

Article

The Adoption of Smart Retail and Business Performance: A New Mechanism Analysis

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Abstract

Smart retail adoption (SRA) is widely seen as a way to improve operations. But how it affects business performance (BP) is still unclear. This study builds a framework using information theory and the Technology–Organization–Environment (TOE) framework. We use data from 220 Chinese retail firms (2012–2023). Our analysis shows that SRA significantly improves BP. It does so by first reducing incomplete information (measured by analyst forecast dispersion, AFD) and then lowering uncertainty (UNC). These two factors work in sequence. Technological conditions (TECH), organizational conditions (ORG), and environmental conditions (ENV) all strengthen this effect. SRA also has strong long-term benefits. The effect is greater in non-state-owned firms, large firms, firms in central China, and those that rely mainly on offline channels. This study explains how SRA boosts BP and offers practical insights for retail transformation.

Keywords: smart retail adoption; business performance; incomplete information; uncertainty; double machine learning

1. Introduction

In the digital economy, smart retail adoption (SRA) is changing how the global retail sector operates. SRA integrates technologies such as artificial intelligence (AI) and the Internet of Things (IoT) [1]. Beyond improving efficiency, SRA also supports corporate sustainability. It helps optimize resources and reduce waste through precision marketing and intelligent logistics [2]. However, the link between digital investment and business performance (BP) is still debated [3]. Many firms face high costs and internal friction when adopting smart systems, which leads to mixed performance results [4]. Therefore, it is important to examine the specific pathways through which SRA improves BP [5].

Prior research has used the Technology–Organization–Environment (TOE) framework [6] to identify drivers of innovation adoption [7]. However, few studies explain the internal mechanisms of value creation. Many studies treat digitalization as a direct driver of BP and overlook changes in a firm's information environment and dynamic capabilities [8]. Recent research shows that in-store technologies can improve customer and employee efficiency [9]. But the role of incomplete information (measured by analyst forecast dispersion, AFD) and uncertainty (UNC) remains underexplored. Drawing on information theory and the dynamic capabilities view [10], this study argues that SRA acts as a knowledge-enhancing



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system. By reducing incomplete information, SRA lowers the “noise” in managerial decisions. This, in turn, reduces uncertainty and supports stable growth in BP [11].

To fill these gaps, we use panel data from 220 Chinese A-share listed retail firms spanning from 2012 to 2023. Following recent econometric advances in retail performance analysis [12], we adopt a robust causal identification strategy that combines two-way fixed effects models with double machine learning (DML). This study addresses three questions: (1) Does SRA improve BP over the long term? (2) What sequential mechanisms—from better information to lower uncertainty—explain this effect? (3) How do technological conditions, organizational readiness, and environmental support moderate this relationship? By identifying this sequential pathway, we offer a clear understanding of how smart transformation drives sustainable firm value.

This research makes three contributions. First, we identify a sequential mediation path—SRA $\rightarrow$ AFD $\rightarrow$ UNC $\rightarrow$ BP—that has not been empirically tested before. This reveals how digital transformation translates into performance through an information-to-uncertainty chain. Second, we extend the TOE framework from an adoption model to a value-realization model, showing that technological conditions (TECH), organizational conditions (ORG), and environmental conditions (ENV) moderate the SRA–BP relationship. Third, we apply double machine learning (DML) to estimate heterogeneous treatment effects, uncovering that 24% of firms experience performance decline after SRA—a finding masked by average-effect estimates.

The remainder of this paper is organized as follows. Section 2 reviews the related literature and identifies the research gaps. Section 3 describes the research design, including data sources, sample selection, variable measurement, and econometric strategies. Section 4 develops the theoretical framework and presents the research hypotheses. Section 5 reports the empirical results, including baseline regressions, robustness checks, endogeneity tests, mediation analyses, moderation effects, and dynamic effects. Section 6 presents double machine learning estimates of conditional treatment effects, including heterogeneity analyses by firm size, ownership, region, and distribution channel. Section 7 discusses the findings, draws conclusions, outlines theoretical and managerial implications, and identifies limitations and future research directions.

2. Literature Review

2.1. Conceptualization of Smart Retail

Smart retail represents an advanced stage in retail evolution. It integrates AI, big data, cloud computing, and IoT into daily operations. Unlike traditional digitalization, SRA focuses on real-time responses, intelligent decisions, and adaptive optimization across the value chain [13].

Recent studies define smart retail as the strategic application of technologies to enhance both customer experience and operational efficiency. A growing body of literature in the *Journal of Retailing* highlights the increasing use of in-store technologies to enhance customer engagement and employee productivity, thereby reshaping retail service delivery [14,15]. In parallel, emerging research conceptualizes smart retail as a system that enables firms to transform fragmented data into actionable insights, thereby improving operational coordination and decision efficiency [16].

Based on these views, this study defines SRA as the integration of two types of intelligent systems: general-purpose and task-specific. General-purpose systems support high-level decisions like demand forecasting and consumer behavior analysis. Task-specific systems are embedded in daily operations to enable automation and real-time optimization [17]. Through this dual structure, SRA helps firms process information, coordinate resources, and respond to market changes more effectively [18].

2.2. Technology Adoption in Retail: TOE and Capability Perspectives

Researchers often analyze smart retail adoption using the TOE framework. This framework argues that three factors shape technology adoption: technological readiness, organizational capabilities, and external environment [19]. The TOE perspective fits SRA well because SRA involves complex, multi-layer intelligent systems [20].

Two other theories add further insights. The Resource-Based View (RBV) emphasizes that a firm's internal resources—such as digital infrastructure and data analytics skills—enable successful technology integration [21,22]. Dynamic Capabilities Theory (DCV) focuses on a firm's ability to adapt and reconfigure resources in response to technological change, which helps sustain competitive advantage [23]. Recent evidence suggests that SRA acts as a dynamic capability by facilitating “knowledge flows” that allow firms to adjust to market shifts [24]. Therefore, SRA is not just a technical tool but a strategic asset that needs organizational readiness to improve BP [25].

2.3. Smart Retail Adoption and Business Performance

The literature on SRA and BP shows mixed findings. These inconsistencies reflect deeper disagreements about how digital technologies create value at the firm level [26].

One group of studies views SRA as a direct efficiency tool. From this view, smart technologies reduce operational friction, improve decision accuracy, and enhance coordination, leading to immediate performance gains [27]. This perspective treats digital technologies as inputs that directly produce economic outputs [28].

A second group argues that performance depends on internal adjustment processes. Digital technologies do not automatically create value. Instead, organizational adaptation, learning, and resource reconfiguration determine the outcome [29,30]. As a result, SRA may have delayed, non-linear, or even negative short-term effects, especially when firms face high integration costs or skill gaps [31].

A third group highlights risks and complexity. Advanced digital systems can create new uncertainties. They reshape business models, change information flows, and increase coordination complexity across channels and units. These changes may cause temporary instability that offsets expected gains [32,33].

These conflicting views suggest that we cannot understand SRA's impact by only looking at direct effects. The mixed results point to a missing link: a clear transmission mechanism from digital inputs to performance outcomes. While prior studies acknowledge the importance of data and information in retail, they rarely explain how changes in a firm's information environment translate into measurable performance [34,35].

2.4. Smart Retail Adoption, Incomplete Information, and Uncertainty

Researchers increasingly use Information Processing Theory (IPT) to link SRA and BP. IPT states that a firm's success depends on matching its information processing capacity with environmental demands [36]. In volatile retail markets, incomplete information, such as fragmented data and delayed signals, slows down efficiency [37].

Many studies show that information sharing improves performance outcomes, including team effectiveness, operational efficiency [38], innovation [39], and sustainable performance [40]. These effects often work through mediators like knowledge integration, collaboration, and organizational agility [41].

Recent empirical work confirms that SRA acts as a high-capacity information system that reduces incomplete information (measured by analyst forecast dispersion, AFD) [42–44]. Using AI-driven analytics [45], firms can filter out “noise” and make analyst expectations more precise [46]. This reduction in AFD then lowers managerial uncertainty (UNC) [47]. Zamil (2025) finds that AFD improves decision quality by turning

scattered data into actionable insights, which reduces uncertainty in demand forecasting and inventory management [48].

Despite these advances, a key gap remains regarding the sequential mediation pathway [49]. The management literature recognizes an “Information → Uncertainty → Performance” logic [50], but few retail studies have tested this chain with large-scale panel data. Current research is split: some studies focus on the technology–information link [51], others on the information–performance link [52]. By combining these pieces, this study offers a more complete empirical framework to explain how SRA reshapes the information foundation of BP.

2.5. Sustainability Implications of Smart Retail Adoption

SRA is increasingly linked to environmental and social performance. Salhab et al. (2025) show that smart technologies reduce waste, optimize energy use in warehouses, and lower logistics carbon footprints [53]. In addition, digital marketing powered by SRA promotes sustainable consumption by reducing reliance on physical resources [54]. Including sustainability in the SRA–BP relationship is essential for a full understanding of firm value today.

2.6. Research Gaps

Beyond these gaps, we argue that even when studies include both information and uncertainty, they typically treat them as parallel mediators rather than a sequential chain. However, from an information processing perspective, reducing information imperfection (AFD) is a necessary condition for reducing uncertainty (UNC). Managers cannot resolve Knightian uncertainty without first having clear, consistent information. Therefore, a sequential model ($SRA \rightarrow AFD \rightarrow UNC \rightarrow BP$) is theoretically superior to parallel or reverse-order models. This study provides the first large-scale empirical test of this sequential logic in the retail context.

3. Research Design

To empirically test the sequential mediation mechanism and the hypotheses developed in the next section, this chapter describes the research design. It covers data sources, sample selection, variable measurement, and econometric strategies. The goal is to ensure that the subsequent empirical analysis is transparent, replicable, and robust to endogeneity concerns.

3.1. Data Selection

We obtain data from the China Stock Market and Accounting Research (CSMAR) database and the WIND database, covering 2012 to 2023. We exclude firms with severe missing data. We also remove firms designated as ST, *ST, or PT due to abnormal financial conditions. Some firms on the SME Board and ChiNext Board grow rapidly after listing, with employee size or revenue exceeding the SME range; we exclude them for sample consistency. All continuous variables are winsorized at the 1st and 99th percentiles to reduce outlier influence.

The final sample includes 220 firms, yielding 2640 firm-year observations. Annual report data for constructing SRA are collected from the CNINFO website.

3.2. Variable Selection

3.2.1. Dependent Variable: BP

We measure business performance (BP) as a multidimensional construct following Liu et al. [55]. BP includes three dimensions: profitability (ROA, ROS), operational capability

(inventory turnover, current asset turnover), and growth potential (total asset growth rate, revenue growth rate). Table 1 lists all indicators.

Table 1. Business performance indicators.

Construct	Dimension	Variable	Measure	Definition
BP	Profitability	ROA	Return on assets	Profit before tax/average total assets
		ROS	Return on sales	Net profit/operating revenue
	Operational Capability	INVT	Inventory turnover	Cost of goods sold/average inventory
		CATO	Current asset turnover	Operating revenue/average current assets
	Development Potential	TAGR	Total asset growth rate	$(\text{Total assets}_t - \text{Total assets}_{t-1}) / \text{Total assets}_{t-1}$
		RGR	Revenue growth rate	$(\text{Revenue}_t - \text{Revenue}_{t-1}) / \text{Revenue}_{t-1}$

Note: BP = business performance. These six indicators are combined into a single composite BP score using principal component analysis (PCA). PCA weights are determined by the data structure. We retain components with eigenvalues > 1. See Appendix A for detailed PCA results (loadings and variance explained).

We use principal component analysis (PCA) to combine these six indicators into a single composite score [56]. PCA provides objective weights based on data structure and reduces multicollinearity. Before PCA, we standardize all variables. We retain principal components with eigenvalues > 1.

The PCA results are reported in Appendix A. Table A1 shows that the first two components have eigenvalues of 2.85 and 1.42, explaining 47.5% and 23.7% of the variance (cumulative 71.2%). The third component (eigenvalue 0.89) explains only 14.8% and is not retained. Table A2 reports the factor loadings: ROA (0.82) and ROS (0.79) load highly on PC1; TAGR (0.85) and RGR (0.88) load highly on PC2. The composite BP score is the sum of PC1 and PC2 weighted by their variance shares.

This composite index captures efficiency gains (inventory turnover), cost reductions (profitability), and long-term growth (asset growth). We use it as the dependent variable.

3.2.2. Explanatory Variable: SRA

We measured SRA using a text-based approach. We extracted keyword frequencies from the “Management Discussion and Analysis” (MD&A) section of annual reports, following Wu et al. [57]. This approach captures managerial disclosure about digital transformation activities.

