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Empirical Analysis of the Impact of Agricultural Enterprise Digitalization on Corporate Price Risk Exposure

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Abstract. This paper investigates whether digital transformation reduces the price risk exposure of agricultural enterprises. Agricultural firms are subject to pronounced seasonality, biological production cycles, weather shocks, product perishability, and frequent commodity price fluctuations, making their price risk more persistent than that of many manufacturing and service firms. Building on research into digital business strategy, smart farming, agricultural information systems, and financial risk exposure, this study constructs a panel data framework using Chinese A-share listed agricultural enterprises covering the period 2018–2022. Price risk exposure is measured as the sensitivity of firm value to changes in agricultural commodity prices. Digital transformation is primarily proxied by digital technology input scaled by total assets, and can be supplemented by a weighted digital transformation index when disaggregated indicators are available. Empirical evidence indicates that digitalization is significantly associated with lower price risk exposure: the standard deviation of product price fluctuations declines by 15.3%, the lag in market price transmission falls by approximately 23.7%, and highly digitalized firms record a 45.3% reduction in price risk exposure. This mitigating effect is stronger among firms with more complete digital systems and integrated operations covering production, processing, storage, logistics, and sales. The findings suggest that digitalization is not merely a technological upgrade, but a risk management capability that enhances market transparency, shortens decision lags, and strengthens resilience to price shocks.

Keywords: digital transformation, agricultural enterprises, price risk exposure, smart farming, panel data

1. Introduction

Agricultural enterprises operate under intertwined market and biological uncertainties. Product prices are shaped by weather shocks, pest and disease outbreaks, storage capacity constraints, logistics disruptions, policy adjustments, international trade conditions, and shifts in consumer demand. Compared with ordinary industrial goods, most agricultural products are highly seasonal and perishable, which limits firms' ability to defer sales or smooth supply across periods. As a result, price fluctuations can be rapidly transmitted to revenue, profitability, inventory valuation, and market expectations. For listed agricultural enterprises, such uncertainty may also be reflected in stock returns, as investors price commodity market changes into firm valuations.

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Digital transformation offers a potential channel for mitigating such exposure. In the management literature, digital transformation refers to the reconfiguration of corporate strategy, operational processes, product offerings, and organizational capabilities enabled by digital technologies [1-3]. In the agricultural sector, digitalization encompasses sensors, Internet of Things devices, remote sensing, big data platforms, intelligent equipment, digital procurement and sales systems, blockchain traceability, and data-driven financial services [4-9]. These tools may reduce information frictions, improve yield forecasting, detect quality problems at an earlier stage, optimize inventory and logistics arrangements, and support more flexible pricing decisions. Conversely, digitalization may also increase exposure if implementation costs are excessive, data quality is poor, or firms become over-reliant on fragile digital infrastructure.

Accordingly, the core research question of this paper is: does digital transformation reduce the price risk exposure of agricultural enterprises? This study contributes to the literature in three ways. First, it links agricultural digitalization to the financial concept of risk exposure, rather than focusing solely on productivity or operational efficiency. Second, it conceptualizes digitalization as a firm-level capability and examines how it affects the sensitivity of firm value to commodity price shocks. Third, it provides an empirical design adapted to panel data, with careful attention to fixed effects, standard error estimation, and robustness checks. This paper argues that digitalization reduces price risk exposure primarily through three channels: improved information transparency, enhanced process coordination, and faster market response.

2. Literature review and hypothesis development

Digital transformation has been studied as a strategic change process that reshapes business models, organizational boundaries, and innovation activities [1-4]. Digital technologies do not only automate existing routines, they change how firms collect information, combine resources, interact with customers, and make decisions. For agricultural enterprises, this point is important because production, circulation, and sales are closely connected. A digital platform that links planting, breeding, processing, storage, logistics, and sales can reduce the uncertainty generated by fragmented information across the supply chain.

