

Article

Does Financial Leverage Promote Sustainable Agricultural Productivity? Firm-Level Evidence from China Using a Risk-Adjusted TFP Approach

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Abstract

This study examines whether financial leverage promotes sustainable agricultural productivity by accounting for the trade-off between profitability and default risk. We construct a risk-adjusted total factor productivity (TFP) measure by incorporating default risk as an undesirable output into a slack-based DEA framework (USBM), with risk estimated via contingent claims analysis (CCA). Using panel data on Chinese listed agricultural firms, we find a robust inverted-U relationship between leverage and TFP, indicating an optimal leverage range. Mechanism analysis reveals a dual-channel effect: leverage improves productivity through profitability and reduced financing constraints at low levels but increases default risk and undermines financial sustainability at high levels. Decomposition results show that leverage promotes efficiency catch-up but inhibits frontier technological progress, implying a trade-off between short-term efficiency gains and long-term sustainability. Substantial heterogeneity across subsectors and market structures further suggests that optimal leverage is context-dependent. This study contributes by developing a risk-adjusted productivity framework, identifying the nonlinear effects of leverage on sustainable TFP, and providing micro-level evidence from agriculture in a developing economy. The findings offer implications for capital structure optimization and sustainable agricultural finance.

Keywords: agriculture; total factor productivity; financial leverage; USBM-DEA

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1. Introduction

Agriculture is fundamental to national economies, particularly in developing countries where productivity growth is closely linked to structural transformation, food security, and long-run competitiveness. China provides a salient case. With less than 9% of the world's arable land, it feeds nearly one quarter of the global population. Under this persistent land constraint, agricultural development can no longer rely primarily on factor expansion, but must increasingly depend on efficiency gains. Total factor productivity (TFP) has therefore become a key indicator of high-quality agricultural development. This transition, however, is constrained by the structure of agricultural finance. In China, agricultural capital formation still depends heavily on government support and policy-based funding, while market-based finance, capital-market services, and formal risk-sharing

arrangements remain underdeveloped. Within this context, financial leverage becomes a critical dimension of firms' capital structure. At moderate levels, leverage may ease financing constraints, support productive investment, and improve resource allocation. At excessive levels, it may increase debt-service pressure, crowd out long-term investment, and amplify financial fragility. Understanding how leverage shapes agricultural productivity is therefore both economically important and policy relevant, especially under heightened global interest-rate volatility and tighter credit conditions.

Although prior studies have examined TFP and the economic effects of leverage, two important gaps remain. First, most efficiency measures are profit-oriented and do not explicitly incorporate risk, which may bias TFP assessment when leverage raises profitability and default risk simultaneously. Second, existing evidence on the leverage–TFP relationship is concentrated at the macro or industrial level, while firm-level evidence for agriculture, especially listed agricultural firms, remains limited. These gaps are nontrivial. Because agriculture plays a foundational role in macroeconomic stability and supply security, a risk-adjusted and firm-level analysis is necessary to understand the boundary conditions and transmission mechanisms of the leverage–productivity relationship. This study addresses these gaps by examining whether and how financial leverage affects agricultural TFP in China from a profit–risk trade-off perspective. Specifically, it incorporates default risk estimated through contingent claims analysis into a DEA framework as an undesirable output and constructs a risk-adjusted composite TFP measure for Chinese agricultural firms and subsectors. On this basis, the study investigates the impact of financial leverage on TFP, identifies the underlying profit and risk channels, and further examines heterogeneity across subsectors and market structures. In doing so, it aims to provide evidence for capital structure optimization, improvements in agricultural financial support and risk sharing, and the transition from factor-driven to efficiency-driven agricultural development.

This study contributes in three ways. First, it extends the measurement of agricultural productivity by incorporating CCA-based default risk as an undesirable output in a DEA framework, thereby constructing a risk-adjusted composite TFP that better captures efficiency under leverage than profit-only measures. Second, it identifies how financial leverage affects agricultural TFP through profit and risk channels, while explicitly testing the nonlinear nature of this relationship and the effective range of moderate leverage. Third, it documents heterogeneity across subsectors and market structures and examines the mediating and moderating roles of financing constraints, thereby providing micro-level evidence for differentiated capital structure adjustment and agricultural financial policy.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 presents the methodology, variable construction, and data. Section 4 reports the empirical results, robustness and endogeneity checks. Section 5 concludes with policy implications and directions for future research.

2. Literature Review and Hypothesis Development

2.1. Agricultural TFP: Measurement and Determinants

Total factor productivity (TFP) is the portion of output not explained by measured factor inputs under a given technology, and its growth is commonly proxied by the Solow residual [1]. Standard decompositions distinguish technical progress, technical efficiency, and scale efficiency, with technical efficiency capturing the effective use of resources given the production frontier [2]. Farrell (1957) systematized the distinction and measurement of technical versus allocative efficiency, laying the groundwork for subsequent parametric and nonparametric analyses [3].

The two main approaches to TFP measurement are stochastic frontier analysis (SFA) and data envelopment analysis (DEA). SFA permits statistical inference and decomposes

productivity change into technical change and efficiency change, but depends on functional-form and distributional assumptions [4]. DEA constructs the production frontier nonparametrically and is particularly suitable for multi-input and multi-output settings. When combined with the Malmquist index, it also captures intertemporal productivity change [5].

Existing studies show that agricultural growth has increasingly relied on TFP rather than factor accumulation since the 1990s [6,7]. TFP is therefore regarded as a key source of sustained and sustainable development [8], especially for developing countries [6]. Cross-country comparisons reveal condition-dependent patterns of catch-up, convergence, and divergence in agricultural productivity and output [9]. In China, the growth engine has shifted from factor expansion to TFP improvement [8,10]. At the same time, agricultural TFP exhibits substantial heterogeneity across subsectors [11] and regions [12], with some gains driven mainly by technical progress and others by efficiency improvement.

In terms of determinants, prior studies show that TFP is shaped by technological progress, financing conditions, and resource allocation. Improvements in technical efficiency, technology adoption, and knowledge-capital investment are widely recognized as key drivers of productivity growth [13,14]. In agriculture, the evidence further highlights the roles of human capital, irrigation conditions, fiscal support, informatization, and the efficient allocation of land and labor [15–20]. Under increasing resource and environmental constraints, green TFP has also become an important pathway to high-quality agricultural development [21]. Together, these studies suggest that agricultural TFP is jointly determined by technology, finance, and sector-specific resource conditions.

2.2. Financial Leverage, Firm Performance, and Firm Risk

Research on firm performance focuses on technological innovation [22], incentive mechanisms [23] and capital structure [24]. Within capital structure, financial leverage is pivotal, influencing firm outcomes through performance and risk channels [25,26].

Through the performance channel, leverage can improve operating results and raise ROE [27] and, via debt discipline, curb overinvestment [28]. Conversely, some studies contend that firm-level deleveraging curbs inefficient investment, thereby improving capital allocation efficiency and overall performance [29]. Evidence indicates heterogeneous leverage effects. Among high-performing firms, higher leverage is associated with better outcomes; among low-performing firms, with worse outcomes [30], and the adverse effect weakens as firm size increases [31]. Deleveraging yields larger performance gains in highly indebted firms and has stronger effects in SOEs than in private firms [32]. Leverage relates to performance and to high-quality development in an inverted-U pattern, implying an optimal capital structure at the interior [33]. Moderate leverage adjustments are also linked to higher capacity utilization and stronger innovation [34].

Through the risk channel, leverage can lower agency costs and strengthen governance via covenants and hard interest-payment constraints, modestly enhancing risk tolerance [35]. Excessive leverage increases financial and operating risk [36], with stronger effects among smaller firms [37]. Debt maturity matters: a lower share of long-term debt is associated with greater operational problems and debt risk [38].

Taken together, the literature suggests that leverage is inherently double-edged. Moderate leverage may enhance firm performance, whereas excessive leverage can undermine firm outcomes by amplifying risk. This dual effect provides the basis for examining how leverage influences agricultural TFP through profitability and default risk.

2.3. Financial Leverage and TFP

Existing evidence on the leverage–TFP relationship is mixed. When leverage expands markedly faster than economic growth, the real sector is crowded out, and TFP declines [39],

and some studies report a negative association between leverage and productivity [40]. By contrast, other studies find that leverage can improve TFP [41], with threshold or inverted-U patterns suggesting an interior optimum [42]. From a resource allocation perspective, sound credit policy can improve factor allocation and thereby enhance TFP [43].

The effect of leverage on TFP is also heterogeneous. Short-term leverage tends to depress TFP growth [44]. Deleveraging harms low-leverage firms but benefits highly leveraged firms [45]. Across the firm life cycle, additional leverage supports TFP during growth and maturity phases but not during downturns [44]. By ownership, the inverted-U relationship is more pronounced in private firms, whereas it is weaker and closer to U-shaped in SOEs [46]. Overall, the literature indicates that the effect of leverage on TFP is double-edged, nonlinear, and context-dependent.

These findings suggest that the leverage–TFP relationship may be especially relevant in agriculture, where firms often face higher exposure to production uncertainty, tighter financing conditions, and weaker risk-sharing arrangements. This consideration motivates an evaluation framework that jointly accounts for profitability and risk.

