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Digital transformation and enterprise productivity: adjustment costs, organizational complementarities, and financial allocation

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ABSTRACT

Investment in digital technologies can improve coordination and resource use while imposing substantial costs before complementary organizational capabilities develop. This study examines that tension using 8,337 observations from 1,599 Chinese listed enterprises over 2007–2020. Digital transformation is measured by the carrying value of information and communications hardware and software relative to total assets. Total factor productivity is estimated through the Olley–Pakes approach, with Levinsohn–Petrin estimates used in a robustness exercise. The reported regressions identify a negative linear coefficient and a positive quadratic coefficient, consistent with a U-shaped relationship within the observed investment range. The fully controlled specification places the estimated turning point at 0.1373, compared with a sample mean digital investment ratio of 0.0090. The curvature persists under alternative fixed effects, a different productivity estimator, the exclusion of real estate firms, and additional city controls. Mechanism regressions suggest favorable contributions through working-capital turnover and the educational composition of employment, alongside an adverse financial-allocation pathway associated with the financing-constraint indicator. The turnover evidence is less decisive than the human-capital evidence because the investment-to-turnover coefficient is not conventionally significant. Subsample estimates retain the same coefficient-sign pattern across asset-size and ownership categories, although they do not establish identical effect magnitudes. These findings favor treating digital transformation as an organizational investment process whose productivity implications depend on complementary skills, operational integration, and the allocation of finance. The estimated turning point describes conditional marginal productivity within the fitted model; it is neither a universal spending prescription nor direct evidence that every enterprise follows the same temporal adjustment path.

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1. INTRODUCTION

Digital investment presents enterprises with a familiar but difficult economic problem. A technology can expand what an organization is capable of doing while initially making its existing operations less efficient. Equipment must be installed, information must be reorganized, employees must learn unfamiliar procedures, and managers must decide which established practices should be retained. The resulting adjustment can consume resources well before the benefits become measurable. Evaluating digital transformation through an assumption of immediate productivity improvement therefore risks misunderstanding both its costs and its longer-term economic value.

The relevant distinction is between acquiring digital assets and integrating them into a productive organization. Computers, communications equipment, and software can improve the movement of information, but they do not determine how decisions are made or responsibilities are coordinated. A firm may accumulate systems that duplicate existing functions, operate in isolation, or require additional administrative effort. Another may use a smaller investment to remove a binding operational constraint. Productivity depends on these relationships between technology and organization, even when the available financial data record only the assets purchased.

This manuscript examines evidence from Chinese enterprises over 2007–2020. The underlying investigation by Cheng, Zhou, and Li uses listed-company data to assess whether digital investment has a nonlinear relationship with total factor productivity and to explore operational, workforce, and financing pathways [1]. The present text reorganizes the argument and preserves the published numerical results. It does not represent an independent empirical study or introduce new observations. Attribution to the original investigation is retained so that rewritten presentation is not confused with newly generated research evidence.

The Chinese context makes the adjustment question economically important. The source reports that the scale of the national digital economy increased 28.5-fold between 2002 and 2019, exceeding GDP growth over that interval [1]. It also reports manufacturing digitization of 48.7 percent, numerical control of key processes of 51.1 percent, and industrial digitalization equivalent to 31.2 percent of GDP by June 2020. These are historical contextual figures rather than observations used to estimate firm productivity. They nevertheless show why the effectiveness of enterprise investment became a significant policy and management concern.

Policy attention developed alongside this expansion. The original paper situates enterprise transformation within priorities expressed at the nineteenth national party congress, the March 2020 emphasis on digital and intelligent upgrading, the April 2021 emphasis on industrial digitalization, and the January 2022 digital-economy development plan. These initiatives promoted infrastructure and the integration of digital technologies with production [1]. Policy support can reduce some coordination and infrastructure barriers, but it cannot eliminate the need for firms to choose appropriate investments and develop the capabilities required to use them. National ambition and enterprise-level efficiency are related questions, not interchangeable measures of progress.

Total factor productivity provides a way to examine the efficiency dimension. In the production-function tradition, output growth can arise from additional labor and capital or from changes in the effectiveness with which those inputs are used [2]. Digital transformation may influence both. It requires new assets, but it may also reduce idle resources, improve coordination, and facilitate innovation. A productivity analysis therefore asks whether the observed transformation is associated with improvements beyond simple input expansion. The answer depends partly on how productivity and digital capital are measured, which makes the construction of both variables consequential.

Prior research does not suggest one unqualified response. Management capabilities can lag behind technological change, delaying observable performance improvements [3]. The information-technology productivity paradox literature similarly highlights the difficulty of translating technological diffusion into measured efficiency [4]. Other studies associate digital technologies with innovation, externalities, and stronger productivity [5], [6], [7]. These positions need not be mutually exclusive. They may describe different parts of an adjustment process or different combinations of technology, organizational capability, and economic environment. A nonlinear specification offers one way to investigate that possibility without assuming a constant return to digital investment.

The present evidence uses the ratio of recorded information and communications technology hardware and software to total assets. The baseline regressions include the ratio and its square, together with enterprise controls and industry and year effects. The resulting negative linear and positive quadratic coefficients imply a declining fitted productivity relationship at lower investment ratios and an increasing relationship after the turning point. This pattern persists across several alternative specifications. It should be interpreted as a relationship across observed enterprise-years, however, rather than proof that every firm experiences an initial decline followed by a predictable recovery.

The mechanism analysis matters because digital assets can affect productivity through different and potentially opposing routes. Faster working-capital turnover can release resources and reduce delays. A more educated workforce can improve the adoption and development of new practices. Greater financing capacity can support productive investment, but it may also encourage borrowing or financial-asset accumulation that diverts resources from production. An average quadratic association can combine these processes. Examining them separately provides a more useful account of digital transformation than describing technology as inherently productivity enhancing.