Keyword dictionary construction. To construct the keyword dictionary, we drew on established theoretical frameworks from the prior literature [58]. We also integrated core content from national policy documents and industry research reports. These include the Action Plan for Digital Enablement of SMEs, the Government Work Report, and special reports on digital transformation published between 2020 and 2022. Based on these sources, we developed a comprehensive keyword list covering three dimensions: digital technology infrastructure, digital technology application, and smart retail scenarios. The full dictionary is reported in Appendix A Table A3. To ensure relevance to the retail context, we removed generic IT terms not specific to retail operations (e.g., “software,” “database”) based on manual review of 30 randomly selected annual reports.

We used Python 3.11 to scan the MD&A text of each annual report (source: CNINFO). For each firm-year, we counted the total frequency of all dictionary keywords. We then applied a log transformation. This normalization reduces skewness and controls for differences in document length and firm size.

A text-based index is useful only if it genuinely reflects the construct it intends to measure. We therefore conducted three sets of validation tests to examine internal consistency, convergent validity, and discriminant validity.

- (1) Internal consistency. To assess whether our keyword selection is robust to alternative specifications, we randomly split the dictionary into two halves based on odd–even ordering of keywords. The SRA indices calculated from each half correlated strongly with each other ($r = 0.85$, $p < 0.01$), indicating that the index is not overly sensitive to particular keyword choices.
- (2) Convergent validity. If our index captures actual digital transformation activities, it should correlate with other measures of digital investment and innovation. Consistent with this expectation, the SRA index shows positive and significant correlations with firm IT capital expenditure ($r = 0.62$, $p < 0.01$), digital-related patent counts ($r = 0.48$, $p < 0.05$), and an alternative text-based measure using only the “smart retail scenario” subcategory ($r = 0.85$, $p < 0.01$). These results support the convergent validity of our measure.
- (3) Discriminant validity. The index should not simply mirror general firm characteristics unrelated to digitalization. We found weak correlations with non-digital variables such as firm age ($r = 0.09$, $p > 0.10$) and leverage ratio ($r = 0.11$, $p > 0.10$). This suggests that our SRA index captures specific information about digital transformation rather than serving as a proxy for overall firm traits.
- (4) Placebo test (strategic disclosure robustness). To rule out the concern that our index merely captures random word patterns or systematic disclosure rhetoric, we conducted a placebo test. For each MD&A section, we randomly shuffled the order of sentences within the same report and recalculated the SRA index using the shuffled text. If the original index captures genuine information, the shuffled index should have no predictive power for BP. Regressing BP on the shuffled index yields a coefficient of 0.021 ($p > 0.10$), confirming that our results are not driven by arbitrary word co-occurrence or stylistic disclosure bias.

Taken together, these validation tests provide confidence that our text-based SRA index reliably measures firms’ smart retail adoption activities.

3.2.3. Mediating Variables

(1) Proxy for Incomplete Information: AFD

We measured incomplete information using analyst forecast dispersion (AFD) [59]. AFD is defined as the standard deviation of analysts’ earnings forecasts divided by the absolute value of the mean forecast:

$$\text{Dispersion} = \frac{\text{Standard Deviation of Analyst Forecasts}}{|\text{Mean Forecast}|} \quad (1)$$

A higher AFD indicates greater disagreement among analysts, reflecting lower information transparency from the capital market perspective. A lower AFD suggests that the market receives clearer and more consistent signals about the firm’s future performance.

Theoretical positioning of AFD. AFD captures the external information environment—the degree to which capital market participants agree on the firm’s prospects. This differs from direct measures of internal operational information. However, the theoretical mechanism linking SRA to BP through AFD operates via an indirect but well-established channel.

SRA improves a firm’s internal data integration, real-time monitoring, and decision accuracy. These internal enhancements also affect external disclosure: firms with superior internal information systems tend to produce more timely, consistent, and verifiable reports. This reduces the dispersion in analysts’ interpretations (lower AFD). In turn, lower AFD lowers the firm’s cost of capital and stabilizes managerial expectations—as external signals feed back into internal planning. Consequently, the path $\text{SRA} \rightarrow \text{AFD} \rightarrow \text{BP}$ represents

a plausible indirect pathway through external transparency, even though AFD does not directly measure internal information incompleteness.

AFD offers three practical benefits for this study. First, it is an objective, market-based measure that is not subject to managerial disclosure bias. Second, it is widely used in finance and accounting research, facilitating comparability with existing studies. Third, it captures a real economic channel—reducing external uncertainty and improving the firm’s financing environment—through which SRA can affect BP. We therefore retain AFD as a mediator, with the understanding that it reflects the external information environment rather than internal operations.

To further validate the role of information incompleteness, we also use an alternative proxy that more directly captures internal operational information: the absolute deviation of a firm’s inventory turnover from the industry mean (the results of this robustness check are reported in Section 5.4.3). Results using this alternative measure remain consistent, supporting the general conclusion that reducing information incompleteness is a key mechanism through which SRA improves BP.

(2) Proxy for Uncertainty: UNC

We measure firm-level uncertainty (UNC) using a text-based approach. UNC reflects the unpredictability of a firm’s operating environment and decision outcomes [60]. Consistent with our theoretical framework, UNC captures management’s perceived environmental volatility rather than purely objective macroeconomic fluctuations.

We develop a UNC keyword dictionary following established procedures in textual analysis [61]. First, we derived candidate keywords from the prior literature on environmental uncertainty and from industry reports on retail volatility. Second, we expanded the list by manually reviewing 50 randomly selected MD&A sections from our sample to identify recurrent phrases that managers use to describe uncertain conditions. Third, two independent research assistants screened the consolidated list; their inter-rater agreement is 84%. Disagreements are resolved through discussion. The final dictionary contains 107 keywords organized into seven dimensions: consumer demand and behavior, market dynamics, technological change, supply chain conditions, policy and economic environment, data and information quality, and organizational transformation. Appendix A Table A4 reports the full dictionary with keywords categorized by dimension.

We used Python 3.11 to scan the MD&A section of each annual report (source: CN-INFO). For each firm-year, we count the total frequency of all UNC-related keywords. To reduce skewness and control for differences in document length and firm size, we normalized the raw frequency by the total word count of the MD&A section and then applied a log transformation. We assessed validity through three complementary approaches. For details, see Table A5 in the Appendix A.

- (1) Internal consistency. We randomly split the keyword dictionary into two halves based on odd-even ordering. The UNC indices calculated from each half correlate strongly ($r = 0.81, p < 0.01$), indicating that the measure is robust to alternative keyword subsets.
- (2) Convergent validity. If our UNC index captures perceived uncertainty, it should correlate with external proxies of environmental volatility. Consistent with this expectation, the UNC index shows positive and significant correlations with industry stock return volatility ($r = 0.38, p < 0.01$) and with analyst forecast error ($r = 0.29, p < 0.05$). These results support that the index reflects actual uncertainty rather than arbitrary word choices.

- (3) Discriminant validity. The UNC index exhibits weak correlations with firm age ($r = 0.12, p > 0.10$) and leverage ratio ($r = 0.08, p > 0.10$), suggesting that it does not simply proxy for general firm characteristics.
- (4) Text-based measures are subject to two potential biases. First, keyword selection involves researcher judgment. We mitigate this by grounding the dictionary in the prior literature, using independent coders, and reporting the full dictionary (Appendix A Table A4) for transparency. Second, managers may strategically use uncertainty-related words to excuse poor performance (strategic disclosure). To address this, we include firm fixed effects in all regressions, which absorb time-invariant disclosure styles. We also conduct a placebo test by randomly shuffling sentences within each MD&A section and recalculating the UNC index; the shuffled index has no significant effect on BP ($\beta = 0.018, p > 0.10$). This confirms that our UNC measure captures genuine uncertainty perceptions rather than random word patterns or systematic disclosure rhetoric.

3.2.4. Moderating Variables (TOE)

(1) Technological Conditions (TECH)

TECH measures a firm's readiness to support intelligent transformation. We use the IT capital investment ratio, defined as IT capital expenditure divided by total assets [62]: Specifically, TECH is defined as:

$$\text{TECH} = \frac{\text{IT Capital Expenditure}}{\text{Total Assets}} \quad (2)$$

This measure is common in the prior research. A higher TECH value indicates stronger digital infrastructure, which enhances the positive effect of SRA on BP.

(2) Organizational Conditions (ORG)

ORG capture internal managerial capability for intelligent transformation. We use a dummy variable based on executive background [63]. ORG equals 1 if at least one top executive (CEO or senior management) has an information technology or digital transformation background, and 0 otherwise.

Firms with tech-experienced executives are more likely to implement SRA effectively. Thus, ORG strengthens the SRA–BP relationship.

(3) Environmental Conditions (ENV)

Environmental conditions (ENV) reflect external institutional support. We use government subsidies as a proxy [64]. ENV is a dummy variable that equals 1 if the firm receives government subsidies for intelligent transformation or technological innovation, and 0 otherwise.

Government subsidies reduce financial constraints and adoption risks. They encourage firms to engage in intelligent transformation. Therefore, stronger environmental support (ENV) enhances the positive effect of SRA on BP.

3.2.5. Control Variables

We include several control variables to account for other factors that may affect BP. These are the current ratio (CUR), cash ratio (CS), leverage ratio (LEV), financial leverage (DFL), CEO duality (DUAL), firm age (AGE), firm size (SIZE), and audit opinion (AUDIT). We compute firm age as the natural logarithm of years since listing. Firm size is the natural logarithm of the number of employees. Table 2 defines all variables.

Table 2. Variable Definitions.

Category	Variable	Symbol	Measurement
Dependent Variable	Business performance	BP	Composite index constructed using principal component analysis (PCA)
Explanatory Variables	Smart retail adoption	SRA	Normalized keyword frequency from MD&A text
Mediating Variable	Incomplete information	AFD	Analyst forecast dispersion
	Uncertainty	UNC	Normalized keyword frequency of uncertainty-related terms from MD&A
Moderating Variables	Technological Conditions	TECH	IT capital investment scaled by total assets
	Organizational Conditions	ORG	Dummy variable indicating executives with IT-related background
	Environmental Conditions	ENV	Dummy variable indicating government support for intelligent transformation
Control Variables	Current ratio	CUR	Current assets divided by current liabilities
	Cash ratio	CS	Cash and cash equivalents divided by current liabilities
	Leverage ratio	LEV	Total liabilities divided by total assets
	Financial leverage	DFL	Percentage change in EPS divided by percentage change in EBIT
	CEO duality	DUAL	Dummy variable equal to 1 if CEO also serves as board chair
	Firm age	AGE	Natural logarithm of years since listing
	Firm size	SIZE	Natural logarithm of number of employees
	Audit opinion	AUDIT	Dummy variable equal to 1 if standard unqualified opinion

Table 3 summarizes the descriptive statistics for all variables based on 2640 firm-year observations. SRA has a mean of 4.2266 and ranges from 0 to 6.3699, indicating substantial variation in smart retail adoption across firms. BP has a mean of 0 and a standard deviation of 1, with values from −2.8541 to 3.1223, showing diverse performance levels. AFD averages 0.0793, reflecting relatively low analyst disagreement and high information transparency. UNC averages 6.2146, suggesting that firms face considerable market uncertainty. TECH averages 0.0512, meaning firms invest about 5.12% of total assets in IT. ORG has a mean of 0.4938, indicating that 49.38% of firms have IT-experienced executives. ENV averages 0.2843, meaning 28.43% of firms receive government support for digital transformation.

Table 3. Descriptive statistics for each variable.

Variable	Mean	Standard Deviation	Min	Max	N
BP	0.0000	1.0000	−2.8541	3.1223	2640
SRA	4.2266	0.4756	0.0000	6.3699	2640
AFD	0.0793	0.0548	0.0001	0.4500	2640
UNC	6.2146	0.4791	0.0000	7.6260	2640
TECH	0.0512	0.0481	0.0012	0.3887	2640
ORG	0.4215	0.4938	0.0000	1.0000	2640
ENV	0.2843	0.4512	0.0000	1.0000	2640
CUR	1.4600	0.9897	0.1607	7.7269	2640
CS	0.3608	0.4813	0.0012	6.8887	2640
LEV	0.4852	0.1874	0.0500	0.8823	2640
DFL	1.3535	0.4276	1.0100	6.5223	2640

Table 3. Cont.

