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The Digital Economy and the Quality of Imported Agricultural Products

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Abstract: China's import trade is shifting from scale expansion towards quality upgrading. The quality of imported agricultural products matters not only for consumer welfare, but also for the optimisation of China's import structure under a higher level of opening-up. Using Chinese customs import data for 2009-2019 and a provincial digital economy development index, this paper measures the quality of imported agricultural products at the province-origin-HS8 product-year level and examines how the digital economy is associated with import quality through a quality-signal identification mechanism. The results show, first, that digital economy development is associated with higher import quality. The baseline coefficient is 0.080; a one-standard-deviation increase in the level of digital economy development corresponds to about a 0.024-standard-deviation increase in the quality of imported agricultural products. This result remains robust after robustness checks and endogeneity tests. Second, in provinces with a higher level of digital economy development, high-quality origins display clearer price differences and quality advantages, and the dispersion of residualised prices is also higher. These patterns indicate a clearer quality premium and price stratification in the import market. Third, origin-relationship screening results show that low-quality origin relationships are more likely not to continue in the following year. Heterogeneity by Rauch product classification further shows that the positive relationship is more stable for organised-exchange goods and reference-priced goods. The paper argues that China should improve digital quality-information infrastructure for imported agricultural products, strengthen importers' capacity to identify high-quality origins, and use digital regulatory tools to improve the screening of low-quality origins.

Keywords: Digital Economy; Imported Agricultural Products; Product Quality; Quality Premium; Origin Screening
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1. Introduction

As demand for agricultural consumption shifts from quantity towards quality, import trade has become an important channel through which China meets demand for higher-quality consumption. Rising income has changed the structure of Chinese consumers' demand for food, increasing their willingness to pay for higher-quality products [1,2]. Upgrading the quality of imports is also central to matching domestic consumers' non-homothetic preferences [3]. China's Fourteenth Five-Year Plan for High-Quality Development of Foreign Trade, jointly issued by the Ministry of Commerce and other departments, explicitly encourages imports of high-quality consumer goods. In practice, however, agricultural products often have credence attributes. Their quality is difficult for consumers to observe before transactions take place. According to information released by the General Administration of Customs on foods denied entry, more than 4,000 batches of food were intercepted at Chinese ports in 2024, with frequent problems such as excessive pesticide residues, microbial contamination and violations of food-additive regulations. These cases indicate that information asymmetry remains common in cross-border agricultural trade, allowing low-quality products to attempt to enter the Chinese import market for arbitrage. When quality signals are weak, high-quality agricultural products find it difficult to escape low-price competition from low-quality products, cannot fully obtain a corresponding quality premium, and face the risk that poor-quality products crowd out better-quality ones.

The rapid development of the digital economy offers a new way to ease information frictions in cross-border trade. Unlike traditional technological progress, the digital economy changes the information structure and cost boundary of import trade through big data, cloud computing and cross-border e-commerce platforms. Digital technologies reduce search, replication, tracking and verification costs [4]. Through digital platforms, domestic importers can identify suppliers with stronger capabilities and better fit with consumption upgrading at very low marginal cost. They are less constrained by the information iceberg associated with geographical distance in traditional trade [5], which makes it easier for high-quality agricultural products to enter the Chinese market. Digital technologies, including blockchain traceability, and the reputation systems accumulated on cross-border e-commerce platforms can convert hidden attributes, such as origin and production standards, into observable and traceable data signals [6]. Greater information transparency reduces information frictions between buyers and sellers, lowers the risk of adverse selection, and enables high-quality agricultural products to obtain market premiums through credible signals, thereby raising the quality of imported agricultural products.

Existing studies have examined product quality from the perspectives of importing-country demand, supply-side conditions, policy environments, trade costs and information frictions. First, the theory of non-homothetic preferences based on the Linder hypothesis regards the importing country's income level and income distribution as core drivers of trade in high-quality products. As income per capita rises, consumers' willingness to pay for higher-quality and safer agricultural products increases, thereby promoting quality upgrading in imported agricultural products from the consumption side [3,1,2]. Income inequality within a country can also affect the quality composition of the import basket by changing the scale of demand for high-quality products [7]. Second, trade liberalisation and non-tariff measures are important determinants of quality. Lower tariffs on intermediate inputs in exporting countries can improve final-product quality through cost-saving and quality-complementarity effects [8]. SPS measures and TBT measures often force exporters to raise product standards in order to cross regulatory thresholds and can therefore play a quality-screening role in the long run [9,10]. Third, transport costs can generate a screening effect on quality. Empirical studies have documented the Washington Apples effect: the high fixed cost of long-distance transport screens out low-quality products, so the quality of imported food tends to rise with distance [11]. Finally, the digital economy affects product quality by reducing search and verification costs. Internet applications, cross-border e-commerce platforms and digital finance can ease information asymmetry in cross-border trade and promote export quality upgrading by reducing search and matching costs and relaxing financing constraints [5,6,12,13]. Recent evidence further links digital and energy transitions to agricultural resilience and the quality of grain productivity, indicating that technology-driven structural change can reshape agricultural performance beyond trade outcomes [14,15]. Yet existing research has focused mainly on export quality upgrading or broader agricultural performance. Less attention has been paid to import quality, especially the quality of imported agricultural products. Nor has enough work explained the internal mechanism through which the digital economy may upgrade import quality.

