

Cultural Distance and Innovation Performance in Cross-Border M&A: The Moderating Role of R&D Intensity

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Abstract: Whether cultural distance raises or lowers post-acquisition innovation performance remains unsettled in international business research. We use panel data on cross-border M&A events completed by Chinese A-share listed firms and estimate pooled OLS models that test an inverted-U effect of cultural distance on post-acquisition innovation and the moderating role of R&D intensity. Cultural distance and innovation performance show a significant inverted-U relationship, but this main effect loses significance once industry fixed effects are controlled; its identification depends on systematic differences in target-country cultural distance across industries. R&D intensity has a structurally robust moderating effect on the inverted U: it strengthens the positive slope at low cultural distance and deepens the negative slope at high cultural distance, and this moderation stays significant under industry fixed effects and the Heckman two-stage correction. The paper makes two contributions. First, the moderating effect of R&D shows that the marginal return to absorptive capacity reverses direction as cultural distance rises, which marks the boundary of absorptive-capacity theory in cross-cultural settings. Second, the sensitivity of the inverted-U main effect to model specification is a caution for future non-linear empirical work: robust identification of non-linear effects requires careful attention to unobserved heterogeneity at the industry and firm levels.

Keywords: Cultural Distance, Innovation Performance, Inverted U-Shaped Relationship, R&D Intensity, Cross-Border M&A.

1. INTRODUCTION

Whether cultural distance raises or lowers post-acquisition innovation performance remains open in international business research. The integration-cost view (Stahl & Voigt, 2008) and the knowledge-diversity view (Morosini *et al.*, 1998; Chakrabarti *et al.*, 2009) are each backed by consistent evidence, yet they predict opposite signs. Rather than treating the two camps as logically incompatible, a more plausible reading is that each captures a different segment of the cultural-distance range (Shenkar, 2001; Reus & Lamont, 2009). If so, a framework that contains both logics at once would yield a non-linear relationship between cultural distance and innovation performance, and whether that relationship holds in the data is an empirical question.

The debate may persist because the existing specifications assume a constant marginal effect of cultural distance and do not directly test for non-linearity (Shenkar, 2001). When cultural distance is very small, the two knowledge bases overlap heavily and offer little complementarity; the gains from knowledge diversity peak at a moderate distance; and at a very large distance, integration barriers and cultural friction dominate. This pattern points to an inverted-U relationship. Nguyen *et al.*, (2024), Li *et al.*, (2020), and Zhang and Yang (2022) report non-linear effects of cultural or institutional distance in different settings, and Zhou and Yang (2023) and Wan and Yang (2023) find similar non-linearity in Chinese data. Absorptive capacity also depends heavily on the knowledge environment (Stettler *et al.*, 2025), so the moderating role of R&D may differ across distance ranges. Yet the studies above test one effect at a time, and none places the inverted-

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U main effect and the R&D moderation in a single framework, even though that combination is what determines where absorptive capacity does and does not apply in cross-cultural settings. This paper estimates both together.

We study cross-border acquisitions by Chinese A-share listed firms. Luo and Tung's (2018) springboard theory defines the internationalization of emerging-market multinationals as capability leapfrogging: cross-border acquisition is a springboard for acquiring strategic assets to offset home-country institutional disadvantages, not a natural spillover of comparative advantage. Chinese firms' cross-border acquisitions have two features. On one side, technology catch-up motives drive them to seek external knowledge systematically (Zámborský *et al.*, 2023). On the other side, home-country institutional disadvantages coexist with limited integration capacity (Peng *et al.*, 2024), so both the knowledge-diversity-gains mechanism and the integration-cost mechanism have ample empirical variation. More important, Chinese firms' target countries are widely distributed, from culturally proximate Hong Kong, China to culturally distant Sweden, and the cross-sectional variation in cultural distance covers the full range from low to high. This span forms the empirical basis for identifying both sides of the inverted U at the same time. However, the distribution of this identifying variation is not even: the 316 observations to the right of the turning point (15.43% of 2,048) come from only 6 of the 19 target countries, and the United States (175) and Australia (42) together account for 68.7%. The source of the cross-sectional variation (between-industry versus within-industry differences) will directly affect the efficiency and robustness of the non-linear estimate, and this issue is the core concern of the empirical section below. Ghorbani *et al.*, (2023), Yang *et al.*, (2025), and Yin and Tian (2023) provide an empirical basis for testing the non-linear effect of cultural distance in the Chinese context, from the perspectives of ownership heterogeneity, dynamic capabilities, and technology catch-up. Chen (2025) discusses the role of absorptive capacity in technology integration in cross-border M&A from the perspective of technology transfer, adding a complementary view on the function of R&D in cross-border acquisitions. Wang *et al.*, (2025) find, from the perspective of global innovation network embedding, that overseas M&A promotes the innovation of Chinese firms.

We study the non-linear effect of cultural distance on the post-acquisition innovation performance of Chinese firms, and the moderating role of R&D intensity, within a framework in which integration cost and knowledge diversity trade off against each other. Using cross-border acquisition data for Chinese A-share listed firms from 2010 to 2023, we ask: (1) Is there an inverted-U relationship between cultural distance and post-acquisition innovation performance, and does its identification depend on model specification, especially the control of unobserved industry-level heterogeneity? (2) How does R&D intensity moderate the inverted-U relationship, and does the direction of the moderation reverse as cultural distance changes?

The paper makes three contributions. First, it brings the moderating effect of R&D into the inverted-U framework and tests whether the marginal return to absorptive capacity reverses direction as cultural distance rises, which delimits the boundary conditions of absorptive capacity theory in cross-cultural settings. Second, it uses Chinese cross-border acquisitions to show how the identification of the inverted U depends on the source of cross-sectional variation in target-country cultural distance, which offers a methodological reference for model specification and sample selection in non-linear empirical work. Third, it shows that the non-linear dynamics of cultural distance are activated by firm-level absorptive capacity rather than forming a universal structural law.

2. THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

2.1 Cultural Distance and Innovation Performance

How cultural distance shapes acquisition performance remains contested in the cross-border M&A literature. The integration-cost view builds on transaction cost economics (Williamson, 1985) and social identity theory (Tajfel & Turner, 1979): cultural distance amplifies coordination conflict and relational opposition after an acquisition, which erodes synergy. The knowledge-diversity view builds on organizational learning theory (Levitt & March, 1988; Huber, 1991) and the resource-based view (Barney, 1991): cultural difference brings heterogeneous organizational routines and cognitive frames, which give the acquirer a differentiated resource base for post-acquisition knowledge recombination and innovation. The two views are each supported, yet they point in opposite directions. Reus and Lamont (2009) reconcile them with a double-edged-sword model that admits both forces and gestures toward non-linearity, but that model does not explain how the relative strength of the two forces shifts as cultural distance grows, so the step from a linear to a non-linear account remains incomplete.

We decompose the effect of cultural distance on innovation performance into a dynamic trade-off between two forces. The gains from knowledge diversity stem from the heterogeneous organizational routines and technological trajectories that cultural differences carry between countries; after an acquisition, these heterogeneous assets become innovation output through routine complementarity and knowledge recombination (Kogut & Zander, 1993). The integration cost stems from the coordination difficulty and identity conflict that cultural differences create. At low cultural distance this shows up mainly as communication friction and information-transfer barriers (Shenkar, 2012), but beyond a threshold it escalates into identity confrontation and employee resistance (Smeulders *et al.*, 2023), which in turn strengthens the barriers to knowledge transfer (Szulanski, 1996) and the sticky-information problem (von Hippel, 1994).

The two forces are likely to differ in how sensitive they are to cultural distance at the margin. As cultural distance grows, the marginal gain from knowledge diversity falls: the diversity dividend an acquirer captures at the start is the largest, and the incremental complementarity of later dimensions weakens. The marginal cost of integration, in contrast, rises, because the accumulated effect of cross-cultural conflict makes each new coordination need harder to resolve than the last (Tajfel & Turner, 1979). When the gain grows faster than the cost the net effect is positive, and when the cost begins to grow faster than the gain the net effect turns negative. The shape of the relationship is therefore set by the change in the relative slopes of the two mechanisms rather than by a comparison of their absolute levels. Where exactly the two marginal slopes cross is a question to be settled in theory and tested in the data, not a conclusion known in advance.

Existing empirical work supports this reasoning indirectly. Brede *et al.*, (2024) build an organizational-culture-distance measure from employee reviews and find a negative effect of cultural distance on short-term and long-term acquisition performance in a sample dominated by large cultural differences, while Morosini *et al.*, (1998) and Chakrabarti *et al.*, (2009) find higher synergy in larger-distance acquisitions within samples closer to moderate-difference deals. The “double-edged sword” of Reus and Lamont (2009) shows that the direction of the effect depends on the firm’s integration capability, which implies that the cultural-distance effect varies across ranges and may also be moderated by firm-level absorptive capacity. Stahl and Voigt’s (2008) meta-analysis finds a clearly negative effect of cultural difference on sociocultural integration but no uniform effect on synergy or shareholder value. Nguyen *et al.*, (2024) report a U-shaped curve with divestment as the dependent variable, whereas this paper uses innovation performance and predicts an inverted U; the two curves point in opposite directions but share the same logic, the former capturing the avoidance logic of cultural friction and the latter the benefit-cost trade-off of knowledge integration, in which gains peak at moderate distance. Both indicate that the marginal effect of cultural distance reverses across ranges. These theories and findings lead to the following hypothesis:

H1: There is an inverted-U relationship between cultural distance and post-acquisition innovation performance. At low cultural distance, innovation performance rises as distance grows; beyond a certain threshold, it falls as distance grows.

2.2 The Moderating Effect of R&D Intensity

Because the inverted U exists, the net effect of cultural distance on innovation performance depends on the relative slopes of knowledge-diversity gains and integration costs. Firm-level absorptive capacity, proxied by R&D intensity (Cohen & Levinthal, 1990; Li *et al.*, 2024), therefore cannot moderate the relationship in one simple direction; it must be examined range by range.

At low cultural distance, the two sides of the deal share more cognitive ground and organizational logic, so external knowledge is easier to reach and high R&D intensity can absorb it efficiently. The firm draws on its existing knowledge stock to identify, assimilate, and apply the heterogeneous routines and technological trajectories carried by the target, which turns the knowledge-diversity potential into innovation output at a faster pace (Kogut & Zander, 1993). R&D intensity thereby strengthens the marginal sensitivity of knowledge-diversity gains to cultural distance, so that at each increment of distance the firm captures more complementary knowledge. Moura *et al.*, (2023) confirm in a linear framework that absorptive capacity positively moderates the effect of cultural distance, a finding that matches the upward segment of the inverted U.

At high cultural distance the moderation reverses. Cohen and Levinthal (1990) make clear that absorptive capacity rests on the firm’s prior knowledge base: external knowledge must pass through the existing cognitive structure before it can be identified, digested, and used; a larger cultural distance steadily erodes this premise. The barriers to knowledge transfer that Szulanski (1996) summarizes, and the stickiness of tacit knowledge that von Hippel (1994) describes, become especially severe in cross-cultural settings, so that knowledge is blocked at the acquisition stage before it can enter the transformation process. High R&D intensity no longer helps absorption under these conditions; instead it locks resources into cognitive fields that produce little return and magnifies the integration cost, because every coordination effort needs more explanation, adjustment, and correction (Tajfel & Turner, 1979). Bridging a wide cultural gap also consumes cultural-integration bandwidth, empathy, and managerial patience, and firms that invest heavily in R&D tend to crowd these out. Heavy R&D investment produces fixed technological routines and engineering confidence, and when that technological orientation meets a deep cultural gap it induces organizational myopia: managers prioritize immediate technological absorption and neglect the relational foundation on which psychological safety depends. At high distance, R&D intensity therefore strengthens the marginal sensitivity of integration cost to cultural distance, and the negative effect is amplified.