2.4. Financing Constraints as a Mediating and Moderating Mechanism

Financing constraints may shape the leverage–TFP relationship through both mediating and moderating channels. As a mediator, leverage affects firms' financing conditions, which then influence productivity. Prior studies show that leverage can improve performance by supporting investment and disciplining overinvestment [36], while deleveraging may also improve performance by curbing inefficient investment and improving capital allocation [37]. This suggests that leverage alters financing conditions and investment behavior, which in turn affect TFP. Consistent with this view, sound credit allocation improves factor allocation and raises productivity [47]. By contrast, when higher leverage increases repayment pressure and refinancing risk, tighter financing constraints may weaken innovation, long-term investment, and resource allocation efficiency, thereby transmitting part of leverage's negative effect to TFP.

Financing constraints may also moderate the productivity effect of leverage. Existing evidence shows that leverage effects vary across debt levels, ownership structures, firm life-cycle stages, and debt maturity structures [15,16,48–52]. Deleveraging benefits highly leveraged firms more than low-leverage firms [15,48], while excessive leverage imposes stronger risks on smaller firms and on firms with less favorable debt structures [49–51]. These findings imply that leverage does not affect productivity uniformly; instead, its impact depends on firms' financing conditions and refinancing capacity.

This mechanism is particularly relevant in agriculture, where firms typically face long investment cycles, high uncertainty, and limited collateralizable assets. Under such conditions, leverage may alleviate funding shortages and raise productivity when financing constraints are binding, but it may also intensify debt pressure and reduce productivity when refinancing capacity is weak. The agricultural context, therefore, provides a suitable setting for examining both the mediating and moderating roles of financing constraints in the leverage–TFP relationship.

2.5. Hypothesis Development

Building on the above literature, agricultural firms' TFP can be viewed as a joint outcome of a desirable output (profit) and an undesirable output (default risk). The preceding discussion suggests that financial leverage affects TFP through both performance and risk channels, while financing constraints may further transmit and condition this effect. Accordingly, the following hypotheses are proposed.

Hypothesis 1 (Overall Effect). *Financial leverage has an inverted-U effect on agricultural TFP. Moderate leverage improves TFP, whereas excessive leverage reduces it.*

Hypothesis 2 (Profit Channel). *Financial leverage affects agricultural TFP through a profit channel. Moderate leverage improves profitability and thus raises TFP, whereas excessive leverage reduces profitability and thereby lowers TFP.*

Hypothesis 3 (Risk Channel). *Financial leverage affects agricultural TFP through a risk channel. Higher leverage increases default risk and worsens risk efficiency, thereby reducing TFP.*

Hypothesis 4a (Mediating Effect). *Financing constraints mediate the relationship between financial leverage and agricultural TFP.*

Hypothesis 4b (Moderating Effect). *Financing constraints moderate the relationship between financial leverage and agricultural TFP.*

Accordingly, leverage's net effect on TFP is double-edged and context-dependent, requiring evaluation within a profit–risk trade-off. The study constructs a composite, risk-adjusted efficiency metric that internalizes default risk to assess leverage's effects on profit and default risk. The mechanism is summarized in Figure 1.

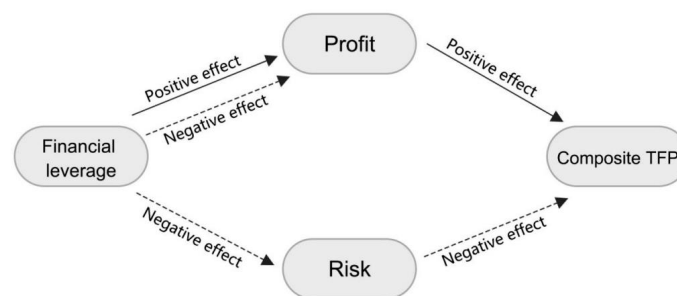


Figure 1. Basic mechanism of financial leverage's impact on agricultural TFP.

3. Methodology

3.1. DEA-Based TFP Measurement and Efficiency Decomposition

This study employs the directional distance function (DDF) as the efficiency metric and, accordingly, develops an undesirable-output slack-based DEA model (USBM-DEA). Based on this model, a Malmquist index is constructed to measure intertemporal TFP change and its decomposition into efficiency change and technical change. The framework imposes no functional-form assumptions and is well-suited to firm-size heterogeneity in agriculture.

A non-radial distance function is used to compute efficiency for the input–output bundle. Let the period- t input vector be $x \in \mathbb{R}_+^M$, the desirable outputs be $y \in \mathbb{R}_+^S$, and the undesirable outputs be $b \in \mathbb{R}_+^H$. The production possibility set is then defined as follows:

$$P^t = \{(x, y, b) : x \geq X^t \lambda, y \geq Y^t \lambda, b \leq B^t \lambda, e' \lambda = 1, \lambda \geq 0\}, \quad (1)$$

where $X^t = [x_{mj}^t]_{M \times N}$, $Y^t = [y_{sj}^t]_{S \times N}$, $B^t = [b_{hj}^t]_{H \times N}$ denote, respectively, the period- t data matrices of inputs, desirable outputs, and undesirable outputs for N decision-making units (DMUs); $\lambda \in \mathbb{R}_+^N$ is the intensity vector; e is the N -dimensional unit vector; and $e' \lambda = 1$ imposes variable returns to scale (VRS). The non-radial distance function is given by

$$D^t(x, y, b; g) = \sup\{w' \beta : (x, y, b) + \beta \cdot g \in P^t\}, \quad (2)$$

where $g = (g_x, g_y, g_b)$, $\beta = (\beta_x, \beta_y, \beta_b)$ and $w = (w_x, w_y, w_b)$ denote, respectively, the direction of improvement, the magnitude of improvement, and the weights for the three variables.

Following Zhang Kai and Xinmiao Zhou (2022) [53], the weights w in the objective function are dynamically adjusted. For panel data with time dimension Γ and J cross-sectional units, the problem is recast as a linear program (LP):

$$D^t(x, y, b; g) = \max_{\beta, \lambda} w_t' \beta = w_{x,t} \frac{\beta_x g_x}{x} + w_{y,t} \frac{\beta_y g_y}{y} + w_{b,t} \frac{\beta_b g_b}{b}$$

$$\text{s.t.} \begin{cases} \sum_{\tau \in \Gamma_t} \sum_{j=1}^J \lambda_{j\tau} x_{j\tau} + S_{j\tau}^x = x + \beta_x \cdot g_x \\ \sum_{\tau \in \Gamma_t} \sum_{j=1}^J \lambda_{j\tau} y_{j\tau} - S_{j\tau}^y = y + \beta_y \cdot g_y, \quad \beta \geq 0; \lambda_{j\tau} \geq 0, j = 1, \dots, J, \\ \sum_{\tau \in \Gamma_t} \sum_{j=1}^J \lambda_{j\tau} b_{j\tau} + S_{j\tau}^b = b + \beta_b \cdot g_b \end{cases} \quad (3)$$

where $S_{j\tau}^x$, $S_{j\tau}^y$ and $S_{j\tau}^b$ denote, respectively, the slack variables for inputs, desirable outputs, and undesirable outputs; $\lambda_{j\tau}$ denotes the λ value for DMU j at time τ .

The Malmquist index decomposes TFP into catch-up (CU) and frontier shift (FS). CU captures changes due to improvements in technical efficiency (e.g., organization, coordination, management), while FS captures movements of the production frontier between two periods.

Let (x^t, y^t) denote, in period t , the input–output bundle that uses inputs x^t to produce y^t units of output. Let $D^t(x^t, y^t)$ be its efficiency value relative to the period- t production possibility set. Consider the intertemporal change from t to $t + 1$, where the bundle moves from (x^t, y^t) to (x^{t+1}, y^{t+1}) . Under period- t technology, the efficiency change is

$$M_t = \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}. \quad (4)$$

Under period- $t + 1$ technology, the efficiency change is

$$M_{t+1} = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}. \quad (5)$$

The Malmquist index from t to $t + 1$ is the geometric mean of the two efficiency changes:

$$Malmquist(x^t, y^t, x^{t+1}, y^{t+1}) = (M_t \times M_{t+1})^{\frac{1}{2}}. \quad (6)$$

Further, the Malmquist catch-up effect (CU) is the ratio of the efficiency scores of the two input–output bundles evaluated against their respective period frontiers, i.e.,

$$CU = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}. \quad (7)$$

The frontier shift (FS) is expressed as the change in efficiency between the two period-specific production possibility frontiers, i.e.,

$$FS = \sqrt{\frac{D^{t+1}(x^t, y^t)}{D^t(x^t, y^t)} \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^{t+1}, y^{t+1})}}. \quad (8)$$

3.2. Undesirable Output Based on Contingent Claims Analysis

This study computes firms' default risk using Contingent Claims Analysis (CCA). Following Merton (1973) [54], equity and the expected loss on debt are modeled, respectively, as a call and a put option written on the market value of firm assets, with the debt as the strike. The Black–Scholes option pricing model (BSM) [55] is then applied, opening the use of option pricing to analyze corporate default risk. According to BSM, the price of a European call is

$$C_t = S_t N(d_{1t}) - K_t e^{-rT} N(d_{2t}), \quad (9)$$

where

$$\begin{cases} d_{1t} = \frac{\ln(S_t/K_t) + (r_t + \sigma_t^2/2)(T-t)}{\sigma_t \sqrt{(T-t)}} \\ d_{2t} = \frac{\ln(S_t/K_t) + (r_t - \sigma_t^2/2)(T-t)}{\sigma_t \sqrt{(T-t)}} = d_{1t} - \sigma_t \sqrt{(T-t)} \end{cases} \quad (10)$$

According to the CCA framework, C_t denotes the firm's equity market value (observed) and S_t is the market value of assets (unobserved). K is debt due at maturity, typically proxied by current liabilities plus half of non-current liabilities. T denotes the option's time to maturity (in years), usually set to the accounting period. r_t is the risk-free rate, commonly the one-year government bond yield. σ_t is the asset-value volatility (unobserved), which is linked to equity volatility σ_{Et} following Bensoussan et al. (1994) [56] as

$$\sigma_t = \frac{C_t}{N(d_{1t}) S_t} \sigma_{Et}. \quad (11)$$

Solving the system (9)–(11) yields S_t and σ_t . The firm's default risk indicator—distance to default (DD)—is then given by

$$DD_t = \frac{S_t}{K_t}. \quad (12)$$

DD is defined as the ratio of the market value of assets to the book value of debt, i.e., the firm's asset-coverage multiple. "DD < 1" indicates insolvency. And larger values imply lower bankruptcy risk.