The study also considers whether the estimated curvature changes with enterprise size or ownership. The same sign pattern appears among smaller and larger enterprises and among state-owned and private enterprises. This supports the relevance of adjustment and complementarity across organizational categories, while leaving room for differences in magnitude and timing. The practical implication is not that all firms should follow the same investment plan. It is that technological purchases require complementary management, skills, and financial discipline if their potential benefits are to become productive capacity.

The argument developed below consequently distinguishes investment intensity, organizational integration, and resource allocation. It preserves the original finding of a U-shaped association while qualifying claims that exceed the empirical design. Particular attention is given to the meaning of the turning point, the relative strength of the mechanism evidence, and the limits of subgroup comparisons. These distinctions are necessary for a measured interpretation of how digital transformation can become a source of productivity rather than merely an additional category of expenditure.

2. LITERATURE REVIEW

The productivity consequences of digital transformation depend on what transformation is understood to involve. A narrow definition concerns the acquisition of equipment and software. A broader definition concerns changes in processes, coordination, and business models made possible by those assets. The distinction is central to interpreting financial measures. Recorded digital capital is observable and comparable across enterprises, but the same asset value can support different organizational arrangements. Research on enterprise architecture emphasizes the need to integrate technological systems with the activities and constraints of smaller and medium-sized firms [8].

Digital investment may improve productivity through information quality and coordination. Timely production and sales information can reduce mismatches between demand, purchasing, and capacity. Shared records can limit repeated work and make it easier to identify where resources are idle. Software can standardize routine procedures while allowing managers to devote attention to exceptions. These mechanisms provide an economic basis for the positive relationships described in research on digital transformation and enterprise performance [9]. Their operation remains conditional on data quality, the compatibility of systems, and the decisions made using the resulting information.

The adjustment-cost argument begins from a different part of the same process. New systems require capital and managerial effort before their functions are fully incorporated into production. During implementation, parallel procedures can coexist, records may need to be converted, and workers may operate below their normal efficiency while learning. Established responsibilities can also conflict with the allocation of information and authority implied by the new system. Heavin and Power's management perspective helps explain why the installation of technology does not necessarily produce an immediate performance response [3].

These costs can create a period in which measured inputs rise faster than usable output. An enterprise may therefore experience lower measured productivity even when its investment has a positive expected longer-term return. The relevant organizational changes are partly intangible, which makes them difficult to record alongside purchased assets. Research on human and organizational capital in production digitalization addresses this complementarity [10]. The theoretical implication is that the return to digital capital depends on investments and practices that may not appear within the same accounting category or the same reporting year.

The productivity-paradox literature provides a broader context for this argument [4]. Weak measured performance need not imply that digital technologies have no value. Benefits may emerge with delay, may occur in dimensions poorly measured by output statistics, or may require changes in organizational arrangements. Equally, the expectation of delayed benefits should not become a reason to treat every unsuccessful investment as productive in the long run. Some technologies are poorly chosen, some implementations remain incomplete, and some benefits may never justify their costs. A careful empirical framework must permit both productive complementarity and persistent misallocation.

A quadratic relationship represents one possible combination. At low investment intensity, adjustment costs and incomplete integration may dominate. At a higher intensity, systems may become sufficiently connected and workers sufficiently capable for coordination benefits to emerge. The resulting fitted curve can decline before rising. Research on Chinese corporate productivity provides evidence relevant to this nonlinear interpretation [6], [7], while work on new-energy enterprises and industrialized electricity sectors demonstrates the diversity of settings in which digitalization and productivity have been examined [11], [12]. Their existence does not establish that one curve fits every industry or organizational history.

The distinction between investment intensity and time is particularly important. A higher digital-asset ratio may indicate a later stage of transformation, but it can also reflect differences in industry, asset composition, or production technology. A service enterprise and a manufacturer can have different ratios even when both operate mature digital systems. The U-shaped specification therefore requires an interpretation grounded in the observed measure. It can support the proposition that marginal associations change with intensity, but it does not directly identify a common chronological sequence of installation, learning, and maturation.

Working capital offers a specific operational pathway. Firms tie funds up in materials, work in progress, inventories, and transactions awaiting settlement. Better information can improve scheduling and reduce the time between resource commitment and revenue collection. Digital systems may also allow more reliable coordination with suppliers and customers. Research on enterprise input–output efficiency provides a related foundation for examining this channel [13]. Faster turnover can improve the use of a given resource base, although an excessively compressed operating cycle may also create supply or liquidity risks.

Turnover is not identical to productive efficiency. A firm can increase its turnover ratio by expanding sales, reducing working capital, changing payment terms, or shifting risk to suppliers. Some of those changes may improve overall productivity, while others mainly redistribute financing burdens. A mechanism regression using turnover can identify a compatible relationship without observing each operational adjustment. This distinction matters especially when the investment-to-turnover coefficient is imprecisely estimated. The conceptual plausibility of the channel cannot substitute for the precision of the empirical evidence supporting it.

Human capital supplies another complement. Digital systems change the tasks employees perform and the skills required to coordinate production. Some routine activities can be automated, while new tasks arise in monitoring, analysis, maintenance, and system design. Acemoglu and Restrepo distinguish displacement from the creation of new tasks [14]. Dengler and Matthes examine substitution potential across occupations [15]. These perspectives suggest that digital transformation can alter employment composition without implying a uniform reduction in labor demand or an automatic improvement in worker welfare.

Education can influence how effectively enterprises use new information and technologies. The human-capital and technological-change literature connects knowledge with innovation, adoption, and diffusion [16], [17]. Research on the

spatial distribution of human-capital structure similarly associates educational composition with productivity outcomes [18]. At the enterprise level, a greater proportion of employees with university qualifications may support implementation and problem solving. Yet formal qualifications remain an incomplete measure of capability. Experience, vocational skills, managerial practices, and the organization of teams can matter even when they are not recorded in the educational indicator.

The human-capital mechanism also has an important compositional interpretation. The proportion of degree-qualified employees can rise through hiring, training that results in formal qualifications, outsourcing, or reductions in less-educated employment. Those processes have different implications for productivity and distribution. An observed increase in educational share does not identify which process occurs. The empirical indicator can therefore support a relationship between workforce composition and productivity, while leaving the broader consequences for employment and inclusion unresolved. This is compatible with treating workforce development as a complement rather than a mere substitution target.