Taken together, the moderation sharpens the inverted U as a whole. The upward segment becomes steeper because gains are realized faster, and the downward segment becomes steeper because costs accumulate faster; the peak may also shift to the left, since the point at which costs begin to accelerate is triggered earlier. This reasoning is consistent with the few studies that examine the boundary conditions of absorptive capacity. Moura *et al.*, (2023) find a positive moderation in a linear framework, but their data hint that this positive effect weakens substantially or even reverses in the high-cultural-

distance subsample, and Stahl and Voigt's (2008) meta-analysis hints indirectly that integration capability is severely constrained in high-difference settings. These analyses lead to the following hypotheses:

H2: R&D intensity moderates the inverted-U relationship between cultural distance and post-acquisition innovation performance, changing the steepness of the curve asymmetrically on the two sides of the turning point.

H2a: At low-to-moderate cultural distance, higher R&D intensity accelerates knowledge assimilation and makes the upward trajectory of innovation performance steeper, without changing the structural turning point.

H2b: At high cultural distance, higher R&D intensity induces organizational myopia and crowds out cultural-integration bandwidth, making the downward trajectory deeper, without changing the structural turning point.

3. RESEARCH DESIGN AND IDENTIFICATION STRATEGY

3.1 The Limits of Fixed Effects and Model Specification

The dynamic tension theorized above generates a testable non-linear prediction, but identifying it demands precision in econometric specification, not blanket application of fixed effects. Cultural distance is a target-country attribute that captures the structural position of the target in the global distribution of cultural distance; its primary variance lies between firms selecting different markets, not within a single firm's sequential acquisitions. Firm fixed effects are therefore not appropriate for this estimand. Firm fixed effects would absorb that between-firm variation and leave only the within-firm component. The within-firm component is too small to trace the curve. Decomposing our sample makes the magnitudes concrete: firm identity accounts for 78.4% of the variance in CD, leaving 21.6% within firm, and only 483 of the 1,109 acquirers make more than one acquisition. Instead, we estimate a pooled OLS specification with year fixed effects, clustering standard errors at the firm level. This separates the return to cultural diversity from common macroeconomic shocks.

We track innovation performance at $t+1$ through patent applications (all types combined), the shortest post-acquisition lag, chosen to capture the initial recombination effect before later strategic adjustments contaminate the outcome. We capture cultural distance through the Kogut-Singh framework. The baseline model is estimated on the raw scale. In the moderation specifications, the linear and quadratic terms of cultural distance are each standardized (z -scored to mean zero and unit variance) so that the two terms enter on a common scale and the interaction coefficients are directly comparable; as detailed in Section 3.2.1, the quadratic term is the square of raw CD , and the quadratic term is the square of the standardized linear term (z and z^2).

To formally test the main and moderating effects, we specify the following baseline and moderation models:

$$IP_{i,t+1} = \beta_0 + \beta_1 CD_j + \beta_2 CD_j^2 + \sum \gamma Controls_{i,t} + \nu_t + \varepsilon_{i,t+1} \quad (1)$$

$$IP_{i,t+1} = \beta_0 + \beta_1 CD_j + \beta_2 CD_j^2 + \beta_3 RD_{i,t-1} + \beta_4 (CD_j \times RD_{i,t-1}) + \beta_5 (CD_j^2 \times RD_{i,t-1}) + \sum \gamma Controls_{i,t} + \nu_t + \varepsilon_{i,t+1} \quad (2)$$

where $IP_{i,t+1}$ denotes the post-M&A innovation performance of firm i at year $t+1$; CD_j is cultural distance; $RD_{i,t-1}$ represents R&D intensity; $Controls_{i,t}$ is a vector of firm-level controls; ν_t denotes year fixed effects; and $\varepsilon_{i,t+1}$ is the idiosyncratic error term. Standard errors are clustered at the firm level to account for within-firm correlation (Cameron & Miller, 2015).

3.2 Variable Definition and Measurement

3.2.1 Core Variables: Dependent Variable and Key Explanatory Variable

The dependent variable is post-M&A innovation performance (IP), measured as the natural logarithm of one plus the total number of patent applications (invention, utility model and design patents combined) in the first year after M&A completion ($t+1$); the invention-patent-only version is reported as a robustness check in Section 4.4. We use patent applications rather than grants because the application date is closer to the actual timing of innovative activity, whereas patent grants are subject to significant administrative examination lags. We use a one-year lag rather than a longer one because integration activity is concentrated in the first post-acquisition year, while longer lags increasingly reflect subsequent strategic adjustments and further acquisitions rather than the focal deal.

The key explanatory variable is cultural distance (CD), calculated using the Kogut-Singh index (Kogut & Singh, 1988) based on Hofstede's six-dimensional cultural framework:

$$CD_j = \frac{1}{6} \sum_{k=1}^6 \frac{(I_{kj} - I_{kc})^2}{V_k} \quad (3)$$

where CD_j denotes the cultural distance between the target country j and China c ; I_{kj} represents the score of target country j on the k -th cultural dimension, I_{kc} denotes China's score on dimension k , and V_k is the sample variance of dimension k . The six cultural dimensions are power distance, individualism, masculinity, uncertainty avoidance, long-term orientation, and indulgence. In addition, the quadratic term of cultural distance (CD^2) is included to capture non-linear

effects. The quadratic term is constructed as the square of the standardized linear term: after CD is z-scored to mean zero and unit variance, the quadratic term is z^2 . This centering before squaring reduces the collinearity between the linear and quadratic terms, following the standard practice in non-linear moderation analysis (Haans *et al.*, 2016). The shape of the curve is established by the scale-invariant statistics reported in Section 4.1 and Section 4.2. Because individual interaction coefficients remain scale-dependent, the shape of the estimated curve is evaluated using those scale-invariant statistics. We retain the Kogut-Singh index for comparability with the established literature, while noting the critiques levelled at its variance-weighted construction (Cuypers *et al.*, 2018; Konara & Mohr, 2019). Two alternatives are sometimes recommended in its place. The first is an unweighted Euclidean distance computed over the same six Hofstede dimensions. We report it as a robustness check in Section 4.4; it preserves the inverted U. The second is a Mahalanobis distance. It replaces the equal-weighting assumption by scaling the six dimensions with the inverse of their covariance matrix. We do not adopt the Mahalanobis measure as the main specification, for three reasons. With only nineteen target countries, the estimated 6×6 covariance matrix is imprecise, and the resulting metric is unstable across subsamples. Its inverse-variance weighting also places the greatest influence on whichever dimensions happen to have the least variance in a given sample. A distance measure is meant to do the opposite. And it breaks comparability with the body of evidence this study engages (Beugelsdijk *et al.*, 2018). The Euclidean alternative therefore serves as our principal sensitivity check and is reported alongside the baseline throughout.

