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# Parent-firm AI Adoption and Foreign Subsidiary Performance

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## Abstract

**This paper examines whether artificial intelligence (AI) adoption by parent firms improves the performance of foreign subsidiaries. Using a matched panel of Chinese A-share listed parent firms and overseas subsidiaries during 2018-2024, we link annual-report-based AI adoption to subsidiary return on assets. Fixed-effects estimates show a positive relationship between parent-firm AI adoption and subsidiary performance. Two instrumental-variable strategies, based on peer adoption and a shift-share design, support the main result, although the shift-share estimate is less precise. Mechanism tests suggest that AI adoption improves performance partly through stronger inventory discipline. The effect is weaker in faster-growing host economies and stronger in resource-dependent host economies.**

## Keywords

**Artificial intelligence, Foreign subsidiaries, Subsidiary performance, Knowledge transfer, Multinational enterprises.**

## 1. Introduction

Artificial intelligence (AI) is increasingly embedded in how multinational enterprises (MNEs) process information, coordinate operations and redeploy capabilities across borders. Yet evidence on AI has mainly focused on parent firms or stand-alone firms [1, 2, 3, 4], while less is known about whether AI capabilities developed at headquarters generate value in foreign subsidiaries. This distinction matters because a parent's digital investment does not automatically improve subsidiary performance. Capabilities must be transferred, adapted and used in local operations that face different institutions, demand conditions and coordination costs.

This paper asks whether parent-firm AI adoption improves the financial performance of foreign subsidiaries and under what host-economy conditions this relationship is stronger or weaker. We build on the resource-based view and the knowledge-transfer literature. The resource-based view treats superior performance as the result of valuable and difficult-to-imitate resources [5]. AI can be such a resource when it combines data, algorithms, technical expertise and routines that improve prediction and decision quality [6]. However, in an MNE, the value of a headquarters-origin capability depends on whether it can be transferred and applied abroad. Knowledge-transfer research therefore suggests that AI adoption should raise subsidiary performance only when foreign affiliates can absorb and implement the underlying routines [7, 8]. This approach is useful because it separates AI ownership from AI value creation. Annual reports may reveal that the parent is building AI capabilities, but subsidiary performance should improve only if these capabilities affect local forecasting, procurement, monitoring, inventory decisions or coordination with headquarters.

Our empirical setting is a matched panel of Chinese A-share listed parent firms and their overseas subsidiaries from 2018 to 2024. Parent-firm AI adoption is measured from AI-related keywords in annual reports. Subsidiary performance is measured by return on assets (ROA).

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The baseline regressions include parent-subsidiary fixed effects and year fixed effects, and control for subsidiary, parent-firm and host-economy characteristics. To address endogeneity, we use two instrumental-variable strategies. The first uses peer AI adoption in the same industry and city. The second uses a shift-share design that combines historical AI exposure with contemporaneous patent shocks, following the logic of Bartik-style instruments.

We report four main findings. First, parent-firm AI adoption is positively associated with subsidiary ROA. Second, the peer-adoption IV and shift-share IV estimates remain positive; the peer-adoption design is strong and precise, while the shift-share design is positive but less precisely estimated. Third, the evidence points to inventory discipline as an operating mechanism: the performance penalty associated with long inventory turnover days is weaker when parent-firm AI adoption is higher. Fourth, the effect is weaker in faster-growing host economies and stronger in resource-dependent host economies, suggesting that the value of transferred AI capabilities depends on local structural conditions.

The contribution is threefold. First, the paper shifts attention from parent-level AI outcomes to subsidiary-level value creation. Second, it connects resource-based and knowledge-transfer arguments by showing that the possession of AI capabilities at headquarters is not sufficient; the relevant test is whether these capabilities travel across the multinational network. Third, it identifies inventory discipline as a concrete operating channel and shows that host-market conditions moderate the returns to transferred AI capabilities. These findings are consistent with the view that digitalization changes the content of firm-specific advantages but does not remove the organizational problem of transferring and adapting them internationally [9, 10]. The short-article format does not allow a full review of AI strategy, international business and operations research, so the theory is deliberately limited to the mechanisms needed for the empirical test.