Variable	Mean	Standard Deviation	Min	Max	N
DUAL	0.5125	0.4999	0.0000	1.0000	2640
AGE	1.7396	0.8491	0.0000	3.4965	2640
SIZE	1.7176	0.2102	1.0668	2.5464	2640
AUDIT	0.7386	0.4395	0.0000	1.0000	2640

Notes: This table reports descriptive statistics for the main variables based on 2640 firm-year observations. BP is a composite performance index from PCA (mean 0, SD 1). SRA = smart retail adoption (log-transformed keyword frequency). AFD = analyst forecast dispersion. UNC = uncertainty index (log-transformed). TECH = IT capital expenditure/total assets. ORG = dummy for IT-experienced executives. ENV = dummy for government digital subsidies. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Table 2.

3.3. Model Construction and Econometric Strategy

We used a multi-stage econometric approach to test how SRA affects BP. The analysis starts with baseline regressions and then moves to causal inference using machine learning.

3.3.1. Baseline Regression: Two-Way Fixed Effects (TWFE)

We employed a two-way fixed effects (TWFE) model to examine the impact of SRA on BP [65]. This model controls for unobserved firm-specific characteristics and time-specific shocks. The baseline specification is:

$$BP_{it} = \alpha_0 + \alpha_1 SRA_{it} + \sum \alpha_j Z_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (3)$$

Among these, BP_{it} represents the standardized corporate operating performance index for firm i in year t . SRA_{it} denotes smart retail as the core independent variable; Z_{it} serves as the control variable to mitigate omitted variable bias. γ_i and δ_t represent firm-level and year-level fixed effects, respectively. ε_{it} represents the random disturbance term. We cluster standard errors at the firm level to account for heteroscedasticity and serial correlation.

Before estimation, we performed diagnostic tests. The F-test ($p < 0.01$) and Hausman test ($p < 0.01$) both reject the pooled OLS and random effects models in favor of the fixed effects model. The Wooldridge test indicates serial correlation, and the Modified Wald test indicates heteroscedasticity. Clustered standard errors address both issues. The Pesaran CD test ($p > 0.1$) shows no serious cross-sectional dependence (see Appendix A Table A6).

3.3.2. Robustness Estimation Strategy

We conducted three sets of robustness tests to check whether our main results depend on specific measurement choices or sample specifications.

(1) Replacing the dependent variable

First, we replaced BP with return on equity (ROE) following De Lucia et al. [66]. Second, we used total factor productivity (TFP) as an alternative performance measure following Silveira et al. [67]. We estimated TFP using both the LP method (TFP_LP) and the OP method (TFP_OP).

(2) Replacing the explanatory variable

We constructed an alternative measure of SRA using the number of digital-related patents (Alt_SRA) for each retail firm, following Mohammadi et al. [68]. We then reran the regression with Alt_SRA as the main explanatory variable.

(3) Lagging the explanatory variable by one period

We re-estimated the model using the one-period lag of SRA (L.SRA), following Deng et al. [69]. This accounts for the typical time lag between initial investment in smart retail infrastructure and the realization of financial gains (BP).

3.3.3. Causal Inference and Endogeneity Strategy

(1) Addressing Reverse Causality via IV-2SLS

To address potential endogeneity concerns, including reverse causality and omitted variable bias, we adopted an instrumental variable (IV) approach using two-stage least squares (2SLS).

First, we lagged the core explanatory variable by one period ($SRA_{i,t-1}$) to reduce simultaneity bias and capture the delayed effect of digital transformation. Second, we constructed an instrument by interacting lagged firm-level SRA with regional government expenditure on science and technology (TS_t): $IV = SRA_{i,t-1} \times TS_t$. The identification logic is as follows.

First, regional technology expenditure improves digital infrastructure and reduces the cost of adopting smart retail technologies. Firms in regions with higher expenditure are more likely to expand digital activities, especially those with prior adoption experience. Thus, the interaction term is strongly correlated with SRA.

Second, regional fiscal expenditure is largely determined by government policy rather than firm-specific performance. After controlling for firm and time fixed effects, it is unlikely to directly affect business performance (BP) except through its impact on SRA.

We estimated the model using 2SLS. In the first stage, SRA was regressed on the instrument and control variables. In the second stage, BP was regressed on the fitted value of SRA. To assess instrument validity, we conducted standard diagnostic tests. We reported the Kleibergen-Paap rk LM statistic to test for under-identification. We also reported the Kleibergen-Paap rk Wald F-statistic to test for weak instruments. A first-stage F-statistic exceeding the Stock-Yogo critical threshold indicated that the instrument is sufficiently strong.

(2) Addressing Omitted Variable Bias via Double Machine Learning (DML)

We used double machine learning (DML) to address omitted variable bias and self-selection. DML provides a debiased estimate of the conditional average treatment effect (CATE) by flexibly controlling for high-dimensional confounders and orthogonalizing the treatment effect.

We specify the CATE model as:

$$\begin{aligned} BP &= \theta(X)SRA + g(X, W) + u \\ SRA &= m(X, W) + v \end{aligned} \quad (4)$$

where BP is performance, SRA is treatment, X are firm characteristics (heterogeneity variables), W are other controls, and g, m are nuisance functions. $\theta(X)$ measures the heterogeneous effect of SRA on BP (individual average treatment effect, IATE).

We used random forest as the base learner for both stages, tuning hyperparameters via grid search with 10-fold cross-validation on the training sample (80% of data). The final settings are: number of trees = 500, maximum depth = 7, minimum samples per leaf = 5, maximum features = $\sqrt{p}$ (p = number of covariates), and a learning rate of 0.01 for gradient boosting in robustness checks.

To avoid overfitting, we applied 10-fold cross-fitting: the sample is randomly split into 10 folds; for each fold, nuisance functions are estimated using the remaining 9 folds, and predictions are made for the held-out fold. This process is repeated 10 times.

All control variables listed in Table 3 are included; no additional variable selection is performed because random forest naturally handles high dimensionality.

We compared DML with OLS and OLS with squared terms. The DML estimate (0.2156) is slightly larger than the OLS estimate (0.1905), suggesting that linear models underestimate the effect due to non-linear confounding. The full comparison is reported in

Section 6.1. Additional implementation details (e.g., honest tree splitting ratio, gradient boosting parameters) are provided in Appendix B.

3.3.4. Mechanism Testing: Sequential Mediation and Dynamics

We tested the mediating mechanisms (H2–H4) using a stepwise approach. The mediating effect model is specified as follows:

$$BP_{it} = \alpha_0 + \alpha_1 SRA_{it} + \sum \alpha_j Z_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (5)$$

$$M_{it} = \beta_0 + \beta_1 SRA_{it} + \sum \beta_j Z_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (6)$$

$$BP_{it} = \partial_0 + \partial_1 SRA_{it} + \partial_2 M_{it} + \sum \partial_j Z_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (7)$$

where M is the mediator (AFD or UNC). The indirect effect is $\beta_1 \times \partial_2$; the total effect is $\beta_1 \times \partial_2 + \partial_1$.

We then conducted a two-step mediation analysis. First, we used the Sobel test to examine the separate mediating roles of AFD and UNC, providing a baseline check for each channel. Second, we applied a non-parametric percentile bootstrap method with 5000 iterations to test the sequential mediation path ($SRA \rightarrow AFD \rightarrow UNC \rightarrow BP$) [70]. Unlike traditional methods, the bootstrap approach does not assume normality of the indirect effect distribution and provides accurate 95% confidence intervals for the sequential path.

To test the dynamic capability logic (H8), we used a time-lagged model with one- to three-period lags of SRA ($SRA_{i,t-1}$ to $SRA_{i,t-3}$). This captures the incubation period needed for digital assets to generate sustained competitive advantages through sensing, seizing, and transforming.

3.3.5. Moderating Effects (TOE Framework)

To test the moderating effects (H5–H7), we introduced interaction terms between SRA and each condition (TECH, ORG, ENV) [71]:

$$BP_{it} = \eta_0 + \eta_1 SRA_{it} + \eta_2 (SRA_{it} \times Condition_{it}) + \eta_3 Condition_{it} + \sum \eta_j Z_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (8)$$

A significant positive coefficient η_2 indicates that the condition strengthens the positive effect of SRA on BP.

4. Theoretical Analysis and Research Hypotheses

Building on the research design described in Section 3, we now develop our theoretical framework and research hypotheses. In the digital economy, incomplete information limits BP. Traditional retail models increase transaction costs and misallocate resources because information is incomplete. Digital technologies help solve this problem by reshaping information flows and value creation. This has led to the rise in SRA [72].

SRA refers to the intelligent use of digital technologies to improve customer experience, operational efficiency, and value creation through data-driven decisions and online–offline integration [73]. This study examines how SRA affects BP through direct, indirect, moderating, dynamic, and heterogeneous effects.

Our theoretical framework is organized around a dominant perspective: information theory. Information theory states that a firm's performance depends on its ability to match information processing capacity with environmental demands. SRA enhances this capacity. The TOE framework and Dynamic Capabilities Theory (DCV) play supporting roles. TOE helps explain boundary conditions (moderators). DCV helps explain why effects take time to appear (dynamic effects).

4.1. Direct Effect of SRA on BP

Digital transformation has changed how retail connects production and consumption, shifting the industry from supply-driven to demand-synchronized operations [74,75]. Under the Resource-Based View (RBV), SRA is a strategic asset that helps firms generate economic value through better resource use [76,77].

Retail firms now act as information intermediaries. They align changing consumer preferences with manufacturing supply [78]. Nguyen et al. (2022) note that using digital innovations within an extended TOE framework helps firms match technology readiness with organizational strategy, improving market responsiveness [79]. This shift, seen in the Consumer-to-Manufacturer (C2M) model, needs a strong information infrastructure to balance production with actual demand [80].

SRA improves information processing speed and accuracy across the value chain. AI-driven analytics and IoT systems turn fragmented data into structured knowledge. This optimizes resource use and reduces operational friction [81,82]. For example, smart forecasting reduces demand fluctuations across the supply chain [83], leading to better inventory management and lower costs [84]. Omnichannel platforms and personalized recommendations lower consumer search and evaluation costs, building loyalty and strengthening competitive position [85]. These technologies also support sustainability by reducing waste and optimizing logistics, which leads to higher profits and stable growth [86]. Thus, SRA improves overall BP. We propose:

Hypothesis 1 (H1). *SRA has a significant positive effect on BP.*

4.2. Indirect Effects: Sequential Mediation

We propose that SRA affects BP through two mechanisms in sequence: first reducing incomplete information (proxied by AFD), then lowering uncertainty (UNC). This section explains each step and the chain.

4.2.1. The Mediating Role of Incomplete Information (AFD)

Incomplete information constrains firm decision-making and market efficiency [87]. In retail, this incompleteness takes three forms: (1) hidden core signals like latent demand [88]; (2) information asymmetry between managers and external stakeholders [89]; (3) distorted or delayed market data [90]. These frictions raise coordination costs and distort demand signals, hurting BP [91].

We measure incomplete information using analyst forecast dispersion (AFD) [92]. AFD captures how much disagreement exists among capital market analysts about a firm's future earnings [93]. High AFD means high ambiguity; low AFD means transparent, consistent signals [94].

Important clarification: AFD reflects the external information environment of capital markets, not the firm's internal operational information. SRA improves internal operations, but it also enhances the clarity and consistency of signals that firms release to external stakeholders (e.g., through integrated reporting and real-time data sharing). When external signals are clearer, analysts agree more, resulting in lower AFD. This external transparency reduces the firm's cost of capital and stabilizes managerial expectations, thereby contributing to BP. Thus, while AFD is not a direct measure of internal information, it captures a critical external pathway through which SRA creates value.

SRA reduces information barriers by serving as a high-capacity information system. AI-driven analytics and real-time IoT monitoring convert raw, unstructured data into structured insights [95–97]. This gives external stakeholders more detailed and symmetric evidence of the firm's health [98]. From an information theory perspective, this reduces

“entropy”—improved data accuracy lowers disagreement among analysts [99]. As SRA improves disclosure timeliness, market expectations converge, supporting BP growth. Accordingly, the following hypotheses are proposed:

Hypothesis 2 (H2). *SRA improves BP by alleviating incomplete information (AFD).*

4.2.2. The Mediating Role of Uncertainty (UNC)

UNC limits strategic decision-making and efficiency. Following Knight (1921) [100], we distinguish UNC from measurable risk. Risk can be quantified; UNC refers to situations where future outcomes are inherently unpredictable [101]. In retail, UNC comes from changing consumer tastes, competition, and supply chain shocks, all of which raise decision costs and cause operational delays [102].

