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Digitalization and the Changing Role of Agriculture in Export Structures: Evidence from Selected ASEAN and South Asian Economies

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Abstract

A sector's declining share of national exports can reflect either its own contraction or faster growth elsewhere in the export basket, and digitalization has been proposed as a driver of both patterns. This study re-examines that question for a panel of 14 ASEAN and South Asian economies (9 ASEAN, 5 South Asia; N = 172; 2010–2023), regressing the agricultural raw-material export share on a Principal Component Analysis (PCA)-based Digital Economy Index constructed from four connectivity indicators, controlling for GDP per capita, trade openness, and inflation. Model-selection tests favor a two-way fixed-effects (TWFE) specification with country and year effects. Because residual diagnostics indicate serial correlation and cross-sectional dependence, inference relies on Driscoll–Kraay (DK) standard errors. In the one-way country fixed-effects model, the Digital Economy Index is negatively and strongly associated with the agricultural raw-material export share, but this association reverses in sign and loses statistical significance once year fixed effects are added (β = 0.409, SE = 0.316, p = 0.197). This result is stable across DK lag lengths of 0 to 3. First-difference and country-specific time-trend specifications instead yield positive coefficients. The evidence therefore suggests that the strong negative association obtained without year effects is intertwined with broader temporal dynamics rather than representing a robust within-country effect of digitalization. The study finds no statistically significant evidence, in the preferred specification, that digitalization systematically reduces agriculture's relative position in national export structures, and cautions against interpreting the earlier negative association causally.

Keywords: *agricultural raw-material export share, ASEAN, digital economy index,Driscoll–Kraay standard errors ,South Asia, two-way fixed effects*

1. INTRODUCTION

Export diversification has long been viewed as a strategic pathway for developing countries to reduce dependence on primary commodities, limit volatility in foreign-exchange earnings, and promote more stable economic growth (Cadot et al., 2011; International Monetary Fund, 2018). Diversification involves not merely increasing export volumes in established sectors, but broadening the export structure across a wider range of products and sectors—a process that systematically accompanies a country's stage of economic development (Parteka & Tamberi, 2013). Across many developing Asian economies, this broadening of export structures has coincided with the rapid expansion of digital infrastructure over the past decade and a half, providing reasonable grounds to expect that the two phenomena are related.

The scale of digital economy expansion in the region has been substantial. ASEAN's digital economy was estimated to generate approximately USD 218 billion in gross merchandise value in 2023 and is projected to reach USD 600 billion by 2030 (Google et al., 2024). Developments in South Asia are more heterogeneous: India has built a globally significant digital services sector, whereas Bangladesh, Nepal, Pakistan, and Sri Lanka continue to lag on most indicators of digital infrastructure (World Bank, 2024). Multilateral assessments similarly note that digital trade is

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reshaping the composition of cross-border commerce for developing economies more broadly (IMF, OECD, UNCTAD, World Bank, & WTO, 2023).

Most of the literature linking digitalization to agricultural trade focuses on trade efficiency, trade costs, and trade volumes rather than on the compositional position of agriculture within the export basket. Studies using firm- and country-level data generally report a positive association between digital technology development and export or trade efficiency (Xing et al., 2025), and digital inputs have been linked to stronger agricultural export performance in China (Liu et al., 2024) and to gains from combining domestic and foreign digital inputs (Huang & Huang, 2025). Evidence from Vietnam similarly points to a digital dividend for agricultural exporters (Do et al., 2025), and internet access has been positively associated with services export diversification, with somewhat stronger associations reported among least-developed economies (Gnangnon, 2020). Digital connectivity has also been associated with agricultural development more broadly (Ye et al., 2024), while internet connectivity and digital trade policy have been linked to export expansion in bilateral panel settings (Herman & Oliver, 2023).