## 2. Methods

We estimate fixed-effects models linking parent-firm AI adoption to subsidiary performance. The baseline specification is:

$$ROA_{ijht} = \alpha_0 + \alpha_1 AI_{jt} + \alpha_2 X_{it} + \alpha_3 X_{jt} + \alpha_4 X_{ht} + d_t + d_{ij} + \varepsilon_{ijht} \tag{1}$$

Where, i, j, h and t denote the subsidiary, parent firm, host economy and year, respectively. ROA is subsidiary performance; AI is parent-firm AI adoption; X represents subsidiary-, parent- and host-economy-level controls; denotes parent–subsidiary fixed effects; and denotes year fixed effects. The remaining term is the idiosyncratic error term. Standard errors are clustered at the parent-firm level. Alternative specifications use separate subsidiary and host-economy fixed effects. The coefficient beta is the parameter of interest. A positive beta indicates that subsidiaries connected to parents with stronger AI adoption exhibit higher ROA, net of time-invariant parent-subsidiary characteristics and common year shocks. Because the dependent variable is measured at the subsidiary level and AI adoption at the parent level, the specification exploits within-link variation in parent AI adoption over time.

The main concern is that parent-firm AI adoption may be endogenous. Better-performing parent firms may both invest more in AI and own stronger subsidiaries; unobserved managerial quality may also affect both AI adoption and foreign performance. We therefore estimate two-stage least squares models. The first instrument set uses the average AI adoption of other firms in the same industry and the average AI adoption of other firms in the same city. These peer measures capture technological and local diffusion pressures that affect a parent's AI adoption but should not directly determine a particular foreign subsidiary's ROA after controls and fixed effects.

The second instrument set uses a shift-share design inspired by Babina et al. [3]. Historical AI exposure in 2017 is interacted with contemporaneous invention-patent and design-patent shocks. The identifying assumption is that historical exposure combined with technology-supply shocks affects subsidiary performance through parent-firm AI adoption rather than through other subsidiary-specific channels. This design is useful because it relies on external variation in the technological environment rather than contemporaneous subsidiary outcomes. Because shift-share instruments may be noisier in smaller samples and can be sensitive to the construction of exposure shares, we interpret this design as complementary evidence rather than as the sole source of identification.

To examine the operating channel, we estimate interaction models in which subsidiary ROA is regressed on parent-firm AI adoption, inventory turnover days, and their interaction. Inventory turnover days capture inventory discipline and operating slack. AI may improve this dimension of performance by sharpening demand forecasts, improving replenishment timing, detecting abnormal inventory accumulation and allowing headquarters to monitor foreign operations more quickly. The interaction is not interpreted as a separate performance hypothesis; it tests whether AI adoption changes the performance relevance of inventory control.

## 3. Data

The dataset combines CSMAR, Orbis and World Bank data. We manually match Chinese A-share listed parent firms to overseas subsidiaries and retain observations from 2018 to 2024. We exclude ST and *ST firms, financial-sector firms, subsidiaries with ROA below -90 percent or above 80 percent, and subsidiaries located in tax havens such as Bermuda, the British Virgin Islands and the Cayman Islands. The descriptive sample contains 6,770 subsidiary-year observations, 384 parent firms, 1,403 subsidiaries and 48 host countries or regions. The baseline regression sample contains 6,451 observations after model-specific listwise deletion. This structure allows us to compare subsidiaries of the same parent-subsidiary relationship over time, rather than comparing unrelated subsidiaries whose technology, governance and local market conditions may differ for many reasons.