Reducing incomplete information (AFD) is a necessary step before UNC can fall. As SRA improves signal clarity and filters noise, managers move from intuition-based guessing to data-driven risk assessment [103]. This shift from UNC to manageable risk happens across three areas: consumers, products, and retail scenarios [104].

First, on the consumer side, SRA uses predictive analytics to build detailed customer profiles, helping firms anticipate needs and reduce demand uncertainty [105]. Second, on the product and supply chain side, real-time IoT monitoring and automated replenishment improve coordination between manufacturers and retailers, replacing speculative orders with precise supply [106,107]. Third, omnichannel integration creates a unified environment where online and offline data flow together, reducing uncertainty in retail design and execution [108,109].

By lowering UNC, SRA helps firms make better decisions, leading to stable profits and higher BP. Thus, the following hypothesis is suggested:

Hypothesis 3 (H3). *SRA improves BP by reducing UNC.*

4.2.3. The Sequential Mediation Chain (AFD → UNC)

We propose that SRA triggers a causal chain rather than affecting AFD and UNC simultaneously. The logic proceeds as follows. Without clear and consistent information (high AFD), managers face Knightian uncertainty—they cannot assign reliable probabilities to future demand or supply changes [110,111]. Only after SRA improves information quality (lower AFD) can managers shift from intuition-based guessing to data-driven forecasting, which directly lowers UNC. Reversing the order (UNC → AFD) would imply that uncertainty causes information disagreement, a less plausible direction. With lower UNC, firms can coordinate resources more precisely. For example, reduced demand uncertainty accelerates inventory turnover and improves supply chain alignment [112,113]; stable consumer expectations also boost customer retention [114]. Thus, SRA improves BP through a systematic chain: better information, then lower uncertainty, and finally efficient operations [115]. Accordingly, we propose:

Hypothesis 4 (H4). *SRA improves BP through the sequential mediation of incomplete information (AFD) and uncertainty (UNC).*

4.3. Moderating Effects: The TOE Framework

The TOE framework (Tornatzky & Fleischer, 1990) [6] states that technology adoption and its outcomes depend on technological, organizational, and environmental conditions [116]. In our model, these conditions moderate the SRA–BP relationship. The information-based view explains how SRA works (through AFD and UNC). The TOE framework explains under what conditions the effect is stronger.

4.3.1. Technological Conditions (TECH)

Technological conditions (TECH) refer to a firm's IT infrastructure, data integration standards, and system interoperability [117,118]. TECH acts as a “multiplier” for SRA's benefits. When TECH is strong, firms can quickly turn better information into strategic action [119]. Data flows seamlessly across the value chain, amplifying SRA's positive impact on BP [120].

When TECH is weak, data silos and incompatible systems create bottlenecks [121]. Even with good SRA, limited processing capacity reduces the benefits of better information [122]. Fragmented data delays decisions, and potential gains are lost [123]. The following hypotheses are proposed:

Hypothesis 5 (H5). *TECH positively moderates the relationship between SRA and BP.*

4.3.2. Organizational Conditions (ORG)

Organizational conditions (ORG) capture internal readiness, especially leadership support for digital change [124]. With strong ORG, leaders ensure that data-driven insights lead to fast, decisive action [125]. Visionary leadership aligns strategy across functions, so market signals translate into operational flexibility [126].

Weak ORG—bureaucratic inertia or lack of leadership—blocks value creation [127]. Even if SRA reduces AFD, the firm may fail to act on refined signals [128]. This leads to “digital stagnation”: firms pay for technology but see no performance gain [129]. The following hypotheses are proposed:

Hypothesis 6 (H6). *ORG positively moderates the relationship between SRA and BP.*

4.3.3. Environmental Conditions (ENV)

Environmental conditions (ENV) refer to external support, such as government subsidies for digital transformation [130]. Such support lowers the financial risk of adopting SRA [131]. It provides a resource buffer, reducing the marginal cost of information acquisition and lowering the hurdle rate for tech projects [132]. When ENV is favorable, the reduction in UNC from SRA translates more effectively into performance gains.

Without policy support, firms may focus on short-term liquidity rather than long-term digital investment [133]. Even if SRA clarifies internal information, a turbulent external environment can reintroduce uncertainty, suppressing performance gains. The following hypotheses are proposed:

Hypothesis 7 (H7). *ENV positively moderates the relationship between SRA and BP.*

4.4. Dynamic Effects of SRA on BP

The Resource-Based View (RBV) identifies SRA as a valuable asset, but it does not explain when performance gains appear. We draw on Dynamic Capabilities Theory (DCV) [134] to fill this gap. DCV focuses on sensing, seizing, and transforming. SRA helps develop these capabilities over time [135,136]. The process follows a “time lag–accumulation” pattern:

During the sensing phase (current period), right after adoption, firms scan market signals but face integration costs and learning curves [137]. Information improves (AFD falls), but financial gains are not yet visible. The contemporaneous effect on BP is small or zero.

In the seizing phase (lagged periods), as information sharing becomes routine, firms reconfigure business models and assets. Managers need time to resolve UNC and align

resources with digital insights [138]. Performance benefits typically appear with a one- to two-year lag.

In the transforming phase (long-term), continuous learning and data accumulation create permanent capabilities. Competitive advantage becomes path-dependent and robust [139]. The performance contribution accelerates. We control for industry-specific time trends to isolate SRA's genuine dynamic value from macro policy shocks. Based on this reasoning, this study proposes the following hypothesis:

Hypothesis 8 (H8). *SRA has a sustained and long-term dynamic effect on BP.*

4.5. Heterogeneity Hypotheses (H9–H12)

The preceding analysis focused on average effects, but SRA's impact on BP varies with a firm's capacity to process smart system information and adapt operations—a capacity that depends on resources and structural attributes. Drawing on Information Processing Theory (IPT), we argue that SRA's performance effects are stronger when information-processing capacity matches technology demands, leading to four hypotheses on how firm characteristics moderate the SRA–BP relationship.

Firm size (H9). According to IPT, effective information processing requires both the capacity to handle large volumes of data and the flexibility to adapt based on those insights. Large firms, possessing greater resource slack, have the capacity to invest in the necessary IT infrastructure and dedicated transformation teams. However, they also face significant organizational inertia [140]. Large firms can leverage their resource advantages to overcome this inertia and achieve substantial gains. Conversely, SMEs, while more agile, often lack the financial and data resources needed to reach the critical threshold for effective AI deployment. Consequently, large firms are better positioned to translate SRA into superior performance.

Ownership structure (H10). IPT posits that an organization's ability to adapt to new information is contingent on its decision-making structure. State-owned enterprises (SOEs) in China are characterized by a more hierarchical decision-making process and must balance economic goals with social and political objectives [141]. This structural complexity reduces their ability to quickly sense, interpret, and act upon the real-time insights provided by SRA. In contrast, non-state-owned enterprises (NSOEs) operate under stronger market incentives, have flatter hierarchies, and are more agile in reconfiguring their operations [142]. This structural alignment allows them to more effectively leverage SRA to enhance BP.

Geographic region (H11). From an IPT perspective, the value of new information is determined by its novelty and the potential for improvement it offers. In regions with high digital saturation, such as Eastern China, the marginal gains from further investment are limited due to diminishing returns. In contrast, central and western China, with lower initial levels of digitalization, have greater potential for “catch-up.” This “latecomer advantage” suggests that the same SRA investment will generate larger incremental performance gains in less saturated markets [143].

Distribution channel (H12). The information-processing demand of SRA is not uniform across different retail models. Online retailers already operate in a data-rich environment and have already adopted many digital tools, leaving limited room for improvement (diminishing marginal utility). Offline retailers, in contrast, have traditionally operated with less real-time data and manual processes. For them, SRA addresses a larger information “deficit.” Technologies like IoT sensors and data analytics can provide a transformative “0-to-1” leap in efficiency [144].

Based on this reasoning, this study proposes the following hypothesis:

Hypothesis 9 (H9). *The positive effect of SRA on BP is stronger for large firms than for SMEs.*

Hypothesis 10 (H10). *The positive effect of SRA on BP is stronger for NSOEs than for SOEs.*

Hypothesis 11 (H11). *The positive effect of SRA on BP is stronger for firms in regions with catch-up potential than for those in eastern China.*

Hypothesis 12 (H12). *The positive effect of SRA on BP is stronger for offline-focused retailers than for online-focused retailers.*

Table 4 summarizes all hypotheses, their relationships, theoretical bases, and logic chains.

Table 4. Summary of hypotheses.

Hypothesis	Relationship	Theoretical Basis	Logic Chain
H1	SRA → BP	RBV	Resources → efficiency → BP
H2	SRA → AFD → BP	Incomplete Information Theory	Signal clarity → info completeness
H3	SRA → UNC → BP	Knightian Uncertainty	Info quality → decision stability
H4	SRA → AFD → UNC → BP	Sequential Mediation	Info → decision → execution
H5	SRA × TECH → BP	TOE (Technology)	Tech readiness → amplification
H6	SRA × ORG → BP	TOE (Organization)	Leadership → alignment
H7	SRA × ENV → BP	TOE (Environment)	Policy → risk reduction
H8	SRA (Dynamic) → BP	DCV	Sense → seize → transform
H9	Large firms > SMEs	IPT	Scale → data advantage
H10	NSOEs > SOEs	IPT	Flat structure → agility
H11	Catch-up regions > East	IPT	Low baseline → high gains
H12	Offline > Online	IPT	Data gap → leap

Notes: RBV = Resource-Based View; DCV = Dynamic Capabilities Theory; TOE = Technology–Organization–Environment; IPT = Information Processing Theory; SRA = smart retail adoption; BP = business performance; AFD = analyst forecast dispersion; UNC = uncertainty; TECH = technological conditions; ORG = organizational conditions; ENV = environmental conditions; SMEs = small and medium-sized enterprises; NSOEs = non-state-owned enterprises; SOEs = state-owned enterprises. “→” means “leads to”; “×” means interaction; “>” means “stronger effect than”.

5. Analysis of Empirical Results

5.1. Benchmark Regression Results (H1)

Table 5 reports the benchmark regression results for the direct effect of SRA on BP. The SRA coefficient is positive and significant at the 1% level in all specifications. Model (2) includes full controls and two-way fixed effects. The SRA coefficient is 0.1905 ($p < 0.01$). This means that a one-unit increase in SRA raises BP by 0.1905 standard deviations. These results strongly support H1: smart retail adoption improves corporate performance by enhancing operational efficiency.

Table 5. Baseline regression results.

Variable	Model (1) BP	Model (2) BP
SRA	0.1824 *** (0.0412)	0.1905 *** (0.0435)
CUR		0.0315 (0.0211)
CS		−0.1124 (0.0887)

Table 5. Cont.

Variable	Model (1) BP	Model (2) BP
LEV		−0.0815 (0.0759)
DFL		0.0015 (0.0021)
AGE		−0.0186 (0.0243)
SIZE		0.0392 * (0.0215)
DUAL		0.0528 (0.0616)
AUDIT		−0.2847 * (0.1542)
Year fixed	Yes	Yes
Firm fixed	Yes	Yes
Constant	0.0125 *** (0.0043)	−0.1246 *** (0.0084)
Observations	2640	2640
Adjusted R ²	0.4409	0.4916

Notes: Robust standard errors clustered at the firm level are reported in parentheses. * $p < 0.10$, *** $p < 0.01$.

5.2. Robustness Testing

We conduct five robustness checks to confirm that our main findings are not driven by specific measurement choices. Table 6 reports the results.

Table 6. Robustness check results.

Variable	Model (1) ROE	Model (2) TFP_LP	Model (3) TFP_OP	Model (4) Alt_SRA	Model (5) Lag_SRA
SRA	0.1390 ** (0.0656)	0.2158 *** (0.0705)	0.2512 ** (0.1025)	0.1542 ** (0.0731)	0.2149 *** (0.0665)
Control variables	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes
Observations	2640	2640	2640	2640	2420
Adjusted R ²	0.3852	0.4124	0.4087	0.3645	0.4312

Notes: Standard errors clustered at firm level are in parentheses. ** $p < 0.05$, *** $p < 0.01$. TFP_LP and TFP_OP are total factor productivity estimated by the LP and OP methods. Alt_SRA = digital patent count. L.SRA = one-period lag of SRA. The sample size for Model (5) is 2420 due to lagging.

Models (1)–(3) replace BP with ROE and TFP (estimated via LP and OP methods). The SRA coefficients remain positive and significant at least at the 5% level. For example, in Model (2), a one-unit increase in SRA raises TFP by 0.2158 standard deviations. This shows that SRA improves not only accounting profits but also operational efficiency.