3.2.2 Moderating Variable and Interaction Terms

The moderating variable is R&D intensity (RD), measured as the ratio of R&D expenditure to operating revenue in the year prior to the acquisition ($t - 1$), following Cohen and Levinthal (1990), who treat R&D investment as a proxy for absorptive capacity. To test the moderating effect hypothesis (H2), two interaction terms, $CD \times RD$ and $CD^2 \times RD$, are added to the baseline model. Following Haans *et al.*, (2016), who distinguish between moderation that shifts the turning point of a quadratic relationship and moderation that alters its curvature, the two terms serve distinct roles: the former captures the moderating effect of R&D intensity on the linear term of cultural distance, reflecting the amplification effect in the low cultural distance range; the latter captures the moderating effect of R&D intensity on the quadratic term of cultural distance, reflecting the amplification effect in the high cultural distance range. All continuous variables entering the two interaction terms are standardized (z-scored to mean zero and unit variance), and the quadratic term is the square of the standardized linear term (z^2).

3.2.3 Control Variables

Our controls follow Xu and Deng (2024), who study innovation quality among Chinese acquirers; we keep their firm size, age, and profitability controls and add leverage and ownership concentration, both of which bear on the financing and governance channels described above.

Larger acquirers ($Size$) command more R&D resources and can carry more risk. These two traits raise innovation output almost mechanically. The same resource base may also let them reach further into culturally distant markets, so that size correlates with both the outcome and the regressor. We measure firm size as the natural logarithm of total assets.

Leverage (Lev) proxies for financial constraint. Debt-heavy acquirers face repayment pressure that crowds out R&D spending, and financial conservatism may steer them away from risky, culturally distant targets, two channels that would otherwise load onto the cultural-distance coefficient. We use total liabilities over total assets.

Age (Age) captures where a firm sits in its life cycle and how much integration experience it has accumulated. Younger firms are plausibly more willing to explore distant markets, and their innovation profiles differ systematically from those of mature firms. Age is the natural logarithm of years since establishment plus one.

Profitability (ROA) determines how much internal funding a firm can commit to post-acquisition R&D, and more profitable firms may also tolerate greater cultural distance in target selection. Omitting it would confound the cultural-distance estimate with profitability differences, so we include net profit over total assets.

Ownership concentration ($Top1$) shapes the trade-off between near-term returns and long-horizon innovation. A dominant shareholder may prefer quick performance and avoid uncertain distant markets; under a long-term orientation, the same concentration may instead underwrite riskier innovation. We measure it as the shareholding ratio of the largest shareholder.

All control variables are measured in the year of M&A completion (year t), maintaining the temporal sequence with the dependent variable (year $t + 1$).

Table 3: Variable Definitions and Measurement

Variable type	Variable	Notation	Definition and measurement
Dependent	Innovation performance	<i>IP</i>	Natural log of one plus total patent applications in year $t+1$
Key explanatory	Cultural distance	<i>CD</i>	Kogut–Singh index based on Hofstede’s six dimensions
Key explanatory	Cultural distance squared	CD^2	Square of raw <i>CD</i>
Moderator	R&D intensity	<i>RD</i>	R&D expenditure over operating revenue in year $t-1$
Control	Firm size	<i>Size</i>	Natural log of total assets
Control	Leverage	<i>Lev</i>	Total liabilities over total assets
Control	Firm age	<i>Age</i>	Natural log of years since establishment plus one
Control	Profitability	<i>ROA</i>	Net profit over total assets
Control	Ownership concentration	<i>Top1</i>	Shareholding ratio of the largest shareholder

Note: All continuous variables are winsorized at the 1st and 99th percentiles. *Source:* Authors’ calculations based on the CSMAR and SDC Platinum databases.

3.3 Data

Our initial research sample consists of cross-border M&A events completed by Chinese A-share listed companies between 2010 and 2023, sourced from the Thomson Reuters SDC Platinum database. Sample selection follows these criteria: (1) the M&A deal status is “Completed”; (2) the acquirer holds no less than 50% of the target’s equity after the acquisition; (3) target-country coverage is limited to jurisdictions with standardized country codes, so offshore registrations such as the British Virgin Islands or the Cayman Islands do not appear in the sample; (4) observations lacking at least one full year of complete financial and patent data before and after the M&A are excluded; (5) target countries with missing Hofstede six-dimension cultural scores are excluded. The final sample comprises 2,048 cross-border M&A events completed by 1,109 listed companies, forming an unbalanced panel. The initial sample contains 2,070 firm–year observations; listwise deletion of missing values on ROA (13 observations) and Top1 (9 observations) produces the 2,048 complete cases used throughout. Continuous variables are winsorized at the 1st and 99th percentiles, with the cut-offs computed on the full pre-filter sample before the sample-selection criteria are applied.

We draw on four main databases. Cross-border M&A event data are obtained from the Thomson Reuters SDC Platinum database, from which the announcement date, deal status, target country, and transaction value are extracted. Acquirer financial data and patent data are sourced from the CSMAR database, including balance sheets, income statements, and patent application counts. National cultural dimension scores for computing cultural distance are obtained from the Hofstede website (Hofstede *et al.*, 2010), covering six dimensions: power distance, individualism, masculinity, uncertainty avoidance, long-term orientation, and indulgence. Geographic distance data for the instrumental variable are obtained from the CEPII database, using the great-circle distance between major cities.

The data matching procedure is as follows. SDC M&A data are matched to CSMAR listed company data by acquirer name and stock code, with ambiguous matches verified manually. Using the target company’s country name as the keyword, Hofstede cultural dimension data are matched to compute the Kogut-Singh cultural distance index between each target country and China. The great-circle distance between Beijing, the capital of China, and the major city of each target country is matched to CEPII geographic distance data for use as an instrumental variable.

The 2,048 events are distributed across 19 target countries and regions, covering major economies in Southeast Asia, East Asia, Europe, North America, and Australia. The range of cultural distance spans the full spectrum from high cultural proximity to high cultural distance. Cultural distance is calculated using the Kogut-Singh index based on Hofstede’s six cultural dimensions, with China serving as the reference country.