Parent-firm AI adoption is measured by the natural logarithm of one plus the frequency of AI-related keywords in annual reports, following text-based measures of AI focus [11]. The keyword dictionary covers artificial intelligence, machine learning, deep learning, natural language processing, computer vision, big data analytics, intelligent manufacturing, cloud computing and related terms. The full keyword list is not reported in the main text to save space, but the construction follows the original annual-report dictionary and can be placed in an online appendix if required. The dependent variable is foreign subsidiary ROA. Control variables capture subsidiary scale and leverage, host-market size and growth, and parent-firm characteristics. Subsidiary size controls for scale economies, subsidiary solvency controls for financial risk, host GDP per capita and growth proxy for local market conditions, and parent characteristics capture the resources and constraints of the headquarters firm.

Table 1 reports descriptive statistics, while Table 2 summarizes the definitions and measurement of the variables. Subsidiary ROA averages 2.672 percent, with substantial dispersion. Parent-firm AI adoption has a mean of 2.189 and a median of 2.197, indicating that AI disclosure is common but heterogeneous across firms. Pairwise correlations are below 0.7 and variance inflation factors are below 3, suggesting no serious multicollinearity problem. The correlation matrix and the AI keyword dictionary are therefore omitted from the main tables and summarized in the notes. If the journal requests replication material, these two items can be supplied as appendix tables without changing the main results.

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**Table 1.** Descriptive statistics

| Variable | Obs | Mean | Std. Dev. | Min | Median | Max |
|---|---|---|---|---|---|---|
| Foreign subsidiary ROA | 6770 | 2.672 | 14.069 | -67.134 | 1.919 | 45.826 |
| Parent-firm AI adoption | 6770 | 2.189 | 1.338 | 0.000 | 2.197 | 4.942 |
| Subsidiary size | 6770 | 9.137 | 2.335 | 2.017 | 9.334 | 13.998 |
| Subsidiary solvency | 6770 | 61.185 | 130.489 | 0.000 | 4.012 | 726.714 |
| Host-economy GDP growth | 6770 | 0.026 | 0.040 | -0.103 | 0.026 | 0.098 |
| Host-economy GDP per capita | 6770 | 10.134 | 1.064 | 7.435 | 10.446 | 11.579 |
| Parent overseas backgrounds | 6770 | 1.721 | 1.603 | 0.000 | 1.000 | 7.000 |
| Parent-firm solvency | 6770 | 0.524 | 0.167 | 0.106 | 0.547 | 0.885 |
| Parent-firm sales growth | 6770 | 0.144 | 0.273 | -0.408 | 0.098 | 2.028 |
| Parent-firm age | 6770 | 3.083 | 0.258 | 2.079 | 3.091 | 3.555 |
| Parent-firm size | 6770 | 9.547 | 1.494 | 5.903 | 9.595 | 12.357 |

Notes:

(1) Obs. refers to the number of available non-missing observations for each variable.

(2) ROA and subsidiary solvency are reported in percentage points; GDP growth and parent-firm sales growth are reported as decimals.

(3) Subsidiary size, host-economy GDP per capita, parent-firm age, and parent-firm size are natural logarithms.

(4) Parent-firm AI adoption equals ln(1 + AI-related keyword frequency in annual reports).

(5) The baseline regression sample is smaller because of model-specific listwise deletion.

**Table 2.** Definitions and measurement of variables

| Variable type | Variable | Definition | Measurement |
|---|---|---|---|
| Dependent variable | Foreign subsidiary ROA | Foreign subsidiary performance | Return on assets of the overseas subsidiary |
| Independent variable | Parent-firm AI adoption | Parent-firm AI adoption | Natural logarithm of (1 + the frequency of AI-related terms obtained from textual analysis of corporate annual reports) |
| Control variables | Subsidiary size | Subsidiary size | Natural logarithm of the overseas subsidiary's total assets |
| | Subsidiary solvency | Subsidiary solvency | Asset-liability ratio of the overseas subsidiary |
| | Host-economy GDP per capita | Host-economy market capacity | Natural logarithm of the host economy's GDP per capita |
| | Host-economy GDP growth | Host-economy market potential | Annual GDP growth rate of the host economy |
| | Parent-firm size | Parent-firm size | Natural logarithm of the number of parent firm employees |
| | Parent overseas backgrounds | Parent executives with overseas backgrounds | Number of executives with overseas backgrounds in the parent firm |
| | Parent-firm age | Parent-firm age | Natural logarithm of the parent firm's age |
| | Parent-firm sales growth | Parent-firm sales growth | Operating revenue growth rate of the parent firm |
| | Parent-firm solvency | Parent-firm solvency | Asset-liability ratio of the parent firm |