This paper makes three contributions. First, it extends the discussion of the trade effects of the digital economy from exports to imports and focuses on imported agricultural products, a market in which information frictions are particularly salient. This provides new evidence for understanding how the digital economy shapes high-quality importing. Second, it measures the quality of imported agricultural products using customs import data at the province-origin-HS8 product-year level. This level of observation captures quality differences across origins within the same product and is therefore closer to the actual choice environment faced by importers. Third, it organises the mechanism through which the digital economy affects import quality around quality-signal identification and provides empirical evidence from observable margins: quality premiums, residualised unit-value stratification, dispersion of residualised prices and adjustments in origin relationships.

2. Theoretical Analysis and Hypotheses

The core friction in the market for imported agricultural products is that quality information is costly to identify and verify. The theory of information asymmetry shows that when buyers cannot observe true quality, prices tend to reflect average expected quality. This depresses the market return to high-quality supply and allows low-quality supply to survive under information opacity [16]. Agricultural products have both experience and credence attributes. Information on origin authenticity, certification credibility, safety, cold-chain fulfilment and origin reputation often needs to be searched, compared and verified before it can become an effective quality signal. High-quality origins usually incur higher costs in variety improvement, quality control, certification management, cold-chain fulfilment and stable supply. When these investments cannot be fully observed by importers and consumers, quality investment cannot be fully converted into price returns and stable trading relationships.

When quality signals are insufficient, the import market tends to display pooling features. High-quality and low-quality origins are difficult to distinguish before a transaction, so importers choose on the basis of average expected quality, observable costs and past trading experience. For high-quality origins, average pricing weakens the market return to quality investment and limits their ability to obtain a sufficient premium. For low-quality origins, opaque origin information, hard-to-verify certification and fragmented fulfilment records reduce the probability of being identified and replaced, allowing them to remain in existing import relationships. The market therefore shows insufficient price rewards for high-quality products and insufficient screening of low-quality products. Quality upgrading is constrained by unclear quality signals.

Digital economy development changes the cost structure through which quality signals are generated, transmitted and verified. Research on trade information frictions shows that search and verification costs shape trade networks, price differences and trade flows; research on digital economics further shows that digital technologies reduce search, tracking and verification costs [5,4]. In the market for imported agricultural products, importers can use platform transaction records, historical procurement data and origin-comparison tools to identify potential high-quality origins more quickly. Customs, market regulation and inspection-quarantine authorities can improve the efficiency of quality verification through digital documents, inspection records, risk profiling and traceability systems. Distribution platforms and supply-chain service providers can use cold-chain records, fulfilment evaluations and return-recall information to increase transaction transparency. Consumers' greater visibility of origin, certification and safety attributes also strengthens demand-side feedback on quality signals. These changes jointly reduce the cost of quality identification and relationship adjustment, making the import market more separating.

Once separation becomes stronger, prices, quality rankings and import relationships should change together. The demand-inversion literature interprets the market-demand residual after controlling for prices as consumers' valuation of product quality. Studies of quality competition also emphasise that market competition and trade openness can change the incentives of firms or origins to upgrade quality [17-19]. In this paper's setting, high-quality origins can obtain clearer price rewards through verifiable information on certification, fulfilment, reputation and stable supply. Importers are also more willing to maintain or expand relationships with such origins. Low-quality origins, by contrast, are more likely to reveal disadvantages in quality records, fulfilment stability and comparison with alternative origins, making subsequent relationship termination more likely. If the digital economy improves quality identification, the market should show not only higher prices for high-quality origins, but also wider residualised price differences after common price factors at the province, product-year and origin levels are removed. Price stratification is therefore not simply a result of transport costs, exchange-rate fluctuations or common product shocks. It is linked to clearer quality signals within the same market. Residualised prices, dispersion of residualised prices and adjustments of low-quality origin relationships can thus be interpreted as different empirical manifestations of the same quality-signal improvement process.

This logic implies that the digital economy should first be associated with higher overall import quality. When quality signals become clearer, importers can more effectively identify high-quality origins within the same HS8 product, and import relationships shift towards origins with stronger demand valuations and higher quality rankings. Second, the digital economy should make price differences and quality advantages of high-quality origins clearer. In provinces with higher digital economy development, high-quality origins should be more likely to obtain price rewards and maintain stronger quality advantages. At the same time, the dispersion of residualised prices within the same market should increase, reflecting clearer price stratification between high- and low-quality origins. Third, the digital economy should increase the probability that low-quality origin relationships do not continue in the following year. Improved quality tracking and search for alternative origins make low-quality origins easier to replace in subsequent import relationships.

The mechanism can therefore be summarised as follows: the digital economy lowers the cost of quality-signal identification and trading-relationship adjustment, enables high-quality origins to receive clearer price rewards, and increases the probability that low-quality origin relationships do not continue in the following year. Through this channel, it is associated with upgrading the quality of imported agricultural products. The paper proposes the following hypotheses:

Hypothesis H1: Digital economy development is associated with higher quality of imported agricultural products.

Hypothesis H2: Digital economy development strengthens the price premium and quality advantage of high-quality origins and increases the dispersion of residualised prices, making the quality premium more visible in the import market.

Hypothesis H3: Digital economy development increases the probability that low-quality origin relationships do not continue in the following year, generating adjustment of low-quality origin relationships.

3. Research Design

3.1 Data Sources

This paper uses a panel of Chinese imports of agricultural products at the province-HS8 product-origin-year level for 2009-2019. Import data come from the database of the General Administration of Customs of China. The raw records include the registered location of the importing firm, origin, HS code, import value, import quantity, trade mode and year. The sample retains agricultural products whose first two HS-code digits are 01-24. It excludes processing trade, abnormal import values or quantities, missing origin information and observations that cannot be harmonised to the HS2007 coding system. The core explanatory variable is the provincial digital economy development index. Its basic indicators are mainly drawn from the China Statistical Yearbook, provincial statistical yearbooks and related publicly available statistical sources. Control variables include provincial economic development, financial development, infrastructure density, technological innovation capacity and income inequality, as well as origin-level economic development, origin agricultural value added and import tariffs. Origin-level macroeconomic variables come mainly from the World Bank WDI database, and tariff data come from the WITS database.