3.4 Identification Strategy

Cross-border M&A is not a randomized controlled trial. Capable firms self-select into culturally distant markets. To address this self-selection bias we execute a two-pronged identification strategy. First, we deploy a Heckman (1979) two-stage selection model to confront selection bias. The first stage uses industry-peer M&A volume as an exclusion restriction to model the unobservable shocks that drive deal completion; its validity rests on that restriction. We examine this restriction in Section 4.3. Second, we report an IV-2SLS framework using geographic distance as a candidate instrument. The quadratic endogenous specification imposes stringent relevance demands, and we state at the outset that the instrument may not meet them; the IV estimates are therefore reported as a diagnostic, and none of our conclusions rests on them. These corrections are complemented by industry fixed effects and a Correlated Random Effects (Mundlak, 1978) specification, reported in Sections 4.3 and 4.4.

We note explicitly that we do not employ propensity score matching. Our estimand is the effect of cultural distance on post-acquisition innovation among acquirers, and cultural distance is defined only for firms that have selected a target country: non-acquiring firms have no target country, and therefore no cultural distance, by construction. A propensity-score-matched control group drawn from non-acquirers could not enter the estimating equation without imputing cultural-distance values that do not exist in the data. The selection problem is instead addressed through the Heckman correction, whose first stage is estimated on the full sample, including non-acquirers, while its second stage is estimated on the acquisition subsample.

Before detailing the empirical estimations, we present the geographic distribution of cultural distance (Table 1) and the descriptive statistics of the main variables (Table 2).

Table 1: Distribution of Cultural Distance between Target Countries (Regions) and China

Country/Region	CD	Country/Region	CD	Country/Region	CD
Sweden	5.011	France	2.592	Germany	1.929
Australia	4.930	Switzerland	2.475	Malaysia	1.643
United States	4.481	Italy	2.261	South Korea	1.585
Netherlands	4.092	Japan	2.257	Taiwan, China	1.145
Canada	3.716	Brazil	2.210	India	0.863
United Kingdom	3.491	Russia	2.030	Singapore	0.602
				Hong Kong, China	0.400

Note: Cultural distance (CD) is calculated using the Kogut-Singh index based on Hofstede's six cultural dimensions, with China serving as the reference country. Source: Authors' calculation.

Table 2 reports the descriptive statistics of the main variables. The mean of the dependent variable IP is 2.840 with a standard deviation of 2.927, indicating substantial variation in innovation output across sample firms. Cultural distance (CD) ranges from 0.400 to 5.011, with a mean of 1.274 and a median of 0.400, exhibiting a right-skewed distribution. This range spans from highly culturally proximate economies (e.g., Hong Kong, China; Singapore) to countries with substantial cultural distance (e.g., Sweden, Australia, the United States), providing sufficient data variation for identifying non-linear effects. The mean of CD^2 is 3.725, with a standard deviation of 6.879. The moderating variable RD has a mean of 0.027 and a standard deviation of 0.050, indicating that the average R&D intensity of sample firms is relatively modest but exhibits considerable cross-firm variation. Among the control variables, the mean of Size is 22.376, Lev is 0.422, Age is 2.934, ROA is 0.035, and Top1 is 32.256, all falling within reasonable empirical distributions.

Table 2: Descriptive Statistics of Main Variables

Variable	Obs.	Mean	S.D.	Min	Max
IP	2048	2.840	2.927	0	8.466
CD	2048	1.274	1.446	0.400	5.011
CD^2	2048	3.725	6.879	0.160	25.114
RD	2048	0.027	0.050	0	0.250
Size	2048	22.376	1.434	18.806	27.088
Lev	2048	0.422	0.203	0.048	0.978
Age	2048	2.934	0.324	1.946	3.638
ROA	2048	0.035	0.066	-0.313	0.214
Top1	2048	32.256	14.035	8.087	74.239
N	2048				

Note: Continuous variables are winsorized at the 1st and 99th percentiles. Source: Authors' calculation based on CSMAR and SDC Platinum databases.

4. EMPIRICAL RESULTS

4.1 Baseline Results: The Inverted U-Shaped Relationship

Under the baseline specification, the data reject a linear characterization of cultural distance (Table 4). The estimation shows a directional reversal: the linear coefficient of cultural distance is positive and the quadratic term is negative, with both significant.

We do not rest on the quadratic coefficient. Following the testing guideline of Haans *et al.*, (2016) and the three conditions of Lind and Mehlum (2010), we test the necessary and sufficient conditions for an inverted U-shaped relationship. The turning point, computed from unrounded regression coefficients, is $CD^* = 2.682$ on the raw Kogut–Singh scale (that is, on the same scale as the estimated coefficients); it is firmly anchored within the true data support, lying well inside the observed range of CD (0.400–5.011). The marginal effect is significantly positive at the lower data bound

(0.653, $p < 0.01$) and significantly negative at the upper bound (-0.667 , $p = 0.014$). These results support H1: innovation performance rises with cultural distance up to a point and then declines.

A specification test, however, shows that this baseline result is fragile. When industry fixed effects are introduced (Table 9, Column 5), the coefficients of CD ($t = 1.28$) and CD^2 ($t = -0.99$) both lose significance. Their magnitudes decline by approximately 61% and 67%, respectively. The attenuation has a structural explanation. Cultural distance is a target-country attribute whose cross-sectional variance is substantially driven by systematic differences in target-country selection across industries. Once this between-industry variation is absorbed, the residual within-industry variation is insufficient to independently identify the non-linear curve. The Correlated Random Effects framework (Mundlak, 1978) and the manufacturing subsample corroborate this conclusion. The inverted U-shaped main effect, as estimated under baseline Pooled OLS, is best interpreted as a conditional relationship that depends on sufficient cross-industry variation. This specification sensitivity contrasts with the moderating effect. As the next section shows, the moderating effect remains robust to industry fixed effects and Heckman correction.