## 4. Results

Table 3 reports the baseline regressions. Across all specifications, the coefficient on parent-firm AI adoption is positive and statistically significant. In the preferred specification with parent-subsidiary fixed effects, year fixed effects and the full set of controls, the coefficient is 0.933,

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significant at the 1 percent level. Substantively, a one-unit increase in the log AI-adoption measure is associated with an increase of about 0.93 percentage points in subsidiary ROA in the preferred model. This is economically meaningful given that the mean subsidiary ROA is 2.67 percent. The result is stable when host-economy controls and parent-firm controls are added, and when fixed effects are specified differently. The stability is important because it reduces the concern that the estimate is mechanically driven by subsidiary scale, leverage, host growth or parent-firm size. It also means that the main conclusion does not depend on whether unobserved heterogeneity is absorbed at the subsidiary-host level or at the parent-subsidiary link level.

**Table 3.** Baseline regressions of subsidiary ROA on parent-firm AI adoption

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Parent-firm AI adoption | 0.751*** | 0.751*** | 0.750** | 0.750** | 0.933*** | 0.933*** |
| | (2.595) | (2.604) | (2.587) | (2.587) | (3.216) | (3.228) |
| Subsidiary size | 2.890*** | 2.890*** | 2.904*** | 2.904*** | 3.039*** | 3.039*** |
| | (5.935) | (5.957) | (5.901) | (5.901) | (5.913) | (5.935) |
| Subsidiary solvency | -0.013*** | -0.013*** | -0.012*** | -0.012*** | -0.012*** | -0.012*** |
| | (-5.945) | (-5.967) | (-5.925) | (-5.925) | (-5.875) | (-5.896) |
| Host-economy GDP growth | | | 13.352 | 13.352 | 12.896 | 12.896 |
| | | | (1.607) | (1.607) | (1.572) | (1.578) |
| Host-economy GDP per capita | | | -4.230 | -4.230 | -4.578 | -4.578 |
| | | | (-0.663) | (-0.663) | (-0.719) | (-0.721) |
| Parent overseas backgrounds | | | | | -0.360 | -0.360 |
| | | | | | (-1.195) | (-1.199) |
| Parent-firm solvency | | | | | -2.658 | -2.658 |
| | | | | | (-0.652) | (-0.655) |
| Parent-firm sales growth | | | | | 0.424 | 0.424 |
| | | | | | (0.504) | (0.506) |
| Parent-firm age | | | | | -13.706* | -13.706* |
| | | | | | (-1.716) | (-1.722) |
| Parent-firm size | | | | | -1.543 | -1.543 |
| | | | | | (-1.627) | (-1.633) |
| Constant | -24.528*** | -24.528*** | 17.803 | 17.803 | 78.733 | 78.733 |
| | (-5.408) | (-5.428) | (0.277) | (0.277) | (1.024) | (1.028) |
| No. observations | 6,451 | 6,451 | 6,451 | 6,451 | 6,451 | 6,451 |
| R-squared | 0.560 | 0.560 | 0.560 | 0.560 | 0.562 | 0.562 |
| Subsidiary fixed effects | Yes | No | Yes | No | Yes | No |
| Parent-subsidiary fixed effects | No | Yes | No | Yes | No | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Host-economy fixed effects | Yes | No | Yes | No | Yes | No |
| F statistics | 21 | 21.15 | 13.67 | 13.67 | 8.732 | 8.796 |

Notes:

(1) The dependent variable in each column is subsidiary ROA.