A gap that remains underexplored is whether these associations are robust once common cross-country time dynamics—such as the near-simultaneous rise of connectivity indicators and simultaneous shifts in global trade composition across many countries—are adequately controlled for. A sector's export share may decline not because the sector itself is contracting, but because other sectors are growing faster, or because common shocks that affect all countries in a given year move the two series together without implying any within-country relationship. This conceptual distinction is often not separated clearly in single-specification empirical work, despite its considerable implications for policy interpretation.

This study addresses that gap using panel data for 14 ASEAN and South Asian economies over 2010–2023 (N = 172 country-year observations), focusing specifically on the agricultural raw-material export share—a narrower and more precisely defined outcome than aggregate agricultural or agrifood exports—and applying a model-selection procedure that tests explicitly whether a one-way country fixed-effects association survives the inclusion of year fixed effects. The paper's central contribution is an empirical demonstration that a strong negative one-way fixed-effects association between the Digital Economy Index and the agricultural raw-material export share is not robust to common year effects, and that this instability is itself informative about how such associations should be interpreted. The remainder of the paper reviews the theoretical framework and hypotheses, describes the data and econometric approach, presents the results, and discusses their implications, limitations, and conclusions.

2. THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES

Two competing mechanisms motivate the association between digital economy development and the agricultural raw-material export share, and they predict opposite signs. The first is a diversification mechanism, grounded in Export Diversification Theory. Digital infrastructure can lower information, coordination, and market-entry costs, and these reductions may benefit manufacturing and services disproportionately relative to commodity-based agriculture, because non-agricultural sectors typically depend more heavily on information flows, logistics integration, and digital market access (Chiappini & Gaglio, 2024; Freund & Weinhold, 2004). If digital expansion accelerates the growth of non-agricultural exports more than agricultural exports, agriculture's relative export share would decline even without any deterioration in agricultural performance itself—a pattern consistent with the broader tendency of diversification to expand at low and middle income levels (Cadot et al., 2011) and with Structural Transformation Theory's account of a shrinking sectoral share alongside continued sectoral growth in absolute terms (Chenery & Syrquin, 1975; McMillan et al., 2014; Gollin, 2023; Timmer et al., 2015).

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The second is an enabling mechanism. Digital infrastructure can also improve market access, logistics coordination, financial inclusion, information access, and exporter-buyer matching for agricultural exporters directly, potentially supporting rather than compressing agricultural export performance (Gnangnon, 2020; Herman & Oliver, 2023; Huang & Huang, 2025; Liu et al., 2024; Mapiye et al., 2023). Under this channel, the Digital Economy Index would be positively, or at least not negatively, associated with the agricultural raw-material export share.

Because these two mechanisms predict opposite signs, this study does not impose a directional hypothesis on the association. Instead, the hypotheses are framed around the conditions under which an estimated association can be meaningfully interpreted:

H1: The Digital Economy Index is associated with the agricultural raw-material export share, with the sign and significance of the association depending on whether common cross-country time dynamics are adequately controlled for.

H2: Any estimated association is interpretable as evidence of a diversification or enabling channel only if it is robust to the inclusion of year fixed effects and to alternative treatments of serial correlation and cross-sectional dependence in the panel.

These hypotheses are deliberately non-directional. Rather than asking only whether the Digital Economy Index is negatively or positively associated with the agricultural raw-material export share, the empirical strategy below tests whether any such association is stable once common temporal dynamics and the panel's error structure are properly accounted for.

3. MATERIALS AND METHODS

3.1 Data

The dataset covers 14 Asian economies over 2010–2023: nine ASEAN members (Indonesia, Malaysia, Thailand, Vietnam, the Philippines, Singapore, Cambodia, Laos, and Brunei Darussalam) and five South Asian countries (India, Bangladesh, Pakistan, Sri Lanka, and Nepal). Myanmar was excluded from the final sample because of insufficient data coverage over the study period. All variables were obtained from the World Bank's World Development Indicators (WDI) database. After observations with incomplete data were removed, the final estimation sample comprised an unbalanced panel of N = 172 country-year observations.