To address market inefficiencies and methodological-fit concerns when applying CCA in China, this study follows Zhang Kai et al. (2025) [57], using the actual financial-statement disclosure date as the sampling point and incorporating audit reports to mitigate data distortions arising from accounting manipulation.

3.3. Econometric Models

To assess the impact of financial leverage on the TFP of Chinese agricultural firms, an individual fixed-effects model is estimated:

$$Efficiency_{it} = \alpha_1 Financial_Leverage_{it} + \alpha_2 Controls_{it} + \mu_i + \varepsilon_{it}, \quad (13)$$

where $Efficiency_{it}$ is the composite efficiency from the USBM model, capturing the profit–risk trade-off.

To identify the underlying channels, the baseline specification is extended by replacing the dependent variable with Profit_Slack and AvDR_Slack, which capture profit-side and default-risk-side efficiency gaps, respectively:

$$Slack_{it} = \beta_1 Financial_Leverage_{it} + \beta_2 Controls_{it} + \mu_i + \varepsilon_{it} \quad (14)$$

These regressions are designed to test whether leverage affects TFP through profitability and risk.

To further examine underlying mechanisms and heterogeneity, this study conducts mediation and moderation analyses using the KZ index to capture the role of financing constraints, and introduces interaction terms to test whether the leverage effect varies with financing frictions. In addition, TFP is decomposed into catch-up (CU) and frontier shift (FS) components using the Malmquist index, and separate regressions are performed. Input-side efficiency and subsample analyses by subsector and market concentration are also employed to capture heterogeneity across production and market environments.

3.4. Variables, Data, and Descriptive Statistics

This study uses panel data on Chinese A-share listed firms in the Agriculture/Forestry/Animal Husbandry/Fishery sector, classified by Wind, over the period from January 2010 to June 2024. Financial and market data are obtained from the Wind database and from firms' financial and audit reports. All continuous variables are winsorized at the 1% tails to reduce the influence of outliers.

For default-risk estimation under the CCA framework, the risk-free rate is proxied by the one-year Chinese government bond yield. The default barrier is defined as current liabilities plus one-half of non-current liabilities, and the time to maturity is set to the interval between two consecutive financial-statement disclosure dates.

For the risk-adjusted TFP measurement, the USBM model uses fixed assets, staff headcount, administrative expenses, selling expenses, and financial expenses as inputs. The desirable output is net profit, and the undesirable output is the probability of default.

In the econometric analysis, the main dependent variable is Efficiency, the composite TFP derived from the USBM model. For comparison, the SBM efficiency without undesirable outputs (Efficiency_SBM) is also used. The core explanatory variable is Financial_Leverage ($Financial_Leverage_{it}$), defined as financial liabilities, including bank loans and bond financing, divided by total assets. Financing constraints are measured by the KZ index. Additional controls ($Controls_{it}$) include the industry-level Herfindahl–Hirschman Index (HHI) for industry concentration, StateOwned for ownership, SetupDuration for firm age, and other covariates used in specific specifications, such as ListDuration, FarmGDP, and ROE. Industry concentration (HHI) is measured by

$$HHI = \sum_{i=1}^k \left(\frac{x_i}{x} \right)^2 = \sum_{i=1}^k S_i^2. \quad (15)$$

where x is total industry revenue and x_i is firm j 's revenue. μ_i denotes firm fixed effects; ε_{it} is the error term; α_1 and α_2 are parameters to be estimated.

Table 1 reports the descriptive statistics for variables used in the empirical analysis.

Table 1. Descriptive statistics of main variables.

Variable	Description	Obs	Mean	Sd	Median	Min	Max	Skew	Kurtosis
SV	Stock value	4499	107.25	288.75	44.11	1.52	4260.29	8.58	89.76
CL	Current liabilities	4421	27.25	83.71	9.42	0.06	1301.25	9.76	114.95
NCL	Non-current liabilities	4420	8.98	34.97	1.38	0	514.01	9.21	98.29
Debt	Default barrier	4499	31.71	97.34	10.32	0.06	1376.83	8.77	90.94
InterestRate	1Y gov bond YTM, %	4499	2.58	0.59	2.46	1.12	4.21	0.46	−0.36
DD	Default distance	4499	10.28	17.09	5.62	0.1	282.5	6.42	64.12
FixedAsset	Fixed assets	3017	14.93	22.46	6.62	0.17	128.31	3.03	9.86
Staff	Employee, persons	3017	5296.15	11,129	1709	58	70,600	4.11	18.27

Table 1. Cont.

Variable	Description	Obs	Mean	Sd	Median	Min	Max	Skew	Kurtosis
AdminCost	Administrative expenses	3017	1.5008	2.6879	0.6228	0.0516	16.8871	3.88	16.64
FinanCost	Finance costs	3017	0.4474	0.8235	0.1576	−0.2802	4.9971	3.37	13.16
SalesCost	Selling expenses	3017	1.1053	2.0374	0.4168	0.0018	13.1538	3.93	17.62
Profit	Net profit	3017	0.8674	3.8806	0.2886	−13.799	21.9155	1.92	13.28
Efficiency	USBM-derived	2980	0.153	0.411	0.087	−1.946	1.000	−1.294	7.950
Efficiency_SBM	SBM-derived	2962	0.147	0.448	0.099	−2.166	1.000	−1.771	8.820
Financial_Leverage	Financial leverage ratio	2795	0.237	0.153	0.236	0.000	0.679	0.464	−0.137
KZ	KZ index	3055	−0.694	0.592	−0.580	−3.274	0.457	−1.410	3.642
HHI	Herfindahl index	3021	0.287	0.151	0.244	0.113	0.867	1.556	3.284
FarmGDP	Agricultural GDP	3055	6.522	4.635	7.628	−5.091	14.679	−0.866	0.216
StateOwned	SOE controlling shareholder (dummy): 1 if state-controlled, 0 otherwise	3055	0.419	0.494	0.000	0.000	1.000	0.327	−1.894
SetupDuration	Firm age (years since founding)	3055	21.29	5.887	20.830	9.719	38.696	0.508	0.131

4. Empirical Analysis

4.1. Efficiency Measurement for Chinese Agricultural Firms

This subsection combines the default-risk indicator from Section 2.3 with the USBM-based DEA approach from Section 2.2, using a USBM model that treats default risk as an undesirable output to compute TFP for Chinese agricultural firms. The resulting efficiency scores provide the basis for the subsequent regressions of TFP on financial leverage.

4.1.1. Default Risk of Chinese Agricultural Firms

To assess the face validity of the CCA approach, Dayu Water-Saving Group is used as a case study, plotting the dynamics of stock price (close), debt level, and distance to default (DD) from May 2010 to April 2024. Figure 2 illustrates the intuition of CCA: when debt is relatively stable (April 2012–June 2015), DD moves broadly with the stock price but with smaller amplitude, indicating that variation in credit risk is largely driven by information impounded in equity prices. When the debt level surges—i.e., leverage rises rapidly (2010–2012; 2020–2023)—DD continues to trend downward even as market value rises (2010–2012) or trades sideways (2020–2023), signaling higher bankruptcy risk. These patterns suggest that DD partly filters out irrational stock-price fluctuations and, conversely, corroborate that excessive leverage elevates default risk.

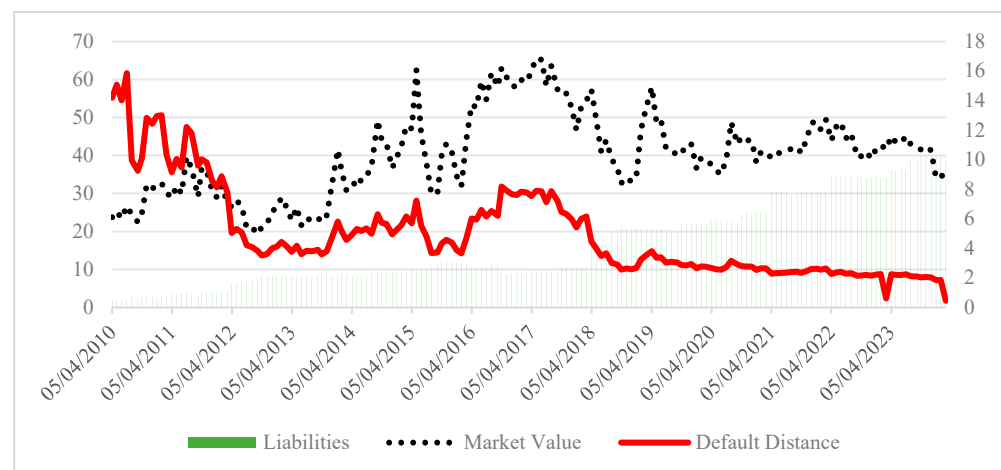


Figure 2. Default risk, market value, and debt: The case of Dayu Water-Saving Group.