Finance introduces a potentially opposing mechanism. Digital systems can improve records, reduce uncertainty, and help enterprises communicate their operating position to lenders. Greater transparency may reduce financing constraints and allow investment that was previously difficult to fund. Research on internal finance and Chinese enterprise growth shows why resource availability matters [19], while leverage and investment research emphasizes the consequences of financial commitments for firm development [20]. The value of improved access depends on what firms finance and on the risks associated with repayment.

The original investigation develops an adverse allocation argument: easier finance can enlarge borrowing capacity and encourage movement toward liquid financial assets, potentially crowding out productive investment [1]. This should be distinguished from the stronger claim that easing financing constraints is intrinsically harmful. Financial resources can support productive projects or provide buffers during uncertainty. The proposed negative channel arises when allocation shifts away from activities that generate productive capacity. Research linking digital finance with innovation through financing constraints provides a related but distinct perspective [21].

The distinction is consequential for mechanism identification. A financing-constraint index based on size and age does not directly measure financial-asset holdings, borrowing decisions, or research expenditure. Even when digital investment predicts that index and the index predicts productivity, additional evidence is needed to establish a diversion toward financial assets. The source's financialization argument is therefore a theoretical interpretation of the reported mediation pattern. Preserving that interpretation requires making its evidential limits clear rather than presenting the unobserved allocation decisions as directly measured facts.

Research design also depends on the scope of the real economy. Financial firms are ordinarily excluded when the focus is production outside financial intermediation. The classification of real estate is less straightforward because construction adds productive output, while property trading and valuation also contain financial characteristics. Work on the meaning of the real economy highlights the conceptual difficulty of treating the boundary as self-evident [22]. Research on the financial crisis provides related context for distinguishing asset-market events from their consequences for production [23]. Examining results with and without real estate offers a practical sensitivity check.

Ownership and size are likewise relevant contextual factors. State-owned enterprises and private firms can differ in finance, objectives, and access to complementary resources. Larger enterprises can fund transformation more easily but may face more complex integration problems. Smaller firms can be more flexible while lacking specialized skills. Research on ICT in Chinese manufacturing, digital transformation in environmentally intensive enterprises, and digital processes in smaller businesses illustrates the diversity of these organizational settings [24], [25], [26]. Such differences motivate subgroup analysis but do not determine in advance whether curvature or magnitude must change.

The literature thus supports an integrated but conditional framework. Digital capital can improve coordination and knowledge use, while installation and organizational adjustment can lower efficiency before those benefits emerge. Workforce composition and operating cycles can support productive use, whereas financial allocation can strengthen or undermine it. The empirical task is to assess whether these relationships appear in enterprise data and to identify which claims the measures can sustain. A U-shaped association is informative when interpreted alongside its observed support, complementary mechanisms, and unresolved sources of selection.

3. METHODS

The sample comprises Shanghai and Shenzhen A-share listed companies observed during 2007–2020. Enterprise financial and classification information comes from Wind, while recorded information and communications technology hardware and software come from CSMAR. The source also identifies CNRDS as the provider of invention-patent information, the China Urban Yearbook as the provider of city economic and demographic data, and the National Bureau of Statistics as a source for additional information. Patent data are listed among the source materials but do not appear as an outcome or control in the reported main regressions [1].

Financial enterprises and companies designated ST or *ST are excluded, as are observations with missing or abnormal data. The retained baseline panel contains 8,337 enterprise-year observations from 1,599 companies. Real estate remains in the baseline sample and is excluded in a separate robustness exercise. Mechanism and city-control models use smaller samples because the additional variables are not available for every observation. Those changes in sample coverage are retained in the tables rather than treated as if every specification estimates an identical enterprise population.

Baseline total factor productivity is the measure labeled OP, calculated using the Olley–Pakes approach. The Levinsohn–Petrin measure, labeled LP, provides an alternative outcome. The source refers to related digital-economy productivity research in choosing these measures [7]. The article does not set out every production-function input, deflator,

sample restriction, or first-stage estimation detail in its main text. The published productivity results are consequently preserved without implying that the production functions have been independently reconstructed from the underlying financial databases.

Digital transformation is measured as the sum of the net carrying values of ICT hardware and software divided by total assets. Hardware includes computers, communication tools, and related equipment; software uses its reported net asset value. The variable's square captures curvature. This measure is grounded in observable investment, consistent with the source's use of the enterprise digitalization literature [6], [26]. It does not measure every aspect of transformation. Internally developed systems, rented services, accumulated organizational knowledge, and differences in depreciation can separate recorded asset intensity from actual technological capability.

The baseline equation is $OP_{it} = a + b1D_{it} + b2D_{it}^2 + cX_{it}$ + industry effects + year effects + e_{it}, where D denotes the digital-asset ratio and X the control vector. A negative b1 combined with a positive b2 implies upward curvature with a positive turning point. The fitted marginal relationship is $b1 + 2b2D$, and the turning point is $-b1$ divided by $2b2$. A substantive U-shaped interpretation additionally requires that the relevant change in slope occur within the observed support. Statistical uncertainty around the turning point and endpoint slopes is not separately reported by the source.

Controls include enterprise age, ownership, return on net assets, cash flow, tax burden, capital intensity, a variable labeled labor investment, and capital investment. Age is the logarithm of the current year minus incorporation year plus one. Ownership equals one for non-state-owned companies and zero for state-owned companies. Profitability divides net profit by net assets, cash flow divides current net cash flow by total assets, and tax burden divides income tax by operating income. Capital intensity is net book assets divided by operating income. These definitions are retained exactly in economic content.

The labor variable is defined in the source as the logarithm of administrative plus selling expenses divided by total assets. Capital investment is the logarithm of cash paid to acquire or construct fixed assets, intangible assets, and other long-term assets. The reported labor-variable distribution is difficult to reconcile with a literal reading of the stated ratio definition. Its values and formula are therefore preserved, with the discrepancy treated as a replication issue. The variable should not be silently reinterpreted as employee counts, payroll, or a different expense measure.