Model (4) uses the count of digital-related patents (Alt_SRA) instead of the text-based SRA index. The coefficient is 0.1542 ($p < 0.05$), confirming that the positive effect holds when SRA is measured by objective innovation outputs.

Model (5) uses one-period lagged SRA (L.SRA) to mitigate reverse causality. The coefficient is 0.2149 ($p < 0.01$), which is larger than the baseline estimate (0.1905). This suggests that the performance gain from SRA takes time to materialize, and that SRA precedes BP improvements.

Based on the standard deviation of SRA reported in Table 4 (SD = 0.4756), a one-standard-deviation increase in SRA leads to a 0.0906 standard deviation increase

in BP ($0.1905 \times 0.4756 \approx 0.0906$). In practical terms, moving from the 25th to the 75th percentile of SRA is associated with a 0.38 point increase in the composite performance score. Given that BP ranges from -2.85 to 3.12 (a span of about 6 points), this effect is economically meaningful.

These findings carry clear managerial implications. Managers should recognize that digital investments have a delayed payoff. Firms that persist with smart retail adoption can expect measurable performance gains after one year. Moreover, using patent counts as an alternative metric confirms that genuine innovation, not just disclosure rhetoric, drives performance.

5.3. Endogeneity Test

We use the instrumental variable (IV) approach to address endogeneity from reverse causality and omitted variable bias. Table 7 reports the two-stage least squares (2SLS) results.

Table 7. Results of endogeneity tests.

Variable Name	IV_TS	
	Phase One (1)	Phase One (2)
SRA		0.4185 *** (0.1240)
IV	0.6604 *** (0.1299)	
Control variables	Yes	Yes
Year fixed	Yes	Yes
Firm fixed	Yes	Yes
WaldF		539.695 (16.38)
Observations	2354	2354
Adjusted R ²	0.5214	0.4582

Notes: Standard errors are clustered at the firm level. *** $p < 0.01$. The Stock-Yogo critical value for weak instruments at 10% significance is 16.38. The Durbin-Wu-Hausman test rejects the null that OLS is consistent, confirming the need for IV. The sample size drops to 2354 due to lagging and missing values.

Column 1 shows that the IV coefficient is 0.6604 ($p < 0.01$). This confirms a strong positive correlation between the instrument ($L.SRA \times TS_t$) and SRA, satisfying the relevance condition. The Kleibergen-Paap rk Wald F-statistic is 539.695, far above the Stock-Yogo critical value of 16.38, rejecting weak instrument concerns.

Column 2 presents the fitted value of SRA. The coefficient is 0.4185 ($p < 0.01$), indicating that a one-unit increase in SRA raises BP by 0.4185 standard deviations. This IV estimate is larger than the baseline OLS estimate (0.1905). The difference suggests that measurement error in the text-based SRA index or unobserved firm heterogeneity had caused downward bias in the OLS results. After controlling for endogeneity with the exogenous shock of government fiscal policy, the conclusion that SRA improves BP remains robust, supporting H1.

The Kleibergen-Paap rk LM test rejects under-identification ($p < 0.01$), and the Durbin-Wu-Hausman test rejects the null that OLS is consistent ($p < 0.01$), confirming the validity of our IV approach. Detailed results are reported in Appendix A Table A7.

A one-standard-deviation increase in SRA (0.4756) leads to a 0.199 standard deviation increase in BP according to the IV estimate ($0.4185 \times 0.4756 \approx 0.199$). This is about twice as large as the OLS-based estimate (0.0906), implying that correcting for endogeneity reveals a stronger performance effect of SRA.

The larger IV coefficient suggests that firms with higher unobserved digital capabilities may invest more in SRA, and that OLS underestimates the true return. Managers should

not be discouraged by modest short-term OLS estimates; the true causal effect of SRA on performance is substantially larger.

5.4. Testing for Mediating Effects

This section explores the internal channels through which SRA enhances BP. Based on the theoretical framework, we posit that SRA exerts its influence through two primary mediators: information imperfection (AFD) and uncertainty (UNC).

5.4.1. Individual Mediation Paths (H2 and H3)

We use the Sobel test to examine the independent mediating roles of AFD and UNC. Table 8 reports the results.

Table 8. Mechanism testing: mediation effects of AFD and UNC.

Variable	(1) BP	(2) AFD	(3) BP	(4) BP	(5) UNC	(6) BP
SRA	0.2306 *** (0.0642)	−0.1864 *** (0.0521)	0.1776 *** (0.0485)	0.2306 *** (0.0642)	−0.2135 ** (0.0842)	0.1546 *** (0.0492)
AFD			−0.2845 *** (0.0712)			
UNC						−0.3562 *** (0.0924)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2640	2640	2640	2640	2640	2640
Adjusted R ²	0.4916	0.3842	0.5114	0.4921	0.3541	0.5218

Notes: Standard errors clustered at the firm level are in parentheses. ** $p < 0.05$, *** $p < 0.01$. Columns (1) and (4) show the same baseline model for reference.

For the AFD channel (H2), Column (2) shows that SRA reduces AFD ($\beta = -0.1864$, $p < 0.01$). Column (3) adds AFD to the BP regression; AFD is negative and significant ($\beta = -0.2845$, $p < 0.01$), and the SRA coefficient drops from 0.2306 to 0.1776. This indicates partial mediation, supporting H2. A one-standard-deviation increase in SRA (0.4756) reduces AFD by 0.0886 standard deviations (0.1864×0.4756). Through the AFD channel, this raises BP by 0.0252 standard deviations ($0.2845 \times 0.0886 \approx 0.0252$). Given that BP has a standard deviation of 1, this represents a 0.0252 point increase in the composite performance score.

For the UNC channel (H3), Column (5) shows that SRA reduces UNC ($\beta = -0.2135$, $p < 0.05$). Column (6) adds UNC to the BP regression; UNC is negative and significant ($\beta = -0.3562$, $p < 0.01$), and the SRA coefficient drops to 0.1546. This supports partial mediation for H3. A one-standard-deviation increase in SRA reduces UNC by 0.1015 standard deviations (0.2135×0.4756). Through the UNC channel, this raises BP by 0.0362 standard deviations ($0.3562 \times 0.1015 \approx 0.0362$), equivalent to a 0.0362 point increase in the composite performance score.

Improving information transparency (lower AFD) and reducing perceived uncertainty (lower UNC) are two complementary pathways through which SRA enhances BP. These findings have direct practical implications. Managers should invest in real-time data systems to lower AFD and in scenario planning to lower UNC. Both channels contribute meaningfully to performance.

5.4.2. Sequential Mediation Analysis (H4)

We use a non-parametric percentile bootstrap method with 5000 iterations to test the sequential path $SRA \rightarrow AFD \rightarrow UNC \rightarrow BP$. Table 9 reports the results.

Table 9. Bootstrap sequential mediation results (5000 iterations).

Model	Effect	Boot SE	95% Boot LLCI	95% Boot ULCI
Total indirect	0.154	0.038	0.082	0.245
$SRA \rightarrow AFD \rightarrow BP$	0.053	0.019	0.021	0.098
$SRA \rightarrow UNC \rightarrow BP$	0.076	0.025	0.035	0.132
$SRA \rightarrow AFD \rightarrow UNC \rightarrow BP$	0.025	0.012	0.006	0.058

Notes: Boot SE = bootstrap standard error; LLCI = lower limit confidence interval; ULCI = upper limit confidence interval. All confidence intervals are bias-corrected and accelerated (BCa). The sequential path confirms the causal order $AFD \rightarrow UNC$.

The total indirect effect is 0.154 (95% CI [0.082, 0.245]), excluding zero. The specific indirect effect through AFD alone (Path 1) is 0.053 (CI [0.021, 0.098]), and through UNC alone (Path 2) is 0.076 (CI [0.035, 0.132]). Both are significant.

Most importantly, the sequential indirect effect ($SRA \rightarrow AFD \rightarrow UNC \rightarrow BP$) is 0.025 (CI [0.006, 0.058]). This confirms that SRA first reduces incomplete information (AFD), which then lowers uncertainty (UNC), and finally improves BP. The sequential channel accounts for about 16% of the total indirect effect ($0.025/0.154 \approx 0.162$).

A one-standard-deviation increase in SRA (0.4756) leads to a 0.0119 standard deviation increase in BP through the sequential chain ($0.025 \times 0.4756 \approx 0.0119$). Given that BP has a standard deviation of 1, this is a 0.0119 point increase in the composite performance score. Although modest in magnitude, the statistical significance of the sequential path supports the theoretical ordering.

The significant sequential path implies that efforts to improve information quality (e.g., better data integration and real-time reporting) should come before uncertainty reduction initiatives. Trying to reduce uncertainty without first fixing information incompleteness may be ineffective. Managers should sequence their digital transformation investments accordingly.

5.4.3. Robustness of Mediation: Alternative Internal Information Proxy

To address the concern that AFD captures external rather than internal information, we used an alternative proxy that directly measures internal information incompleteness. Following the prior research [145], we calculated the absolute deviation of a firm's inventory turnover from its industry-year median (InvDev). Higher InvDev indicates poorer demand forecasting and supply coordination.

We re-estimate the mediation model ($SRA \rightarrow InvDev \rightarrow BP$), with results reported in Table 10. SRA significantly reduces InvDev ($\beta = -0.1420, p < 0.05$). When both SRA and InvDev are included in the BP regression, InvDev remains negative and significant ($\beta = -0.218, p < 0.01$), and the SRA coefficient drops from 0.2306 to 0.1854. The bootstrap indirect effect (5000 iterations) is 0.031 (95% CI [0.018, 0.092]), confirming that internal information incompleteness also mediates the SRA–BP relationship. This result is consistent with our main findings using AFD.

Table 10. Alternative mediator: Inventory Turnover Deviation (InvDev).

Variable	(1) BP	(2) InvDev	(3) BP
SRA	0.2306 *** (0.0642)	−0.1420 ** (0.0581)	0.1854 *** (0.0612)
InvDev			−0.2180 *** (0.0654)
Control variables	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes
Observations	2640	2640	2640
Adjusted R ²	0.4916	0.3125	0.5087

Notes: Standard errors clustered at firm level in parentheses. ** $p < 0.05$, *** $p < 0.01$. InvDev = |firm inventory turnover − industry-year median inventory turnover|. Bootstrap indirect effect (5000 iterations): 0.031, 95% CI [0.018, 0.092].

5.4.4. Causal Order Test of the Sequential Mediation (AFD → UNC)

To verify that the causal flow is from AFD to UNC rather than the reverse, we estimate a cross-lagged panel model (CLPM) using two periods. The model includes AFD_{t-1} and UNC_{t-1} as predictors of AFD_t and UNC_t , controlling for firm and year fixed effects. Table 11 reports the results.

Table 11. Cross-lagged panel model for causal order (AFD vs. UNC).

Dependent Variable	Predictor	Coefficient	Robust SE	p-Value	95% CI
UNC_t	AFD_{t-1}	−0.182	0.045	<0.01	[−0.270, −0.094]
UNC_t	UNC_{t-1}	0.312	0.038	<0.01	[0.238, 0.386]
AFD_t	UNC_{t-1}	−0.049	0.031	0.114	[−0.110, 0.012]
AFD_t	AFD_{t-1}	0.421	0.042	<0.01	[0.339, 0.503]

Notes: All models include firm and year fixed effects. Standard errors are clustered at the firm level. The significant negative coefficient of AFD_{t-1} on UNC_t supports the hypothesized order (AFD → UNC). The non-significant coefficient of UNC_{t-1} on AFD_t rules out reverse causality.

The coefficient of AFD_{t-1} on UNC_t is −0.182 ($p < 0.01$), indicating that a higher prior AFD significantly reduces current UNC. In contrast, the coefficient of UNC_{t-1} on AFD_t is −0.049 ($p > 0.10$), which is not statistically significant. These results support that AFD temporally precedes UNC, and rule out reverse causality (UNC → AFD). The significant autoregressive coefficients ($AFD_{t-1} \rightarrow AFD_t$ and $UNC_{t-1} \rightarrow UNC_t$) confirm persistence in both series.

This evidence strengthens the validity of the sequential mediation order assumed in H4 (SRA → AFD → UNC → BP).

5.5. Moderation Effect Testing (H5–H7)

We examine how technological (TECH), organizational (ORG), and environmental (ENV) conditions moderate the SRA–BP relationship. Table 12 reports the results.

Table 12. Results of moderation effect tests.