The main sample ends in 2019 in order to avoid the unusual disruptions caused by the COVID-19 pandemic during 2020-2022. The pandemic affected cross-border logistics, port clearance, inspection and quarantine procedures, and the structure of agricultural imports. Import quantities, origin composition and transport costs all experienced abnormal fluctuations. Including those years in the main sample would risk mixing the relationship between the digital economy and import quality with shocks from a public-health emergency. The paper therefore uses the pre-pandemic period as the main analysis window so that the estimates mainly reflect the relationship between the digital economy and import quality under normal trading conditions.

The level of observation also requires clarification. The core explanatory variable, digital economy development, is measured at the province-year level, while import quality is observed at the province-origin-HS8 product-year level. The estimates therefore describe the relationship between changes in the provincial digital economy environment and quality outcomes across import relationships within the province.

3.2 Variables and Measurement

3.2.1 Dependent Variable

Quality of imported agricultural products. Following the demand-inversion approach of Khandelwal, Schott and Wei [18], this paper uses import prices and quantities to measure within-product quality differences. Let q_{poht} denote the quantity imported by province p from origin o for HS8 product h in year t, let p_{poht} denote the import price, and let σ denote the elasticity of substitution. Under the CES demand framework, the part of import demand that cannot be explained by prices and fixed effects can be used to infer within-product quality differences. The paper first constructs the demand-inversion term:

$$Y_{poht} = lnq_{poht} + \sigma lnP_{poht}$$

and then estimates the following residual equation:

$$Y_{poht} = \alpha_{ph} + \delta_{ot} + u_{poht}$$

where α_{ph} denotes province-HS8 product fixed effects, δ_{ot} denotes origin-year fixed effects, and u_{poht} is the demand residual after the above factors are controlled for. The main specification sets $\sigma = 5$ and recovers the quality term as follows:

$$\hat{\lambda}_{poht} = \frac{\hat{u}_{poht}}{\sigma - 1}$$

The recovered quality term is then standardised within the HS6 category using min-max normalisation:

$$Quality_{poht} = \frac{\hat{\lambda}_{poht} - \min(\hat{\lambda}_g)}{\max(\hat{\lambda}_g) - \min(\hat{\lambda}_g)}$$

where g denotes the HS6 category to which the HS8 product belongs. The resulting quality measure ranges from 0 to 1, with comparisons made among origin-products within the same HS6 category. An increase in this measure indicates both an improvement in the import relationship relative to its own comparable historical status and a higher position on the relevant HS6 quality ladder. The baseline regression uses this measure as the dependent variable. When interpreting economic magnitude, the paper reports standard-deviation changes: according to Table 1, a one-standard-deviation increase in the level of digital economy development is associated with about a 0.024-standard-deviation increase in the quality of imported agricultural products.

3.2.2 Core Explanatory Variable

Level of digital economy development. Drawing on the framework of He et al. [20], this paper constructs a provincial digital economy development index from three dimensions: digital infrastructure, digital industrial development and the digital economy environment. The index is measured using the entropy-weighted TOPSIS method. The raw indicators are first standardised to remove differences in units of measurement. Objective weights are then calculated according to the entropy principle. A weighted decision matrix is constructed, positive and negative ideal solutions are identified, and the Euclidean distances between each province-year observation and the ideal solutions are calculated to obtain a relative closeness measure of digital economy development. Let Z_{kpt} denote the standardised value of indicator k, w_k its weight, and Z_k^+ and Z_k^- the positive and negative ideal solutions. Then:

$$D_{pt}^{+} = \sqrt{\sum_{k} w_k \left(Z_{kpt} - Z_k^{+}\right)^2}, \quad D_{pt}^{-} = \sqrt{\sum_{k} w_k \left(Z_{kpt} - Z_k^{-}\right)^2}$$

$$Dige_{pt} = \frac{D_{pt}^{-}}{D_{pt}^{+} + D_{pt}^{-}}$$

A higher value of the index indicates stronger provincial capacity for importers to acquire information, compare origins, verify quality signals and organise cross-border transactions. In the robustness tests, mobile-phone penetration is used as an alternative measure of digital economy development to assess whether the results depend on the composite index.

3.2.3 Mechanism Variables

High-quality and low-quality origins. The paper identifies quality groups within each province-year-HS8 product market according to the quality measure defined above. Specifically, it calculates the 75th and 25th percentiles of the quality distribution among origins within the same province, year and HS8 product. Import relationships with quality not below the 75th percentile are defined as high-quality origins, and those with quality not above the 25th percentile are defined as low-quality origins. The high-quality-origin dummy is denoted by $HighQ_{poht}$, and the low-quality-origin dummy by $LowQ_{poht}$. These variables are used to test whether the digital economy strengthens the price differences and quality advantages of high-quality origins and whether it increases the probability that the next-year exit dummy for low-quality origins equals one. To reduce the risk that current quality grouping is mechanically linked with current price or quality outcomes, the paper further constructs two auxiliary groupings. First, origins whose quality in the previous period is not below the 75th percentile within the same province-HS8 product market are defined as lagged high-quality origins. Second, historical quality is measured as the import-value-weighted average quality at the HS8-origin level in 2009-2011, and origins whose historical quality is not below the 75th percentile within the same HS8 product are defined as historical high-quality origins.