To evaluate the effectiveness of CCA for agricultural firms and to characterize structural patterns, this study computes market-cap-weighted default-risk indicators by subsector, based on distance to default (DD). Figures 3 and 4 compare the evolution of subsector risk and its comovement with the market interest rate (proxied by the one-year government bond yield). Risks move broadly in the same direction across subsectors, but with differing amplitudes: Agribusiness consistently exhibits the highest risk, while Animal Health shows the lowest; Forestry and Animal Health appear more resilient to external shocks. Three pronounced high-risk episodes are evident—2010Q1–2013Q1, 2017Q1–2019Q1, and post-2023Q1—which align with phase-specific macro fluctuations in China, supporting the validity of the risk metric.

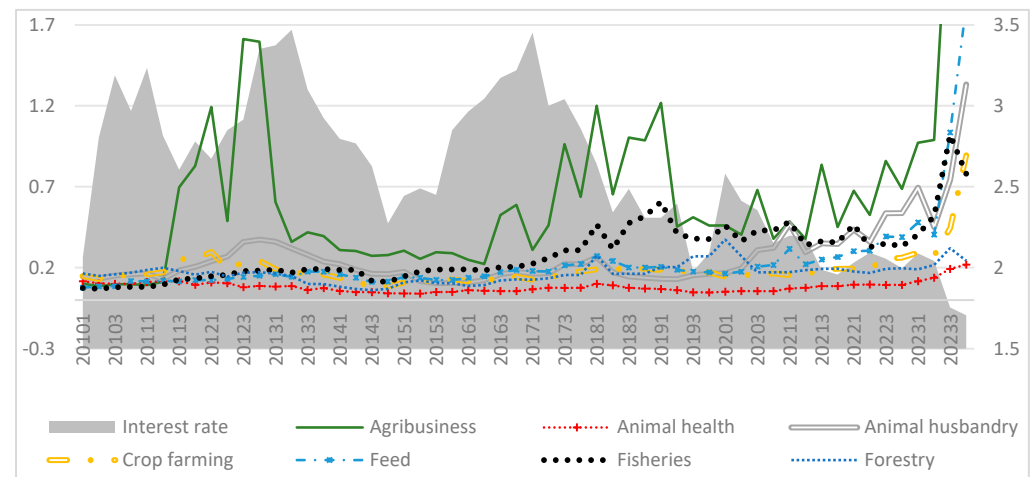


Figure 3. Trends in the market interest rate and the subsectors' default risk in agriculture.

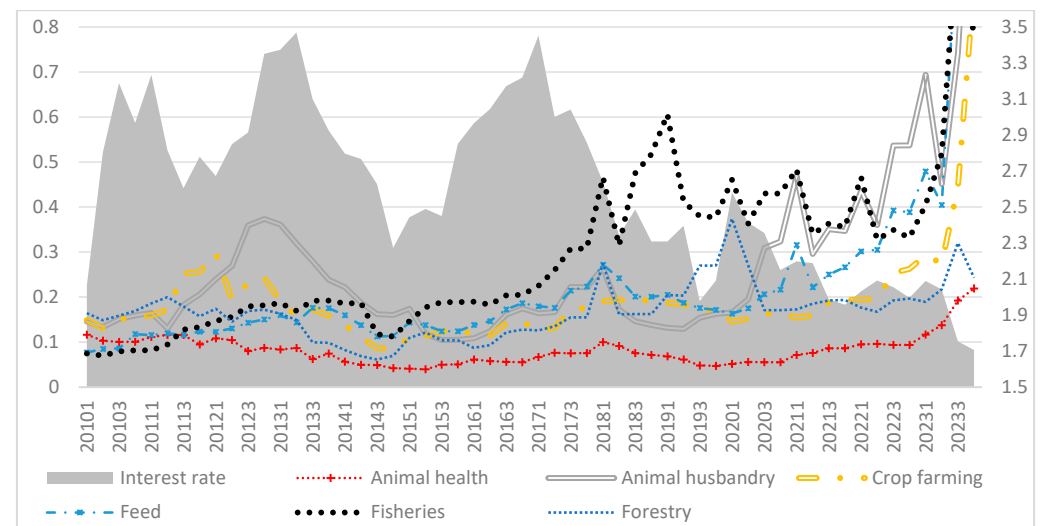


Figure 4. Trends in the market interest rate and subsectors' default risk in agriculture (excluding agribusiness).

Figure 3 shows that default risk in Agribusiness and Fisheries is strongly correlated with movements in the market interest rate. To more precisely identify the rate–risk relation in the remaining subsectors, Agribusiness is excluded (Figure 4), and a similar pattern of interest-rate comovement emerges across the remaining subsectors. These patterns indicate a significant association between default risk and financial leverage, with the market rate serving as a proxy for borrowing costs.

4.1.2. TFP of Chinese Agricultural Firms

Embedding default risk as an undesirable output in the USBM-DEA yields a risk-adjusted composite TFP and associated efficiency-improvement directions for Chinese listed agricultural firms. Figure 5 shows pronounced comovement in market-cap-weighted subsector-average TFP. Forestry exhibits persistently higher efficiency scores, whereas Fisheries is the lowest-performing subsector for most of the sample period.

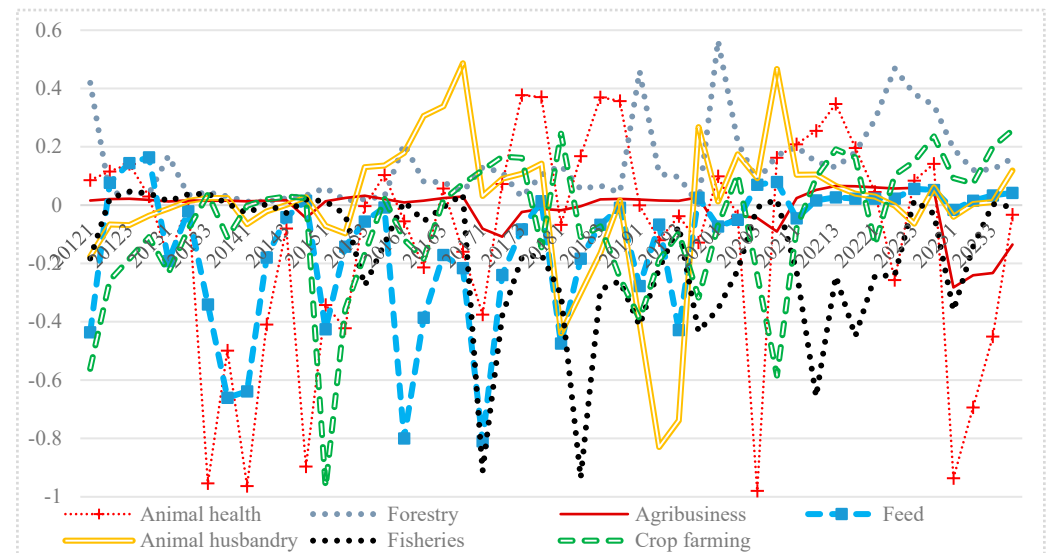


Figure 5. TFP by subsector in Agriculture.

Table 2 reports the means of composite TFP (denoted “efficiency” in the table) and the required percentage adjustments to reach the efficiency optimum (slacks, denoted “_Slack”). Forestry has the highest average composite TFP. Crop farming has the lowest, with Fisheries having the second lowest.

Table 2. TFP and efficiency improvements by subsector.

Industries	Efficiency	FixedAsset_Slack	Staff_Slack	AdminCost_Slack	FinanCost_Slack	SalesCost_Slack	Profit_Slack	DR_Slack
Animal health	−0.2710	0.5124	0.5194	0.4474	8.0862	0.7027	0.8549	0.3576
Forestry	0.1363	0.5930	0.7364	0.6660	0.9259	0.7261	7.3056	0.7695
Agribusiness	−0.2266	0.8795	0.8742	0.7917	2.5489	0.9090	3.1985	0.9265
Feed	−0.2589	0.6424	0.7897	0.7309	3.1154	0.8183	11.0924	0.4548
Animal husbandry	−0.4554	0.7670	0.7787	0.6877	4.1129	0.7614	1.3128	0.6507
Fisheries	−0.4951	0.7926	0.8314	0.7240	4.0681	0.8754	4.4068	0.7873
Crop farming	−1.3325	0.6577	0.7114	0.6448	8.5522	0.7186	1.8648	0.6034

On the output side, TFP shortfalls stem mainly from insufficient profit (with default risk also contributing), implying a need to re-optimize the input mix to support earnings. On the input side, the model’s targets indicate that financing-related input (financial expenses) is the binding constraint. Its required adjustment is markedly larger than for other inputs, consistent with interest outlays dominating financial expenses.

Overall, default risk depresses TFP, but profit shortfalls are the primary driver of low efficiency. The evidence points to financing constraints/capital structure as the key bottleneck. Subject to manageable risk and cost, moderate increases in leverage are likely to improve composite TFP in agriculture.

Figures 6–11 trace, over time, subsector TFP and input-adjustment paths in agriculture. The overall conclusion aligns with Table 1: to raise efficiency, financial expenses are the input requiring the largest adjustment for most firms. Yet patterns vary across period and subsectors in three respects. (1) The directions and magnitudes of input adjustments comove strongly with TFP, implying that, beyond compositional optimization, overall scale expansion is needed. Most subsectors appear not yet in a decreasing-returns-to-scale region. (2) Heterogeneity is time-varying: the marginal effects of inputs on TFP differ across phases and subsectors. For Animal Health, selling expenses (excluding financial expenses) were most negatively correlated with efficiency before 2019Q3, and this relation dissipated thereafter. (3) In Forestry, the scope for improving financial expenses is relatively small. Especially after 2022, efficiency gains from better use of financial expenses contributed less to TFP than in other subsectors.