(2) Values in parentheses are robust t-statistics adjusted for clustering at the parent-firm level.

(3) Columns (1), (3), and (5) include subsidiary and host-economy fixed effects; columns (2), (4), and (6) include parent–subsidiary fixed effects. All columns include year fixed effects.

(4) Significance levels: *: 0.10; **: 0.05; ***: 0.01.

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**Table 4.** Instrumental-variable results: peer-adoption instruments

| | First Stage | 2SLS |
|---|---|---|
| City-level peer AI adoption | 0.651*** | |
| | (9.491) | |
| Industry-level peer AI adoption | 0.659*** | |
| | (7.024) | |
| Subsidiary size | -0.005 | 3.044*** |
| | (-0.268) | (5.943) |
| Subsidiary solvency | -0.000 | -0.012*** |
| | (-0.181) | (-5.886) |
| Host-economy GDP growth | -0.657 | 12.858 |
| | (-1.630) | (1.575) |
| Host-economy GDP per capita | 0.740** | -4.538 |
| | (1.992) | (-0.712) |
| Parent overseas backgrounds | 0.011 | -0.383 |
| | (0.545) | (-1.294) |
| Parent-firm solvency | -0.039 | -2.552 |
| | (-0.163) | (-0.630) |
| Parent-firm sales growth | -0.006 | 0.440 |
| | (-0.089) | (0.516) |
| Parent-firm age | -0.325 | -14.300* |
| | (-0.286) | (-1.814) |
| Parent-firm size | 0.091 | -1.631* |
| | (0.836) | (-1.754) |
| Parent-firm AI adoption | | 1.270*** |
| | | (3.086) |
| Constant | -7.998 | |
| | (-1.342) | |
| No. observations | 6,451 | 6,451 |
| R-squared | 0.929 | 0.043 |
| Parent-subsidiary fixed effects | Yes | Yes |
| Year fixed effects | Yes | Yes |
| Kleibergen-Paap rk LM statistic | | 21.96 |
| Kleibergen-Paap rk Wald F | | 137.7 |
| Hansen J p-value | | 0.642 |

Notes:

(1) Column (1) reports the first-stage regression with parent-firm AI adoption as the dependent variable.

(2) Column (2) reports the second-stage regression with subsidiary ROA as the dependent variable.

(3) Values in parentheses are robust t-statistics adjusted for clustering at the parent-firm level.

(4) Significance levels: *: 0.10; **: 0.05; ***: 0.01.

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**Table 5.** Instrumental-variable results: shift-share design instruments

| | First Stage | 2SLS |
|---|---|---|
| Invention-patent shock × AI share (2017) | -0.201*** | |
| | (-4.613) | |
| Design-patent shock × AI share (2017) | 0.075*** | |
| | (3.254) | |
| Subsidiary size | -0.008 | 2.639*** |
| | (-0.337) | (5.234) |
| Subsidiary solvency | 0.000 | -0.012*** |
| | (0.064) | (-5.680) |
| Host-economy GDP growth | -0.472 | 21.768*** |
| | (-0.656) | (2.811) |
| Host-economy GDP per capita | 0.071 | -6.849 |
| | (0.131) | (-1.001) |
| Parent overseas backgrounds | 0.071* | -0.500 |
| | (1.808) | (-1.497) |
| Parent-firm solvency | -0.549 | -3.827 |
| | (-1.349) | (-0.842) |
| Parent-firm sales growth | -0.205** | 2.253** |
| | (-2.226) | (2.438) |
| Parent-firm age | 1.024 | -15.360* |
| | (0.704) | (-1.763) |
| Parent-firm size | 0.367** | -1.910 |
| | (2.053) | (-1.619) |
| Parent-firm AI adoption | | 2.429* |
| | | (1.866) |
| Constant | -2.532 | |
| | (-0.354) | |
| No. observations | 5,441 | 5,441 |
| R-squared | 0.869 | 0.029 |
| Parent-subsidiary fixed effects | Yes | Yes |
| Year fixed effects | Yes | Yes |
| Kleibergen-Paap rk LM statistic | | 8.952 |
| Kleibergen-Paap rk Wald F | | 11.88 |
| Hansen J p-value | | 0.259 |