The dependent variable is the agricultural raw-material export share, WDI code TX.VAL.AGRI.ZS.UN, reported by the World Bank as “Agricultural raw materials exports (% of merchandise exports).” This indicator is a narrower category than total agricultural or agrifood exports, and it is used and reported as such throughout this paper; no claim is made about aggregate agricultural or agrifood export shares beyond this specific indicator.

3.2 Digital Economy Index Construction

The main independent variable is a composite Digital Economy Index constructed through Principal Component Analysis (PCA) using four WDI connectivity indicators: internet users (% of population), mobile-cellular subscriptions (per 100 people), fixed-broadband subscriptions (per 100 people), and secure internet servers (per 1 million people). This set of indicators follows common approaches in the digital-economy measurement literature (Bukht & Heeks, 2017).

The first principal component explained approximately 67% of total variation across the four indicators, and the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.97, indicating that the data were well suited to PCA. Factor loadings were 0.92 for fixed-broadband subscriptions, 0.88 for internet use, 0.81 for mobile-cellular subscriptions, and 0.62 for secure internet servers. The resulting index was standardized to a mean of zero and a standard deviation of one, so that

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estimated coefficients can be interpreted as the association with a one-standard-deviation increase in the composite index. Three control variables are included in every specification: GDP per capita (constant USD), trade openness (exports plus imports as a percentage of GDP), and annual inflation (%).

3.3 Econometric Specification

The preferred econometric specification is a two-way fixed-effects (TWFE) panel model with country and year effects:

$$Y_{it} = \beta \cdot DigitalIndex_{it} + \gamma' X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$$

where Y_{it} is the agricultural raw-material export share, $DigitalIndex_{it}$ is the PCA-based Digital Economy Index, X_{it} is the vector of controls (GDP per capita, trade openness, inflation), α_i is a vector of country fixed effects, λ_t is a vector of year fixed effects, and ε_{it} is the idiosyncratic error. Pooled OLS, random-effects, one-way country fixed-effects, first-difference, and country-specific linear-trend specifications are also estimated for comparison and robustness.

3.4 Model Selection and Inference

Model selection proceeded in three steps. First, an F-test comparing pooled OLS with a one-way country fixed-effects model strongly favored country fixed effects ($F = 50.615$; df = 13, 154; $p < 2.2\times10^{-16}$). Second, a Hausman test comparing the fixed-effects and random-effects models rejected the null hypothesis that country effects are uncorrelated with the regressors ($\chi^2 = 63.102$; df = 4; $p = 6.459\times10^{-13}$), favoring fixed effects over random effects. Third, an F-test comparing the one-way country fixed-effects model with the two-way fixed-effects model found that year effects are jointly significant ($F = 2.606$; df = 13, 141; $p = 0.003$), favoring the inclusion of year fixed effects and the two-way fixed-effects specification as preferred.

A battery of diagnostic tests was then applied to the preferred TWFE model. A Breusch–Pagan test found no evidence of heteroskedasticity (BP = 7.268; df = 4; $p = 0.1224$). However, a Breusch–Godfrey/Wooldridge test indicated serial correlation ($\chi^2 = 34.103$; df = 7; $p = 1.648\times10^{-5}$), a result corroborated by a Wooldridge-type test for serial correlation in panel data ($F = 61.565$; df = 1, 156; $p = 6.367\times10^{-13}$). Cross-sectional dependence was indicated both by a Pesaran CD test ($z = -2.1984$; $p = 0.02792$) and by a Breusch–Pagan LM test ($\chi^2 = 194.4$; df = 91; $p = 1.766\times10^{-9}$).

Because conventional panel standard errors are inappropriate when serial correlation and cross-sectional dependence are both present, inference for the preferred TWFE model relies on Driscoll–Kraay (DK) standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence, with a preferred maximum lag of 2. DK standard errors are used here as a correction to the estimated standard errors given the diagnosed error structure; they are not a solution to omitted-variable bias and are not treated as a causal identification strategy.