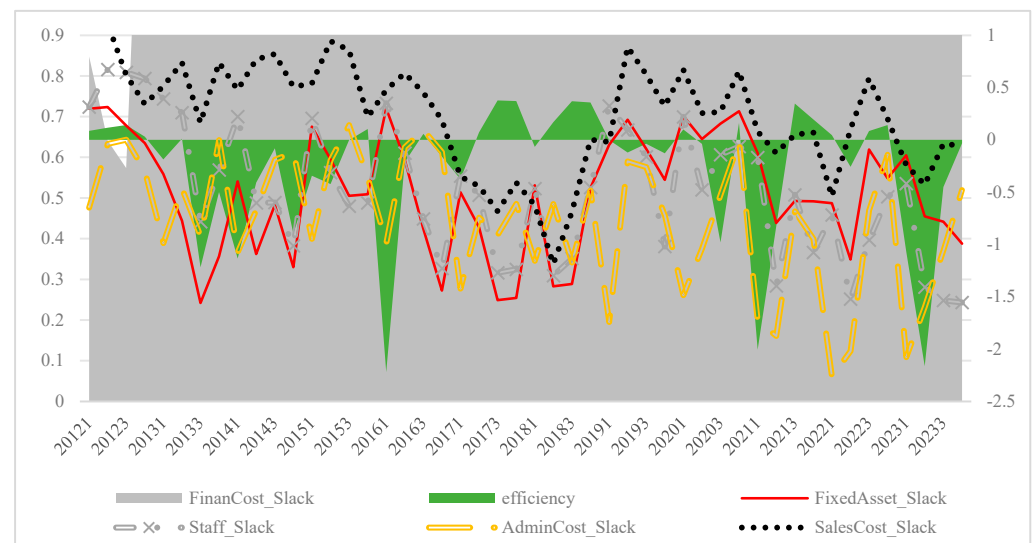


Figure 6. Efficiency improvements in Animal Health.

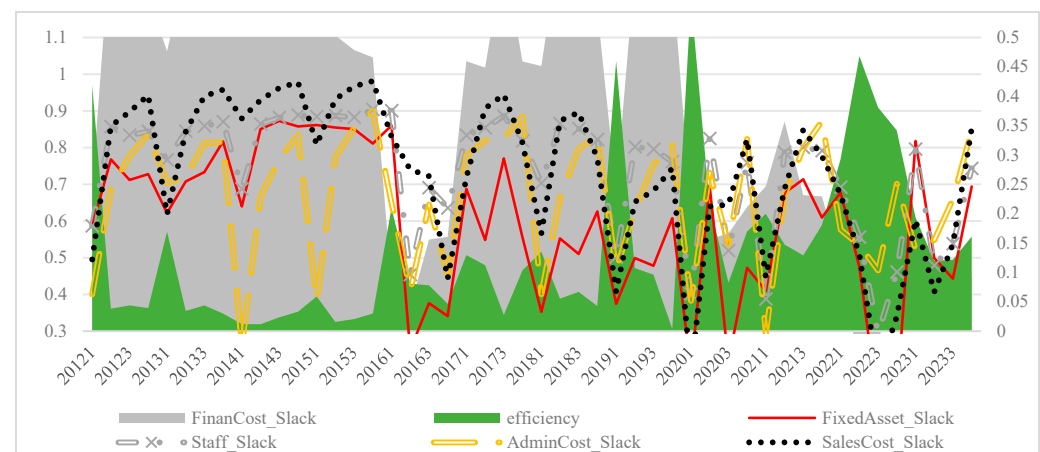


Figure 7. Efficiency improvements in Forestry.

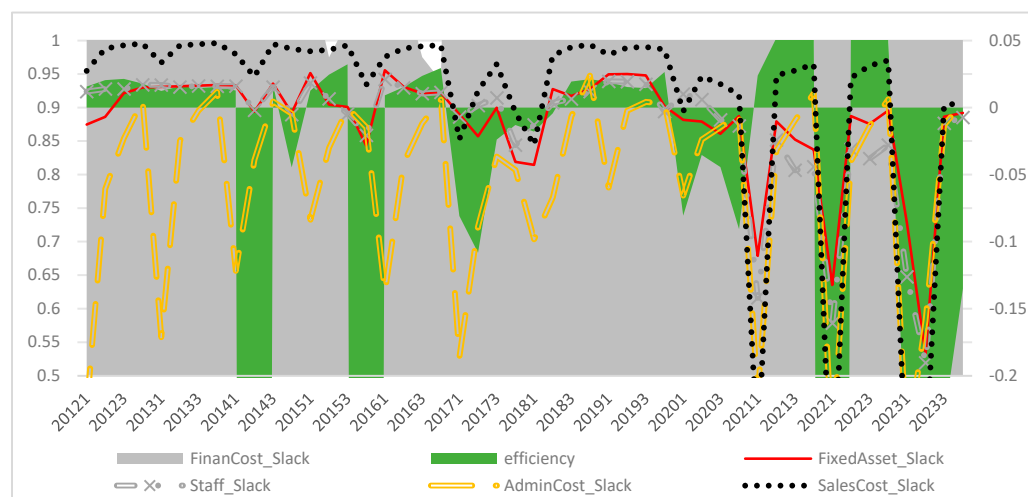


Figure 8. Efficiency improvements in Agribusiness.

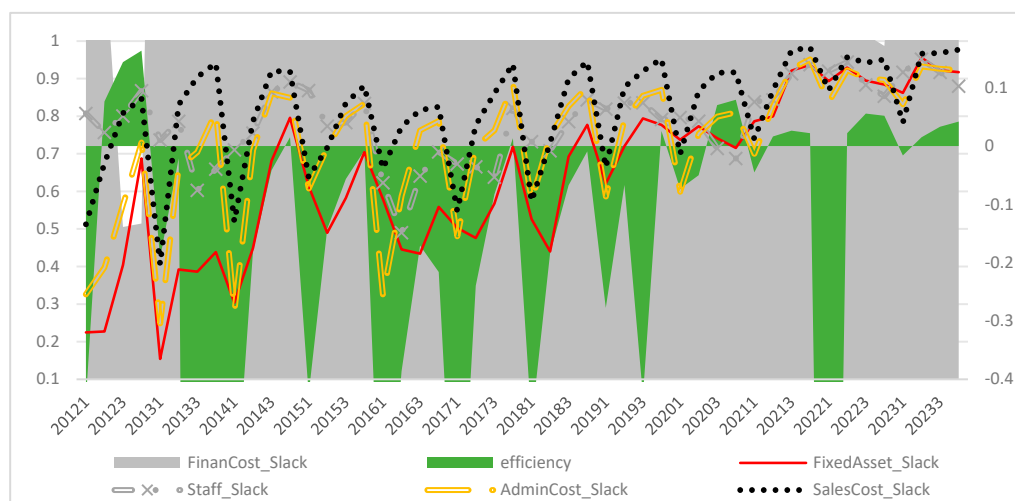


Figure 9. Efficiency improvements in Feed.

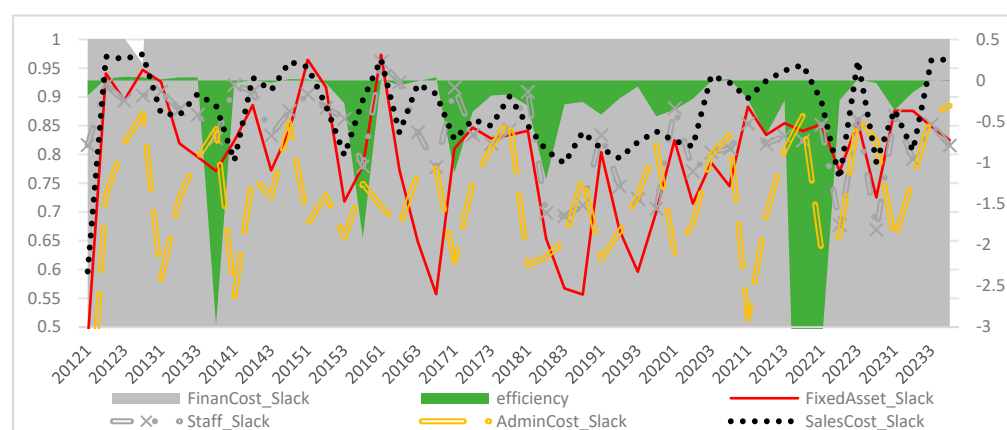


Figure 10. Efficiency improvements in Fisheries.



Figure 11. Efficiency improvements in Crop Farming.

4.2. Effects of Financial Leverage on Composite TFP

4.2.1. Baseline Regressions

The regression results (Table 3) show that, in the USBM specifications (USBM1–USBM3), financial leverage has a significantly positive effect on composite TFP. After adding the squared term (Financial_Leverage_square), the relation becomes inverted-U (USBM3), implying an optimal leverage of about 50%.

Table 3. Effect of financial leverage on TFP under alternative methods.

