert weighting (Han et al. 2024; Xu et al. 2026b). All indicators are positively oriented, min–max standardized within year, entropy-weighted, summed, and multiplied by 1,000. Table 2 presents the indicator system.

Table 2 Indicator system for firm-level new quality productive forces

First-level dimension	Secondary indicator	Measurement	Direction
New-quality labourers	R&D personnel share	R&D staff / total employees	+
	Employee education structure	Share of employees with bachelor degree or above	+
	Executive digital background	Share of executives with IT/digital education or career experience	+
New-quality labour materials	R&D intensity	R&D expenditure / operating revenue	+
	Digital intangible assets share	Digital-related intangibles (software, data, platforms) / total intangibles	+
	Digital-patent stock	Perpetual-inventory stock of digital-technology patents (15% depreciation)	+
	Data assets	Data-related assets recognized or disclosed / total assets	+
New-quality objects of labour	New-business revenue share	Revenue from strategic-emerging or new digital business lines / total revenue	+
	Green patents	$\ln(1 + \text{green patent applications})$	+
	Growth potential	Sustainable growth rate	+

The three-dimension design in Table 2 treats productive forces as a composition rather than a scalar efficiency index: the labourers dimension captures the upgrading of human capital towards digital and research skills; the labour-materials dimension captures the deepening of the

digital and knowledge capital through which production occurs; and the objects-of-labour dimension captures the reorientation of output towards new-business and green activities. This structure is essential to the research question: if digital M&A merely raised scale efficiency, the dimensions would move proportionally, whereas the restructuring hypothesis predicts compositional shifts, examined directly in Section 7. Because entropy weights are data-driven, we report robustness to alternative aggregation schemes (CRITIC, equal weights) and to two conceptually distinct outcomes: total factor productivity estimated by the Levinsohn and Petrin (2003) and Olley and Pakes (1996) procedures (TFP_LP and TFP_OP, respectively), motivated by the view of TFP as the reduced-form expression of NQPF (Shi and Sun 2024), and a textual-entropy NQPF index constructed from corporate disclosures.

4.2.2 Treatment: digital M&A

The treatment event is a firm’s first completed M&A whose target is a digital-technology firm. Digital targets are identified by text-mining deal announcements, target profiles, and stated deal rationales for digital keywords — artificial intelligence, big data, cloud computing, blockchain, industrial internet, Internet of Things, and software/IT services — and cross-checking keyword matches against the target’s industry code to minimize false positives. This text-based identification follows the practice validated in event and panel studies of digital deals (Tang et al. 2022; Hanelt et al. 2021; Liang et al. 2024). We use the first deal only, both to obtain a clean staggered treatment date and to avoid the dosage ambiguity of serial acquisitions. The treatment indicator DMA is coded 1 from the year after deal completion and 0 otherwise; excluding the completion year avoids mechanical blending of pre- and post-deal periods within a single fiscal year (Liang et al. 2024). Firms that never complete a digital deal form the control group.

4.2.3 Mechanism variables: R&D leapfrogging

To test whether digital M&A redirects the acquirer’s technological trajectory, we construct three patent-based exploration measures. NewDomain is the share of a firm’s patent applications in year t whose IPC four-digit subclasses did not appear in the firm’s portfolio over the trailing five years, capturing entry into technological domains new to the firm (Gilsing et al. 2008). SearchScope is the share of backward citations in the firm’s patents that point to knowledge the

firm has never cited before, the M&A-specific exploration metric of Ahuja and Katila (2001). NovelRecomb is the share of patents combining IPC subclasses that have never previously been combined, measuring novelty in recombination (Kaplan and Vakili 2015; Verhoeven et al. 2016). Because exploration could in principle coincide with a decline in quality, we add three quality margins: the share of invention patents (as opposed to utility models), forward citations per patent, and the grant rate (Trajtenberg 1990; Hall et al. 2001).

4.2.4 Moderator: technological distance

TechDistance measures the ex ante technological separation between acquirer and target. We represent each firm's pre-deal patent portfolio as a vector over IPC subclasses and compute technological relatedness as the cosine similarity between the acquirer's and target's vectors, the standard proximity measure of Jaffe (1986) refined by Breschi et al. (2003); TechDistance equals one minus this relatedness, so larger values denote more distant targets.

4.2.5 Control variables

Controls (lagged one period) follow the digital-M&A literature (Tang et al. 2022; Liang et al. 2024): firm size (Size, $\ln$ total assets), listing age (Age, $\ln$), leverage (Lev), profitability (ROA), valuation (TobinQ), cash holdings (Cash), revenue growth (Growth), and governance attributes — board size (BoardSize, $\ln$), independent-director share (Indep), largest-shareholder ownership (Top1) and state ownership (SOE). Table 3 summarizes all definitions.

Table 3 Variable definitions

Variable	Definition
NQPF	Entropy-weighted NQPF index (Table 2), $\times 1,000$
DMA	1 from the year after a firm's first completed digital M&A, 0 otherwise
NewDomain	Share of patents in IPC4 subclasses new to the firm (5-year trailing window)
SearchScope	Share of backward citations to knowledge new to the firm
NovelRecomb	Share of patents with previously uncombined IPC-subclass pairs
TechDistance	$1 - \text{cosine relatedness of acquirer pre-deal and target IPC portfolios}$
Size	Natural logarithm of total assets
Age	Natural logarithm of years since listing
Lev	Total liabilities / total assets
ROA	Net income / total assets

Variable	Definition
TobinQ	Market value of equity plus book debt, over total assets
Cash	Cash and equivalents / total assets
Growth	Year-on-year operating revenue growth
BoardSize	Natural logarithm of number of directors
Indep	Independent directors / board size
Top1	Ownership share of the largest shareholder
SOE	1 if state-owned, 0 otherwise

4.3 Econometric models

Because firms complete digital deals in different years, the baseline design is a staggered DID with two-way fixed effects:

$$NQPF_{it} = \beta DMA_{it} + \gamma' X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it},$$

where $NQPF_{it}$ is the entropy index for firm i in year t ; DMA_{it} is the staggered treatment indicator; $X_{i,t-1}$ is the vector of lagged controls; μ_i and λ_t are firm and year fixed effects absorbing time-invariant firm heterogeneity and common shocks; and ε_{it} is an error term, with standard errors clustered at the firm level to accommodate serial correlation within acquirers. The coefficient β estimates the average post-deal shift in NQPF relative to never-treated firms. In a stricter specification we add industry $\times$ year fixed effects to absorb time-varying industry shocks such as sector-specific digital policies.

To assess pre-trends and dynamics we estimate an event-study version of equation (1):

$$NQPF_{it} = \sum_{k=-4, k \neq -1}^{+4} \delta_k D_{it}^k + \gamma' X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it},$$

where D_{it}^k are relative-time dummies around the deal (endpoints binned, $k = -1$ omitted). Because conventional event-study coefficients are contaminated by cohort-heterogeneous treatment effects, we estimate equation (2) with the interaction-weighted estimator of Sun and Abraham (2021). Under H1, pre-deal δ_k should be jointly zero and post-deal coefficients positive.