4. RESULTS

4.1. Descriptive Statistics

The sample displays substantial cross-country and cross-time heterogeneity in both the agricultural raw-material export share and the Digital Economy Index. Table 1 reports descriptive statistics for all study variables over the full estimation sample.

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Table 1. Descriptive Statistics of the Study Variables (N = 172)

Variable	Mean	Std. Dev.	Min	Max	N
Agricultural raw-material export share (%)	2.67	2.21	0.01	11.86	172
Digital Economy Index (PCA)	0.00	1.00	−1.80	3.90	172
Internet users (% of population)	42.91	28.64	0.25	98.97	172
Mobile-cellular subscriptions (per 100 people)	115.62	33.20	33.63	181.22	172
Fixed-broadband subscriptions (per 100 people)	9.84	14.20	0.01	65.90	172
Secure internet servers (per 1 million people)	7,141.22	30,969.90	0.20	228,648.40	172
GDP per capita (constant USD)	9,732	17,513	585	90,299	172
Trade openness (% of GDP)	101.89	81.71	24.70	379.10	172
Annual inflation (%)	4.84	5.11	−1.61	49.72	172

Source: World Development Indicators (WDI), World Bank. N = 172 country-year observations; 14 economies; 2010–2023.

The agricultural raw-material export share ranges from 0.01% to 11.86% of merchandise exports across the panel, while the Digital Economy Index, standardized to mean zero and unit standard deviation, ranges from −1.80 to 3.90, reflecting the wide gap in digital connectivity between the least-connected economies at the start of the period and the most digitally mature economies by 2023.

4.2 Model Selection

As summarized in Section 3.4, model-selection tests favor country and year two-way fixed effects over pooled OLS, random effects, and one-way country fixed effects, and diagnostic tests indicate serial correlation and cross-sectional dependence in the preferred TWFE model, motivating the use of Driscoll–Kraay standard errors with a maximum lag of 2 for the primary inference.

4.3 Main Results

Table 2 reports the coefficient on the Digital Economy Index across the full sequence of specifications considered. The pooled OLS coefficient (−0.061) is small and statistically insignificant (SE = 0.190; p = 0.749). Once random effects are introduced, the coefficient becomes strongly negative and significant (−0.671; p < 0.001), and it remains close to that value and highly significant in the one-way country fixed-effects model, both with conventional standard errors (−0.706; SE = 0.119; p < 0.001) and with Driscoll–Kraay standard errors at a maximum lag of 2 (−0.706; SE = 0.132; p < 0.001).

Table 2. Digital Economy Index Coefficient Across Specifications

Specification	Coefficient	SE	p-value	Sig.
Pooled OLS	−0.061	0.190	0.749	ns
Random effects	−0.671	0.118	<0.001	***
One-way country FE, conventional SE	−0.706	0.119	<0.001	***
One-way country FE, DK max lag = 2	−0.706	0.132	<0.001	***
Two-way FE (country + year), DK — preferred	+0.409	0.316	0.197	ns
First difference, DK	+0.775	0.355	0.030	*
Country FE + country-specific linear trends, DK	+0.657	0.171	<0.001	***

Source: Authors' calculations. Dependent variable: agricultural raw-material export share (% of merchandise exports). DK = Driscoll–Kraay. * p < 0.05; *** p < 0.001; ns = not significant.

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The central result of this study is that this strong negative association does not survive the inclusion of year fixed effects. In the preferred two-way fixed-effects specification with Driscoll–Kraay standard errors, the coefficient on the Digital Economy Index reverses in sign and becomes statistically insignificant (+0.409; SE = 0.316; p = 0.197). The one-way fixed-effects coefficient should therefore not be read as the study's final estimate of the association, and the results do not support a claim that digitalization reduces the agricultural raw-material export share, nor that it causes export diversification; the panel design is observational and does not permit causal claims of either kind.