Notes:
(1) Column (1) reports the first-stage regression with parent-firm AI adoption as the dependent variable.
(2) Column (2) reports the second-stage regression with subsidiary ROA as the dependent variable.
(3) Values in parentheses are robust t-statistics adjusted for clustering at the parent-firm level.
(4) The shift-share instruments combine 2017 AI exposure with contemporaneous patent shocks.
(5) Significance levels: *: 0.10; **: 0.05; ***: 0.01.

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Tables 4 and 5 report the instrumental-variable estimates. In the peer-adoption design, both city-level and industry-level peer AI adoption strongly predict parent-firm AI adoption. The Kleibergen-Paap Wald F statistic is 137.7 and the Hansen J test does not reject the overidentifying restrictions. The second-stage coefficient on parent-firm AI adoption is 1.270 and significant at the 1 percent level. This estimate is larger than the fixed-effects estimate, which is consistent with attenuation from measurement error in the text-based AI measure.

The shift-share design also supports the main result, but the evidence is weaker. The first-stage instruments are significant and the Kleibergen-Paap Wald F statistic is 11.88. The second-stage coefficient is 2.429 and significant at the 10 percent level. The point estimate remains positive and economically meaningful, but the lower precision suggests that the shift-share results should be read as corroborative rather than definitive. Taken together, the two IV designs are consistent with the main fixed-effects estimates: exogenous variation related to AI diffusion and technology-supply shocks predicts stronger parent AI adoption, and the predicted adoption is associated with better subsidiary performance.

Table 6 reports the mechanism test, Table 7 presents robustness checks, and Table 8 reports the heterogeneity analysis. The mechanism results show that inventory turnover days are negatively related to subsidiary ROA and that the interaction between parent-firm AI adoption and inventory turnover days is negative and significant. Because long inventory cycles indicate slower adjustment and higher working-capital commitment [12, 13], this pattern is consistent with stronger inventory discipline under higher parent-firm AI adoption. In substantive terms, subsidiaries appear better able to convert headquarters AI capabilities into operating control. This does not mean that AI simply reduces inventory in all circumstances; rather, it suggests that AI-enabled information helps subsidiaries manage the performance consequences of inventory-related slack.

The robustness results show that the core result is not driven by the dependent-variable choice, the AI measure, the COVID-19 year or clustering level. To keep the article short, these checks are reported in condensed form rather than as separate full tables. The coefficient remains positive when ROE replaces ROA, when AI adoption is measured from the MD&A section, AI-related sentence share or AI-related word share, and when observations from 2020 are excluded. Inference is also unchanged when standard errors are clustered by host economy, subsidiary industry or parent-firm industry.

The heterogeneity results show two boundary conditions. The interaction between AI adoption and high host-economy GDP-per-capita growth is negative, implying that the AI effect is weaker in faster-growing host economies. One interpretation is that broad host-market expansion already supports subsidiary performance, reducing the marginal value of headquarters-origin capabilities. Faster-growing markets may also provide stronger local opportunities and external knowledge sources, making subsidiaries less dependent on parent-origin AI routines. By contrast, the interaction between AI adoption and resource dependence is positive. Subsidiaries in resource-dependent host economies have lower baseline performance but benefit more from parent-firm AI adoption, consistent with AI being more valuable where coordination, forecasting and resource allocation frictions are more severe. In these environments, AI-enabled monitoring and prediction may help subsidiaries cope with volatility and extract more value from existing operations.