Residualised price and dispersion of residualised prices. To reduce interference from common cost components in unit values when testing the quality premium mechanism, the paper constructs residualised prices. It first calculates the logarithm of import unit value, $LnUV_{poht}$, and then controls for province fixed effects, HS8 product-year fixed effects and origin fixed effects. The residual component that cannot be explained by these common price factors is obtained from:

$$LnUV_{poht} = \alpha + \mu_p + \mu_{ht} + \mu_o + \widetilde{Price}_{poht}$$

where $\widetilde{Price}_{poht}$ is the residualised price. The paper then calculates price dispersion within each province-HS8 product-year market using the residualised prices of different origins. The main text uses a range-based dispersion measure, defined as the difference between the maximum and minimum residualised price within the same market:

$$Dispersion_{pht} = \max_o(\widetilde{Price}_{poht}) - \min_o(\widetilde{Price}_{poht})$$

A larger value indicates clearer price stratification across origins within the same market after common price factors have been removed.

Exit and survival of import relationships. The paper constructs next-year exit and next-year survival dummies according to whether a province-origin-HS8 product import relationship continues in adjacent years. The risk set is restricted to import relationships that exist in year t. If the relationship exists in year t but does not appear in year $t+1$, then $Exit_{poh,t+1}=1$; if it continues to appear in $t+1$, then $Survive_{poh,t+1}=1$. Since 2019 has no following-year observation, exit and survival are not defined for 2019 relationships. Relationships already present in 2009 are left-censored, and the empirical analysis mitigates this issue through corresponding controls and sample treatment. If a relationship disappears in $t+1$ but reappears in $t+2$, it is still treated as a relationship interruption in $t+1$. The mechanism test uses a linear probability model; the coefficient indicates the change in the conditional mean of the exit or survival dummy associated with a change in the relevant explanatory variable.

3.2.4 Instrumental Variables and Historical-Trend Placebo Variables

To address possible reverse causality and omitted-variable concerns between the digital economy and import quality, the paper constructs Bartik instruments using historical postal and telecommunications foundations. The instruments interact the number of fixed-line telephones or post offices at the provincial level in 1984 with the national trend in internet development during the sample period. These instruments combine historical cross-provincial differences with national digitalisation trends. The paper also constructs historical economic trend placebo variables using interactions between historical GDP per capita in 2000 or 2005 and the national internet trend. These variables are used to assess whether the main instrument merely captures a general historical economic path rather than the digital economy channel.

3.3 Model Specification

The baseline model is specified as follows:

$$Quality_{poht} = \alpha + \beta Dige_{pt} + \gamma Controls_{poht} + FE + \varepsilon_{poht} \tag{1}$$

where $Quality_{poht}$ denotes the quality of imported agricultural products, $Dige_{pt}$ denotes the level of digital economy development, $Controls_{poht}$ denotes control variables, and FE denotes the fixed effects included in different specifications. The coefficient of interest is β. Standard errors are clustered at the province level in the baseline regressions.

For the endogeneity test, the first-stage and second-stage equations are:

$$Dige_{pt} = \alpha + \pi IV_{pt} + \gamma Controls_{poht} + FE + \nu_{poht} \tag{2}$$

$$Quality_{poht} = \alpha + \beta \widehat{Dige}_{pt} + \gamma Controls_{poht} + FE + \varepsilon_{poht} \tag{3}$$

where IV_{pt} denotes the Bartik instrument constructed from 1984 postal and telecommunications foundations and the national internet trend.

The quality premium mechanism is tested using interaction terms between the digital economy and quality groups:

$$Y_{poht} = \alpha + \beta_1 Dige_{pt} + \beta_2 HighQ_{poht} + \beta_3 Dige_{pt} \times HighQ_{poht} + \gamma Controls_{poht} + FE + \varepsilon_{poht} \tag{4}$$

where Y_{poht} is unit value, import quality, or unit value after controlling for lagged import quality. If $\beta_3 > 0$, high-quality origins display a stronger price difference or quality advantage in provinces with a higher level of digital economy development. In some columns, $HighQ_{poht}$ is replaced by lagged or historical high-quality-origin groupings to reduce synchronous-construction concerns. The residualised unit-value specification uses the residualised price defined above as the dependent variable and includes both high-quality and low-quality origin groups. The price-dispersion specification uses the province-HS8 product-year market as the observation level and regresses the dispersion of residualised prices on the level of digital economy development.

The origin-relationship screening mechanism tests whether the digital economy increases the probability that the next-year exit dummy of low-quality origins equals one. The model is:

$$Exit_{poh,t+1} = \alpha + \beta_1 Dige_{pt} + \beta_2 LowQ_{poht} + \beta_3 Dige_{pt} \times LowQ_{poht} + \gamma Controls_{poht} + FE + \varepsilon_{poht} \quad (5)$$

where $Exit_{poh,t+1}$ denotes exit in the following year. If $\beta_3 > 0$, low-quality origin relationships are more likely not to continue in the following year in provinces with higher digital economy development.

4. Empirical Results

4.1 Baseline Estimates

Table 1 reports the baseline estimates of the relationship between digital economy development and the quality of imported agricultural products. The specifications gradually add controls and fixed effects to examine how the coefficient on the digital economy changes across settings. The results show that the coefficient remains positive after controlling for province, year, origin and HS8 product fixed effects. After further adding origin characteristics, tariffs and other controls, the estimate remains positive, indicating a positive relationship between digital economy development and the upgrading of import quality within provinces.