4.4 Driscoll–Kraay Lag Sensitivity

Table 3 reports the sensitivity of the preferred TWFE coefficient to the choice of Driscoll–Kraay maximum lag length. The point estimate is unchanged at +0.409 across all tested lag lengths (0 to 3), and the coefficient remains statistically insignificant throughout, with p-values ranging from 0.138 to 0.243. The sign and the substantive conclusion of statistical insignificance are therefore stable and are not an artifact of the specific lag length chosen for inference.

Table 3. Driscoll–Kraay Lag Sensitivity for the Preferred TWFE Model

Max lag	Coefficient	SE	p-value
0	+0.409	0.317	0.199
1	+0.409	0.349	0.243
2	+0.409	0.316	0.197
3	+0.409	0.275	0.138

Source: Authors' calculations. Dependent variable: agricultural raw-material export share. Two-way fixed-effects model with Driscoll–Kraay standard errors.

4.5 Alternative Temporal Specifications

Two alternative temporal specifications were estimated to further probe the sign obtained under the preferred TWFE model. A first-difference specification with Driscoll–Kraay standard errors produced a positive and statistically significant coefficient (+0.775; SE = 0.355; p = 0.030), and a country-fixed-effects specification that additionally includes country-specific linear time trends, also with Driscoll–Kraay standard errors, produced a positive and highly significant coefficient (+0.657; SE = 0.171; p < 0.001). Both alternative treatments of the panel's temporal structure yield coefficients of the same sign as the preferred TWFE estimate, supporting the direction of that estimate even where statistical precision differs across specifications.

Table 4. Leave-One-Country-Out Robustness for the One-Way Country Fixed-Effects Model

Statistic	Value
Number of leave-one-out iterations	14
Minimum coefficient (Digital Economy Index)	−0.969
Maximum coefficient (Digital Economy Index)	−0.626
Statistical significance across all iterations	p < 0.001

Source: Authors' calculations. Robustness check applies to the one-way country fixed-effects model only, not to the preferred TWFE specification.

A leave-one-country-out robustness check was also performed, but only for the one-way country fixed-effects model, since that is the specification in which the negative association was originally obtained. Table 4 summarizes this check: across all 14 leave-one-out iterations, the coefficient on the Digital Economy Index remains negative and statistically significant, ranging from −0.626 to −0.969 (all p < 0.001). This result indicates that the negative one-way fixed-effects association was not driven by any single country in the sample; it does not, however, establish the robustness of the preferred TWFE coefficient, which was not the subject of this particular check.

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4.6 Descriptive Time Trends

Table 5 reports yearly sample means of the Digital Economy Index and the agricultural raw-material export share from 2010 to 2023. Over this period, the Digital Economy Index rises steadily and substantially, from −0.627 in 2010 to +1.020 in 2023, while the agricultural raw-material export share generally declines, from 2.76% in 2010 to 1.84% in 2023, with most of the decline concentrated in the first half of the panel.

Table 5. Yearly Sample Means of the Digital Economy Index and the Agricultural Raw-Material Export Share

Year	Digital Economy Index	Agricultural raw-material export share (%)
2010	−0.627	2.76
2011	−0.488	3.23
2012	−0.394	2.91
2013	−0.319	2.69
2014	−0.197	2.64
2015	−0.235	2.19
2016	−0.070	2.04
2017	+0.117	2.24
2018	+0.275	2.00
2019	+0.437	1.89
2020	+0.518	1.99
2021	+0.837	1.99
2022	+0.956	1.86
2023	+1.020	1.84

Source: Authors' calculations from World Development Indicators, World Bank.