Research on smart farming emphasizes the role of data in reducing agricultural uncertainty. Wolfert et al. show that big data in smart farming supports decision-making across the cyber-physical farm management cycle [5]. Klerkx et al. further argue that digital agriculture is not only a technical phenomenon but also a social and organizational transformation [6]. Digital tools change advisory services, farmer-firm relationships, market access, and governance arrangements. Aker and Jensen provide influential evidence that information and communication technologies can improve agricultural market performance by reducing information asymmetry and price dispersion [7, 8]. These studies imply that better information can lower the cost of responding to price signals.

A separate financial literature defines exposure as the sensitivity of firm value to an external risk factor. Adler and Dumas formalize exposure as a regression coefficient, and Jorion applies this logic to firm returns and exchange-rate movements [10-12]. The same logic can be adapted to agricultural commodity price risk: if a firm's stock return or operating performance is highly sensitive to agricultural price movements, its price risk exposure is high. Digitalization may reduce this sensitivity by improving hedging, contract management, production planning, traceability, and inventory turnover.

Based on these arguments, the core hypothesis is: H1: The higher the level of digital transformation of an agricultural enterprise, the lower its price risk exposure. A secondary hypothesis is that the effect is stronger for firms with integrated supply chains, because digital data

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can be used more effectively when production, processing, storage, and sales are coordinated within the same organizational system.

3. Research design

3.1. Sample and data

This study uses Chinese A-share listed agricultural enterprises as the empirical sample. The sample-selection criteria combine enterprise-nature and data-quality requirements. The enterprise-nature criterion requires that the main business of the firm belongs to agriculture-related fields, including crop farming, breeding, agricultural product processing, and other related agricultural industries. The data-quality criterion excludes ST firms, observations with serious missing data, and firms experiencing major asset restructuring during the study period.

The empirical period is 2018-2022, and the data are organized at quarterly frequency. Digitalization-related information is obtained from enterprise production and operation information, digital equipment investment, digital technology expenditure, IoT facilities, data centers, intelligent agricultural machinery, production-management systems, public annual reports, and announcements. Price-risk information is measured using market price volatility indicators, agricultural product price changes, consumer demand data, and related market supply-demand information.

The sample is further classified by enterprise size, ownership nature, geographical location, and business type. Firm size is divided by the median of total assets, ownership is divided according to property-rights characteristics, and regions are grouped into eastern, central, and western areas according to regional economic-development conditions. The underlying materials do not report the final number of firms or firm-period observations, therefore, the sample-size information should be added when the original dataset is available.

3.2. Variable measurement

The dependent variable is price risk exposure (PRE), measured as the sensitivity of enterprise stock prices to agricultural commodity price movements. Specifically, PRE is defined as the coefficient of firm stock returns on the change rate of agricultural product prices. A higher PRE indicates that the firm is more strongly affected by product-price fluctuations.

The core explanatory variable is the digital transformation level (DTL). The main operational proxy is digital technology input divided by total assets. When detailed indicators are available, DTL can also be measured as a weighted composite index based on digital infrastructure investment, digital technology application depth, digital talent reserve, digital equipment investment, intelligent production-line coverage, and related digital indicators. In the composite-index approach, standardized indicators are weighted by the analytic hierarchy process (AHP). Table 1 summarizes definition of variables.

Table 1. Variables definition

Variable type	Variable name	Symbol	Measurement
Dependent variable	Price risk exposure	PRE	Coefficient measuring the sensitivity of stock prices to agricultural commodity price movements

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Table 1. (continued)

Core explanatory variable	Digital transformation level	DTL	Digital technology input divided by total assets, extended index can be built with AHP weights
Control variable	Enterprise size	SIZE	Natural logarithm of total assets
	Asset-liability ratio	LEV	Total liabilities divided by total assets
	Profitability	ROA	Net profit divided by total assets

The model includes year and industry dummy variables to control for time effects and industry differences. Continuous variables are winsorized at the 1st and 99th percentiles to reduce the influence of extreme values [13-15]. Variables are then standardized with mean zero and standard deviation one to facilitate coefficient interpretation. VIF statistics are not reported in the available empirical materials, so multicollinearity should be checked when the original dataset is used for final estimation.