Under the specification that includes province, year, origin and HS8 product fixed effects, the coefficient on the digital economy is 0.080 and is significant at the 5% level. In terms of economic magnitude, a one-standard-deviation increase in the level of digital economy development is associated with an increase of about 0.024 standard deviations in the quality of imported agricultural products. This specification is used as the fixed-effect benchmark for the subsequent empirical tests. The following sections further use endogeneity tests and historical economic trend placebo tests to ease concerns about reverse causality and omitted variables.

Table 1. Baseline regression

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Digital economy	0.474***	0.068	0.067*	0.080**	0.063*
	(0.129)	(0.044)	(0.039)	(0.037)	(0.033)
Economic development	0.101**	0.048	-0.024	-0.027	-0.035
	(0.039)	(0.030)	(0.032)	(0.034)	(0.034)
Financial development	0.001	0.003	0.004**	0.005***	0.004**
	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)
Infrastructure density	0.055*	0.002	0	-0	-0.010
	(0.028)	(0.014)	(0.013)	(0.016)	(0.013)
Technological innovation	-0.054***	-0.023*	-0.019*	-0.017	-0.010
	(0.016)	(0.011)	(0.011)	(0.010)	(0.010)
Income inequality	-0.036	0.067	0.045	0.053	0.027
	(0.041)	(0.056)	(0.045)	(0.050)	(0.031)
Origin GDP				0.019	0.010
				(0.018)	(0.018)

	(1)	(2)	(3)	(4)	(5)
Origin agricultural value added				-0.036***	-0.011
				(0.013)	(0.012)
Import tariff				-0.010**	0
				(0.005)	(.)
Constant	-1.555***	-1.236**	-0.430	0.247	-0.138
	(0.373)	(0.465)	(0.432)	(0.528)	(0.473)
Province fixed effects	No	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes	No
Origin fixed effects	No	No	Yes	Yes	Yes
HS8 product fixed effects	No	No	Yes	Yes	No
HS8 product-year fixed effects	No	No	No	No	Yes
Observations	218,459	218,459	218,414	199,220	198,269
Adjusted R^2	0.014	0.044	0.223	0.231	0.368

Note: Standard errors clustered at the province level are reported in parentheses; *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The same applies below. Subsequent regressions use the fixed-effect structure in column (4). In the following tables, “Fixed effects = Yes” indicates that this benchmark fixed-effect structure is included, and some control variables may be absorbed under high-dimensional fixed effects.

4.2 Robustness Tests

First, the paper changes the dependent variable. To rule out the possibility that the results depend on the substitution-elasticity parameter used to measure quality, it follows Shi and Zeng [21] and Fan, Li and Yeaple [8] by setting $\sigma=10$ and recalculating import quality. It also uses import unit value as an alternative price-based outcome. Table 2 shows that, after quality is recalculated, the coefficient on the digital economy remains significantly positive at the 5% level. This indicates that the result does not depend on a single substitution-elasticity setting. Column (1) uses unit value as the dependent variable. The coefficient on the digital economy is not significant, suggesting that unit values contain transport costs, exchange-rate movements and market power components and cannot be treated as quality directly. This column is used to illustrate the limitation of unit value as a quality proxy rather than as the main robustness evidence.

Second, the paper excludes extreme years. To avoid the influence of abnormal macroeconomic fluctuations in particular years, the sample excludes 2009 and 2019. The year 2009 followed the global financial crisis, while 2019 was affected by China-US trade frictions and changes in the agricultural trade structure. Table 2 shows that the coefficient on the digital economy remains significantly positive after these years are excluded.

Third, the paper excludes samples affected by the China-US trade war. Trade frictions may change agricultural trade flows and quality composition through additional tariffs. Based on the announcements of the Customs Tariff Commission of the State Council on additional tariffs on selected imports originating in the United States, the paper identifies agricultural HS codes directly affected by the trade war and excludes the corresponding observations for 2018-2019. The coefficient on the digital economy remains significantly positive.

Fourth, the paper changes the explanatory variable. To address possible measurement error in the composite digital economy index, it uses provincial mobile-phone penetration as an alternative measure of digital economy development. Column (5) of Table 2 shows that the coefficient on mobile-phone penetration is 0.041 and is significantly positive at the 5% level, indicating a stable positive relationship between improvement in digital infrastructure and the quality of imported agricultural products.

Table 2. Robustness tests

	(1)	(2)	(3)	(4)	(5)
	Unit value	Alternative elasticity *σ=10*	Excluding first and last years	Excluding trade-war sample	Mobile-phone penetration
Digital economy	0.068	0.107**	0.144**	0.081**	
	(0.231)	(0.048)	(0.054)	(0.038)	
Mobile-phone penetration					0.041**
					(0.019)
Constant	2.126	0.206	0.520	0.205	0.319
	(2.677)	(0.567)	(0.691)	(0.519)	(0.571)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	203,411	199,253	161,331	194,167	199,220
Adjusted R^2	0.727	0.263	0.231	0.229	0.231

Note: Column (1) uses import unit value as the dependent variable. Column (2) changes the quality-measurement parameter. Column (3) excludes 2009 and 2019. Column (4) excludes samples affected by the trade war. Column (5) replaces the digital economy index with mobile-phone penetration.

4.3 Endogeneity Test

Although the baseline regressions control for multiple fixed effects and a set of control variables, two endogeneity concerns remain. First, higher import quality may induce local governments or market actors to improve digital infrastructure, smart logistics and cross-border e-commerce services, creating reverse causality. Second, some historical development foundations or long-term trade capabilities may affect both digital economy development and import quality. The paper therefore constructs Bartik instruments using 1984 historical postal and telecommunications foundations interacted with the national internet-development trend, and further implements historical economic trend placebo tests.