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**Table 6.** Mechanism test: inventory discipline

| | **Subsidiary inventory turnover days** |
|---|---|
| Parent-firm AI adoption | 0.396 |
| | (1.015) |
| Subsidiary inventory turnover days | -0.001** |
| | (-1.997) |
| Parent-firm AI adoption × inventory turnover days | -0.001* |
| | (-1.746) |
| Subsidiary size | 2.498*** |
| | (4.091) |
| Subsidiary solvency | -0.011*** |
| | (-4.383) |
| Host-economy GDP growth | 18.138* |
| | (1.877) |
| Host-economy GDP per capita | -2.449 |
| | (-0.337) |
| Parent overseas backgrounds | -0.351 |
| | (-0.760) |
| Parent-firm solvency | -1.241 |
| | (-0.293) |
| Parent-firm sales growth | 1.519* |
| | (1.811) |
| Parent-firm age | 0.594 |
| | (0.046) |
| Parent-firm size | -0.181 |
| | (-0.178) |
| Constant | 4.388 |
| | (0.055) |
| No. observations | 3,406 |
| R-squared | 0.590 |
| Parent-subsidiary fixed effects | Yes |
| Year fixed effects | Yes |
| F statistics | 6.609 |

Notes:

(1) The dependent variable in each column is subsidiary ROA.

(2) Column (1) tests the inventory-turnover-days mechanism.

(3) Values in parentheses are robust t-statistics adjusted for clustering at the parent-firm level.

(4) Significance levels: *: 0.10; **: 0.05; ***: 0.01.

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**Table 7.** Robustness checks

| | Alternative dependent variable | Alternative measures of AI adoption | Alternative measures of AI adoption | Alternative measures of AI adoption | Excluding the year 2020 |
|---|---|---|---|---|---|
| Parent-firm AI adoption | 4.809*** | | | | 0.786*** |
| | (2.788) | | | | (2.607) |
| Subsidiary size | 8.591*** | 3.043*** | 3.031*** | 3.028*** | 3.323*** |
| | (4.043) | (5.945) | (5.926) | (5.925) | (5.775) |
| Subsidiary solvency | -0.040* | -0.012*** | -0.012*** | -0.012*** | -0.011*** |
| | (-1.667) | (-5.940) | (-5.917) | (-5.923) | (-5.116) |
| Host-economy GDP growth | 60.741 | 13.024 | 12.287 | 12.349 | 11.165 |
| | (1.051) | (1.592) | (1.494) | (1.496) | (1.271) |
| Host-economy GDP per capita | -40.927 | -4.705 | -3.875 | -3.885 | -2.780 |
| | (-1.159) | (-0.743) | (-0.608) | (-0.610) | (-0.437) |
| Parent overseas backgrounds | -1.577 | -0.455* | -0.359 | -0.345 | -0.312 |
| | (-1.215) | (-1.672) | (-1.203) | (-1.136) | (-0.943) |
| Parent-firm solvency | 17.943 | -2.466 | -2.781 | -2.871 | -3.084 |
| | (0.566) | (-0.604) | (-0.684) | (-0.706) | (-0.729) |
| Parent-firm sales growth | 2.884 | 0.459 | 0.400 | 0.396 | -0.011 |
| | (0.738) | (0.550) | (0.494) | (0.488) | (-0.011) |
| Parent-firm age | -47.276 | -12.452 | -11.885 | -11.411 | -12.135 |
| | (-0.984) | (-1.554) | (-1.512) | (-1.450) | (-1.501) |
| Parent-firm size | 7.739 | -1.497 | -1.424 | -1.395 | -1.324 |
| | (0.881) | (-1.585) | (-1.476) | (-1.457) | (-1.319) |
| Parent-firm AI adoption (MD&A) | | 0.677*** | | | |
| | | (2.607) | | | |
| AI-related sentence share | | | 113.028* | | |
| | | | (1.903) | | |
| AI-related word share | | | | 3,026.012* | |
| | | | | (1.816) | |
| Constant | 395.440 | 76.506 | 66.287 | 64.636 | 51.441 |
| | (0.920) | (1.005) | (0.875) | (0.855) | (0.679) |
| No. observations | 6,419 | 6,451 | 6,444 | 6,444 | 5,501 |
| R-squared | 0.396 | 0.562 | 0.562 | 0.562 | 0.583 |
| Parent-subsidiary fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| F statistics | 3.227 | 7.990 | 7.802 | 7.832 | 7.149 |