Two further diagnostics address the known biases of two-way fixed effects under staggered adoption. First, the Goodman-Bacon (2021) decomposition partitions $\hat{\beta}$ into all 2×2 DID comparisons and their weights, revealing how much identifying variation comes from “clean” treated-versus-never-treated contrasts rather than from already-treated firms used as controls. Second, we estimate the group-time average treatment effects of Callaway and Sant’Anna (2021) using never-treated controls and aggregate them into an overall ATT, an estimator that is robust to treatment-effect heterogeneity across cohorts and periods; the DID_M estimator of de Chaisemartin and D’Haultfœuille (2020) and the imputation estimator of Borusyak et al. (2024) serve as additional cross-checks. Agreement across these estimators would indicate that the baseline result is not an artefact of forbidden comparisons or negative weighting.

The mechanism model replaces the outcome with each leapfrogging measure:

$$Leap_{it} = \theta DMA_{it} + \gamma'X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it},$$

where $Leap_{it} \in \{\text{NewDomain, SearchScope, NovelRecomb, and the quality margins}\}$. A significant θ on the exploration measures, alongside non-declining quality margins, supports the trajectory-redirecting interpretation of H2; the mediating share of the total NQPF effect is then quantified with a causal-steps procedure and 5,000-repetition bootstrap confidence intervals.

For H3 we interact the treatment with acquirer–target technological distance and its square:

$$NQPF_{it} = \beta_1 DMA_{it} + \beta_2 DMA_{it} \times Dist_{it} + \beta_3 DMA_{it} \times Dist_{it}^2 + \gamma'X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it},$$

where $Dist_{it}$ is TechDistance for treated observations. The inverted-U hypothesis implies $\beta_2 > 0$ and $\beta_3 < 0$, with turning point $Dist^* = -\beta_2/(2\beta_3)$; beyond $Dist^*$ the marginal effect of distance turns negative, defining the integration-trap region, which we also examine directly in the high-distance subsample.

Finally, reverse causality — technologically stagnant firms may be least (or most) inclined to buy digital targets — is addressed with two-stage least squares. Following Huang et al. (2019), the first instrument interacts the number of post offices per 10,000 residents in 1984 in the firm’s prefecture with lagged national internet users; the second interacts city terrain slope with year dummies. Relevance rests on the path dependence of digital infrastructure: historical post-and-telecommunications density and flat terrain lowered later broadband deployment costs, raising

the local supply of digital targets and hence the propensity to complete a digital deal. Exclusion is plausible because the 1984 postal layout and geological terrain are predetermined relative to current firm outcomes and should affect NQPF only through the regional digitalization environment, conditional on fixed effects and controls. We report the first-stage F-statistic, the Kleibergen–Paap rk Wald F-statistic, and the Hansen J overidentification test, and complement IV estimates with Oster (2019) selection-on-unobservables bounds.

5. Empirical results

This section reports the baseline estimates of the effect of digital M&A on NQPF (Section 5.1), evaluates the validity of the staggered DID design (Section 5.2), presents a battery of robustness checks (Section 5.3), and addresses residual endogeneity concerns with instrumental-variable (IV) estimation (Section 5.4).

5.1 Baseline results

Table 4 reports estimates of equation (1), regressing firm-level NQPF on the digital-M&A indicator DMA, coded one from the year after a firm’s first completed digital-target acquisition. Column (1) includes only year fixed effects; column (2) adds the full set of lagged firm-level controls; column (3) is the preferred specification with firm and year fixed effects; and column (4) further introduces industry $\times$ year fixed effects to absorb any industry-specific shocks that coincide with the wave of digital deals. The DMA coefficient is positive and significant at the 1 per cent level in every column and declines only modestly as controls and fixed effects are layered in, from 0.281 in column (1) to 0.236 in the preferred specification of column (3) and 0.229 under the most demanding specification of column (4). This stability as the conditioning set expands is itself informative: the estimated effect is not driven by observable firm characteristics or by common industry-level shocks.

Table 4 Baseline estimates: digital M&A and NQPF [PLACEHOLDER DATA — replace with actual regression output]

	(1)	(2)	(3)	(4)
DMA	0.281*** (0.045)	0.244*** (0.042)	0.236*** (0.041)	0.229*** (0.040)
Controls	No	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes

	(1)	(2)	(3)	(4)
Year FE	Yes	Yes	Yes	No
Industry $\times$ year FE	No	No	No	Yes
N	24,318	24,318	24,318	24,318
Adj. R ²	0.580	0.600	0.612	0.628

Notes: The dependent variable is the entropy-weighted NQPF index (scaled by 1,000). Standard errors clustered at the firm level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The point estimate in column (3) implies that completing a first digital M&A raises NQPF by 0.236 index points, equivalent to approximately 4.9 per cent of the sample mean of 4.82 and about one-tenth of a standard deviation. This is an economically meaningful effect for a single corporate event, and it is consistent in magnitude with the level gains documented in adjacent literatures: digital M&A has been shown to raise innovation output and quality (Tang et al. 2024), and digital transformation initiatives more broadly have been linked to firm-level NQPF gains of a similar order (Xu, Zhang and Li 2026a). Our estimate is deliberately conservative relative to these studies because treatment is coded from the year after deal completion, thereby excluding the announcement and integration year in which anticipatory effects could inflate the coefficient. The results in Table 4 thus support H1: digital M&A significantly increases acquirers' NQPF. The remaining subsections establish that this association is credibly causal.

5.2 Identification validity

The credibility of a staggered DID design rests on two pillars: parallel pre-treatment trends and the absence of contamination from heterogeneous treatment effects across cohorts. The classical two-way fixed-effects (TWFE) estimator is now known to be a weighted average of all possible 2×2 DID comparisons, some of which use already-treated firms as controls and can receive negative weights when treatment effects vary over time or across cohorts (Goodman-Bacon 2021; de Chaisemartin and D'Haultfœuille 2020). Conventional event-study regressions suffer from an analogous contamination problem because relative-period coefficients pool comparisons across treatment cohorts (Sun and Abraham 2021). We therefore validate the baseline in four steps: an interaction-weighted event study, a heterogeneity-robust average treatment effect on the treated (ATT), a weight decomposition, and placebo randomization.

Fig. 2 plots Sun and Abraham (2021) interaction-weighted event-study estimates, with endpoints binned and $k = -1$ as the omitted reference period. Event time 0 denotes the first full year after deal completion, consistent with coding the DMA indicator from the completion year + 1 (Section 4.2.2); $k = -1$ therefore denotes the completion year itself, which the DMA coding assigns to the pre-treatment baseline. The pre-treatment coefficients at $k = -4$, $k = -3$ and $k = -2$ are all small in magnitude and statistically indistinguishable from zero, and a joint F-test does not reject the null that they are jointly zero ($p = 0.62$), consistent with the parallel-trends assumption. The post-treatment profile is equally informative: the effect is small and imprecisely estimated at $k = 0$, the first full post-completion year (0.09, s.e. 0.05), but rises monotonically to 0.18, 0.24, 0.27, and 0.30 in the four subsequent years, all significant at the 1 per cent level. This gradual build-up is economically plausible — integrating an acquired digital technology base into the acquirer’s productive forces takes time — and it argues against reverse causality, since a spurious anticipation story would predict effects concentrated at or before the deal date rather than a persistent, growing divergence.