City robustness controls include the logarithm of population, the logarithm of current-year GDP, and the ratio of year-end loans to deposits at local financial institutions. These variables address the possibility that digital infrastructure and local economic conditions jointly influence enterprise investment and productivity. Adding them reduces the available observations from 6,872 in the first city-control specification to 4,779 in the fullest model. Differences in coefficients across those columns can reflect the added controls and changing sample composition. The design does not separately identify those contributions.

Three sets of mechanism regressions examine working-capital turnover, human-capital structure, and financing constraints. For each mechanism, the source reports a productivity model on the mechanism-specific sample, a model predicting the mediator, and a productivity model including the mediator. The productivity equations contain both digital investment terms, while the published mediator equations display only the linear investment term. This difference is retained. It means that a constant first-stage mechanism relationship is combined with a nonlinear total relationship, rather than estimating a fully nonlinear mediation system throughout.

Working-capital turnover is gross operating income divided by the average of beginning- and end-period working capital, with working capital defined as current assets minus current liabilities. The source expresses the ratio using twice operating income divided by the sum of those balances and multiplies by 100 percent. The natural logarithm is used in estimation. Handling of negative or zero working capital is not fully described, although it matters for logarithmic construction. The turnover sample contains 7,355 observations from 1,526 enterprises after missing values are excluded.

Human-capital structure is the number of employees with at least a bachelor's degree divided by total employment. The corresponding regressions contain 7,229 observations from 1,551 enterprises. Financing constraints are represented by an SA-style measure defined as -0.737 times size plus 0.043 times squared size minus 0.04 times listing age. The article labels the resulting variable FC. Its precise sign interpretation, scaling of size, and distinction between enterprise age and listing age require care. The financing models contain 8,096 observations from 1,567 enterprises.

The source interprets significant investment-to-mediator and mediator-to-productivity relationships as evidence of mediation, with a Sobel test used when one link is not significant. These tests describe statistical pathways but do not independently establish causal indirect effects. Digital investment, workforce composition, financing, and productivity can be jointly determined. No separate instrument or exogenous allocation mechanism for enterprise digital capital is reported. Accordingly, the results are discussed as conditional relationships consistent with the proposed channels, rather than proof that investment changes each mediator independently of other enterprise decisions.

Robustness analysis changes the fixed-effect specification, replaces OP with LP, excludes real estate, and adds city controls. The reported standard errors are described as two-way cluster-robust, although the precise clustering dimensions are not fully specified in the table note. Industry and year controls are included in the displayed models; a separate specification adds enterprise and time fixed effects. Subsample analysis divides observations around the median asset scale and classifies state-owned and private enterprises using Wind. Firm counts across these categories need not be disjoint if classifications change over time, but the source does not document that issue in detail.

4. RESULTS

Five tables consolidate the original descriptive, baseline, robustness, mechanism, and heterogeneity evidence. All published regression coefficients, standard errors, available goodness-of-fit statistics, enterprise counts, and observation

counts are retained. Interpretations distinguish the fitted curvature from causal claims and from a temporal sequence of transformation. This distinction is especially relevant because the investment ratio measures recorded digital assets rather than a direct assessment of organizational maturity.

Table 1 describes the distribution of the principal variables. It establishes the range over which the quadratic models are estimated and shows the relatively low average recorded digital-asset intensity. The dispersion in profitability, taxation, and capital intensity is also relevant to assessing the empirical environment in which investment decisions occur.

Table 1. Descriptive statistics for productivity digital investment and enterprise characteristics

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
OP productivity	8,337	3.8723	0.7082	1.6728	7.6349
Digital investment ratio	8,337	0.0090	0.0143	0.0000	0.3120
Enterprise age	8,337	2.8283	0.3451	0.6931	4.1744
Non-state ownership	8,337	0.7479	0.4343	0.0000	1.0000
Return on net assets	8,337	7.5004	43.3684	−3,706.0747	413.7494
Cash flow	8,337	0.0468	0.0736	−0.4964	0.5155
Tax burden	8,337	0.0187	0.0914	−7.9104	1.2671
Capital intensity	8,337	2.6197	18.3544	0.0876	1,538.8811
Labor investment	8,337	16.9140	1.6125	7.0901	22.9154
Capital investment	8,337	18.4394	1.6578	7.4978	24.8784

The mean digital ratio of 0.0090 lies well below the reported turning point of 0.1373, while the maximum of 0.3120 lies above it. This establishes that the estimated turning point is inside the overall observed range. It does not reveal how many observations lie on either side or whether the upper tail provides dense support. The extreme values of some financial ratios also show why the treatment of unusual observations matters. The source excludes abnormal records but does not provide sufficient detail to reconstruct every filtering decision.

Table 2 presents the five stepwise baseline specifications. Controls are introduced progressively so that changes in the digital coefficients can be assessed without obscuring the other reported estimates. All models contain industry and year controls and use the same 8,337 observations.

Table 2. Stepwise baseline estimates of the quadratic productivity relationship

Regressor or statistic	B1	B2	B3	B4	B5
Digital ratio	−7.0805*** (0.6928)	−7.0892*** (0.6927)	−7.0990*** (0.6884)	−7.3036*** (0.6799)	−8.2859*** (0.6788)
Squared digital ratio	25.3061*** (3.8243)	25.3443*** (3.8242)	25.3968*** (3.7949)	26.1656*** (3.7506)	30.1787*** (3.7421)
Age	—	0.0755** (0.0367)	0.0732** (0.0368)	0.0647* (0.0360)	0.0636* (0.0351)
Ownership	—	−0.0054 (0.0241)	−0.0139 (0.0241)	−0.0258 (0.0237)	−0.0006 (0.0234)
Return on net assets	—	—	0.0011*** (0.0001)	0.0012*** (0.0001)	0.0010*** (0.0001)
Cash flow	—	—	0.3395*** (0.0573)	0.3312*** (0.0567)	0.2961*** (0.0567)
Tax burden	—	—	—	−0.8176*** (0.0829)	−0.7969*** (0.0826)
Capital intensity	—	—	—	−0.0062*** (0.0004)	−0.0061*** (0.0004)
Labor investment	—	—	—	—	0.0336*** (0.0049)
Capital investment	—	—	—	—	0.0327*** (0.0038)
Constant	3.8942*** (0.1105)	3.7365*** (0.1359)	3.7107*** (0.1366)	3.7918*** (0.1334)	2.6318*** (0.1579)
Industry and year controls	Yes	Yes	Yes	Yes	Yes
Observations	8,337	8,337	8,337	8,337	8,337
Enterprises	1,599	1,599	1,599	1,599	1,599
Within-group R^2	0.0372	0.0369	0.0577	0.0836	0.0927