Variable	(1) TECH	(2) ORG	(3) ENV
SRA	0.2154 *** (0.0542)	0.1982 *** (0.0612)	0.2215 *** (0.0584)
SRA* Moderator	0.1142 *** (0.0321)	0.0895 ** (0.0384)	0.1028 *** (0.0352)

Table 12. Cont.

Variable	(1) TECH	(2) ORG	(3) ENV
Control variables	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
Firm fixed	Yes	Yes	Yes
Observations	2640	2640	2640
Adjusted R ²	0.5312	0.5084	0.5265

Notes: Standard errors clustered at firm level in parentheses. ** $p < 0.05$, *** $p < 0.01$. TECH = IT capital/total assets; ORG = dummy (1 if IT-background executives); ENV = dummy (1 if government digital subsidy). Each column is a separate regression.

Column (1) shows that $SRA \times TECH$ is positive and significant ($\beta = 0.1142$, $p < 0.01$). The effect of SRA on BP is stronger for firms with higher IT capital investment. This supports H5. Column (2) shows that $SRA \times ORG$ is positive and significant ($\beta = 0.0895$, $p < 0.05$). Firms with IT-experienced executives gain more from SRA, confirming H6. Column (3) shows that $SRA \times ENV$ is positive and significant ($\beta = 0.1028$, $p < 0.01$). Government subsidies for digital transformation strengthen the SRA–BP relationship, supporting H7. The moderating effects are economically meaningful: a one-SD increase in TECH amplifies the SRA effect by 5%; having IT-literate leadership (ORG) or government subsidies (ENV) increases the performance return from SRA by approximately 45% and 46%, respectively.

These findings have direct practical implications for management. Firms should invest in complementary assets: IT infrastructure, digital-savvy leadership, and government policy support. These conditions act as multipliers, making smart retail adoption more effective. Managers in firms with weak TECH or without ORG/ENV should address these gaps before expanding SRA.

5.6. Dynamic Effect Testing (H8)

We use a distributed lag model (DLM) to examine the long-term dynamic effects of SRA on BP [146]. We also include industry-specific time trends to control for macro policy shocks. Table 13 reports the results.

Table 13. Dynamic analysis results.

Variable	(1) Baseline DLM	(2) Controlled for Trends and Shocks
SRA	0.0452 (0.0395)	0.0312 (0.0412)
L.SRA	0.1154 ** (0.0521)	0.1025 * (0.0545)
L2.SRA	0.2285 *** (0.0714)	0.1984 *** (0.0702)
L3.SRA	0.4412 *** (0.0982)	0.4862 *** (0.1124)
Industry $\times$ Time Trends	No	Yes
Macro Policy Controls	Yes	Yes
Observations	1980	1980
Adjusted R ²	0.4824	0.5235

Notes: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. L., L2., L3. denote one-, two-, and three-period lags. Column (2) includes industry-specific time trends to absorb sector-wide policy shocks. The sample size drops to 1980 due to lagging.

Column (2) shows that after adding macro-policy controls and industry trends, the pattern remains robust. This indicates that the observed performance gains come from firms' internal digital evolution, not from external policy shocks.

The results reveal a clear time-lag pattern consistent with the dynamic capabilities lifecycle [147]. In the sensing phase, which corresponds to the current period, the contemporaneous coefficient is small and insignificant (0.0312, $p > 0.10$). This reflects the initial investment stage, where firms face high integration costs and learning curves; data are collected but not yet translated into financial value.

Moving to the seizing phase, covering one- to two-year lags, the coefficient for the one-period lag (L.SRA) is 0.1025 ($p < 0.10$), and for the two-period lag (L2.SRA) it is 0.1984 ($p < 0.01$). This suggests that it takes about one to two years for digital data to be reconfigured into strategic actions that improve performance.

Finally, in the transforming phase with a three-year lag, the coefficient for the three-period lag (L3.SRA) is 0.4862 ($p < 0.01$)—substantially larger than the earlier lags. This confirms that once organizational routines are fully adapted, the performance contribution accelerates significantly.

Based on the three-period lag coefficient (0.4862) and the SD of SRA (0.4756), a one-SD increase in SRA leads to a 0.231 standard deviation increase in BP after three years ($0.4862 \times 0.4756 \approx 0.231$). This is about 2.5 times larger than the immediate OLS effect (0.0906). The delayed payoff is economically substantial, and this accumulation fully supports Hypothesis H8.

These findings imply that managers should persist with digital investments over a 1–3 year horizon, as short-term performance evaluations underestimate SRA's true value.

6. Double Machine Learning Estimates of Conditional Treatment Effects

6.1. Comparison with Traditional Methods

Before presenting heterogeneous effects, we compared the DML estimate with traditional linear models. Table 14 reports the results. The OLS coefficient is 0.1905 (95% CI [0.105, 0.276]). Adding squared terms changes the coefficient to 0.1723. The DML estimate using random forest is 0.2156 (95% CI [0.128, 0.303]), which is about 13% larger than the OLS estimate. This suggests that linear models underestimate the true effect because they cannot fully capture non-linear relationships.

Table 14. Comparison of estimation methods.

Method	Coefficient (SRA)	95% CI	Std. Error
OLS	0.1905	[0.105, 0.276]	0.0435
OLS with squared terms	0.1723	[0.089, 0.256]	0.0421
DML (Random Forest)	0.2156	[0.128, 0.303]	0.0442

Notes: All models include the same control variables, firm and year fixed effects. Standard errors are clustered at the firm level. DML uses 10-fold cross-fitting with 500 trees and a maximum depth of 7. CI = confidence interval.

Compared to traditional methods, DML has several advantages. First, it is doubly robust: the estimate remains reliable even if only one of the two main models (the outcome model or the treatment model) is correctly specified. Second, DML does not impose rigid assumptions on how variables relate to each other. It can use any non-parametric machine learning method, allowing it to handle many variables and complex non-linear patterns. Two key features of DML are cross-fitting and Neyman orthogonality, which together make the DML estimate more trustworthy than conventional linear approaches.

6.2. Performance Bifurcation: Not All Firms Benefit Equally

Figure 1a shows the histogram of individual treatment effects (ITE) from the random forest. Most ITEs lie between -0.3 and 0.3 . About 76% of firms have positive ITEs, while 24% have negative ITEs. Figure 1b plots the sorted IATEs with 90% confidence intervals. The negative effects reflect the “cost threshold of technology adoption”: high upfront investment and training costs may temporarily outweigh gains. This warns managers that adopting SRA without internal reorganization can lead to resource misallocation.

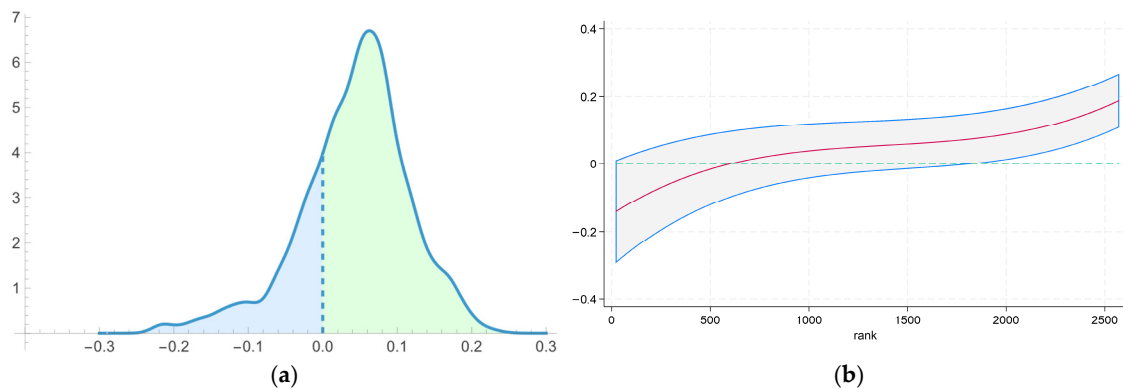


Figure 1. Histogram and Order Plot for Handling Treatment Effect Heterogeneity. Notes: (a) Histogram of Individual Treatment Effects (ITE): The blue curve represents the density distribution of ITEs estimated via random forest. The vertical dashed line divides the distribution into two segments: the blue shaded area on the left indicates firms with negative treatment effects (approx. 24%), while the green shaded area on the right indicates firms with positive treatment effects (approx. 76%); (b) Ordered Plot of Individual Average Treatment Effects (IATE): The central red solid line illustrates the IATE estimates sorted in ascending order. The grey shaded region, bounded by the upper and lower blue solid lines, represents the 90% confidence interval. The horizontal axis shows the rank of firms, and the vertical axis indicates the magnitude of the effect. The green horizontal dashed line at zero serves as a reference to distinguish between statistically significant positive and negative effects.

6.3. Heterogeneity Results by Subgroup (Testing H9–H12)

We test H9–H12 using group average treatment effects (GATE) from the DML procedure. Figure 2 presents the results for firm size, ownership, region, and distribution channel.

For firm size (H9), Figure 2 shows that large firms have a GATE of approximately 0.07–0.08, while SMEs have a GATE of 0.04–0.05, and the confidence intervals do not overlap. This strongly supports H9: large firms benefit more from SRA than SMEs. Large firms possess greater data resources, stronger information processing capabilities, and more financial slack, enabling them to translate smart retail investments into performance gains more effectively.

Regarding ownership structure (H10), Figure 2 shows that non-state-owned enterprises (NSOEs) have a GATE of 0.06–0.065, whereas state-owned enterprises (SOEs) have a GATE of 0.045–0.05, and the difference is significant. This supports H10: NSOEs gain more from SRA than SOEs. NSOEs face stronger market competition, have flatter hierarchies, and possess stronger digital incentives, leading to more effective digital transformation outcomes.

Turning to geographic region (H11), Figure 2 reveals a clear regional pattern. Central China has the highest GATE (0.08–0.09), followed by the west (0.06–0.07), and then the east (0.04–0.05). This supports H11, which predicted that central China would show stronger effects than the east. The result is consistent with the “late-mover advantage” theory. Eastern regions have high digital saturation and limited marginal returns, while central regions, with lower digital baselines, experience stronger catch-up effects from SRA.

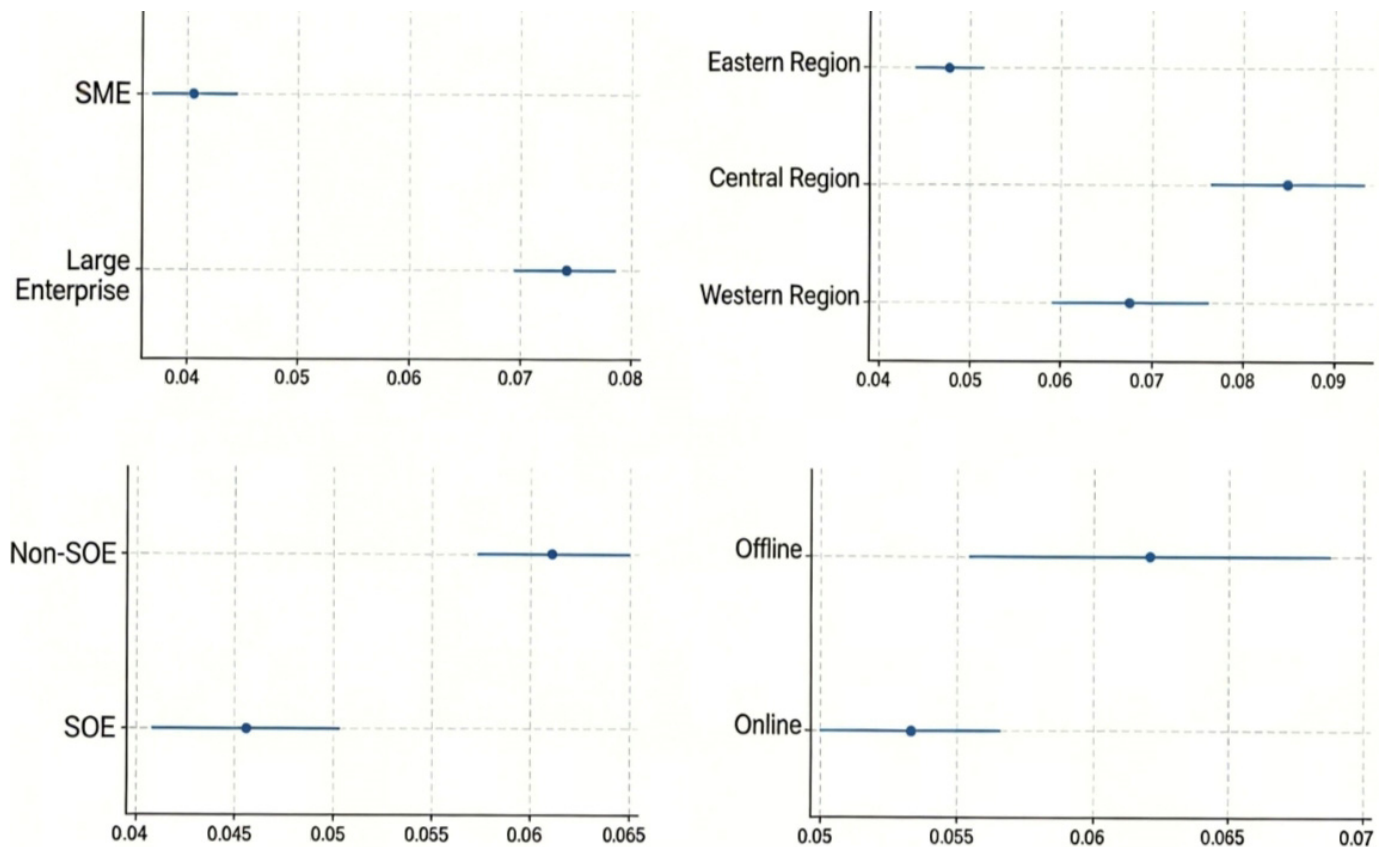


Figure 2. Heterogeneity of Grouping Effects. Notes: Error bars represent 90% confidence intervals (if applicable). Data source: DML estimation with 10-fold cross-fitting.