	USBM1	USBM2	USBM3	SBM1	SBM2	SBM3
	Efficiency	Efficiency	Efficiency	Efficiency_SBM	Efficiency_SBM	Efficiency_SBM
Financial_Leverage	0.859 ***	0.870 ***	1.936 ***	0.059	0.057	0.016
HHI		0.473	0.521 *		0.216	0.214
StateOwned		−0.212 *	−0.230 **		−0.105 **	−0.104 **
SetupDuration		−0.237 ***	−0.216 ***		0.007 ***	0.006 ***
ListDuration		0.242 ***	0.222 ***			
Financial_Leverage_square			−1.948 ***			0.077
FarmGDP					0.004 **	0.004 **
Num.Obs.	2616	2587	2587	2670	2640	2640
R2	0.011	0.017	0.020	0.000	0.008	0.008
R2 Adj.	−0.014	−0.010	−0.007	−0.025	−0.019	−0.019
RMSE	0.76	0.76	0.75	0.36	0.35	0.35

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

This nonlinearity reflects both diminishing marginal returns to capital and the institutional constraints of China's bank-dominated financial system. Because agricultural firms rely heavily on bank credit and lack diversified risk-sharing and hedging instruments, rising leverage translates quickly into financial risk, causing composite efficiency to decline beyond a critical threshold. This institutional setting also justifies treating default risk as an undesirable output. Consistently, when the dependent variable is replaced by profit-only SBM efficiency, the leverage coefficient becomes insignificant, indicating that the leverage–efficiency relationship cannot be captured without accounting for risk.

Among the controls, HHI is significantly positive, suggesting that greater market concentration improves resource-use efficiency, while StateOwned is significantly negative, implying lower efficiency in SOEs. This finding is consistent with soft budget constraints in China's agricultural sector, where policy burdens and implicit guarantees weaken the disciplining role of debt.

4.2.2. Mechanisms: Financial Leverage Effects on Profit and Risk

Table 4 reports the estimates. For Profit_Slack, leverage shows a down-then-up pattern (Model 1). Since slack is the shortfall to be reduced, this implies an inverted-U relation between leverage and profit efficiency, with an optimal leverage of 0.3686. For risk efficiency (AvDR_Slack), leverage exhibits a U-shaped relation (Model 2), with the worst efficiency at leverage 0.8337. Given the sample mean (0.2379) and maximum (0.6780), leverage reduces risk efficiency over the observed range, and the marginal harm diminishes as leverage rises.

Table 4. Mechanisms of financial leverage's effect on TFP in agricultural firms.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Profit _Slack	AvDR _Slack	Efficiency	KZ	Efficiency	Efficiency
Financial_Leverage	−13.216 ***	1.458 ***	0.870 ***	0.553 ***	0.934 ***	1.412 ***
Financial_Leverage_square	19.311 **	−0.874 ***				
AvDR_Slack	2.651 ***					
HHI	6.141 *	0.375 ***	0.473		0.450	0.444
ListDuration	−0.210 ***		0.242 ***		0.237 ***	0.235 ***
StateOwned	−1.062		−0.212 *		−0.213 *	−0.219 *
Profit_Slack		0.003 ***				
SetupDuration			−0.237 ***		−0.231 ***	−0.229 ***
KZ					−0.106 ***	−0.271 ***
Financial_Leverage × KZ						0.688 ***
Num.Obs.	2587	2587	2587	2758	2587	2587
R2	0.020	0.101	0.017	0.012	0.022	0.027
R2 Adj.	−0.007	0.077	−0.010	−0.012	−0.005	−0.001
RMSE	8.61	0.31	0.76	0.48	0.75	0.75

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.3. Mediation and Moderation via Financing Constraints

To further probe the mechanism, financing constraints are proxied by the KZ index. Originally proposed by Kaplan and Zingales (1995) [58] and subsequently adapted to the Chinese context [59,60], the index is constructed using the coefficients in Li and Xu [60]. Based on Model 4 in Table 4, the KZ index has a significantly negative effect on TFP, indicating that tighter financing constraints are associated with lower efficiency, consistent with economic intuition. Building on Models 3–6 in Table 4, both mediation and moderation roles are examined.

For mediation, comparing Model 3 and Model 5 shows that, after including the KZ index, the leverage coefficient rises from 0.870 to 0.934. This pattern is consistent with leverage being associated with stronger financing constraints (Model 4) and financing constraints lowering TFP, yielding a negative indirect effect. Using Models 3–5, the estimated mediation effect is −0.059, accounting for 6.74% of the leverage's total effect on efficiency.

For moderation, Model 6 augments Model 5 with the interaction between financing constraints and leverage. After controlling for the direct effect of the KZ index, the interaction coefficient is significantly positive, implying that the efficiency-enhancing effect of leverage is stronger when financing constraints are tighter. A plausible interpretation is that constrained firms face greater funding pressure, and higher leverage alleviates financing frictions, thereby improving operating efficiency.

4.3. Effects of Financial Leverage Across Efficiency Types

4.3.1. Decomposing TFP: Technical Change vs. Efficiency Change

Using the Malmquist decomposition in Section 3, intertemporal TFP change is split into catch-up (CU) and frontier shift (FS). Firm fixed-effects models are estimated with financial leverage as the core regressor and CU or FS as the dependent variable.

Table 5 reports that leverage has a significantly positive effect on CU (Model 1–Model 2), whereas its effect on FS is statistically insignificant (Model 3–Model 4). The positive CU effect is consistent with higher leverage enhancing capital allocation and resource-use efficiency, in line with Section 4.1.2’s indication that most subsectors have not yet reached decreasing returns to scale. In a mixed-effects specification (Model 5), leverage is significantly negatively associated with FS, suggesting that rising leverage may dampen technical progress at the industry level. Firms’ increasing leverage may divert resources from technological innovation to market-share competition.

Table 5. Effect of financial leverage on catch-up and frontier shift efficiency.

	Model 1	Model 2	Model 3	Model 4	Model 5
	CU	CU	FS	FS	FS
Intercept					$1.83 \times 10^{14} ***$
Financial_Leverage	2.562 ***	2.553 ***	-2.81×10^{13}	-2.66×10^{13}	$-1.59 \times 10^{14} ***$
HHI		1.487			
StateOwned		−0.078		3.23×10^{12}	$5.94 \times 10^{13} ***$
SetupDuration		−0.178		-3.06×10^{12}	$-4.76 \times 10^{12} ***$
ListDuration		0.171			
GDP				$8.33 \times 10^{12} ***$	$7.49 \times 10^{12} **$
Num.Obs.	2758	2725	2586	2586	2586
R2	0.003	0.003	0.000	0.004	0.011
R2 Adj.	−0.021	−0.023	−0.026	−0.023	0.010
RMSE	4.73	4.65	4.7×10^{14}	4.6×10^{14}	4.8×10^{14}

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3.2. Input Utilization Efficiency

Earlier results show that higher leverage raises TFP overall, but the effects differ across output dimensions. To probe the mechanism, this subsection examines the leverage’s impact on input utilization efficiency. Based on Table 6, leverage for fixed assets, staff, administrative expenses, and selling expenses exhibits a decline-then-rebound nonlinearity in utilization efficiency. Because the dependent variable is the percentage improvement required (a larger value indicates lower utilization efficiency), this pattern implies that efficiency deteriorates at low leverage increases but recovers beyond a threshold, consistent with gains from scale expansion or input reallocation. In contrast, for financial expenses, leverage shows an improve-then-deteriorate pattern: utilization efficiency rises with leverage at low levels but falls at high levels, indicating an interior optimal leverage at which the utilization of financial expenses is maximized.

Table 6. Effect of financial leverage on input efficiency improvement.

	Model 1	Model 2	Model 3	Model 4	Model 5
	FixedAsset	Staff	AdminCost	FinanCost	SalesCost
Financial_Leverage	1.757 ***	1.523 ***	1.578 ***	−12.681 ***	1.319 ***
Financial_Leverage_square	−1.477 ***	−1.471 ***	−1.514 ***	10.960 **	−0.991 ***
HHI	0.290 ***	0.263 ***	0.233 **	−3.378 **	0.423 ***
ListDuration	0.003 **	−0.008 ***	0.005 ***	−0.015	−0.006 ***
StateOwned	−0.109 ***	−0.004	−0.069 *	1.548 **	−0.031
ROE	−0.004 ***	−0.002 ***	−0.003 ***	0.021 **	−0.003 ***
Num.Obs.	2552	2552	2552	2552	2551
R2	0.128	0.124	0.123	0.029	0.102
R2 Adj.	0.103	0.099	0.098	0.002	0.076
RMSE	0.27	0.23	0.23	4.29	0.27

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4. Heterogeneity in the Leverage–TFP Relationship for Agriculture

4.4.1. Sources of Heterogeneity

The full-sample analysis identifies average patterns in how financial leverage affects firms' TFP and the channels through which it does so. These patterns may not hold in more granular settings. Building on the same framework, this subsection investigates the sources of heterogeneity.

Substantial intrasector differences exist across agricultural subsectors. Because development stages, intensity of financial support, and resource endowments vary, the leverage–TFP effect may differ across subsectors. This study, therefore, conducts subsector-specific tests. Market structure is another key determinant: variation in market concentration changes firms' financing conditions and competitive pressure, potentially altering leverage's transmission to TFP. To capture the competitive landscape, we measure concentration with the HHI at the subsector level and examine how the leverage–TFP relationship differs across concentration regimes.

4.4.2. Heterogeneity by Subsector and Market Concentration

Table 7 reports each subsector's optimal and average leverage. Significant gaps are pervasive, indicating substantial scope to raise TFP by increasing leverage toward the optimum. Fisheries has the highest optimal leverage (47.73%) but a low mean (23.93%), implying the largest headroom. By contrast, Agribusiness averages 29.17%, close to its optimal 35.02%, so further gains are more limited.