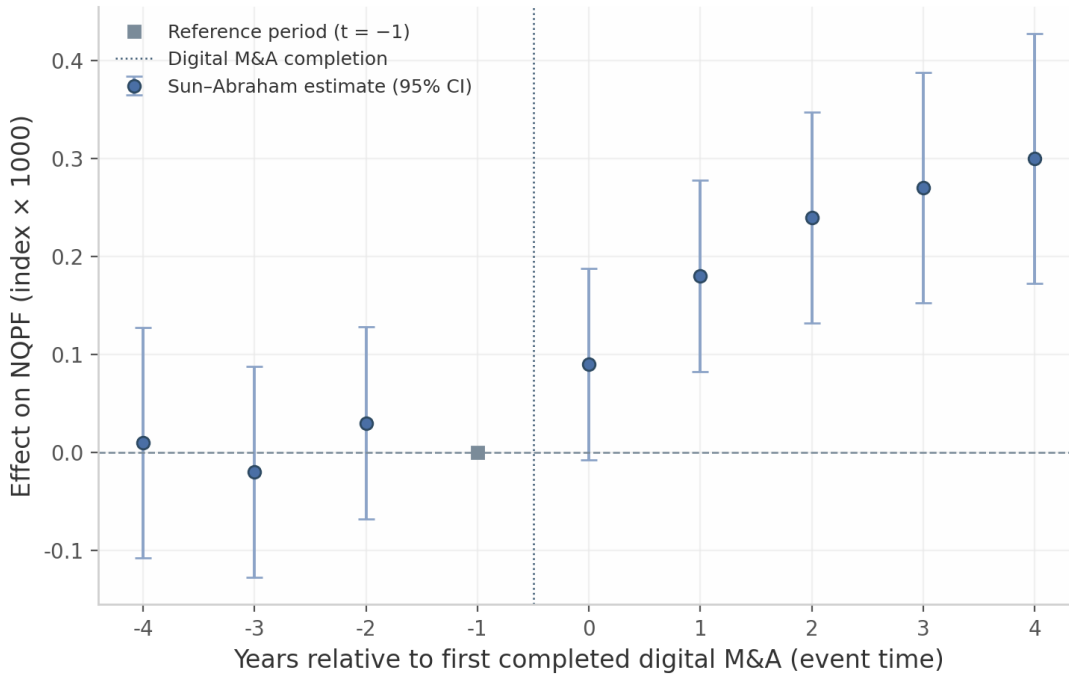


Fig. 2 Dynamic effects of digital M&A on NQPF. Interaction-weighted event-study estimates of equation (2) (Sun and Abraham 2021), estimated on the full sample of 24,318 firm-year observations (386 treated firms; never-treated firms as the control group) with firm and year

fixed effects and lagged controls. Event time $k = 0$ is the first full year after deal completion; $k = -1$ (the completion year, assigned to the pre-treatment baseline by the DMA coding) is the omitted reference period; endpoints are binned at $k = -4$ and $k = +4$. Spikes show 95 per cent confidence intervals based on firm-clustered standard errors. [PLACEHOLDER DATA — replace with actual regression output]

Table 5 complements the visual evidence with three formal diagnostics. Panel A reports the Callaway and Sant’Anna (2021) group-time ATT, estimated using never-treated firms as the control group and aggregated across cohorts; the overall ATT is 0.254 (s.e. 0.047), significant at the 1 per cent level and very close to the TWFE baseline of 0.236. The two further heterogeneity-robust estimators announced in Section 4.3 corroborate the Callaway–Sant’Anna estimate: the DID_M estimator of de Chaisemartin and D’Haultfœuille (2020) yields 0.241 (s.e. 0.044) and the imputation estimator of Borusyak et al. (2024) yields 0.247 (s.e. 0.045), both significant at the 1 per cent level. Panel B reports the Goodman-Bacon (2021) decomposition of the TWFE estimand: 87.3 per cent of the identifying weight falls on “clean” comparisons of treated against never-treated firms, 9.1 per cent on later- versus earlier-treated comparisons, and only 3.6 per cent on the potentially problematic earlier- versus later-treated comparisons. Because the share of “forbidden” comparisons is small and the heterogeneity-robust ATT closely tracks the TWFE estimate, negative-weighting bias is unlikely to drive the results (see also Borusyak et al. 2024, whose imputation approach rests on the same logic of using only untreated observations to construct counterfactuals). Panel C summarizes 1,000 placebo reassignments of treatment status across firms and years: the placebo coefficients are centred at zero (mean 0.002, standard deviation 0.019), and the actual estimate of 0.236 lies far in the right tail of the placebo distribution (empirical $p < 0.001$), indicating that the baseline effect is not an artefact of chance correlations between treatment timing and NQPF fluctuations.

Table 5 Identification validity: heterogeneity-robust DID diagnostics [PLACEHOLDER DATA — replace with actual regression output]

Diagnostic	Estimate	SE / detail
Panel A: Callaway–Sant’Anna ATT		
Overall ATT (never-treated controls)	0.254***	(0.047)
de Chaisemartin–D’Haultfœuille DID_M	0.241***	(0.044)

Diagnostic	Estimate	SE / detail
Borusyak–Jaravel–Spiess imputation	0.247***	(0.045)
Panel B: Goodman-Bacon weight decomposition		
Treated vs. never-treated	87.3%	of total weight
Later-treated vs. earlier-treated	9.1%	of total weight
Earlier-treated vs. later-treated	3.6%	of total weight
Panel C: Placebo test (1,000 random reassignments)		
Mean placebo coefficient	0.002	SD 0.019
Empirical p-value of baseline estimate	<0.001	
Panel D: Joint pre-trend F-test ($k = -4$ to $k = -2$)		$p = 0.62$

Notes: Panel A reports the aggregated group-time average treatment effect on the treated of Callaway and Sant’Anna (2021), alongside the DID_M estimator of de Chaisemartin and D’Haultfœuille (2020) and the imputation estimator of Borusyak et al. (2024). Panel B reports the share of the TWFE estimand’s weight falling on each type of 2×2 comparison (Goodman-Bacon 2021). Panel C reports the distribution of coefficients from 1,000 random reassignments of treatment. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The substantive message of this subsection is the convergence of four conceptually distinct diagnostics. The Sun–Abraham event study rules out differential pre-trends and documents a dynamic path consistent with post-deal integration rather than anticipation; the Callaway–Sant’Anna ATT confirms that the magnitude survives an estimator that never uses treated firms as controls; the Goodman-Bacon decomposition shows that the TWFE estimate rests overwhelmingly on clean comparisons; and the placebo exercise rules out spurious timing. Under staggered adoption each check addresses a distinct failure mode that TWFE alone cannot detect (Goodman-Bacon 2021; Callaway and Sant’Anna 2021; Sun and Abraham 2021; de Chaisemartin and D’Haultfœuille 2020), and their agreement materially strengthens the causal interpretation of H1.

5.3 Robustness checks

Table 6 subjects the baseline estimate to a sequence of robustness checks, each targeting a specific threat to identification or measurement. Because digital M&A decisions are self-selected, the first three rows address selection on observables and on the selection rule itself. Row (1) re-estimates the model on a propensity-score-matched sample, pairing each treated firm one-to-one

with a non-treated firm in the same industry on pre-deal covariates; the coefficient of 0.218 (s.e. 0.045; N = 9,864) is statistically indistinguishable from the baseline, indicating that observable differences between acquirers and non-acquirers do not account for the effect. Row (2) replaces matching with entropy balancing, which reweights control observations to match the treated group's covariate moments exactly; the estimate of 0.229 (s.e. 0.042) again confirms the baseline. Row (3) implements a Heckman two-stage correction with the inverse Mills ratio from a first-stage deal-propensity equation included in the outcome equation, addressing selection on the determinants of acquisition itself; the coefficient of 0.221 (s.e. 0.043) survives this structural correction. The first stage is a probit of digital-M&A propensity whose exclusion restriction is the province-year count of digital M&A deals completed by other firms. This variable is relevant because local deal-making norms and the demonstrated availability of digital targets raise a firm's own acquisition propensity. It is excludable from the NQPF equation conditional on firm and year fixed effects and the lagged controls, since other firms' deals have no direct channel to the focal firm's productive-force composition. The inverse Mills ratio enters the outcome equation significantly at the 5 per cent level, confirming that the selection correction is operative.