Every specification has a negative linear coefficient and a positive quadratic coefficient, both marked significant at one percent. In B5 the estimates are −8.2859 and 30.1787. The fitted curve therefore declines before its estimated minimum and rises thereafter. Profitability, cash flow, and the two input-investment controls have positive coefficients in that model, while tax burden and capital intensity have negative coefficients. Ownership is insignificant. The consistency of the curvature across controls supports the reported nonlinear pattern, although it does not by itself address endogenous investment selection.

The turning point identifies where the marginal fitted relationship changes sign. It does not indicate the investment level at which the enterprise has recovered all productivity lost relative to a zero-investment comparison, nor does it establish a welfare optimum. Because the variable is an asset ratio, it can also change through movements in the denominator or asset depreciation. These considerations limit the use of 0.1373 as a managerial target despite its relevance to describing the fitted association.

Table 3 consolidates the three alternative-specification models and the three city-control models. Keeping all coefficients visible shows that the quadratic result remains stable in direction even when the samples, control sets, or

productivity estimator change. The city-control columns reproduce the controls displayed in the original table rather than assume that unlisted labor and capital variables were included.

Table 3. Alternative estimators sample restrictions and city controls

Regressor or statistic	Enterprise effects	LP outcome	Exclude real estate	City population	Add city GDP	Add city finance
Digital ratio	−7.0734*** (0.7530)	−6.3648*** (0.7539)	−7.8586*** (0.6525)	−8.4174*** (0.7388)	−8.4866*** (0.8597)	−9.7495*** (0.8007)
Squared digital ratio	25.2573*** (3.2757)	20.4437*** (4.1406)	29.0642*** (3.5909)	30.3332*** (3.9902)	29.7279*** (4.6753)	34.4717*** (4.2601)
Age	−0.0262 (0.0701)	0.1859*** (0.0394)	0.0722** (0.0341)	0.0633* (0.0374)	0.0747* (0.0396)	0.0813** (0.0370)
Ownership	−0.0028 (0.0405)	−0.1513*** (0.0264)	−0.0422* (0.0230)	−0.0229 (0.0279)	−0.0313 (0.0299)	−0.0393 (0.0279)
Return on net assets	0.0035*** (0.0006)	0.0045*** (0.0003)	0.0025*** (0.0003)	0.0009*** (0.0001)	0.0005*** (0.0001)	0.0004*** (0.0001)
Cash flow	0.2960*** (0.0804)	0.2136*** (0.0642)	0.1168** (0.0582)	0.2869*** (0.0620)	0.3852*** (0.0746)	0.0747 (0.0708)
Tax burden	−0.7366*** (0.1818)	−0.9994*** (0.0926)	1.6415*** (0.2041)	−0.8593*** (0.0876)	−0.8874*** (0.2725)	0.2622 (0.2516)
Capital intensity	−0.0057*** (0.0010)	−0.0063*** (0.0005)	−0.0257*** (0.0014)	−0.0063*** (0.0042)	−0.0076*** (0.0050)	−0.0238*** (0.0047)
Labor investment	0.0281*** (0.0077)	0.0154*** (0.0055)	0.0277*** (0.0047)	—	—	—
Capital investment	0.0207*** (0.0049)	0.0142*** (0.0043)	0.0144*** (0.0038)	—	—	—
Logged city population	—	—	—	0.0965*** (0.0213)	0.1118*** (0.0269)	0.0914*** (0.0250)
Logged city GDP	—	—	—	—	−0.0256 (0.0175)	−0.0266* (0.0161)
City loan–deposit ratio	—	—	—	—	—	−0.0909 (0.0605)
Constant	3.0882*** (0.2076)	3.2363*** (0.1824)	2.6074*** (0.1537)	1.9036*** (0.2183)	2.1567*** (0.3031)	2.8258*** (0.2904)
Industry and year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,337	8,192	8,096	6,872	5,171	4,779
Enterprises	1,599	1,587	1,567	1,465	1,436	1,432
Within-group R^2	0.1066	0.4698	0.1199	0.1008	0.0986	0.2762

The digital coefficients retain their negative-linear and positive-quadratic signs in every robustness model. The LP specification uses 8,192 observations from 1,587 enterprises, while excluding real estate leaves 8,096 observations from 1,567 enterprises. The fullest city-control model uses 4,779 observations from 1,432 enterprises and estimates coefficients of −9.7495 and 34.4717. These results show stability of the reported curvature across several empirical choices. They do not establish an identical turning point across models, and they cannot distinguish the effects of changing controls from those of changing sample coverage.

Table 4 collects the three mechanism sequences. Each begins with a productivity model using the relevant sample, followed by a mediator equation and then a productivity model including that mediator. The joint display is important because the statistical support differs across mechanisms. A favorable mediator coefficient alone is insufficient when the preceding link from digital investment remains uncertain.