Table 7. Efficiency-optimal financial leverage by agricultural subsector.

Industries	Agro-Processing	Forestry	Feed	Crop Farming	Animal Husbandry	Fisheries	Agribusiness	Animal Health
Best Financial Leverage	0.4380	0.4430	0.3951	0.3363	0.3577	0.4773	0.3502	0.2283
Median Financial Leverage	0.2550	0.2828	0.2081	0.1860	0.2509	0.2393	0.2917	0.1097
Max Financial Leverage	0.6780	0.6447	0.5604	0.6395	0.6780	0.6780	0.4784	0.4147
Min Financial Leverage	0.0027	0.0004	0.0032	0.0004	0.0035	0.0008	0.1638	0.0004

As shown in Table 8, market concentration significantly shapes the strength of leverage's effect on TFP. The sample is partitioned by HHI quartiles, and the leverage effect is estimated within each group. Within the first three quartiles, higher concentration is associated with a stronger positive impact of leverage on firm TFP, with the corresponding regression coefficients rising monotonically.

Table 8. Heterogeneity across market concentration levels.

	HHI < 0.18	0.18 < HHI < 0.25	0.25 < HHI < 0.36	HHI > 0.36
	Efficiency	Efficiency	Efficiency	Efficiency
Financial_Leverage	0.964 ***	1.030 **	1.806 ***	0.693 ***
StateOwned	−0.269	−0.072	0.254	−0.117
SetupDuration	−0.454 ***	−0.424 *	−0.199	−0.148
ListDuration	0.474 ***	0.400 *	0.179	0.164
Num.Obs.	629	647	623	688
R2	0.041	0.022	0.023	0.026
R2 Adj.	−0.011	−0.041	−0.061	−0.021
RMSE	0.75	0.77	0.89	0.49

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5. Robustness Checks and Endogeneity

To assess the reliability of the findings, robustness and endogeneity checks are conducted (full regressions appear in the Appendix A).

4.5.1. Robustness Checks

Because technological barriers differ markedly across agricultural subsectors, pooling all firms to estimate TFP may impair comparability. This research, therefore, re-computes firm-level TFP within each subsector and re-estimates the leverage effect. Appendix A Tables A1 and A2 show that subsector-specific estimation modestly changes the coefficients in the “leverage–efficiency/efficiency improvement” regressions, but the overall conclusions remain intact.

Because default risk is incorporated into TFP as an undesirable output, measurement accuracy is critical. Following standard CCA practice, the default barrier is initially defined as current liabilities plus one-half of non-current liabilities. Kealhofer et al. (1998) [61], using a large default sample, argue that the barrier should be short-term debt plus one-half of long-term debt. This calibration may not fit contemporary Chinese firms. Based on bond credit-spread adjustments, Chen et al. (2012) [62] estimate a long-term debt weight of about 0.7654 for Chinese listed banks. Moreover, Gilson et al. (1990) [63] document that nearly half of distressed firms avoid liquidation through restructuring, implying that default does not occur the instant asset value touches a fixed threshold. Hence, the weight assigned to long-term liabilities can materially influence default-risk estimates.

Accordingly, the coefficient on long-term liabilities is set to 0.2 and 1 for robustness (see Tables A3–A5; dependent variables labeled “02” and “1,” respectively). The results show that, although numerical estimates vary, the signs, magnitudes, and significance patterns remain consistent, confirming the robustness of the findings.

4.5.2. Endogeneity

Firm fixed effects are employed to mitigate unobserved heterogeneity, yet time-varying omitted variables and reverse causality may still induce endogeneity. To address this, the lagged value of financial leverage is used as an instrument (see Appendix A Tables A6–A10). The comparisons indicate some endogeneity, but the core conclusion remains unchanged.

5. Conclusions, Policy Implications, and Future Research

5.1. Conclusions

Agriculture is foundational to the national economy, and its high-quality development is pivotal for overall growth. In many developing countries, agricultural progress has long relied on fiscal support, which is useful at early stages but ultimately constrained by weak market allocation. Harnessing the resource allocation role of financial markets, especially the disciplining and funding functions of financial leverage, is therefore essential. Against this backdrop, this study examines how leverage affects agricultural firms’ TFP.

Although prior research has advanced TFP measurement and its determinants, two gaps remain: (i) conventional efficiency metrics are typically profit-only, underestimating the cost of rising risk; and (ii) leverage–TFP evidence is concentrated at macro or industrial levels, with limited attention to agriculture. Given agriculture’s role in economic security, the inquiry is both practically and theoretically significant.

This study incorporates default risk as an undesirable output in a DEA framework to construct a composite, risk-adjusted TFP, using data on Chinese listed agricultural firms. The main findings are:

- (1) Using CCA to measure default risk and the USBM model to compute TFP yields indicators with sound validity.
- (2) Panel regressions show that leverage affects TFP through profit and risk channels. Financing constraints act as a negative mediator and, among highly constrained firms, as a positive moderator.

- (3) Decomposition reveals that leverage promotes catch-up but dampens frontier shift. For input utilization, most factors exhibit a decline-then-rebound pattern, whereas financial expenses display an improve-then-deteriorate pattern.
- (4) Heterogeneity tests indicate sizable gaps between average and optimal leverage across subsectors, implying substantial headroom. The leverage–TFP effect strengthens with higher market concentration.

Robustness checks, including subsector-specific efficiency estimation and alternative parameter settings, do not materially alter the results, confirming robustness. Some endogeneity persists, but the conclusions remain unchanged.

Overall, leverage’s impact on agricultural TFP is multidimensional: it reflects a profit–risk trade-off, varies across subsectors, and is moderated by market structure. The study both extends TFP measurement for agriculture and deepens understanding of the mechanisms through which financial leverage supports high-quality agricultural development.

5.2. Policy Recommendations

Building on the analysis of leverage and agricultural TFP, three recommendations follow.

- (1) Broaden financing channels and strengthen market-based support. Based on this study’s findings, the effect of financial leverage on agricultural TFP remains in the productivity-enhancing range. Policy should expand financial capital for agriculture, shifting from fiscal subsidies to market financing. Measures include encouraging private participation via concessions and equity stakes, creating local–private agricultural development funds, increasing the use of local government bonds for agricultural projects, mobilizing market-based funding for agricultural infrastructure, and issuing clear rules that guide industrial and commercial capital into agriculture.
- (2) Adopt subsector-specific financial policies. Optimal leverage differs markedly across subsectors. Policy should be refined at the subsector level to steer firms toward their optimal leverage. Establish a real-time monitoring system to track subsector TFP and optimal leverage and adjust credit allocation accordingly.
- (3) Balance technical efficiency and technical progress. Leverage raises catch-up but may dampen frontier shifts. Financial policy should support short-term efficiency gains while safeguarding incentives for innovation and be adapted to local development conditions, to promote high-quality and sustainable agricultural growth.

5.3. Directions for Future Research

This study develops a unified theoretical and empirical framework to examine how financial leverage affects agricultural TFP and offers policy-relevant conclusions. Limitations remain, suggesting two extensions:

- (1) Methodological refinement: The CCA-based default metric assumes equity prices follow a geometric Brownian motion, whereas actual prices may exhibit jumps. Future work can relax this assumption (e.g., jump-diffusion or stochastic-volatility processes) and develop default measures that better reflect market features to improve estimation accuracy.
- (2) Data expansion: The sample comprises listed agricultural firms, ensuring data quality but not fully representing the sector. In the absence of financial and market data on unlisted agricultural firms, future work can draw on administrative or survey microdata to enhance external validity.

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Appendix A

Appendix A.1. Regression Results for Robustness Checks

Table A1. Robustness check: Regressions with subsector efficiency and output-side efficiency improvement as dependent variables.

	(1)	(2)	(3)	(4)
	Indus_Efficiency	Indus_Efficiency	Indus_Proft_Slack	Indus_AvDR_Slack
Intercept	−0.299 *	−0.460 **		
Financial_Leverage	0.862 ***	2.569 ***	104.894 **	1.945 ***
Financial_Leverage_square		−3.099 **	−107.166	−1.424 ***
HHI	0.169	0.136	64.865 **	0.090
StateOwned	−0.248 ***	−0.241 **	−1.751	
SetupDuration	0.007	0.006		
ListDuration	0.002	0.004	−0.866 *	
Indus_AvDR_Slack			−16.320 ***	
Indus_Proft_Slack				0.004 ***
Num.Obs.	2663	2663	2663	2663
R2	0.008	0.010	0.008	0.168
R2 Adj.	0.006	0.008	−0.018	0.146
RMSE	1.95	1.94	80.36	0.26

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The regressions are conducted with efficiency value and output efficiency improvement as the dependent variables.

Table A2. Robustness check: Regressions with Subsector Input-Side Efficiency Improvement as the Dependent Variable.

	(1)	(2)	(3)	(4)	(5)
	FixedAsset_Slack	Staff_Slack	AdminCost_Slack	FinanCost_Slack	SalesCost_Slack
Financial_Leverage	1.654 ***	1.534 ***	1.502 ***	−13.499 **	1.412 ***
Financial_Leverage_square	−1.635 ***	−1.691 ***	−1.371 ***	16.698 *	−1.289 ***
HHI	−0.344 ***	0.064	−0.046	−6.569 *	0.075
ListDuration	0.011 ***	0.004 ***	0.009 ***	0.009	0.003
StateOwned	−0.081 **	−0.072 *	−0.095 **	1.278	−0.019
ROE	−0.005 ***	−0.006 ***	−0.006 ***	−0.002	−0.006 ***
Num.Obs.	2628	2628	2628	2628	2627
R2	0.146	0.106	0.129	0.005	0.098
R2 Adj.	0.122	0.082	0.105	−0.023	0.074
RMSE	0.24	0.25	0.26	9.75	0.27

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The regressions are conducted with input efficiency improvement as the dependent variable.