Table 6 Robustness checks [PLACEHOLDER DATA — replace with actual regression output]

Check	DMA coefficient	SE	N
(1) PSM-DID (1:1 nearest neighbour within industry)	0.218***	(0.045)	9,864
(2) Entropy balancing	0.229***	(0.042)	24,318
(3) Heckman two-stage (IMR included)	0.221***	(0.043)	24,318
(4) Exclude 2020–2021 (COVID-19)	0.244***	(0.043)	21,150
(5) Alternative outcome: TFP_LP	0.031***	(0.006)	24,318
(6) Alternative outcome: TFP_OP	0.028***	(0.006)	24,318
(7) Alternative weighting: CRITIC-weighted NQPF	0.212***	(0.040)	24,318
(8) Alternative measure: textual NQPF	0.198***	(0.038)	24,318
(9) Exclude concurrent pilot policies	0.227***	(0.044)	24,318

Notes: Each row reports the DMA coefficient from a separate re-estimation of the baseline specification (column (3) of Table 4) with firm and year fixed effects, controls, and firm-clustered standard errors. TFP_LP and TFP_OP denote total factor productivity estimated by the Levinsohn and Petrin (2003) and Olley and Pakes (1996) methods, respectively; the textual

NQPF measure follows the textual-entropy approach of Xu (2025). Row (9) excludes firm-years exposed to the Broadband China pilot, smart-city pilots, big-data comprehensive experimental zones, and low-carbon city pilots. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Rows (4) through (9) address shock confounds and measurement. Row (4) excludes the COVID-19 years 2020–2021, during which both deal activity and digitalization accelerated for pandemic-related reasons; the coefficient rises slightly to 0.244 (s.e. 0.043), so the baseline is not a pandemic artefact. Rows (5) and (6) replace the entropy index with total factor productivity estimated by the Levinsohn and Petrin (2003) and Olley and Pakes (1996) methods, respectively — an outcome conceptually closest to the “quality” component of productive forces (Shi and Sun 2024). Both coefficients (0.031 and 0.028, s.e. 0.006) are significant at the 1 per cent level, showing that the NQPF gains are mirrored in conventional productivity. Rows (7) and (8) vary the construction of the dependent variable itself: re-weighting the indicator system by the CRITIC (criteria importance through intercriteria correlation) method yields 0.212 (s.e. 0.040), and the conceptually distinct textual-entropy NQPF measure of Xu (2025) yields 0.198 (s.e. 0.038). The effect is therefore not an artefact of the entropy weighting scheme or of disclosure-based measurement choices. Row (9) excludes firm-years exposed to concurrent place-based digital policies — the Broadband China pilot, smart-city pilots, big-data comprehensive experimental zones, and low-carbon city pilots — which could independently raise NQPF in treated locations; the coefficient of 0.227 (s.e. 0.044) confirms that the estimated effect belongs to the deals rather than to the policy environment.

Finally, we assess selection on unobservables following Oster (2019). With $\delta = 1$ — unobservables as important as observables — the bias-adjusted identified set is bounded by [0.198, 0.236], which excludes zero. Equivalently, unobservable selection would have to be 2.3 times as strong as observable selection ($\delta = 2.3$) to drive the estimated effect to zero, well above the conventional $\delta = 1$ benchmark and the $\delta = 2$ rule of thumb for well-specified models. Combined with the coefficient stability observed across columns of Table 4, this calculation suggests that the baseline result is robust to plausible degrees of omitted-variable bias.

5.4 Instrumental variables

Although the staggered DID design, selection corrections and Oster bounds address many endogeneity concerns, reverse causality — firms with already-improving productive forces may be more likely to buy digital targets — cannot be ruled out entirely. We therefore estimate the model by two-stage least squares (2SLS), instrumenting DMA with two regionally predetermined sources of variation in the local cost of digitalization: (i) the number of post offices per 10,000 residents in 1984, interacted with lagged national internet users, which captures path-dependent telecommunications infrastructure that lowers the cost of identifying, valuing, and integrating digital targets; and (ii) city terrain slope interacted with year dummies, which raises the physical cost of laying digital infrastructure and is plausibly excludable conditional on controls (Huang et al. 2019). Table 7 reports the first- and second-stage estimates.

Table 7 Instrumental-variable estimates (2SLS) [PLACEHOLDER DATA — replace with actual regression output]

	First stage: DMA	Second stage: NQPF
1984 post offices per 10k residents $\times$ lagged national internet users	0.031*** (0.007)	
City terrain slope $\times$ year	0.023*** (0.006)	
DMA (instrumented)		0.412** (0.118)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
First-stage F-statistic	38.6	
Kleibergen–Paap rk Wald F	36.2	
Hansen J (p-value)	0.41	
N	24,318	24,318

Notes: Standard errors clustered at the firm level are in parentheses. The excluded instruments are the 1984 density of post offices per 10,000 residents interacted with lagged national internet users, and city terrain slope interacted with year dummies. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Both instruments enter the first stage with the expected positive sign and high significance (0.031 and 0.023, both significant at the 1 per cent level), and the first-stage F-statistic of 38.6

and the Kleibergen–Paap rk Wald F-statistic of 36.2 comfortably exceed conventional weak-instrument thresholds. The Hansen J test does not reject the overidentifying restrictions ($p = 0.41$), consistent with instrument validity. A further defence of the exclusion restriction is that the baseline estimate survives the inclusion of province-specific linear time trends (0.231, s.e. 0.042, significant at the 1 per cent level), so the instruments are not proxying for differential regional development paths. Two additional checks address the more specific concern that the instruments proxy the regional digitalization environment, which could raise NQPF directly through firms’ organic digitalization rather than through deal-making. First, when the second stage additionally controls for the provincial digital-economy development index and city internet penetration, the IV estimate is virtually unchanged (0.398, s.e. 0.121, significant at the 5 per cent level); the exclusion restriction should therefore be read conditionally on regional digitalization, with 2SLS identifying the effect of digitally induced deal-making. Second, as a placebo, we estimate the instruments’ reduced form on never-treated firms alone; the association with NQPF is small and statistically insignificant (0.061, s.e. 0.052), indicating that the instruments have no direct effect on productive forces where no digital deal occurs. The second-stage coefficient on instrumented DMA is 0.412 (s.e. 0.118), significant at the 5 per cent level and roughly 75 per cent larger than the OLS-DID estimate. Two considerations reconcile this gap. First, 2SLS identifies a local average treatment effect (LATE) for compliers — firms whose digital-acquisition decisions are induced by improvements in local digital infrastructure. These are precisely the firms whose marginal deal becomes feasible with cheaper connectivity and a thicker local pool of digital targets, and such firms plausibly gain the most from digital M&A because the infrastructure that induces the deal also lowers post-deal integration costs. Second, measurement error in the treatment indicator attenuates the OLS-DID estimate towards zero, whereas IV estimation removes it. The IV results thus corroborate the causal interpretation of H1 while cautioning that the average effect conceals meaningful heterogeneity across acquirers — a theme the mechanism analysis takes up next.