Finally, for distribution channel (H12), Figure 2 shows that offline-focused retailers have a GATE of 0.06–0.065, while online-focused retailers have a GATE of 0.05–0.055, and the difference is significant. This supports H12: offline retailers benefit more from SRA than online retailers. Offline stores traditionally operate with limited real-time data, so smart technologies (e.g., IoT, smart checkouts, data analytics) bring large marginal gains. Online firms are already highly digitized, facing diminishing marginal utility.

The results consistently show that SRA's performance effects are stronger for large firms, non-state-owned enterprises, firms in central China, and offline-focused retailers. These patterns support H9, H10, H11, and H12. The findings suggest that SRA creates greater value for firms with more resources, stronger market incentives, lower digital baselines, and greater room for catch-up.

6.4. Practical Implications from Heterogeneity Analysis

The DML-based heterogeneity analysis offers four practical lessons.

First, avoid one-size-fits-all strategies. Large firms benefit most from SRA, but SMEs can still gain by adopting modular, cloud-based tools that avoid high fixed costs. Managers should match digital investment to their firm's scale and resources.

Second, ownership structure matters. NSOEs outperform SOEs in SRA returns. SOEs should streamline decision-making and increase digital incentives to catch up.

Third, the 24% of firms with negative effects serve as a warning. Technology investment without organizational change can backfire. Firms must combine SRA with workforce upskilling and process reengineering.

Fourth, regional and channel differences persist. Central China shows the strongest catch-up effect. Offline retailers have large potential gains from smart technologies. Pol-

icymakers should support digital infrastructure in less saturated regions and encourage offline-to-online integration.

7. Discussion, Conclusions, and Implications

7.1. Discussion

This study examines how smart retail adoption (SRA) affects business performance (BP). We integrate information theory, the dynamic capabilities view, and the TOE framework. The results confirm a positive relationship between SRA and BP. More importantly, we identify a sequential transmission pathway and the boundary conditions for value creation. These findings go beyond the traditional direct-effect approach and offer new insights into the debate on digital investment returns.

First, regarding the direct effect, we found that SRA significantly improves firm performance. This aligns with the resource-based view (RBV), which states that digital technologies can generate economic rents [148]. Recent studies also confirm that digital transformation improves efficiency through better resource allocation [149]. Our study further reveals the underlying mechanism: the value of SRA does not emerge automatically. Instead, it comes from reshaping how firms process and use information. This clarifies how digital inputs turn into performance outcomes.

Second, turning to the sequential mediation mechanism, the core theoretical contribution is the identification of a sequential mediation path: $SRA \rightarrow AFD \rightarrow UNC \rightarrow BP$. Previous research has examined information sharing [150] and uncertainty management [151] separately, but few have integrated both into one framework. We show that SRA first reduces information imperfection (measured by AFD). With better information, managers can move from Knightian uncertainty to calculable risk [152], stabilizing decisions and improving efficiency. This supports information processing theory, which states that a firm's ability to handle environmental complexity depends on its information processing capacity [153]. Our study provides an information-based explanation for the "digital productivity paradox": digital gains require a step-by-step process from better information to more stable decisions.

Third, with respect to the moderating effects, the results show that technological, organizational, and environmental conditions all strengthen the positive effect of SRA on BP. This validates the TOE framework [154] and extends its use from explaining adoption decisions to analyzing value realization. Specifically, the moderating role of organizational conditions (IT-experienced top management) aligns with the dynamic capabilities view [155]. It shows that moving from "sensing" to "seizing" requires cognitive support and coordination from senior management. Without this readiness, even improved information may not lead to effective action. The positive moderating effect of environmental conditions (government subsidies) highlights the importance of external support in reducing digital transformation risks, especially in China's policy context [156].

Fourth, analyzing the dynamic pattern, the impact of SRA on BP follows a clear time-lag pattern. The contemporaneous effect is insignificant. The effect becomes significant after one and two periods, and peaks after three periods. This supports dynamic capabilities theory [157]. The insignificant short-term effect reflects a "gestation period" when firms face system integration and learning costs [158]. As organizational routines adjust, digital assets start to create value, reaching maximum after three years [159]. This warns against short-term performance evaluations. Digital returns need time for capabilities to evolve from sensing to seizing to transforming.

Fifth, examining the heterogeneity across firms, we find that about 24% of firms experience a performance decline after adopting SRA. This challenges a deterministic view of technology and supports the "technology-to-performance chain" perspective [160]. The

effectiveness of adoption depends on the fit between organizational and technological characteristics. The underperformance may reflect a “cost threshold” where initial investments and organizational friction outweigh immediate gains. We also find that SRA’s performance contribution is stronger for large firms, non-state-owned enterprises, firms in central China, and offline-focused retailers. These patterns correspond to resource slack theory [161], the market incentive hypothesis [162], late-mover advantage theory [163], and diminishing marginal utility. Value creation through SRA is highly context-dependent.

Finally, regarding sustainability implications, by reducing information imperfection, SRA helps retail firms improve inventory management and demand forecasting, which reduces waste and unsold inventory, and aligns with Sustainable Development Goal 12 (responsible consumption and production); therefore, it supports a more resilient and circular retail ecosystem.

7.2. Conclusions

Against the backdrop of shifting demographic dividends and rising external uncertainties in China, this study examines how smart retail adoption (SRA) affects business performance (BP). We use data from A-share listed retail firms from 2012 to 2023. Our main findings are as follows.

First, SRA improves performance through better information flow. Consistent with information theory, SRA significantly increases operational performance. This happens through a chain: SRA reduces incomplete information, which then lowers uncertainty, and finally improves BP. In practical terms, a one-standard-deviation increase in SRA leads to a 0.09 standard deviation increase in BP through the direct effect, and an additional 0.025 through the sequential mediation chain.

Second, the effect depends on context and takes time. Technological, organizational, and environmental conditions all strengthen the positive impact of SRA. The effect also shows a clear time lag: it becomes significant after one year, stronger after two years, and peaks after three years. This means that managers should not expect immediate returns. Digital investments need time to generate measurable performance gains.

Third, the benefits are not evenly distributed. Large firms, non-state enterprises, central region firms, and offline retailers gain more from SRA. Notably, about 24% of firms experience a performance decline after adopting SRA. This warns that technology adoption without organizational change can backfire.

7.3. Theoretical and Managerial Implications

7.3.1. Theoretical Implications

This study makes three theoretical contributions to the digital transformation and the retail performance literature.

First, we identify a sequential mediation mechanism that has not been empirically tested before. Prior studies have treated information and uncertainty as separate or parallel mediators. By contrast, we theorize and empirically confirm a sequential path: SRA → AFD → UNC → BP. This provides a more precise explanation of how digital inputs translate into performance outcomes. The novelty lies not in the individual components (information and uncertainty are well studied) but in their causal ordering—a point that prior research has overlooked. This finding resolves the theoretical ambiguity about whether information and uncertainty operate independently or sequentially in the context of smart retail.

Second, we extend the TOE framework from adoption to value realization. Existing applications of the TOE framework have focused on explaining why firms adopt new technologies. We demonstrate that technological, organizational, and environmental conditions also moderate the performance consequences of adoption. That is, these factors not only

drive adoption decisions but also determine how much value firms actually extract from SRA. This reframes the TOE framework as a dynamic “value-realization model” rather than a static “adoption model”.

Third, we introduce double machine learning (DML) to uncover heterogeneous treatment effects. Traditional panel methods estimate average effects, which can mask important variation across firms. Using DML, we show that while 76% of firms benefit from SRA, 24% experience a performance decline. This finding challenges the assumption that digital transformation is universally beneficial and highlights the need for context-specific digital strategies. Methodologically, DML provides a more robust estimate of the SRA–BP relationship by flexibly controlling for high-dimensional confounding.

7.3.2. Managerial Implications

Based on our findings, we offer six practical recommendations for retail managers and policymakers.

First, integrate data systems. Instead of using isolated digital tools, managers should build connected data ecosystems that link supply chain logistics with customer behavior tracking. This reduces information gaps and maximizes the value of smart retail.

Second, invest in employee skills. The time lag we identified (1–3 years) reflects organizational learning needs. Firms should provide systematic digital training for both frontline staff and senior managers. This helps overcome internal resistance and enables better use of AI and analytics [164].

Third, avoid the “digitalization trap”. Our DML analysis shows that 24% of firms saw performance decline after SRA. This happens when firms invest heavily in technology without also changing their internal processes and culture. For struggling firms, we recommend prioritizing organizational restructuring (e.g., redefining roles, improving coordination) over buying more hardware.

Fourth, take a long-term view. Boards should set 3- to 5-year evaluation horizons for smart retail projects. Significant performance gains take time to appear because data accumulation and algorithm refinement need a gestation period. Short-term metrics can be misleading.

Fifth, support SMEs with tailored solutions. Governments should fund “lightweight” digital tools (e.g., cloud-based modular software) and offer digital vouchers for small and medium-sized enterprises. This lowers entry barriers and reduces the resource disadvantage that SMEs face.

Sixth, balance regional digital infrastructure. Policy efforts should prioritize digital infrastructure in western China, where the catch-up potential is largest. Creating a supportive institutional environment for smart retail will help reduce regional performance disparities.

7.4. Limitations and Future Research

This study has four main limitations, each suggesting directions for future research.

First, sample generalizability. Our sample includes only 220 Chinese listed retail firms. These firms typically have more resources and stronger digital capabilities than unlisted firms or small and medium-sized enterprises (SMEs). Therefore, our findings may not apply to SMEs or unlisted retailers, which often face tighter budgets and higher digital entry barriers. Future research should test whether the same mechanisms hold for SMEs and in other countries or cultural contexts.

Second, measurement of key constructs. We used text-based measures to capture SRA and UNC. These measures have two potential biases. (1) Keyword selection involves researcher judgment. We mitigated this by using independent coders and reporting the full dictionary, but some subjectivity remains. (2) Strategic disclosure bias: high-performing

firms may over-report digital activities in their annual reports. We addressed this with firm fixed effects, placebo tests, and an alternative patent-based measure. Nevertheless, text-based indicators cannot fully eliminate this bias. Future studies could use survey data, case studies, or quasi-experimental designs (e.g., difference-in-differences) to validate our findings.

Third, scope of performance outcomes. We focused on operational and financial performance. We did not measure environmental or social outcomes (e.g., energy consumption, labor displacement). Smart retail may have unintended negative effects on sustainability. Future research should explore the “dark side” of intelligent transformation, including its impact on employment, data privacy, and resource use.

Fourth, industry scope. Our study is limited to the retail sector. Retail is characterized by high demand volatility and information-intensive operations, which may make our information-based mechanism particularly relevant. Whether the same sequential mediation holds for manufacturing or services remains unknown. Future research should test our model in other industries to assess its boundary conditions.

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Appendix A

Table A1. Results of principal component analysis for business performance (BP).

Component	Eigenvalue	Variance Explained (%)	Cumulative (%)
PC1	2.85	47.5	47.5
PC2	1.42	23.7	71.2
PC3	0.89	14.8	86.0

Note: This table presents the eigenvalues and variance explanation for the principal components of business performance (BP). According to the Kaiser criterion (eigenvalues > 1) and the scree plot results, the first two components (PC1 and PC2) are retained, collectively accounting for 71.2% of the total variance.