The relevance of the instrument comes from the interaction between historical communications foundations and the national digitalisation trend. Provinces with better telephone and post-office foundations in 1984 were more likely to develop advantages in the digital economy as the internet diffused and digital infrastructure expanded. The instrument can therefore explain cross-provincial differences in digital economy development. Its exogeneity rests on two points. First, the 1984 historical postal and telecommunications foundation predates the sample period and is unlikely to be directly determined by the quality of specific HS8 agricultural imports during 2009-2019. Second, after the benchmark fixed-effect structure and relevant controls are included, the interpretation that historical foundations affect import quality through current digital economy development is consistent with the identification logic of the paper. Historical advantages may nevertheless still be related to long-term openness, additional technological capacity and institutional capacity. To ease this concern, the paper uses historical economic trend variables to construct placebo tests and examines whether the main instrument merely reflects a long-term historical development path.

Table 3 reports the endogeneity tests and historical-trend exclusion tests. The first four columns report the main instrumental-variable results. The 1984 telephone Bartik instrument is significant in the first stage, and the KP Wald F statistic is above common weak-instrument thresholds. The second-stage coefficient on the digital economy is positive and significant. When the telephone Bartik and post-office Bartik instruments are used jointly, the second-stage result remains positive, and the over-identification test does not reject the null of instrument exogeneity. These results indicate that the instrumental-variable specifications continue to support a positive relationship between the digital economy and the quality of imported agricultural products.

The last four columns report the historical economic trend placebo tests. The paper constructs alternative instruments by interacting historical GDP per capita in 2000 and 2005 with the national internet trend. The results show that these historical economic variables significantly explain changes in the digital economy in the first stage, suggesting that they do capture a form of historical development path. In the second stage, however, the effect of the digital economy on import quality is not significant. This pattern suggests that general historical economic foundations can affect digital economy development, but they do not reproduce the import-quality results obtained from the 1984 postal and telecommunications instruments. The placebo tests therefore help ease the concern that the main instrument merely captures a general historical economic path.

Table 3. Endogeneity test and historical-trend exclusion test

Variable	**(1) First stage**	**(1) Second stage**	**(2) First stage**	**(2) Second stage**	**(3) First stage**	**(3) Second stage**	**(4) First stage**	**(4) Second stage**
Model	Telephone Bartik	Telephone Bartik	Telephone + post-office Bartik	Telephone + post-office Bartik	2000 GDP per capita placebo	2000 GDP per capita placebo	2005 GDP per capita placebo	2005 GDP per capita placebo
Dependent variable	Digital economy	Import quality	Digital economy	Import quality	Digital economy	Import quality	Digital economy	Import quality
Telephone Bartik (coefficient x 10^7)	2.406***	—	2.366***	—	—	—	—	—
	(0.266)	—	(0.277)	—	—	—	—	—
Post-office Bartik (coefficient x 10^11)	—	—	1.550	—	—	—	—	—
	—	—	(3.890)	—	—	—	—	—
Historical GDP per capita placebo	—	—	—	—	0.010***	—	0.013***	—
	—	—	—	—	(0.002)	—	(0.002)	—
Digital economy	—	0.172**	—	0.231**	—	0.068	—	0.085
	—	(0.080)	—	(0.105)	—	(0.214)	—	(0.169)
First-stage F	81.804	—	73.153	—	42.823	—	65.831	—
KP Wald F	—	83.435	—	38.000	—	39.954	—	63.003
Hansen p-value	—	—	—	0.864	—	—	—	—
Observations	198,269	198,269	199,220	199,220	198,269	198,269	198,269	198,269
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Province	Province	Province	Province	Province	Province	Province	Province

Note: Each model reports first-stage and second-stage results. The observation count for each model follows the corresponding second-stage estimation sample. "—" indicates that the coefficient or statistic is not reported for that stage or is not applicable. To avoid displaying coefficients as 0.000 because the instruments are measured on a very small scale, the first-stage coefficients and standard errors for the telephone Bartik and post-office Bartik instruments are rescaled by the factors shown in parentheses. Model groups (3) and (4) are placebo-IV tests based on historical economic trends.

4.4 Mechanism Tests

According to the theoretical analysis, if the digital economy reduces search, verification, tracking and relationship-adjustment costs in the import market, quality signals should become clearer and should be reflected in two margins: price stratification and trading-relationship adjustment. High-quality origins should be more likely to obtain price rewards and maintain quality advantages, the dispersion of residualised prices within the same market should be higher, and low-quality origins should be more likely to be adjusted in subsequent trading relationships. The paper therefore tests the quality premium, dispersion of residualised prices and origin-relationship screening mechanisms.

4.4.1 Quality Premium Mechanism

Table 4 reports the quality premium mechanism. Column (1) uses import unit value as the dependent variable, and column (2) uses import quality. The interaction terms between the digital economy and high-quality origins are significantly positive in both columns, indicating that high-quality origins display clearer price differences and quality advantages in provinces with higher digital economy development. Since current high-quality origins are defined by current quality rankings, columns (1) and (2) mainly describe price-quality stratification in the import market. Column (3) adds lagged import quality to the unit-value equation, and the interaction term remains positive, suggesting that price differences remain after existing quality levels are considered. Column (4) uses lagged high-quality-origin grouping, and column (5) uses historical high-quality-origin grouping. The interaction terms remain positive, indicating that a similar stratified relationship is observed after the timing of the quality grouping is adjusted.