3.3. Econometric model

To examine the impact of digital transformation on agricultural enterprise price risk exposure, the baseline panel model is specified as follows:

$$\mathrm{PRE_{it}} = \alpha + \beta_1 \mathrm{DTL_{it}} + \beta_2 \mathrm{X_{it}} + \mu_\mathrm{i} + \lambda_\mathrm{t} + \varepsilon_\mathrm{it} \tag{1}$$

In equation (1), PRE_{it} denotes the price risk exposure of firm i in period t, DTL_{it} denotes the firm-level digital transformation level, X_{it} is the vector of control variables, including SIZE, LEV, and ROA, μ_i represents firm fixed effects, λ_t represents time fixed effects, and ε_{it} is the idiosyncratic error term. The coefficient β_1 captures the relationship between digital transformation and price risk exposure. A negative β_1 is consistent with the hypothesis that digital transformation reduces price risk exposure.

To analyze heterogeneous effects and mechanisms, the extended model introduces an interaction term:

$$\mathrm{PRE_{it}} = \alpha + \beta_1 \mathrm{DTL_{it}} + \beta_2 \left(\mathrm{DTL_{it}} \times Z_\mathrm{it}\right) + \beta_3 \mathrm{X_{it}} + \mu_\mathrm{i} + \lambda_\mathrm{t} + \varepsilon_\mathrm{it} \tag{2}$$

In equation (2), Z_{it} denotes moderating factors such as enterprise characteristics, supply-chain integration, or industry competition. The sign and significance of β_2 indicate whether the effect of digital transformation differs across enterprise types or competitive environments.

To address potential endogeneity from omitted variables or reverse causality, the empirical design proposes an instrumental-variable robustness test. Industry-average digitalization is used as an instrument for firm-level digitalization, and the relationship is estimated through two-stage least squares. The first-stage regression predicts DTL using the instrument and controls, while the second-stage regression estimates the effect of predicted DTL on PRE.

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4. Empirical findings

4.1. Baseline evidence

The available empirical evidence indicates that digital transformation significantly mitigates the price risk exposure of agricultural enterprises. After agricultural enterprises adopt digital technology, the standard deviation of product-price fluctuations decreases by 15.3%, and the lag in market price transmission decreases by approximately 23.7%. These indicators suggest that digitalization improves the speed with which firms acquire market information and respond to price signals.

Table 2. Price-risk-control effects by digitalization level

Digitalization Level	Price Risk Exposure Reduction ratio	Information Acquisition Efficiency Improvement	Inventory Turnover Change
Highly digitalized	45.3%	78.6%	+32.1%
Moderately digitalized	28.7%	52.4%	+18.9%
Low digitalization	12.4%	25.8%	+8.5%

Table 2 shows a clear gradient. Highly digitalized agricultural enterprises report a 45.3% reduction in price risk exposure, a 78.6% improvement in information acquisition efficiency, and a 32.1% increase in inventory turnover. Moderately digitalized enterprises show smaller but still meaningful improvements, while low-digitalization enterprises show the weakest risk-control effect. This pattern is consistent with H1: stronger digital transformation is associated with lower price risk exposure.

4.2. Mechanism analysis

Three mechanisms explain the risk-reduction effect. First, digital transformation improves information acquisition. IoT systems, production-management systems, online transaction data, and market-monitoring tools enable firms to observe price and demand changes earlier. Second, digital transformation improves operational flexibility. Intelligent warehousing and data-based production systems help firms adjust harvesting, processing, inventory, and shipment decisions before price shocks are fully reflected in revenue. Third, digital transformation strengthens product differentiation and bargaining power. Traceability, quality-control systems, online brand management, and e-commerce channels help firms communicate product quality and reduce dependence on spot-market price fluctuations.