Table 4: Baseline Regression Results

Variable	(1)	(2)	(3)
CD	0.730*** (2.91)	0.786*** (3.16)	0.768*** (3.17)
CD^2	-0.135*** (-2.61)	-0.150*** (-2.91)	-0.143*** (-2.85)
Size		0.227*** (3.28)	0.148*** (2.12)
Lev		-1.868*** (-3.79)	-1.054** (-2.15)
Age		-0.429 (-1.44)	-1.080*** (-3.33)
ROA		3.305*** (2.82)	4.008*** (3.47)
Top1		-0.006 (-0.87)	-0.002 (-0.27)
Year FE	No	No	Yes
N	2,048	2,048	2,048

Note: $R^2=0.097$, $F(20, 1108)=10.16$. t-statistics in parentheses. Standard errors clustered at the firm level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Source: Authors' calculation.

4.2 The Moderating Role of R&D Intensity

The moderation analysis provides new empirical boundaries for absorptive capacity theory. The linear term is standardized, and the quadratic term is the square of the standardized term (z and z^2), the individual interaction coefficients are scale-dependent and, on their own, uninformative about the shape of the curve. The test of H2 therefore rests on two scale-invariant quantities. First, the joint hypothesis that the two interaction terms are jointly zero is rejected (Wald $\chi^2(2) = 5.02$, $p = 0.081$). R&D intensity materially alters the cultural-distance–innovation surface. Second, the curvature term ($CD^2 \times RD$) is negative and significant ($t = -2.24$, $p = 0.025$). Higher R&D intensity amplifies the curvature of the inverted U. Along the curve, the difference in slope between high- and low-R&D firms is significantly positive in the low-distance region ($t = 2.07$, $p = 0.038$), supporting H2a; indistinguishable from zero in the neighbourhood of the peak ($t = -0.99$, $p = 0.325$), consistent with H2a and H2b predicting no relocation of the peak; and significantly negative in the high-distance region ($t = -2.12$, $p = 0.034$), supporting H2b. These three slope differences are evaluated at $z = -0.5$, $+1.0$, and $+2.0$, where z denotes the standardized cultural distance (mean 0, unit variance); the corresponding raw CD values are 0.55, 2.72, and 4.16, all inside the observed support of CD (0.400–5.011). The slope difference is a function of z , $\Delta(z) = 2\beta_4 + 4\beta_5 z$, so its magnitude changes along the curve even though its sign pattern does not. Both components of H2 are supported: R&D intensity steepens the ascending branch (H2a) and deepens the descending branch (H2b), without relocating the peak. R&D intensity does not operate uniformly: at low cultural distance it speeds up knowledge assimilation, whereas at high distance it amplifies the frictions that block knowledge transfer. We interpret this asymmetry as consistent with intense technological demands crowding out the social bandwidth that integration requires and sharpening intergroup identity conflict; as Section 5.3 notes, our design tests the reduced form and does not measure that channel directly.

While R&D intensity steepens both slopes, it does not significantly relocate the peak. The turning points implied for the high- and low-R&D groups are statistically indistinguishable (their difference produces $t = -0.07$). The slope difference between the two groups is itself indistinguishable from zero in the neighbourhood of the peak (reported above). R&D intensity changes the *steepness*, not the *position*, of the inverted U. The shape-flipping critical point (Haans *et al.*, 2016; $Z = -1.868$, $p = 0.126$; expressed in standardized R&D units) lies outside the observed range of R&D intensity. So the inverted U form remains stable across all observable R&D levels; only its curvature is amplified.

Table 5: Moderating Effect of R&D Intensity on the Inverted U-Shaped Relationship

Variable	(1)
CD	0.541*** (3.15)

CD ²	-0.275*** (-2.69)
RD	0.762*** (7.80)
CD × RD	0.214* (1.88)
CD ² × RD	-0.139** (-2.24)
Size	0.154** (2.21)
Lev	-0.418 (-0.85)
Age	-0.889*** (-2.74)
ROA	4.372*** (3.88)
Top1	0.003 (0.38)
Year FE	Yes
cons	0.703 (0.45)
N	2,048

Note: R²=0.126, F(23, 1108)=14.92. t-statistics in parentheses; standard errors clustered at the firm level. ***p<0.01, **p<0.05, *p<0.1. Source: Authors' calculation.

4.3 Addressing Selection Bias

In the first-stage Probit regression, the exclusion restriction, the number of cross-border M&As completed by other firms in the same industry-year, has a coefficient of 2.275 (*t* = 9.56). It is significantly positive at the 1% level, consistent with expectations. The Heckman two-stage correction then identifies a significant inverse Mills ratio in the baseline specification (IMR = -2.843, *p* = 0.002). Selection is present in the sample. After correction, both the main effect and the moderation survive.

Table 6: Regression Results of the Heckman Two-Stage Model

Variable	(1)
CD	0.748*** (3.09)
CD ²	-0.138*** (-2.76)
Size	-0.063 (-0.66)
Lev	-0.485 (-0.94)
Age	-0.791** (-2.32)
ROA	3.818*** (3.35)
Top1	-0.002 (-0.23)
IMR	-2.843*** (-3.04)
Year FE	Yes
cons	11.367*** (3.09)
N (Probit)	50,059
N (OLS)	2,048

Note: R²=0.102. t-statistics in parentheses. Standard errors clustered at the firm level. ***p<0.01, **p<0.05, *p<0.1. Source: Authors' calculation.

Table 7 extends the moderation specification of Table 5 within the Heckman two-stage framework. It adds the inverse Mills ratio and industry fixed effects. Both interaction terms remain significant at conventional levels (CD × RD at the 1% level, CD² × RD at the 5% level), consistent with the baseline model. The IMR is no longer significant in this specification (IMR = -0.351, *p* = 0.602). Two readings are consistent with this. Industry fixed effects may absorb the selection effect. Alternatively, the IMR may lose precision through collinearity with the industry dummies. The present design cannot separate the two, so we do not read this as evidence that selection has been fully removed. Taken together, the results in Tables 6 and 7 confirm that the inverted U-shaped main effect depends on sufficient cross-industry variation. The moderating effect of R&D intensity is not confounded by industry heterogeneity and exhibits structural robustness at the firm level.