Column (6) further uses residualised unit value as the dependent variable and applies the benchmark fixed-effect structure used in the other mechanism columns. Residualised unit value is the residual component of import unit value after province, origin and HS8 product-year common price factors have been removed. The results show that the interaction between the digital economy and high-quality origins is significantly positive, while the interaction between the digital economy and low-quality origins is significantly negative. This indicates that price stratification between high- and low-quality origins remains after common price factors are removed. Column (7) uses the dispersion of residualised prices within the province-HS8 product-year market as the dependent variable. The coefficient on the digital economy is significantly positive, indicating that residualised price stratification within the same market is clearer in provinces with higher digital economy development. Overall, the results in Table 4 are consistent with the mechanism that the digital economy improves quality-signal identification and makes the quality premium and price stratification clearer.

Table 4. Quality premium mechanism

Variable	(1) Unit value	(2) Import quality	(3) Unit value	(4) Unit value	(5) Import quality	(6) Residual-ised unit value	(7) Price dispersion
Digital economy	-0.393**	-0.040	-0.143	-0.274	-0.002	-0.309**	1.739***
	(0.167)	(0.043)	(0.176)	(0.206)	(0.016)	(0.155)	(0.606)
High-quality origin	0.770***	0.347***	0.577***	—	—	0.557***	—
	(0.025)	(0.007)	(0.027)	—	—	(0.023)	—
Low-quality origin	—	—	—	—	—	-0.381***	—
	—	—	—	—	—	(0.018)	—
Lagged high-quality origin	—	—	—	0.359***	—	—	—
	—	—	—	(0.024)	—	—	—
Digital economy x high-quality origin	0.376***	0.057***	0.268***	—	—	0.321***	—
	(0.086)	(0.020)	(0.084)	—	—	(0.078)	—
Digital economy x low-quality origin	—	—	—	—	—	-0.332***	—
	—	—	—	—	—	(0.058)	—
Digital economy x lagged high-quality origin	—	—	—	0.390***	—	—	—
	—	—	—	(0.080)	—	—	—
Digital economy x historical high-quality origin	—	—	—	—	0.035*	—	—
	—	—	—	—	(0.018)	—	—
Lagged import quality	—	—	0.582***	—	—	—	—
	—	—	(0.023)	—	—	—	—
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	155,337	154,730	92,900	87,578	95,541	155,337	29,286
Adjusted R^2	0.772	0.536	0.805	0.766	0.545	0.218	0.398

Note: Columns (1), (3) and (4) use unit value as the dependent variable. Columns (2) and (5) use import quality. Column (6) uses residualised unit value. Column (7) uses range-based price dispersion calculated from residualised prices. Column (7) is observed at the province-HS8 product-year market level; the other columns are observed at the province-origin-HS8 product-year import-relationship level. Column (3) additionally controls for lagged import quality. Column (4) uses lagged high-quality-origin grouping. Column (5) uses historical high-quality-origin grouping. Column (6) first residualises import unit value against common price factors, then tests price stratification under the benchmark fixed-effect structure while including low-quality origin and its interaction with the digital economy.

4.4.2 Origin-Relationship Screening Mechanism

Table 5 reports the origin-relationship screening mechanism. Column (1) uses next-year exit of low-quality origins as the dependent variable. The interaction between the digital economy and low-quality origins is significantly positive, indicating that low-quality origin relationships are more likely not to continue in the following year in provinces with higher digital economy development. This is consistent with the theoretical expectation that the digital economy reduces quality-tracking costs and the cost of searching for alternative origins.

Column (2) uses next-year survival of high-quality origins as the dependent variable. The interaction term is positive but does not reach conventional significance levels. This result indicates that the current data more consistently support subsequent adjustment of low-quality origins, but do not directly imply a fully symmetric result in which high-quality origins are significantly more likely to survive. The origin-relationship screening mechanism should therefore be centred on the adjustment of low-quality origin relationships.

Table 5. Origin-relationship screening mechanism

Variable	(1) Exit of low-quality origins	(2) Survival of high-quality origins
Digital economy	0.219**	-0.247**
	(0.102)	(0.104)
Low-quality origin	0.104***	
	(0.008)	
Digital economy x low-quality origin	0.095***	
	(0.026)	
High-quality origin		0.075***
		(0.007)
Digital economy x high-quality origin		0.028
		(0.025)
Controls	Yes	Yes
Fixed effects	Yes	Yes
Clustering	Province	Province
Observations	128,168	128,168
Adjusted R^2	0.162	0.152

Note: Column (1) uses next-year exit as the dependent variable, and column (2) uses next-year survival. The high-quality-origin survival column is reported to show the evidence boundary.

Taken together, the mechanism tests show that import markets in provinces with higher digital economy development display clearer quality-signal identification and trading-relationship adjustment. On the price side, high-quality origins, including lagged and historical high-quality groupings, display clearer price differences and quality advantages, and the dispersion of residualised prices is higher. On the relationship side, low-quality origin relationships are more likely not to continue in the following year. These results are consistent with the paper's mechanism: the digital economy improves quality-signal identification and thereby supports the upgrading of imported agricultural product quality.