Table 4. Working capital human capital and financing mechanism regressions

Regressor or statistic	W1	W2	W3	H1	H2	H3	F1	F2	F3
Outcome	OP	Log turnover	OP	OP	Educated share	OP	OP	FC	OP
Digital ratio	−8.577 4*** (0.7363)	1.3364 (0.9573)	−8.608 6*** (0.7070)	−8.136 8*** (0.6980)	0.4395 *** (0.1122)	−8.289 2*** (0.6988)	−7.858 6*** (0.6525)	−4.699 7*** (0.4912)	−5.369 0*** (0.6119)
Squared digital ratio	36.522 9*** (5.1391)	—	35.237 6*** (4.9392)	29.393 4*** (3.6363)	—	29.928 9*** (3.6374)	29.064 2*** (3.5909)	—	21.360 1*** (3.3706)
Log working-capital turnover	—	—	0.1286 *** (0.0052)	—	—	—	—	—	—
Educated employee share	—	—	—	—	—	0.1434 *** (0.0414)	—	—	—
Financing constraint indicator	—	—	—	—	—	—	—	—	0.3002 *** (0.0081)
Age	0.1086 *** (0.0351)	0.4819 *** (0.0597)	0.0284 (0.0339)	0.1151 *** (0.0370)	−0.034 3*** (0.0115)	0.1199 *** (0.0369)	0.0722 ** (0.0341)	−0.278 1*** (0.0437)	0.1727 *** (0.0302)
Ownership	−0.005 7 (0.0251)	−0.185 6*** (0.0468)	0.0137 (0.0241)	−0.010 4 (0.0245)	−0.016 0** (0.0072)	−0.007 5 (0.0245)	−0.042 2* (0.0230)	−0.348 2*** (0.0292)	0.0724 *** (0.0211)
Return on net assets	0.0069 *** (0.0004)	0.0035 *** (0.0009)	0.0063 *** (0.0004)	0.0022 *** (0.0003)	0.0003 *** (0.0001)	0.0022 *** (0.0003)	0.0025 *** (0.0003)	0.0014 *** (0.0003)	0.0021 *** (0.0002)
Cash flow	0.0977 * (0.0585)	0.6704 *** (0.1325)	0.0108 (0.0562)	0.1115 * (0.0587)	−0.008 3 (0.0160)	0.1135 * (0.0587)	0.1168 ** (0.0582)	−0.401 3*** (0.0729)	0.2248 *** (0.0548)
Tax burden	−1.331 7*** (0.1045)	−3.512 1*** (0.2391)	−0.936 4*** (0.1015)	1.6484 *** (0.1896)	−0.037 1 (0.0518)	1.6529 *** (0.1895)	1.6415 *** (0.2041)	−0.870 0*** (0.2557)	1.8744 *** (0.1917)
Capital intensity	−0.008 7*** (0.0005)	−0.021 8*** (0.0012)	−0.006 2*** (0.0005)	−0.024 5*** (0.0013)	0.0022 *** (0.0003)	−0.024 8*** (0.0013)	−0.025 7*** (0.0014)	0.0071 *** (0.0018)	−0.028 1*** (0.0013)
Labor investment	0.0407 *** (0.0051)	0.1451 *** (0.0105)	0.0222 *** (0.0049)	0.0379 *** (0.0051)	−0.000 3 (0.0014)	0.0380 *** (0.0051)	0.0277 *** (0.0047)	0.2507 *** (0.0060)	−0.049 6*** (0.0049)
Capital investment	0.0249 *** (0.0039)	0.0654 *** (0.0086)	0.0195 *** (0.0038)	0.0312 *** (0.0040)	0.0021 * (0.0011)	0.0310 *** (0.0040)	0.0344 *** (0.0038)	0.2265 *** (0.0048)	−0.035 4*** (0.0041)
Constant	2.6236 *** (0.1615)	−2.743 6*** (0.2973)	2.9630 *** (0.1560)	2.4297 *** (0.1651)	0.1954 *** (0.0505)	2.3982 *** (0.1652)	2.6074 *** (0.1537)	−3.718 0*** (0.1967)	3.7418 *** (0.1412)
Industry and year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,355	7,355	7,355	7,229	7,229	7,229	8,096	8,096	8,096
Enterprises	1,526	1,526	1,526	1,551	1,551	1,551	1,567	1,567	1,567
Within-group R^2	0.1387	0.1136	0.2020	0.1372	0.1003	0.1386	0.1199	0.6474	0.2198

The turnover equation estimates a positive digital coefficient of 1.3364 but does not mark it significant, while turnover enters productivity positively at 0.1286. The source's Sobel statistic supplies limited supporting evidence under its stated interpretation, but the channel is less firmly established than a reading based only on the productivity coefficient would suggest. The human-capital sequence is clearer: digital investment predicts the educated share with a coefficient of 0.4395, and the share enters productivity at 0.1434, both marked significant at one percent.

In the financing sequence, the digital coefficient is −4.6997 in the FC equation and FC enters productivity at 0.3002. The opposite signs are consistent with a negative statistical pathway through the indicator. The original paper interprets this as easier financing encouraging debt expansion and financialization that reduce productive efficiency. Debt growth and financial-asset allocation are not separately reported as mechanism outcomes, so that interpretation remains broader than the direct measurement. The FC formula's direction also requires explicit validation before a negative movement can be equated unambiguously with a relaxation of actual financing constraints.

Table 5 reports the asset-size and ownership comparisons. The sample division uses median assets and the Wind ownership classification. Showing the complete coefficients preserves the evidence behind the claim that the general curvature appears across categories, while allowing readers to see that the parameter magnitudes are not identical.