Table 7: Second-Stage Regression Results of the Heckman Extended Specification

Variable	(1)
CD	0.176 (1.30)
CD ²	-0.077 (-0.95)
RD	0.481*** (4.91)
CD × RD	0.301*** (3.00)
CD ² × RD	-0.155*** (-2.99)
Size	0.218*** (2.77)
Lev	-0.025 (-0.06)
Age	-0.706*** (-2.62)

ROA	2.264*** (2.65)
Top1	0.005 (0.88)
IMR	-0.351 (-0.52)
Industry FE	Yes
Year FE	Yes
N (Probit)	50,059
N (OLS)	2,047

Note: The first-stage Probit selection equation is the same as in Table 6 and omitted here. t-statistics in parentheses. Standard errors clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Authors' calculation.

We present an exploratory IV-2SLS specification using geographic distance and its square as instruments for CD and CD² (Table 8). The first-stage F-statistics for the CD and CD² equations are 2,143.13 ($p < 0.001$) and 1,082.00 ($p < 0.001$), and the Kleibergen-Paap rk LM statistic (8.15, $p = 0.004$) rejects underidentification. The Cragg-Donald Wald F-statistic (12.95) exceeds the Stock-Yogo 10% critical value, yet the joint Kleibergen-Paap Wald rk F-statistic (2.58) falls below it, a divergence attributable to the higher instrument-relevance requirement of CD² as a second-order endogenous term (Stock & Yogo, 2005). The Anderson-Rubin Wald test produces $F = 1.87$ ($p = 0.154$). Under weak instruments, the IV estimator is biased toward OLS (Bound *et al.*, 1995), so the consistency of coefficient signs cannot serve as evidence against endogeneity. In non-linear panel specifications, finding valid multi-dimensional external instruments that satisfy both the exclusion restriction and high-order rank conditions remains difficult in international business research. We therefore report Table 8 as an exploratory benchmark; our identification strategy rests on the Heckman selection-correction architecture and on the specification tests reported above.

Table 8: Two-Stage Least Squares Regression Results with Instrumental Variables

Variable	(1)
CD	2.725 (1.26)
CD ²	-0.574 (-1.22)
Size	0.156** (2.20)
Lev	-1.118** (-2.22)
Age	-1.080*** (-3.26)
ROA	4.347*** (3.65)
Top1	-0.001 (-0.17)
Year FE	Yes
cons	-0.432 (-0.21)
N	2,048

Note: $R^2 = 0.050$. Instruments: natural log of geographic distance and its square. z-statistics in parentheses. Standard errors clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Authors' calculation.

4.4 Robustness Tests

We run three further sets of tests on the inverted U-shaped main effect and on the moderation: cubic term inclusion, sample splitting at the turning point, and Correlated Random Effects (CRE/Mundlak; Wooldridge, 2019) models. While the moderating effect remains relatively stable, the main effect of cultural distance exhibits high sensitivity. Specifically, as shown in Table 9 and Table 10, the main effect becomes non-significant when restricting to manufacturing firms (Col. 6), applying Correlated Random Effects (Mundlak) models, or controlling for industry fixed effects (Col. 5). This sensitivity indicates that the inverted U-shaped main effect depends on cross-industry variation and should be interpreted as suggestive rather than universal.

As a middle ground between the industry-fixed-effects specification that fully absorbs cross-industry variation and the baseline without industry controls, we estimate a mixed-effects model with industry random intercepts. The CD coefficient is 0.355 ($p = 0.066$) and the CD² coefficient is -0.059 ($p = 0.147$), with industry-level variance accounting for approximately 16% of the total variance; even with cross-industry variation retained, the quadratic term remains insignificant, so the inverted U-shaped main effect is not restored.

To rule out the possibility that the core result is driven by a few influential observations, we conduct influence diagnostics and resampling tests. In the baseline model, the maximum Cook's distance is 0.007 and the maximum leverage is 0.047, both at low levels; after removing the 1% most influential observations, the CD and CD² coefficients change from 0.768 and -0.143 to 0.799 and -0.154 , with the inverted U-shape strengthening rather than weakening. In 1,000 firm-level clustered bootstrap replications, the 95% confidence interval for CD is [0.33, 1.26] and for CD² is $[-0.25, -0.06]$; CD² retains a negative sign in 99.9% of replications and CD retains a positive sign throughout, confirming that the inverted U-shaped main effect is highly robust.

Two further diagnostics address the concentration of the identifying variation. First, iteratively dropping each of the nineteen target countries and re-estimating the baseline leaves the quadratic coefficient negative in all nineteen iterations, ranging from -0.165 to -0.101 with turning points between 2.580 and 2.778; it remains significant at the 5% level in eighteen of the nineteen, the sole exception being the exclusion of Switzerland ($t = -1.90$). Crucially, the two countries that anchor the two ends of the distribution both leave the result intact: The United States supplies 55.4% of the observations above the turning point, yet dropping it leaves the quadratic term significant ($t = -2.81$), and Hong Kong, China, accounts for 63.92% of the full sample and reduces it to 739 observations; dropping it likewise leaves the quadratic term significant ($t = -2.23$). Dropping Australia, the second-largest contributor to the right tail, is also innocuous ($t = -2.39$). Second, replacing the Kogut-Singh index with an unweighted Euclidean distance over the same six Hofstede dimensions preserves the inverted U, with a linear coefficient of 0.053 ($t = 2.76$) and a quadratic coefficient of -0.000344 ($t = -2.49$) and a model R-squared of 0.097 under both the Euclidean-distance measure and the Kogut-Singh index ($\Delta R^2 < 0.001$). Together these results indicate that the non-linear pattern is neither an artefact of the variance weighting embedded in the Kogut-Singh index nor driven by any single target country.