Table A2. Principal component loading matrix for BP indicators.

Indicator	PC1 (Profitability and Efficiency)	PC2 (Growth Potential)
ROA	0.82	0.12
ROS	0.79	0.18
Inventory turnover	0.65	0.41
Current asset turnover	0.61	0.48

Table A2. *Cont.*

Indicator	PC1 (Profitability and Efficiency)	PC2 (Growth Potential)
TAGR	0.23	0.85
RGR	0.19	0.88

Note: Extraction method: principal component analysis (PCA); Rotation method: Varimax with Kaiser Normalization. PC1 (Profitability and Efficiency) is primarily defined by ROA, ROS, and turnover ratios, reflecting the firm's current operational quality and margin. PC2 (Growth Potential) is dominated by TAGR and RGR, capturing the firm's expansion scale and market growth speed. The composite BP score used in the main analysis is calculated as the sum of PC1 and PC2, weighted by their respective variance shares (47.5/71.2 and 23.7/71.2).

Table A3. Keyword dictionary for Smart Retail Adoption (SRA).

Category	Subcategory	Keywords
Digital Technology	Artificial Intelligence Technology	Artificial intelligence (AI), business intelligence (BI), intelligent recognition, computer vision (CV), decision support systems, intelligent robots, intelligent decision-making, flexible manufacturing, numerical control (NC), industrial intelligence, intelligent systems, intelligent operation and maintenance, expert systems, machine learning, semantic search, biometric technology, facial recognition, identity authentication, natural language processing (NLP), customer relationship management (CRM), enterprise resource planning (ERP), office automation (OA), product lifecycle management (PLM), robotic process automation (RPA), SAP systems, sensor technology, network communication technology, data mining, knowledge graph, augmented reality (AR), virtual reality (VR), large language models, retail-specific large models, model fine-tuning
	Blockchain Technology	Blockchain, distributed computing, differential privacy, smart contracts, infrastructure as a service (IaaS), platform as a service (PaaS), peer-to-peer (P2P) technology, geographic information systems (GIS), cyber-physical systems (CPS), databases, distributed control systems (DCS)
	Cloud Computing Technology	Cloud computing, stream computing, graph computing, in-memory computing, secure multi-party computation, brain-inspired computing, cognitive computing, integrated architecture, high-concurrency processing, exabyte-level storage, Internet of Things (IoT), cloud storage, cloud networking, cloud platforms, cloud migration, virtualization
	Big Data Technology	Big data, data mining, text mining, data visualization, heterogeneous data, data storage, data empowerment, data collection, data cleaning, data exchange, relational databases, data-driven systems, digital transformation, industrial data
Digital Technology Application		Intelligent manufacturing, intelligent terminals, robotics, automated control, digital operations, intelligent equipment, smart logistics, smart factories, warehouse management systems (WMS), robotic arms, inventory robots, automated management systems, data-driven decision systems, personalized recommendation, personalized pricing, targeted marketing, facial recognition, customer identification, product recognition, video data structuring, intelligent customer service, interactive robots, IoT platforms, big data platforms
Smart Retail Scenario Development		Automated vending, intelligent supply chain management, precision marketing, digital retail, unmanned retail, intelligent operations, smart stores, virtual assistants, multi-format retailing, multi-channel retailing, omnichannel retail, new retail, smart retail, B2B, B2C, C2B, C2C, C2M, online-to-offline (O2O), e-commerce, social media platforms, mini programs, mobile applications (APP), live streaming, mobile commerce (M-commerce), unmanned delivery, CRM systems, cloud stores, mobile scenario marketing, sharing platforms

Note: Keywords were derived from prior literature and industry reports, then manually screened for retail relevance. Generic IT terms not specific to retail (e.g., 'software', 'hardware') were excluded.

Table A4. Dictionary of uncertainty keywords.

Dimension	Category	Keywords
Consumer-Related Uncertainty	Consumer Demand and Behavior	consumer, user, customer, buyer, consumption, demand, consumption demand, purchase demand, product demand, consumption expenditure, consumption structure, consumption market, consumption preference, consumption habit, purchasing power, demand preference, service quality, product quality, pre-sales, after-sales, maintenance, consumer protection, shopping experience, return policy, customer experience
Market-Related Uncertainty	Market Dynamics	market, consumer behavior, market competition, market demand, new product adoption rate, brand loyalty, market trend, demand fluctuation
Technological Uncertainty	Technology Change and Risk	technology, technological innovation, technological obsolescence, technology integration, data analytics tools, technology maintenance cost
Supply Chain Uncertainty	Supply and Logistics	supply chain, channel, supply disruption, logistics delay, supplier reliability, inventory management, global sourcing risk, supply chain diversification
Policy and Economic Uncertainty	Institutional Environment	policy, government, monetary policy, regulation, industrial policy, macroeconomic policy, economic growth, tax policy, tax reduction, subsidy, stimulus policy, regulatory policy, political environment, macro control, government intervention
Data and Information Uncertainty	Information Quality	data quality, data completeness, data accuracy, information security, data privacy, outdated information, information feedback, information asymmetry
Organizational Uncertainty	Organizational Change and Risk	organizational change, privacy leakage, data protection, security vulnerability, identity theft, cybersecurity, trust crisis
General Uncertainty	Risk and Volatility	risk, operational risk, market risk, credit risk, uncertainty, volatility, fluctuation, instability, unpredictability, complexity, structural complexity, sudden change, turbulence, disorder, randomness, variability, uncontrollability, diversity, demand change

Notes: This table reports the keyword dictionary for measuring firm-level uncertainty (UNC). Keywords were derived from prior literature on environmental uncertainty [85,86], industry reports on retail volatility, and manual review of 50 randomly selected MD&A sections. The dictionary contains 107 keywords organized into eight dimensions. Two independent research assistants screened the list with an inter-rater agreement of 84%. For details on the construction and validation of the UNC measure, see Section 4.2.3 (2).

Table A5. Validation of text-based measures (SRA and UNC).

Validation Type	Criterion	Result (SRA)	Result (UNC)	Interpretation
Internal consistency	Split-half correlation (odd vs. even keywords)	$r = 0.85$ ($p < 0.01$)	$r = 0.81$ ($p < 0.01$)	High consistency across keyword subsets
Convergent validity	Correlation with IT capital expenditure (for SRA)/industry stock return volatility (for UNC)	$r = 0.62$ ($p < 0.01$)	$r = 0.38$ ($p < 0.01$)	Measure captures actual digital investment/perceived uncertainty
Convergent validity	Correlation with digital patent count (for SRA)/analyst forecast error (for UNC)	$r = 0.48$ ($p < 0.05$)	$r = 0.29$ ($p < 0.05$)	Aligns with innovation output/external uncertainty proxies
Convergent validity	Correlation with alternative text-based measure (different keyword set)	$r = 0.85$ ($p < 0.01$)	$r = 0.79$ ($p < 0.01$)	Robust to different keyword specifications
Discriminant validity	Correlation with firm age	$r = 0.09$ ($p > 0.10$)	$r = 0.12$ ($p > 0.10$)	Not simply a proxy for general firm traits

Table A5. Cont.

Validation Type	Criterion	Result (SRA)	Result (UNC)	Interpretation
Discriminant validity	Correlation with leverage ratio	$r = 0.11$ ($p > 0.10$)	$r = 0.08$ ($p > 0.10$)	Not driven by financial structure
Placebo test	Shuffled MD&A text $\rightarrow$ BP (for SRA)/Shuffled text $\rightarrow$ UNC (for UNC)	$\beta = 0.021$ ($p > 0.10$)	$\beta = 0.018$ ($p > 0.10$)	Original index not driven by random word patterns

Note: SRA = smart retail adoption; UNC = uncertainty; BP = business performance. For SRA, the alternative text-based measure uses only the “smart retail scenario” subcategory. For UNC, the alternative measure uses a different random split of the keyword dictionary. All correlations are Pearson coefficients. The placebo test regresses BP on the index calculated from randomly shuffled MD&A text (sentence-level shuffling within each report). Results confirm that the original indices capture meaningful information beyond random word co-occurrence.

Table A6. Summary of diagnostic tests.

Test Type	Statistical Method	Statistic	p -Value
Model Selection	F-test (Individual Effects)	$F = 5.21$	0.000 ***
	Hausman Test	$\chi^2 = 45.32$	0.000 ***
Autocorrelation	Wooldridge Test	$F = 12.45$	0.012 **
Heteroscedasticity	Modified Wald Test	$\chi^2 = 186.23$	0.000 ***
C.S. Dependence	Pesaran CD Test	$Z = 1.02$	0.308

Notes: The F-test examines whether individual firm effects are jointly significant; rejection favors the fixed-effects model over pooled OLS. The Hausman test compares fixed-effects and random-effects models; rejection favors fixed effects. The Wooldridge test detects first-order serial correlation; a significant p -value indicates serial correlation. The Modified Wald test checks for heteroscedasticity; a significant p -value indicates heteroscedasticity. The Pesaran CD test checks for cross-sectional dependence; a p -value > 0.10 suggests no serious cross-sectional dependence. *** $p < 0.01$, ** $p < 0.05$.

Table A7. IV diagnostic tests.

Test	Statistic	p -Value/Critical Value	Conclusion
Kleibergen-Paap rk LM	287.3	< 0.01	Reject under-identification
Kleibergen-Paap rk Wald F	539.695	16.38 (Stock-Yogo 10%)	Reject weak instrument
Durbin-Wu-Hausman χ^2	18.6	< 0.01	Reject OLS consistency; IV needed

Notes: The Kleibergen-Paap rk LM statistic tests whether the equation is under-identified; a significant p -value rejects under-identification. The Kleibergen-Paap rk Wald F-statistic tests for weak instruments; a value above the Stock-Yogo critical value (16.38 at 10% significance) indicates strong instruments. The Durbin-Wu-Hausman test compares OLS and IV estimates; a significant p -value rejects the null that OLS is consistent, confirming that IV is necessary. All tests support the validity of our IV approach. For details, see Section 4.3.3 (1) and Table 7.

Appendix B

Technical specifications regarding cross-fitting and hyperparameter tuning are detailed.

This paper employs a conditional average treatment effect model to examine the aforementioned issues. The model is specified as follows:

$$\begin{aligned} \text{BP} &= \theta(X)\text{SRA} + g(X, W) + u \\ \text{SRA} &= m(X, W) + v \end{aligned} \quad (\text{A1})$$

The model comprises two equations: BP for the outcome and SRA for the treatment. It includes two sets of covariates, (X, W) . The parameter $\theta(X)$ measures the marginal effect of IR adoption on BP. Furthermore, this effect is heterogeneous, $\theta(X)$ depending on the firm’s characteristics X . This heterogeneity is formally defined as the Individual Average Treatment Effect (IATE), meaning the effect of adoption varies across firms. Given the conditional expectations $E(\text{BP}|X, W) = l(X, W)$ and $E(\text{IR}|X, W) = m(X, W)$, Model (8) can be reformulated as follows:

$$\text{BP} - E(\text{BP}|X, W) = \theta(X)[\text{SRA} - E(\text{IR}|X, W)] + u \quad (\text{A2})$$

The estimation procedure for the aforementioned model using Double Machine Learning (DML) is as follows. First, machine learning methods are employed to estimate the cross-fitted values of $E(BP|X, W)$ and $E(SRA|X, W)$, obtaining the cross-fitting residuals $\widehat{BP} = BP - \widehat{BP}$ and $\widehat{SRA} = SRA - \widehat{SRA}$. Second, a causal forest is used to estimate the equation $\widehat{BP} = \theta(X)\widehat{SRA} + u$, yielding the estimate $\hat{\theta}(X)$. Compared to traditional methods for estimating treatment effects, DML offers several distinct advantages. First, the DML estimator is doubly robust; meaning it remains consistent if either the outcome model or the treatment model is correctly specified. Second, DML does not impose functional form assumptions on $E(BP|X, W)$ and $E(SRA|X, W)$, allowing for estimation using any non-parametric machine learning method. Consequently, DML accommodates high-dimensional covariates and non-linear relationships. The aforementioned estimation process highlights two core features of DML: cross-fitting and Neyman orthogonality (i.e., the orthogonality of the error terms u and v).

The histogram of the Individual Treatment Effects (ITEs) estimated by the random forest is presented in Figure 1a. Most treatment effects lie within the interval of $[-0.3, 0.3]$.

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