Table 5. Productivity relationships across asset-size and ownership categories

Regressor or statistic	Smaller enterprises	Larger enterprises	State-owned enterprises	Private enterprises
Digital ratio	−5.7509***	−11.9120***	−10.5924***	−8.9463***
	(0.8422)	(1.4521)	(2.0186)	(0.7607)
Squared digital ratio	22.0097***	81.0303***	96.7502***	31.6992***
	(5.4884)	(14.0675)	(23.7453)	(3.9097)
Age	0.0569	0.0591	0.0642	0.0793**
	(0.0420)	(0.0475)	(0.0671)	(0.0400)
Ownership	0.1407***	−0.0369	—	—
	(0.0354)	(0.0277)		
Return on net assets	0.0003**	0.0035***	0.0003**	0.0027***
	(0.0001)	(0.0004)	(0.0002)	(0.0003)
Cash flow	0.2018***	0.3596***	0.5691***	0.0688
	(0.0681)	(0.0794)	(0.1045)	(0.0656)
Tax burden	−0.6707***	1.8245***	−0.7582***	1.7872***
	(0.1020)	(0.2587)	(0.1211)	(0.2048)
Capital intensity	−0.0051***	−0.0214***	−0.0054***	−0.0246***
	(0.0005)	(0.0014)	(0.0007)	(0.0013)
Labor investment	0.0115*	0.0016	0.0234**	0.0313***
	(0.0062)	(0.0074)	(0.0091)	(0.0056)
Capital investment	0.0091*	0.0115**	0.0529***	0.0242***
	(0.0049)	(0.0056)	(0.0073)	(0.0043)
Constant	3.7541***	3.3665***	2.0056***	3.2885***
	(0.2233)	(0.2194)	(0.2732)	(0.2041)
Industry and year controls	Yes	Yes	Yes	Yes
Observations	4,122	4,215	2,102	6,235
Enterprises	1,157	947	376	1,293
Within-group R^2	0.1053	0.1534	0.1208	0.1385

All four subsamples retain a negative linear term and a positive squared term, each marked significant at one percent. The evidence therefore supports a common qualitative sign pattern. It does not establish that asset scale or ownership has no influence on the strength of the relationship. The coefficients differ substantially, and the paper does not report a joint equality test or confidence intervals for subgroup turning points. The defensible conclusion is that the reported curvature is not confined to one size or ownership category, rather than that all enterprises face identical investment returns.

5. DISCUSSION

The main finding is best understood as evidence that recorded digital investment and productive efficiency are related nonlinearly within the observed enterprise panel. At lower values of the digital-asset ratio, the fitted productivity relationship is negative; after the estimated minimum, it becomes positive. This pattern is consistent with an organizational adjustment argument in which costs emerge before complementary capabilities become effective. It is also compatible with broader productivity research that treats technology as dependent on managerial, human, and organizational resources [3], [4], [5]. The evidence does not require the assumption that technology is either uniformly beneficial or inherently disruptive.

The economic interpretation begins with the distinction between available functions and usable capacity. New software can make information accessible while simultaneously requiring data conversion and staff training. Connected equipment can permit more precise scheduling but generate little benefit if purchasing, sales, and production continue to operate through separate routines. During such adjustment, additional capital is recorded before its contribution to output is fully realized. Once complementary procedures become established, the same assets can support more effective coordination. The source's U-shaped association is consistent with this sequence, although the sequence itself is not directly observed.

That qualification matters because investment intensity is not a clock. An enterprise can have a low digital-asset ratio because its systems are incomplete, because it leases services, because its production requires extensive nondigital assets, or because older systems are largely depreciated. A high ratio can reflect substantial implementation or simply a different asset base. Treating all observations as stages on one transformation path would therefore impose more uniformity than the measure warrants. Longitudinal evidence on adoption dates, implementation milestones, and process changes would be needed to identify the adjustment sequence more directly.

The reported turning point should be used with similar care. Its location within the observed range supports the substantive relevance of the fitted curve. The large distance between that point and the sample mean also suggests that the increasing segment is not representative of the average investment ratio. However, a mean alone does not establish the proportion of firms below the threshold, and an observed maximum does not establish dense statistical support above it. The distribution near the turning point and at the upper end would help assess how much information identifies the rising portion of the relationship.

Nor is the estimated minimum a recommendation to increase digital assets until they reach a fixed share of total assets. Such a rule would ignore industry technology, existing systems, depreciation, financing conditions, and the purpose of the investment. The minimum identifies a change in the marginal fitted association, not the point at which every enterprise obtains a positive total return. A managerial decision requires comparing expected benefits, implementation risks, and opportunity costs for a specific organization. The quadratic estimate informs that assessment by challenging constant-return assumptions, but it cannot substitute for it.

The working-capital results provide a plausible operational account, though their statistical support is limited. A strong positive turnover coefficient in the productivity equation indicates that enterprises with faster turnover have higher conditional productivity in that sample. The digital-investment coefficient in the turnover equation is positive but imprecise. The source's reported Sobel statistic is also sensitive to whether a one-sided or two-sided test is used. The appropriate conclusion is that working-capital coordination is a credible pathway with suggestive evidence, rather than a mechanism established as decisively as the headline interpretation might imply.

Operational interpretation would also benefit from decomposing turnover. Better scheduling can reduce inventory holding, but changes in customer payments or supplier terms can produce similar movements. A firm may improve its own turnover by shifting pressure to another participant in the supply chain. The resulting enterprise-level gain need not represent an equivalent improvement for the entire production network. More detailed measures of inventories, receivables, payables, and delivery reliability would help identify whether digital investment reduces real coordination losses or mainly reallocates financing requirements between organizations.

The human-capital findings offer stronger evidence of complementary capability. Digital investment is positively associated with the share of degree-qualified employees, and that share is positively associated with productivity. This is consistent with the view that new technologies require workers who can interpret information and coordinate unfamiliar processes [16], [17]. Yet the educational share does not reveal whether the firm develops existing employees or changes its workforce composition through hiring and separation. Training, experience, and team organization remain important dimensions that cannot be inferred from formal education alone.

Policy should therefore interpret human-capital upgrading as a development challenge rather than a mechanical replacement objective. Expanding university–enterprise cooperation, improving practical training, and creating incentives for employees to use new systems can support the productive complementarity suggested by the estimates. Such measures should include workers whose skills are acquired through experience or vocational education. The labor-market literature shows why automation can displace tasks while also creating new ones [14], [15]. A productivity-oriented transformation can be more durable when it addresses that adjustment rather than treating workforce substitution as its sole mechanism.