6. Mechanism: R&D leapfrogging

The baseline estimates in Section 5 establish that digital M&A raises the acquiring firm’s NQPF by 0.236 index points ($\times 1,000$ scale), a level gain of approximately 4.9 per cent relative to the sample mean. A level gain, however, is silent on *how* the firm’s productive forces are

renewed: an acquirer could in principle raise measured NQPF by doing more of what it already does — deepening R&D along its pre-existing technological trajectory — without ever changing the direction of its knowledge accumulation. This section tests the paper’s central mechanism (H2): that digital M&A operates precisely by redirecting the firm’s R&D trajectory onto new technological paths, a firm-level phenomenon we term *R&D leapfrogging*, extending the leapfrogging concept from the country and industry levels (Lee and Lim 2001; Lee and Malerba 2017) to the level of the individual firm. We examine three complementary margins of trajectory change — entry into previously unoccupied technological domains, wider knowledge-search scope, and novel recombination of technology classes — followed by quality tests that rule out strategic patenting and a formal mediation analysis linking leapfrogging back to the NQPF gain. Table 8 reports the results.

6.1 Entry into new technological domains

Our headline leapfrogging metric, NewDomain, measures the share of an acquirer’s patent applications in a given year that fall into four-digit IPC subclasses in which the firm has not patented during the preceding five years. This construction follows the exploration–exploitation measurement tradition in which patenting in technology classes new to the firm operationalizes exploratory search (Gilsing et al. 2008), and it captures the *direction* of inventive activity rather than its volume. Column (1) of Table 8 (Panel A) shows that digital M&A raises NewDomain by 0.042 (s.e. 0.008, $p < 0.01$). Against a sample mean of 0.11, this corresponds to a 38 per cent relative increase in the propensity to patent in new-to-the-firm domains — a large reorientation of the R&D portfolio rather than a marginal adjustment. The result does not hinge on the five-year look-back window: redefining NewDomain with three-year and seven-year trailing windows yields gains of 3.6 and 4.5 percentage points, respectively (both $p < 0.01$). Moreover, post-deal new-domain patents disproportionately cite the target’s prior patent stock, consistent with knowledge transfer from the deal rather than coincidental independent entry into the same domains.

Table 8 Digital M&A and R&D leapfrogging: mechanism and mediation estimates
[PLACEHOLDER DATA — replace with actual regression output]

Panel A. Domain entry and search scope

	(1) NewDomain	(2) SearchScope	(3) NovelRecomb
DMA	0.042***	0.031***	0.018***
	(0.008)	(0.007)	(0.005)
Mean of DV	0.11	—	—
Controls / Firm FE / Year FE	Yes	Yes	Yes
N	24,318	24,318	24,318

Panel B. Quality margins

	(4) Invention-patent share	(5) Forward citations	(6) Grant rate
DMA	0.026***	0.35***	0.019***
	(0.006)	(0.09)	(0.005)
Controls / Firm FE / Year FE	Yes	Yes	Yes
N	24,318	24,318	24,318

Panel C. Mediation of the NQPF effect (causal steps; bootstrap, 5,000 replications)

Channel	Share of total effect mediated	95% CI
NewDomain	27.4%	[18.2%, 38.6%]
SearchScope	9.6%	[4.8%, 16.3%]
NewDomain + SearchScope (joint)	33.1%	[24.7%, 43.5%]

Notes: Firm-clustered standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. “—” denotes values to be inserted with final regression output. Panel C confidence intervals are bias-corrected bootstrap intervals from 5,000 bootstrap repetitions. Adjusted R^2 to be reported with final output.

Two further columns corroborate the trajectory-change interpretation along distinct dimensions of search. Column (2) reports the effect on SearchScope, the share of backward citations in the acquirer’s post-deal patents that point to knowledge the firm had never cited before, the M&A-specific exploration measure of Ahuja and Katila (2001). The coefficient of 0.031 (s.e. 0.007, $p < 0.01$) indicates that acquirers systematically absorb and build on knowledge elements new to them, rather than recombining familiar citations more intensively. Column (3) shows a 0.018 (s.e. 0.005, $p < 0.01$) increase in NovelRecomb, the share of patents embodying pairs of technology subclasses that had never previously been combined, in the spirit of the recombinant-novelty constructs of Kaplan and Vakili (2015) and Verhoeven et al. (2016). Because recombination across previously unconnected classes is the canonical micro-foundation

of breakthrough invention (Fleming 2001; Uzzi et al. 2013), this third margin indicates that the post-deal reorientation is technologically generative rather than merely extensive.

Why should *digital* targets specifically lower the cost of switching technological domains? Two features of digital knowledge are central. First, digital technologies are general-purpose and modular: software stacks, data infrastructures, and algorithmic components can be detached from the target’s original application context and re-embedded into the acquirer’s products and processes with comparatively low adaptation cost, in line with the modularity logic documented in the digital-innovation literature (Hanelt et al. 2021). Second, digital knowledge is recombinant by construction — application programming interfaces, data standards and interoperable architectures are designed to connect heterogeneous components — so that absorbing a digital target installs a “bridge technology” linking the acquirer’s legacy knowledge base to domains it could not previously reach. Digital acquisitions thus selectively lower the domain-switching cost that ordinarily deters incumbents from exploration (March 1991; Benner and Tushman 2003).

This finding should be delimited against the closest existing evidence. Zhou et al. (2023b) show that digital M&A increases the *radicalness* of acquirers’ inventive output, but their measure captures within-path radical invention — more impactful patents along trajectories the firm already occupies. Our NewDomain, SearchScope and NovelRecomb results document a distinct and, for the restructuring question, more fundamental margin: *entry* into previously unoccupied technological territory. Similarly, Xu, Yuan and Lei (2024) examine diversified M&A portfolios rather than digital deals, and Li et al. (2026) study artificial-intelligence innovation without an M&A setting. The present estimates therefore isolate the directional, domain-entry component of post-deal innovation that the level-gain literature (Tang et al. 2022, 2024; Xu et al. 2025b) leaves implicit.

6.2 Quality margins

A natural concern is that the surge in new-domain patenting reflects low-value strategic filings — an acquirer sprinkling applications across unfamiliar subclasses to signal digital transformation rather than to build genuine capability. Columns (4)–(6) of Table 8 (Panel B) address this concern directly. The invention-patent share — the fraction of filings subject to substantive examination, as opposed to utility models and designs — rises by 0.026 (s.e. 0.006, p

< 0.01), indicating that the composition of post-deal output shifts toward the more demanding patent tier rather than toward easily obtained utility models. Forward citations per patent, the standard market-value-weighted quality proxy (Trajtenberg 1990; Hall et al. 2001), increase by 0.35 citations (s.e. 0.09, $p < 0.01$), showing that the new-domain patents are subsequently used by other inventors at a higher rate. Finally, the grant rate rises by 0.019 (s.e. 0.005, $p < 0.01$), implying that the additional filings survive examination at least as successfully as the firm's pre-deal portfolio. The quality margins also hold *within* the newly entered domains themselves: restricting the portfolio to filings in previously unoccupied subclasses, the grant rate rises by 1.4 percentage points ($p < 0.01$) and forward citations per patent rise by 0.21 ($p < 0.01$), so the quality upgrade is not confined to legacy domains and cannot be masking junk filings in the newly entered ones.