4.3. Heterogeneity evidence

The risk-control effect differs by enterprise type. Large agricultural enterprises and enterprises with integrated industrial-chain operations benefit more because they are more likely to have complete risk-monitoring systems, digital platforms connecting production, processing, storage, transportation, and sales, and sufficient resources to transform digital information into managerial action. By contrast, traditional agricultural enterprises face higher unit costs because of fragmented

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land, weaker information access, and limited digital infrastructure. For enterprises with strong seasonality, the price-risk-control effect of digital transformation is reduced by about 18.6%, indicating that seasonal and regional characteristics still constrain the effectiveness of digital risk management.

4.4. Robustness and endogeneity discussion

For robustness, continuous variables are winsorized at the 1st and 99th percentiles and standardized before regression analysis. The empirical design also proposes an instrumental-variable approach in which the industry-average digitalization level is used as an instrument for firm-level digitalization, and the relationship is estimated with two-stage least squares. Because first-stage and second-stage coefficient estimates are not reported in the available empirical materials, the instrumental-variable design should be interpreted as a robustness strategy rather than completed causal evidence. The final empirical version should add the actual 2SLS output when the dataset is available.

5. Discussion

The findings have theoretical and practical implications. Theoretically, the paper extends digital-transformation research by linking digital capability to financial risk exposure. Prior studies often emphasize efficiency, innovation, and productivity [1-6,10]. This study highlights resilience: digitalization matters because it changes how quickly and accurately firms recognize and respond to price shocks. In agricultural markets, where uncertainty is frequent and information is often fragmented, this resilience function is especially important.

Practically, agricultural enterprises should avoid treating digital transformation as a one-time purchase of equipment. The value of digitalization depends on data quality, organizational integration, and decision use. A sensor system that is not connected to procurement, production, storage, and pricing decisions cannot meaningfully reduce risk. A data platform without trained employees may become an accounting label rather than a managerial capability. Firms should therefore prioritize digital projects that directly address price risk: market-monitoring dashboards, production forecasting, inventory warning systems, contract-management tools, and traceability systems that support premium pricing.

The results also matter for policymakers. Agricultural digitalization requires infrastructure, standards, training, and data governance. Public support should not only subsidize hardware but also help build interoperable data platforms, agricultural market information services, digital-skills training, and secure data-sharing mechanisms. Because small and medium-sized agricultural enterprises face higher financing and talent constraints, policy support should be differentiated. Demonstration projects are useful only when their experience can be transferred to firms with limited resources.

At the same time, digital transformation introduces new risks. Cybersecurity failures, platform dependence, algorithmic errors, and privacy concerns may create operational vulnerabilities. Blockchain and traceability technologies can increase transparency in food supply chains [9], but they also require credible data input and governance. Digital tools can reduce price risk only when they are embedded in reliable institutions and disciplined management systems.

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6. Conclusion

This paper analyzes the impact of digital transformation on the price risk exposure of agricultural enterprises. Using a panel-data research design for Chinese listed agricultural firms, it argues that digitalization is associated with lower exposure to agricultural commodity price shocks. The effect operates through better information acquisition, stronger supply-chain coordination, faster market response, and improved product differentiation. The evidence is strongest for firms with integrated supply chains and more complete digital infrastructure.

The study contributes to the literature by combining digital-transformation theory, agricultural information economics, and financial exposure measurement. It also provides practical guidance: agricultural enterprises should focus digital investment on decision-relevant systems rather than symbolic disclosure. For policymakers, the results suggest that digital agriculture policy should combine infrastructure, standards, training, and data governance.

Several limitations remain. The digital-transformation index is based partly on public disclosure, which may contain measurement error. The sample is limited to listed firms and may not represent small unlisted agricultural enterprises. Causal identification is also limited because digital adoption is not random. Future research should use policy pilots, broadband expansion, digital-agriculture demonstration zones, or platform adoption shocks to identify causal effects more convincingly. More granular transaction, inventory, and contract data would also help reveal how digitalization changes price pass-through and risk management at the operational level.

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