Table A3. Robustness check based on the non-current-liability conversion ratio (dependent variables: efficiency and output-side efficiency improvement).

	(1)	(2)	(3)	(4)	(5)	(6)
	Efficiency02	Efficiency1	Proft _Slack02	Proft _Slack1	AvDR _Slack02	AvDR _Slack1
Intercept	−0.332 **	−0.685 **				
Financial_Leverage	2.637 ***	1.975 ***	105.134 **	103.921 **	1.373 ***	1.985 ***
Financial_Leverage_square	−2.421 **	−3.216 **	−106.572 *	−107.552	−1.405 ***	−1.562 ***
HHI	0.127	0.131	63.792 **	64.706 **	0.098	0.083
StateOwned	−0.198 **	−0.257 **	−1.685	−1.711		
SetupDuration	0.014	0.007				
ListDuration	0.003	0.004	−0.809 *	−0.905 *		
Indus_AvDR_Slack			−16.106 ***	−15.953 ***		
Indus_Proft_Slack					0.006 ***	0.002 ***
Num.Obs.	2663	2663	2663	2663	2663	2663
R2	0.011	0.009	0.010	0.009	0.168	0.158
R2 Adj.	0.009	0.007	−0.019	−0.017	0.146	0.149
RMSE	1.89	1.96	78.05	81.03	0.26	0.27

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.**Table A4.** Robustness check based on the non-current-liability conversion ratio (dependent variable: input-side efficiency improvement).

	(1)	(2)	(3)	(4)	(5)	(6)
	FixedAsset _Slack02	FixedAsset _Slack1	Staff _Slack02	Staff _Slack1	AdminCost_Slack02	AdminCost_Slack1
Financial_Leverage	1.703 ***	1.652 ***	1.552 ***	1.491 ***	1.513 ***	1.483 ***
Financial_Leverage_square	−1.627 ***	−1.706 ***	−1.701 ***	−1.812 ***	−1.329 ***	−1.382 ***
HHI	−0.336 ***	−0.411 ***	0.063	0.061	−0.043	−0.054
ListDuration	0.0108 ***	0.011 ***	0.005 ***	0.003 ***	0.007 ***	0.011 ***
StateOwned	−0.073 **	−0.082 **	−0.072 *	−0.073 *	−0.096 **	−0.085 **
ROE	−0.005 ***	−0.007 ***	−0.005 ***	−0.006 ***	−0.007 ***	−0.005 ***
Num.Obs.	2628	2628	2628	2628	2628	2628
R2	0.143	0.147	0.107	0.105	0.131	0.127
R2 Adj.	0.121	0.123	0.083	0.080	0.108	0.103
RMSE	0.25	0.23	0.24	0.26	0.25	0.27

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.**Table A5.** Robustness check based on the non-current-liability conversion ratio (dependent variable: input-side efficiency improvement) (continued).

	(7)	(8)	(9)	(10)
	FinanCost _Slack02	FinanCost _Slack1	SalesCost _Slack02	SalesCost _Slack1
Financial_Leverage	−12.983 **	−13.701 **	1.501 ***	1.389 ***
Financial_Leverage_square	16.703 *	16.652 *	−1.351 ***	−1.402 ***
HHI	−5.963 *	−7.120 *	0.078	0.069
ListDuration	0.010	0.009	0.003	0.002
StateOwned	1.305	1.213	−0.017	−0.020
ROE	−0.002	−0.003	−0.005 ***	−0.007 **
Num.Obs.	2628	2628	2627	2627
R2	0.006	0.005	0.010	0.095
R2 Adj.	−0.024	−0.022	0.076	0.073
RMSE	9.71	9.74	0.26	0.28

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A.2. Regression Results for Endogeneity Tests

Table A6. Endogeneity test 1: Effect of financial leverage on TFP under alternative methods.

	USBM1_iv Efficiency	USBM2_iv Efficiency	USBM3_iv Efficiency	SBM1_iv Efficiency_SBM	SBM2_iv Efficiency_SBM	SBM3_iv Efficiency_SBM
Financial_Leverage_Ratio	1.322 ***	1.349 ***	3.251 ***	0.228 **	0.234 **	0.545 **
HHI		0.576 *	0.665 **		0.232	0.247 *
StateOwned		−0.263 **	−0.292 **		−0.123 **	−0.127 **
SetupDuration		−0.205 **	−0.168 *		0.008 ***	0.008 ***
ListDuration		0.210 **	0.174 **			
Financial_Leverage_Ratio_square			−3.477 ***			−0.570
FarmGDP					0.004 **	0.004 **
Num.Obs.	2517	2488	2488	2571	2541	2541
R2	0.012	0.017	0.020	0.001	0.009	0.008
R2 Adj.	−0.014	−0.011	−0.008	−0.025	−0.018	−0.019
RMSE	0.73	0.73	0.73	0.35	0.35	0.35

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.**Table A7.** Endogeneity test 2: Mechanisms of financial leverage's effect on TFP in agricultural firms.

	Model 1_iv Profit_Slack	Model 2_iv AvDR_Slack	Model 3_iv Efficiency	Model 4_iv KZ	Model 5_iv Efficiency	Model 6_iv Efficiency
Financial_Leverage_Ratio	−20.622 ***	1.458 ***	1.349 ***	0.224 *	1.324 ***	1.978 ***
Financial_Leverage_Ratio_square	32.652 ***	−0.874 ***				
AvDR_Slack_per	2.477 ***					
HHI	6.547 *	0.375 ***	0.576 *		0.570 *	0.539 *
ListDuration	−0.225 ***		0.210 **		0.197 **	0.186 **
StateOwned	−0.837		−0.263 **		−0.254 **	−0.264 **
Proft_Slack_per		0.003 ***				
SetupDuration			−0.205 **		−0.192 **	−0.180 **
KZ					−0.119 ***	−0.342 ***
Financial_Leverage_Ratio × KZ						0.902 ***
Num.Obs.	2488	2587	2488	2656	2488	2488
R2	0.018	0.101	0.017	0.009	0.022	0.029
R2 Adj.	−0.010	0.077	−0.011	−0.015	−0.006	0.001
RMSE	8.54	0.31	0.73	0.48	0.73	0.72

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.**Table A8.** Endogeneity test 3: Effect of financial leverage on catch-up (CU) and frontier shift (FS) efficiency.

	(1) CU	(2) CU	(3) FS	(4) FS	(5) FS
Financial_Leverage_Ratio	3.393 ***	3.118 **	$−3.8 \times 10^{13}$	$−4.961 \times 10^{13}$	$−1.275 \times 10^{14} *$
HHI		1.599			$−7.6256 \times 10^{13}$
StateOwned		0.062		2.446×10^{13}	$5.401 \times 10^{13} ***$
SetupDuration		−0.134		$−2.802 \times 10^{12}$	$−4.193 \times 10^{12} **$
ListDuration		0.123			
GDP				$8.311 \times 10^{12} ***$	$6.847 \times 10^{12} **$
(Intercept)					$1.874 \times 10^{14} ***$
Num.Obs.	2656	2625	2487	2487	2459
R2	0.003	0.004	0.000	0.004	0.010
R2 Adj.	−0.021	−0.023	−0.026	−0.024	0.008
RMSE	4.71	4.71	4.6×10^{14}	4.6×10^{14}	4.7×10^{14}

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9. Endogeneity test 4: Effect of financial leverage on input efficiency improvement.

	(1)	(2)	(3)	(4)	(5)
	FixedAsset	Staff	AdminCost	FinanCost	SalesCost
Financial_Leverage_Ratio	2.218 ***	1.842 ***	2.010 ***	−20.412 ***	1.674 ***
Financial_Leverage_Ratio_square	−1.744 ***	−1.733 ***	−1.981 ***	19.437 ***	−1.151 ***
HHI	0.259 **	0.274 ***	0.233 **	−4.245 **	0.427 ***
ListDuration	0.003 *	−0.008 ***	0.004 ***	−0.014	−0.006 ***
StateOwned	−0.153 ***	−0.025	−0.089 **	1.871 ***	−0.073 *
ROE	−0.003 ***	−0.002 ***	−0.003 ***	0.019 *	−0.003 ***
Num.Obs.	2453	2453	2453	2453	2453
R2	0.123	0.122	0.112	0.031	0.097
R2 Adj.	0.097	0.097	0.087	0.003	0.071
RMSE	0.27	0.22	0.23	4.15	0.27

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.**Table A10.** Endogeneity test 5: Heterogeneity across market concentration levels.

	HHI < 0.18	0.18 < HHI < 0.25	0.25 < HHI < 0.36	HHI > 0.36
	Efficiency	Efficiency	Efficiency	Efficiency
Financial_Leverage_Ratio	1.027 **	1.699 ***	3.358 ***	1.335 ***
StateOwned	−0.332	−0.146	0.253	−0.271 *
SetupDuration	−0.312 **	−0.339	−0.291	−0.099
ListDuration	0.321 **	0.325	0.263	0.119
Num.Obs.	602	628	598	660
R2	0.022	0.017	0.026	0.029
R2 Adj.	−0.033	−0.048	−0.057	−0.018
RMSE	0.70	0.73	0.90	0.44

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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