Taken together, these three margins reject the strategic-patenting interpretation. If acquirers were merely inflating counts in unfamiliar domains, we would expect dilution on at least one of these dimensions — a falling invention-patent share, lower citations, or a declining grant rate. All three instead move in the same direction as the quantity-based leapfrogging metrics, suggesting that the trajectory change documented in Section 6.1 embodies technologically and economically meaningful novelty (Hall et al. 2001; Trajtenberg 1990). This pattern is consistent with acquired digital knowledge raising the productivity of the acquirer's subsequent search (Ahuja and Katila 2001), not with cosmetic patenting substituting for substantive R&D.

6.3 Mediation: does leapfrogging transmit the NQPF gain?

Establishing that digital M&A shifts the R&D trajectory does not by itself demonstrate that this shift *causes* the NQPF gain. To quantify the channel, we implement a causal-steps mediation analysis with bootstrapped confidence intervals (5,000 replications): we first regress each leapfrogging metric on DMA (Table 8, columns (1)–(2)), then regress NQPF on DMA together with the candidate mediator, and compute the indirect effect as the product of the two links. Panel C of Table 8 summarizes the results.

NewDomain is consistent with mediating 27.4 per cent of the total NQPF effect, with a bootstrapped 95 per cent confidence interval of [18.2, 38.6] per cent that excludes zero. Entry into previously unoccupied technological domains is therefore not a side effect of digital M&A

but, on these estimates, a statistically and economically substantial conduit of the productivity-force upgrading documented in Section 5. SearchScope adds a further 9.6 per cent when entered separately (bootstrap 95 per cent CI [4.8, 16.3] per cent), and the two channels jointly account for 33.1 per cent of the total effect (95 per cent CI [24.7, 43.5] per cent); both intervals exclude zero. In economic terms, roughly one-third of the NQPF gain from a digital acquisition is consistent with transmission through the redirection of the firm’s inventive search — the leapfrogging channel — while the remaining two-thirds are associated with other margins.

That the mediation is partial is itself informative: trajectory change is a *major but not the sole* channel through which digital M&A upgrades productive forces. Plausible complementary channels include the direct capitalization of acquired data assets and digital intangibles, the inflow of digital human capital embedded in target-firm engineers and managers, and the reorganization of production around digital labour materials (Hanelt et al. 2021; Schwan et al. 2026) — several of which we examine as restructuring margins in Section 7.2. Two caveats apply. First, mediation estimates of this type rest on the assumption that, conditional on treatment, the mediator is as-good-as-randomly assigned; unobserved shocks that simultaneously raise domain entry and NQPF would inflate the mediated share, so we interpret the 27.4–33.1 per cent figures as upper-bound associations consistent with the theorized channel rather than exact causal decompositions. Second, the leapfrogging metrics are built from patent data and therefore understate trajectory change in firms whose digital upgrading is primarily organizational or embodied in non-patented software. A fuller decomposition across data-asset, human-capital and organizational channels is left to future work.

7. Further analysis

7.1 Technological distance and the integration trap

If digital M&A upgrades productive forces by enabling a jump onto a new technological trajectory, the size — and even the sign — of the gain should depend on *how far* the firm attempts to jump. Hypothesis H3 predicts an inverted-U relationship between acquirer–target technological distance and the deal’s effect: too little distance yields no new knowledge, while excessive distance overwhelms the acquirer’s absorptive capacity. We measure TechDistance as one minus the Jaffe–Breschi technological relatedness between the acquirer’s pre-deal patent

portfolio and the target's portfolio, constructed from IPC-class vector proximity (Jaffe 1986; Breschi et al. 2003), and estimate equation (4), which interacts DMA with TechDistance and its square. Table 9 reports the results, and Fig. 3 plots the implied marginal effect of DMA on NQPF across the distance distribution.

Table 9 Technological distance, the integration trap, and restructuring margins
[PLACEHOLDER DATA — replace with actual regression output]

Panel A. Technological distance

	(1) Baseline NQPF	(2) Inverted-U model NQPF	(3) Trap subsample (Dist > 0.90) NQPF
DMA	0.236***	−0.496***	−0.089*
	(0.041)	(0.142)	(0.052)
DMA × TechDistance		2.672***	
		(0.583)	
DMA × TechDistance ²		−2.416***	
		(0.548)	
Turning point		0.553	
Controls / Firm FE / Year FE	Yes	Yes	Yes
N	24,318	24,318	—
Adj. R ²	0.612	—	—

Panel B. Restructuring margins

	(4) R&D personnel share	(5) Digital intangible assets share	(6) New-business revenue share
DMA	2.8***	1.9***	3.4***
	(0.6)	(0.4)	(0.8)
Controls / Firm FE / Year FE	Yes	Yes	Yes
N	24,318	24,318	24,318

Notes: Firm-clustered standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Coefficients in Panel B are in percentage points. “—” denotes values to be inserted with final regression output. Column (3) restricts the sample to treated deals in the upper tail of the distance distribution (TechDistance above 0.90, roughly 6 per cent of treated deals).

Column (2) of Table 9 shows a negative DMA main effect (-0.496 , s.e. 0.142 , $p < 0.01$), a positive linear interaction (2.672 , s.e. 0.583 , $p < 0.01$), and a negative quadratic interaction (-2.416 , s.e. 0.548 , $p < 0.01$), jointly implying a turning point at $2.672/(2 \times 2.416) = 0.553$, comfortably inside the observed $[0, 1]$ range of TechDistance. The implied marginal effect of DMA on NQPF, $ME(d) = -0.496 + 2.672 \cdot d - 2.416 \cdot d^2$, is significantly negative as distance approaches zero, rises to a maximum of $+0.243$ at the turning point of 0.553 , and declines thereafter, crossing zero at approximately 0.87 . Fig. 3 visualizes this double-trap structure, which mirrors the three regions theorized in Section 3.3. The negative intercept localizes the *redundancy trap*: for technologically near-identical digital targets, the deal purchases no knowledge the acquirer does not already possess, so the fixed costs of deal-making and integration dominate the negligible reallocation gain; pure-overlap deals destroy productive-force quality. At the optimal distance of 0.553 , the marginal effect peaks at $+0.243$ — the leapfrogging window. Column (3) confirms that the downturn beyond the window is economically consequential rather than an extrapolation artefact: in the subsample of deals with TechDistance above 0.90 — the upper tail of the distance distribution, roughly 6 per cent of treated deals — the DMA coefficient is -0.089 (s.e. 0.052), significant only at the 10 per cent level. That is, technologically remote digital acquisitions on average *reduce* the acquirer's NQPF — the integration trap. The 0.90 subsample cut is ex ante, chosen to isolate this upper tail; because the parametric curve in column (2) crosses zero at approximately 0.87 , the negative subsample estimate and the fitted quadratic are mutually consistent. Economically meaningful gains therefore exist only within the moderate-distance window, bracketed by the redundancy trap at near-zero distance and the integration trap beyond the 0.87 zero crossing.