The financing result points to a different tension. Improved information and access to resources can support productive investment, but available funds may also be directed toward activities with limited contribution to operating efficiency. The source interprets the negative statistical pathway through FC as a sign that easier financing encourages debt expansion and financialization [1]. That interpretation is economically possible, but the actual allocation decision is not observed in the mechanism table. The index measures a size-and-age-related financing condition, not the value of financial assets or the composition of borrowing.

This boundary prevents a general inference that relaxing financing constraints reduces productivity. Many firms need external resources to fund equipment, training, and organizational change. The concern is how

financing opportunities interact with incentives and investment choices. A firm may hold liquid assets as a precaution or as a substitute for productive expenditure, and those motives have different implications. Direct observations of borrowing, financial-asset purchases, research investment, and operating investment would make it possible to distinguish them. The present evidence motivates that inquiry without settling the underlying financial behavior.

The subgroup results indicate that the qualitative curvature extends beyond one organizational category. Both asset-size groups and both ownership groups have the same linear and quadratic coefficient signs. This supports broad relevance of the complementarity problem. However, shared signs do not imply equal returns. Different coefficient magnitudes can imply different turning points, and neither formal equality tests nor interval estimates for those differences are provided. The findings therefore favor making transformation support available across ownership and size while preserving enterprise-specific assessment of capabilities and constraints.

The asset-size classification also deserves a temporal interpretation. A listed enterprise can move above or below the sample median over time, so observation-level categories need not correspond to permanent groups of firms. Ownership can likewise change, although the source does not explain how such changes are treated in the subgroup counts. This may help explain why reported enterprise totals overlap, but it cannot be assumed without documentation. Clear classification rules would improve the reproducibility of the heterogeneity analysis and determine whether the results concern stable organizational types or changing enterprise conditions.

The robustness checks strengthen confidence in the coefficient-sign pattern but have narrower implications than a definitive causal identification strategy. Alternative productivity measurement addresses sensitivity to the production-function estimator. Excluding real estate addresses one contested sectoral boundary. Enterprise effects account for persistent firm characteristics, while city controls address selected local conditions. None directly isolates an exogenous change in digital investment. Productive firms may invest differently, anticipated demand can affect both investment and productivity, and unobserved managerial quality can influence implementation. Reverse causality and time-varying selection remain relevant possibilities.

Measurement deserves equal attention. Recorded digital assets omit some investments while including depreciation and accounting choices that can alter the ratio independently of actual use. Productivity estimates depend on output and input definitions, deflation, and assumptions about enterprise decisions. The labor-variable formula, unusual financial ratios, and minor inconsistencies between the source's prose and tables further limit exact replication. These issues do not require discarding the results. They require preserving the published values, avoiding unsupported corrections, and identifying which conclusions remain conditional on documentation that is not available in the article.

The study's broader policy implications concern complementary investment and coordination. Enterprises should identify the operational problem a digital project is intended to solve and adapt management responsibilities alongside the technology. Public support can help firms bear training and integration costs, while leading enterprises can assist suppliers and customers in adopting compatible processes. Shared infrastructure and information standards may reduce duplication. These recommendations follow the source's emphasis on supply-chain coordination and organizational reengineering, but the regressions do not compare the cost effectiveness of particular subsidy instruments or implementation sequences.

Resource sharing should also be coordinated with credible data rights and privacy protection. Firms may be reluctant to share useful information if ownership, access, or accountability is uncertain. Conversely, excessive restrictions can prevent the coordination gains that interconnected systems are intended to create. The source proposes developing a digital ecosystem alongside stronger protection for data-related rights [1]. A practical interpretation is to make responsibilities clear and sharing purposeful. The productivity objective is more effective coordination, rather than greater data circulation without regard to commercial sensitivity or operational need.

Future research could separate the adjustment process from the cross-sectional intensity relationship by combining investment records with adoption histories and implementation measures. Flexible nonlinear models and turning-point confidence intervals would help assess whether the quadratic approximation describes the observed support adequately. Direct measures of financing and workforce transitions would strengthen mechanism analysis. Evidence from unlisted enterprises would also broaden applicability because listed firms have different reporting capacity and resource access from many smaller businesses. These extensions would clarify when digital investment becomes productive capability and which forms of support help that transition occur.

6. CONCLUSION

Digital transformation is associated with a U-shaped productivity relationship in the reported panel of Chinese listed enterprises over 2007–2020. The negative linear and positive quadratic coefficients persist across stepwise controls, alternative fixed effects, a different productivity estimator, the exclusion of real estate, and additional city conditions. The fully controlled baseline places the fitted minimum at a digital-asset ratio of 0.1373, while the sample mean is 0.0090. These values describe the estimated relationship within the observed sample and should not be interpreted as a universal investment prescription.

The mechanism evidence suggests that productive benefits depend on how enterprises use digital resources. The educated employee share provides a favorable statistical pathway with significant links in both reported equations. Working-capital turnover is also positively related to productivity, although the preceding investment-to-turnover relationship is less precise and its mediation test requires qualification. The financing sequence has opposite-signed links, which the source interprets as an adverse allocation channel. That interpretation remains conditional because borrowing and financial-asset investment are not directly measured in the mechanism results.

The same qualitative coefficient pattern appears across asset-size and ownership categories. This indicates that the estimated curvature is not limited to one enterprise type, while leaving differences in strength and turning points unresolved. More generally, the findings favor treating digital transformation as an organizational process in which equipment, skills, management, and finance must be coordinated. Support for training, compatible supply-chain processes, appropriate resource sharing, and clear data rights can help firms turn technological functions into usable capacity. Financing support should encourage productive application rather than assume that greater access alone ensures better allocation.

The conclusions remain bounded by observational identification and measurement. Digital-asset intensity is not a direct measure of transformation maturity, and separately estimated mechanism equations do not establish causal indirect effects. The source also contains reporting details that require clarification for exact replication. Retaining those limits alongside the results yields a measured conclusion: digital capital can contribute to enterprise productivity, but its return depends on complementary organizational development and the choices governing resource use. Early inefficiency and later gains are plausible parts of that relationship, not an inevitable trajectory for every enterprise.

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