Notes:

(1) Column (1) uses ROE as the dependent variable; columns (2)-(5) use subsidiary ROA.

(2) Columns (2)-(4) use alternative AI-adoption measures; column (5) excludes observations from 2020.

(3) Values in parentheses are robust t-statistics adjusted for clustering at the parent-firm level.

(4) Significance levels: *: 0.10; **: 0.05; ***: 0.01.

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**Table 8.** Heterogeneity analysis

| | High host-economy GDP-per-capita growth | Resource-dependent host economy |
|---|---|---|
| Parent-firm AI adoption | 0.9471*** | 0.4054 |
| | (3.2547) | (1.3224) |
| High host-economy GDP-per-capita growth | 0.8376 | |
| | (1.5399) | |
| Parent-firm AI adoption × high host-economy GDP-per-capita growth | -0.3851* | |
| | (-1.8625) | |
| Resource-dependent host economy | | -1.7683** |
| | | (-2.0813) |
| Parent-firm AI adoption × resource dependence | | 0.6165** |
| | | (2.1344) |
| Constant | 40.0225 | 35.9877 |
| | (0.6030) | (0.5394) |
| No. observations | 6,451 | 6,451 |
| R-squared | 0.565 | 0.565 |
| Parent-subsidiary fixed effects | Yes | Yes |
| Year fixed effects | Yes | Yes |
| F statistics | 9.634 | 9.836 |

Notes:

(1) The dependent variable in each column is subsidiary ROA.

(2) Values in parentheses are robust t-statistics adjusted for clustering at the parent-firm level.

(3) Significance levels: *: 0.10; **: 0.05; ***: 0.01.

## 5. Concluding Remarks

This paper examines whether AI adoption by parent firms improves the performance of foreign subsidiaries. Using a matched panel of Chinese listed parents and overseas subsidiaries from 2018 to 2024, we find that parent-firm AI adoption is positively associated with subsidiary ROA. The result is robust across fixed-effects specifications and alternative measures. Two IV strategies support the interpretation that AI adoption improves subsidiary performance, although the shift-share evidence is less precise than the peer-adoption evidence.

The results extend the resource-based view and knowledge-transfer research by showing that AI is valuable not merely as a parent-firm investment, but as a capability bundle that can be redeployed within the multinational network. A capability becomes a multinational advantage only when it can be transferred, interpreted and embedded in subsidiary routines. The evidence on inventory discipline suggests one operating pathway through which headquarters

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AI capabilities become subsidiary-level value. The heterogeneity results further show that transferred AI capabilities are not equally valuable everywhere: they matter less in faster-growing host economies and more in resource-dependent host economies.

For managers, the implication is that AI adoption should be governed as a cross-border capability rather than a headquarters-only technology. Investments in algorithms and data infrastructure need to be accompanied by routines that help subsidiaries absorb, adapt and use AI-enabled information in operations. Practical examples include shared data standards, inventory dashboards, headquarters-subsidiary review routines and training that helps local managers act on algorithmic forecasts. The study is limited by the use of annual-report text to measure AI adoption and by its focus on Chinese listed firms. Textual measures capture communicated AI emphasis and may not fully distinguish symbolic disclosure from implementation depth; the findings should therefore be interpreted as evidence on observable AI adoption signals and their associated performance consequences. Future research could combine textual measures with patents, job postings or survey data, and examine other mechanisms such as innovation, workforce skills and subsidiary absorptive capacity.

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