4.5 Heterogeneity Analysis

The paper further examines heterogeneity by Rauch product classification and domestic region. Rauch [22] classifies products into organised-exchange goods, reference-priced goods and differentiated goods according to trading mode and price comparability. For organised-exchange goods and reference-priced goods, quality attributes and price benchmarks are easier to compare, so importers can more easily use digital information for horizontal screening. Differentiated goods contain more brand, taste, origin-reputation and relationship-network information that is difficult to standardise, so the marginal role of the digital economy in quality identification may be more complex. Table 6 shows that, under the benchmark fixed-effect structure, the coefficients of the digital economy are significantly positive for organised-exchange goods, reference-priced goods and the pooled non-differentiated group. The coefficient is positive but not significant for differentiated goods. This indicates that the quality-upgrading relationship is more stable for products whose prices and quality signals are easier to compare. For differentiated goods, quality identification may still depend on brand, relationship networks and long-term reputation, which are less standardised.

Table 6. Heterogeneity by Rauch product classification

Variable	(1) Organised-exchange goods	(2) Reference-priced goods	(3) Differentiated goods	(4) Pooled non-differentiated goods
Digital economy	0.138**	0.074**	0.029	0.101***
	(0.051)	(0.035)	(0.043)	(0.035)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	34,742	66,943	94,565	101,696

Note: In the Rauch classification, organised-exchange goods correspond to organised exchange, reference-priced goods to reference priced, and differentiated goods to differentiated. The pooled non-differentiated group includes organised-exchange goods and reference-priced goods.

Regional heterogeneity is analysed according to the official eastern, central and western regional classification of the National Bureau of Statistics of China. Eastern provinces have larger import scales, better port infrastructure, more developed trade-service systems and a stronger digital application environment. Importers in these provinces are therefore better placed to use digital platforms, digitalised customs clearance and supply-chain traceability tools to identify high-quality origins. Table 7 shows that the coefficient on the digital economy is positive and significant at the 10% level in the eastern region, while the coefficients in the central and western regions do not reach conventional significance levels. The relationship between the digital economy and import quality is therefore more stable in the eastern sample. The results for central and western regions should be interpreted cautiously in light of sample size, port conditions and the basis of digital trade services.

Table 7. Regional heterogeneity

Variable	(1) Eastern region	(2) Central region	(3) Western region
Digital economy	0.102*	0.422	0.070
	(0.055)	(0.355)	(0.290)
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
Observations	171,231	12,143	15,873

Note: Eastern, central and western regions are defined according to the regional classification of the National Bureau of Statistics of China.

5. Conclusions and Policy Implications

5.1 Conclusions

Using Chinese customs import data for 2009-2019 and a provincial digital economy development index, this paper measures the quality of imported agricultural products at the province-origin-HS8 product-year level and examines the relationship between the digital economy and import quality. The main conclusions are as follows.

First, digital economy development is associated with higher quality of imported agricultural products. The baseline regression shows that, after province, year, origin and HS8 product fixed effects and relevant controls are included, the coefficient on the digital economy remains positive. Under this benchmark fixed-effect specification, the coefficient is 0.080 and is significant at the 5% level. A one-standard-deviation increase in the level of digital economy development corresponds to about a 0.024-standard-deviation increase in import quality. The endogeneity test produces similar conclusions. The historical economic trend placebo test shows that interactions between general historical economic foundations and the national internet trend cannot significantly explain changes in import quality. This helps ease the concern that the main instrument simply reflects a general historical economic path.

Second, provinces with higher digital economy development display clearer quality premiums and price stratification in the import market. The mechanism tests show that high-quality origins in these provinces display clearer price differences and quality advantages. After lagged import quality is included and after lagged and historical high-quality-origin groupings are used, the stratified relationship remains observable. After common price factors at the province, origin and product-year levels are removed, high-quality origins have higher residualised unit values, low-quality origins have lower residualised unit values, and the dispersion of residualised prices within province-HS8 product-year markets is larger. These results indicate that the digital economy helps importers identify high-quality signals and makes the relationship between price and quality stratification clearer.

Third, provinces with higher digital economy development show adjustment of low-quality origin relationships, and the quality-upgrading relationship varies with product comparability. The origin-relationship screening test shows that low-quality origin relationships are more likely not to continue in the following year, while the survival result for high-quality origins is less stable. Heterogeneity by Rauch classification shows that the positive relationship between the digital economy and import quality is more stable for organised-exchange goods and reference-priced goods. This suggests that the information-identification role of the digital economy is more visible for products whose prices and quality signals are easier to compare. This heterogeneity result mainly describes the boundary of the relationship rather than serving as an independent mechanism.

5.2 Policy Implications

First, the General Administration of Customs, the State Administration for Market Regulation and local port-management authorities should improve digital quality-information infrastructure for imported agricultural products. Inspection and quarantine, customs clearance, cold-chain records, certification, return and recall, and risk-monitoring data should be linked to form an import-quality information platform that can be searched, traced and verified. For agricultural products whose quality information is difficult to observe, a digitalised quality-information system can reduce verification costs and improve the identification of high-quality origins.

Second, commerce departments, the Ministry of Agriculture and Rural Affairs, and local import-promotion agencies should support importers in expanding their ability to search for and compare high-quality origins. Policy tools may include building databases of high-quality origins, promoting mutual recognition of origin certification, improving cross-border e-commerce and supply-chain service platforms, and facilitating customs clearance for high-quality agricultural products. For origins with stable quality, clear certification information and good fulfilment records, mutual certification recognition and supply-chain services can strengthen stable cooperation and allow the digital economy to better support import quality upgrading.

Third, customs, market regulation and food-safety authorities should establish dynamic risk monitoring and relationship-adjustment mechanisms for low-quality origins. Regulators can use historical transaction records, inspection and quarantine results, return and recall information, and platform evaluation data to conduct risk-based warnings, targeted inspections and dynamic monitoring of origin-products with higher quality risks. This would guide import relationships towards origins with more stable quality and more reliable fulfilment.

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