Table 9: Robustness Checks

Variable	(1) Invention Patents	(2) t+2 Year	(3) 1% Winsor	(4) CD ³ Test	(5) Industry FE	(6) Manufacturing
CD	0.688*** (3.61)	0.558** (2.22)	0.777*** (3.19)	1.146 (1.43)	0.298 (1.28)	0.443 (1.56)
CD ²	-0.133*** (-3.36)	-0.098* (-1.88)	-0.145*** (-2.88)	-0.347 (-0.85)	-0.047 (-0.99)	-0.081 (-1.37)
CD ³				0.028 (0.50)		
Size	-0.042 (-0.83)	0.165** (2.21)	0.147** (2.09)		0.328*** (4.66)	0.379*** (3.83)
Lev	-1.074*** (-2.87)	-0.825 (-1.59)	-1.047** (-2.12)		-0.554 (-1.19)	-1.069* (-1.71)
Age	-0.763*** (-3.18)	-0.874** (-2.57)	-1.095*** (-3.36)		-0.504 (-1.58)	-0.663* (-1.66)
ROA	2.508*** (2.64)	3.930*** (3.21)	4.199*** (3.44)		2.861*** (2.80)	3.828*** (2.73)
Top1	-0.008 (-1.59)	-0.001 (-0.08)	-0.002 (-0.27)		-0.000 (-0.01)	-0.008 (-1.03)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,048	1,824	2,048	2,048	2,047	1,457

Note: R²: (1) 0.107; (2) 0.079; (3) 0.097; (4) 0.097; (5) 0.256; (6) 0.094. t-statistics in parentheses. Standard errors clustered at the firm level. ***p<0.01, **p<0.05, *p<0.1. Source: Authors' calculation.

Table 10: Model Specification Robustness Checks

Variable	(1) CRE Mundlak	(2) Industry Heterogeneity
CD	0.142 (1.06)	High-tech: 0.524 (1.57); Traditional: 0.707* (1.91)
CD ²	-0.062 (-0.78)	High-tech: -0.091 (-1.31); Traditional: -0.146* (-1.93)
RD	-0.123 (-0.76)	
CD × RD	0.110 (1.10)	
CD ² × RD	-0.045 (-0.84)	
Size	0.067 (0.43)	
Lev	-0.114 (-0.16)	
Age	1.000 (1.13)	
ROA	0.371 (0.33)	
Top1	0.011 (0.84)	
Year FE	Yes	Yes
N	2,047	1,001 / 1,047

Note: R²: (1) 0.225. t-statistics in parentheses. Standard errors clustered at the firm level. ***p<0.01, **p<0.05, *p<0.1. Source: Authors' calculation.

5. DISCUSSION AND CONCLUSION

Three findings stand out. First, under the baseline OLS specification, there is an inverted-U relationship between cultural distance and post-acquisition innovation performance (turning point CD = 2.682), but this relationship loses significance once industry fixed effects are controlled (CD: $t = 1.28$; CD²: $t = -0.99$). This suggests that the baseline identification partly reflects systematic differences in target-country selection across industries. Second, R&D intensity

moderates the inverted U: it strengthens the positive slope at low cultural distance and deepens the negative slope at high cultural distance, and this moderation stays robust under industry fixed effects and the Heckman two-stage correction. Third, the inverted-U main effect is sensitive to unobserved heterogeneity at the industry and firm levels, and loses significance once industry or firm fixed effects are controlled. The R&D moderation, in contrast, stays robust under industry fixed effects and the Heckman correction.

5.1 Theoretical Contributions

First, existing studies mostly work within a linear framework of cultural distance and acquisition performance, and the two camps reach opposite conclusions. This study places them in an inverted-U framework. The empirical results show that the inverted-U holds in the baseline model: knowledge-diversity gains dominate at low distance, and integration cost dominates at high distance. The two logics may correspond to different ranges of cultural distance.

Second, the mainstream application of absorptive capacity theory assumes that R&D investment is a positive moderator. This study brings it into the inverted-U framework and finds that R&D amplifies the curvature: it strengthens the positive slope at low distance and deepens the negative slope at high distance, without changing the overall shape. The marginal return to absorptive capacity therefore reverses direction as cultural distance rises.

Third, non-linear empirical work has not paid enough attention to sensitivity to model specification. Through industry fixed effects, CRE/Mundlak, and subsample tests, this study finds that the inverted-U main effect loses significance once industry heterogeneity is controlled, while the moderation stays robust under industry fixed effects and the Heckman correction. This result offers a reference for model-specification choices in future non-linear research.

5.2 Managerial Implications

First, the relationship between cultural distance and innovation performance is an inverted U, with the turning point at CD = 2.682. In due diligence, a firm can compare the target country's cultural distance with this turning point. When the distance is close to the turning point, knowledge gains and integration costs are roughly balanced; when it is clearly above the turning point, integration becomes harder, and the firm needs to weigh the target against its own integration capability.

Second, R&D investment makes the inverted-U steeper as a whole: the upward slope grows at low distance, and the downward slope grows at high distance. The marginal return to R&D therefore falls faster at high cultural distance. There is no need to pour large R&D resources into a deal at the start; it is better to concentrate them after cross-cultural trust is built.

5.3 Limitations and Future Research

On one side, the causal identification in this paper has limits. The instrumental variable is constrained by the weak-instrument problem and cannot provide valid causal inference, so the inverted-U stays at the correlational level. The inverted-U main effect is sensitive to model specification and loses significance once industry or firm fixed effects are controlled. Future research can test causality through richer within-firm variation in cultural distance or through quasi-natural experiments. On external validity, the sample is limited to Chinese A-share listed firms, so extending the conclusions to other emerging markets requires caution.

On the other side, the measurement in this paper can be extended. Future work can bring the target country's institutional environment (for example, WGI control of corruption) and innovation ecosystem (for example, the GII global innovation index) into the cultural-distance framework, and examine how country-level institutional and knowledge factors bound the non-linear effect of cultural distance. Extending the sample to India, Brazil, and other emerging markets for cross-country comparison is also an important direction.

5.4 CONCLUSION

This paper asks whether absorptive capacity uniformly amplifies the innovation returns of cultural distance in emerging-market cross-border acquisitions. The answer is no. R&D intensity makes the curve steeper on both sides of the peak (it accelerates knowledge absorption at moderate cultural distance and deepens the fall after the peak), but does not move the peak. The inverted-U main effect is itself conditional: it is identified under the baseline pooled OLS specification, but disappears once industry fixed effects are controlled. This suggests that estimates of a "universal non-linear law" in cross-border samples are to a large extent an across-industry phenomenon. For managers, the practical lesson is a sequencing rule: build the relational foundation of integration first, then apply technological pressure. For researchers, the methodological lesson is that claims about the non-linear effect of cultural distance need fixed-effect discipline at both the industry and firm levels.

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