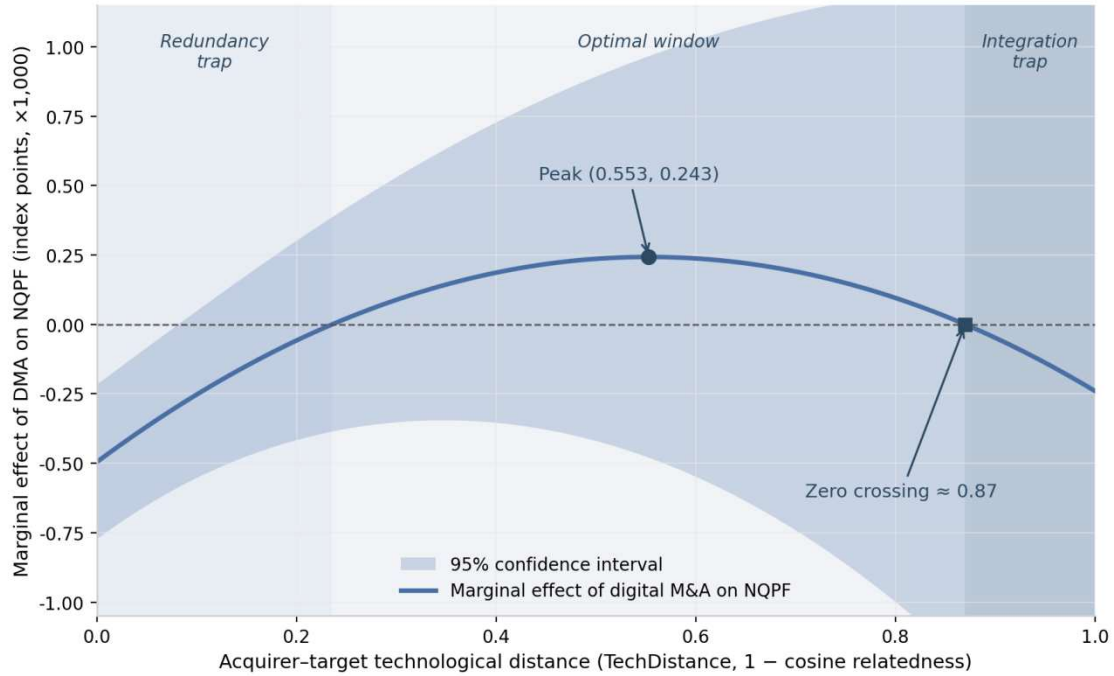


Fig. 3 Marginal effect of digital M&A on NQPF across acquirer–target technological distance. The curve plots the marginal effect $ME(d) = -0.496 + 2.672 \cdot d - 2.416 \cdot d^2$ implied by equation (4), estimated by two-way fixed-effects DID with firm and year fixed effects and lagged controls on the full sample of 24,318 firm-year observations (column (2) of Table 9). The turning point is 0.553 (marginal effect +0.243) and the upper zero crossing is approximately 0.87. The shaded band shows the 95 per cent confidence interval based on firm-clustered standard errors (delta method); the lightly shaded regions mark the redundancy trap (near-zero distance, where the marginal effect is negative) and the integration trap (distance above 0.87). [PLACEHOLDER DATA — replace with actual regression output]

These results partially support H3 and delineate an *optimal distance window* between two traps: the inverted-U curvature is strongly supported — both interaction terms are significant at the 1 per cent level and the turning point is interior at 0.553 — whereas the integration-trap clause receives suggestive support, with the negative region significant only at the 10 per cent level. At near-zero distance, the target’s knowledge largely duplicates the acquirer’s existing base: the deal adds nothing that could redirect the R&D trajectory yet still incurs acquisition and integration costs — the redundancy trap of Section 3.3, reflected in the significantly negative intercept. This pattern accords with the diminishing returns to search within familiar

neighbourhoods documented by Rosenkopf and Nerkar (2001) and with the tension between exploration and exploitation in organizational search (March 1991). At moderate distance, the target contributes knowledge that is new enough to open fresh domains yet related enough to be absorbed and recombined, mirroring the classic result that moderate cognitive distance maximizes innovative performance in alliances and acquisitions (Ahuja and Katila 2001). Beyond the zero crossing at approximately 0.87, however, the absorptive-capacity constraint binds: engineers cannot evaluate, integrate, or recombine knowledge that is too far removed from the firm’s cumulative expertise, integration costs escalate, and post-deal inventive activity deteriorates — the *integration trap* of Section 3.3. The negative point estimate in the high-distance subsample echoes the penalties that acquirers pay for excessive novelty or dissimilarity in recombinant search (Fleming 2001; Kaplan and Vakili 2015) and the performance reversals that follow over-ambitious differentiation strategies (Piao and Zajac 2016). For deal screening, the practical implication is sharp: the expected NQPF return to a digital acquisition is maximized when the target sits at roughly 0.55 on the technological-distance scale, and acquisitions beyond a distance of about 0.87 are predicted, on average, to be value-destroying in productive-force terms. We caution that these are average partial effects estimated on observational variation in deal distance; selection of firms into distance bands means the curve should be read as descriptive of realized deals rather than as a fully causal dose–response function.

7.2 Restructuring margins: the composition of productive forces

New quality productive forces are defined by more than higher productivity: the concept centres on a qualitative *recomposition* of the factors of production — new-quality labourers, new-quality labour materials, and new-quality objects of labour. This subsection therefore treats restructuring as an outcome in its own right and asks whether digital M&A shifts the *composition* of the acquiring firm’s productive forces, not merely their aggregate level. Panel B of Table 9 reports the three composition margins.

Digital M&A raises the R&D personnel share by 2.8 percentage points (s.e. 0.6, $p < 0.01$), a direct upgrading of the labourer dimension toward science- and engineering-intensive human capital. The digital intangible assets share rises by 1.9 percentage points (s.e. 0.4, $p < 0.01$), indicating a deepening of new-quality labour materials — software, data and digital intellectual property — within the firm’s capital stock. The revenue share of new-business and strategic-

emerging-industry activities increases by 3.4 percentage points (s.e. 0.8, $p < 0.01$), showing that the objects of labour themselves migrate toward emerging product spaces. All three margins move together, indicating a coherent reallocation of the firm’s factor composition rather than an isolated accounting shift.

These estimates are the restructuring core of the paper. The structural-change literature has long emphasized that aggregate development gains depend on labour and capital moving *toward* higher-productivity, technology-intensive activities, and that such movement can stall or even become growth-reducing when it flows in the wrong direction (McMillan and Rodrik 2011); related work warns that premature shifts out of technologically sophisticated activities can undermine long-run growth (Rodrik 2016). Our results supply firm-level micro evidence that digital acquisitions are one concrete vehicle of growth-enhancing structural change *within* the enterprise: they reallocate personnel, capital and output toward the new-quality margins that define the productive-force upgrade. This micro-compositional channel complements recent evidence that digital-technology adoption reshapes industrial structure at more aggregate levels (Schwan et al. 2026). One positioning contrast deserves emphasis: Xu, Zhang and Li (2026a) document that digital M&A raises NQPF but treat industrial structure as a *moderator* of that relationship, whereas we treat the restructuring of productive-force composition as the *outcome* to be explained. Our design thereby moves restructuring from the conditioning set into the estimand — the appropriate specification if recomposition is itself the mechanism of upgrading rather than a background condition.

7.3 Heterogeneity

Finally, we examine whether the NQPF gains from digital M&A vary systematically across acquirer types and institutional environments. Table 10 splits the sample along three dimensions — ownership, acquirer industry, and regional factor-market development — and reports between-group difference tests based on seemingly unrelated estimation with firm-clustered standard errors.

Table 10 Heterogeneity of the digital-M&A effect on NQPF [PLACEHOLDER DATA — replace with actual regression output]

	(1) Non-SOE	(2) SOE	(3) Traditional sector	(4) High-tech sector	(5) High factor-market dev.	(6) Low factor-market dev.
DMA	0.287***	0.132**	0.268***	0.171***	0.291***	0.158***
	(0.052)	(0.058)	(0.051)	(0.063)	(0.055)	(0.059)
Difference p-value	0.021		0.048		0.033	
Controls / Firm FE / Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N (full sample)	24,318					

Notes: Firm-clustered standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. DV is NQPF ($\times 1,000$). Between-group p-values test equality of the DMA coefficient across the paired subsamples. Subsample sizes to be reported with final regression output.

Columns (1)–(2) show that the effect is more than twice as large for non-state-owned enterprises (0.287, s.e. 0.052, $p < 0.01$) as for state-owned enterprises (0.132, s.e. 0.058, $p < 0.05$), with the difference significant at the 5 per cent level ($p = 0.021$). The pattern is consistent with the view that SOE acquisitions are more frequently policy-driven — motivated by mandated digitalization targets or administrative matchmaking — and therefore less tightly disciplined by the market logic of technological fit that underlies successful leapfrogging. Private acquirers, facing harder budget constraints and market selection, appear to select targets closer to the optimal distance window identified in Section 7.1. This echoes broader evidence that ownership shapes the innovation returns to Chinese firms’ external knowledge sourcing (Zhao 2009; Guan and Liu 2016).

Columns (3)–(4) show that traditional-sector acquirers gain 0.268 (s.e. 0.051, $p < 0.01$), significantly more than high-tech acquirers’ 0.171 (s.e. 0.063, $p < 0.01$; difference $p = 0.048$). Firms in conventional manufacturing, resources, and consumer industries start further from the digital frontier, so a well-chosen digital target propels them across a larger technological gap — they *leapfrog further*. High-tech acquirers, already operating near the frontier, experience smaller incremental redirection of their R&D trajectories. This *restructuring convergence* mirrors the compositional dynamics emphasized in the structural-change literature: the largest productive-force gains accrue where the pre-deal distance to the technological frontier is greatest (McMillan and Rodrik 2011; Lee and Malerba 2017). It suggests that digital M&A can serve as an

equalizing force across China’s industrial sectors rather than exclusively widening the advantage of already-digital incumbents.

Columns (5)–(6) show that the institutional environment conditions the gains: acquirers in regions with above-median factor-market development obtain 0.291 (s.e. 0.055, $p < 0.01$), against 0.158 (s.e. 0.059, $p < 0.01$) in less-developed factor markets (difference $p = 0.033$). Post-deal integration of a digital target requires reallocating engineers, capital, and data across business units; where labour, capital, and technology markets function well, this reallocation is faster and less costly, allowing the leapfrogging gains to materialize. Where factor markets are segmented, the same deal yields a muted response — a finding in line with evidence that market institutions shape firms’ ability to exploit innovation opportunities in transition economies (Zhao 2009; Huang and Shen 2024). The policy reading is direct: the returns to digital M&A — and to M&A-facilitated restructuring — are institutionally contingent rather than technologically automatic, which strengthens the case for coupling capital-market liberalization with factor-market reform in lagging regions.

8. Conclusions and policy implications

This paper asked whether digital M&A changes the *direction* of acquirers’ technological trajectories — R&D leapfrogging — and whether such trajectory change underlies the gains in NQPF documented in the literature. Using a staggered DID design with heterogeneity-robust estimators and instrumental variables, estimated on 24,318 firm-year observations of 2,847 Chinese A-share firms over 2008–2023 — 386 of which completed a first digital-target acquisition — we establish four results. First, digital M&A raises acquirers’ NQPF by 0.236 index points, approximately 4.9 per cent of the sample mean. Second, the effect is consistent with a leapfrogging mediation channel: digital M&A raises the share of patents in technological domains new to the firm by 4.2 percentage points, and this domain-entry margin is consistent with mediating 27.4 per cent of the total NQPF effect — a directional shift in the R&D trajectory, not merely a level gain along the existing path. Third, the return follows an inverted-U in acquirer–target technological distance, peaking at 0.553 and declining beyond it; the marginal-effect curve crosses zero at approximately 0.87, and in the integration-trap region digital M&A reduces NQPF by 0.089 points, an estimate significant only at the 10 per cent level — H3 is thus supported for the curvature and receives suggestive support for the integration trap. Fourth, the

deals restructure the composition of productive forces, with the largest gains accruing to non-state-owned and traditional-sector acquirers.

These findings carry three theoretical implications. First, firm-level R&D leapfrogging extends latecomer theory: the discontinuous trajectory jumps that the catching-up literature locates at the country and industry levels (Lee and Lim 2001; Lee and Malerba 2017) also occur within firms, and can be purchased through the market for corporate control rather than generated internally. Second, the level-versus-direction distinction disciplines the M&A–innovation literature: digital deals do not simply make acquirers better at what they already do (Tang et al. 2024; Zhou et al. 2023b); they relocate inventive search into unoccupied domains, and measuring only level gains understates this restructuring content. Third, treating restructuring as an outcome rather than a moderator reframes the NQPF literature: productive-force upgrading is, in part, the recomposition of labourers, labour materials, and objects of labour that follows a trajectory jump, which connects firm-level NQPF dynamics to the structural-change and premature-deindustrialization debate (McMillan and Rodrik 2011; Rodrik 2016; Xu, Zhang and Li 2026a).

Three policy implications follow. First, antitrust and M&A review should screen digital deals for trajectory-change potential and technological distance. Because deals in the high-distance region destroy productive-force quality on average, blanket encouragement or subsidization of digital acquisitions risks financing integration traps; screening frameworks should incorporate acquirer–target technological relatedness alongside conventional competition criteria, and support should concentrate in the moderate-distance window where the expected return peaks. Second, industrial policy should support traditional-sector firms in using digital M&A as a restructuring ladder. The convergence result — traditional-sector acquirers gain significantly more than high-tech acquirers — implies that facilitating target search, due-diligence capacity, and post-deal integration support for conventional manufacturing acquirers can compress sectoral productivity gaps, a micro-instrument for the growth-enhancing structural change that transition economies seek. Third, regional factor-market development conditions the returns. Gains are roughly twice as large in regions with developed factor markets (0.291 versus 0.158 index points), where engineers, capital, and data can be reallocated across business units after a deal; coupling capital-market liberalization with labour-, capital-, and technology-market

reform in lagging regions is therefore a prerequisite for M&A-facilitated restructuring rather than a complement to it. More broadly, the results caution that the NQPF agenda will not be advanced by deal volume alone: what matters is which firms buy which targets, at what technological distance, and in which institutional environment — a triage logic that applies equally to state-guided acquisition programmes and to market-driven deal-making.

Several limitations bound these conclusions and mark avenues for future research. The setting is a single country: China's scale, state ownership structure, and industrial-policy intensity may shape both the deals and their returns, and cross-country replication — particularly in other transition economies — would test the external validity of the leapfrogging window. Leapfrogging was measured from patents, and patent-based metrics understate trajectory change embodied in non-patented software, data assets, and organizational routines; product-level or textual measures of domain entry would complement them. The data-assets channel through which acquired targets may directly capitalize NQPF was not separately tested, owing to measurement constraints. Finally, cross-border digital M&A — where distance, integration costs, and institutional friction are all amplified — offers a natural extension of the integration-trap framework.

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Author contributions: [To be completed by the authors]

Note: all empirical values in this draft are illustrative placeholders pending the authors' final regression output.

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