This common temporal movement—a steadily rising Digital Economy Index alongside a generally declining agricultural raw-material export share—helps explain why the one-way fixed-effects estimate, which does not net out year-specific common shocks, is strongly negative, and why the coefficient changes materially once year fixed effects are included. A supporting diagnostic computed on country-demeaned data (that is, variables expressed as deviations from country-specific means, but without removing year means) yields a correlation of −0.411 between the Digital Economy Index and the agricultural raw-material export share. This country-demeaned correlation indicates a moderate negative association in deviations from country-specific means; however, because year means were not removed, it should not be interpreted as a formal TWFE partial correlation or as evidence of an association net of common year effects. The yearly trends in Table 5 are consistent with, but do not by themselves prove, a common-trend explanation for the instability of the coefficient's sign across specifications.

4.7 Multicollinearity

Table 6. Variance Inflation Factors (VIF), Preferred TWFE Model

Variable	VIF
Digital Economy Index	3.08
GDP per capita	3.17
Trade openness	3.48
Annual inflation	1.11

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Table 6 reports variance inflation factors (VIF) for the regressors in the preferred TWFE model. All VIF values (Digital Economy Index = 3.08; GDP per capita = 3.17; trade openness = 3.48; inflation = 1.11) are well below conventional concern thresholds, indicating that multicollinearity does not appear to materially distort the estimated coefficients.

5. DISCUSSION

The central finding of this study is not the sign of any single coefficient, but the instability of that sign across specifications that treat common cross-country time dynamics differently. The one-way country fixed-effects model, which does not remove year-specific common shocks, produces a strong and highly significant negative coefficient (−0.706). Once year fixed effects are added, the coefficient in the preferred TWFE specification reverses sign and becomes statistically insignificant (+0.409; $p = 0.197$). This pattern is stable across Driscoll–Kraay lag lengths of 0 to 3, and both first-difference and country-specific-trend specifications independently produce positive coefficients, reinforcing that the negative one-way association is not the more credible characterization of the within-country relationship.

The leave-one-country-out check confirms that the initial negative one-way association is not an artifact of any single influential country, but this finding pertains only to the one-way specification and should not be read as evidence that the preferred TWFE coefficient is itself robust in the same sense. Taken together, the evidence assembled here therefore does not allow a strong choice between the diversification mechanism and the enabling mechanism described in Section 2: the data are consistent with a scenario in which the earlier negative association mainly reflects common temporal dynamics—such as the simultaneous global expansion of connectivity indicators and simultaneous shifts in trade composition across many countries in the same years—rather than a systematic within-country relationship running from digitalization to the agricultural raw-material export share in either direction.

Consistent with this reasoning, the appropriate interpretive language is that the data provide no statistically significant evidence of an association in the preferred specification, not that the two-way fixed-effects results “prove” the absence of any effect. Statistical insignificance under TWFE indicates that the null hypothesis of no association cannot be rejected at conventional levels once year effects and the diagnosed error structure are accounted for; it does not establish that the true association is exactly zero. No causal mechanism is claimed by this study: the panel is observational, and while the model-selection and diagnostic procedures applied here are intended to produce a more credible association than a simple pooled or one-way specification would, they do not constitute a causal identification strategy.

The empirical contribution of this study is therefore the demonstration that a compelling negative one-way fixed-effects association between digital economy development and the agricultural raw-material export share is not robust to the inclusion of common year effects. This has a direct implication for how export-share indicators are interpreted in digitalizing economies: a negative association obtained from a specification that does not net out common time trends should not, on its own, be read as evidence that digital expansion is reshaping the relative position of agriculture in national export structures, whether through a diversification channel or an enabling channel.

6. LIMITATIONS

Several limitations should be considered when interpreting these results.

First, the dependent variable is the agricultural raw-material export share (WDI code TX.VAL.AGRI.ZS.UN), which is narrower than total agricultural or agrifood exports; the findings apply

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specifically to this indicator and should not be generalized to broader agricultural or agrifood export categories.

Second, the data are observational, and the panel design used here cannot establish causality between digital economy development and the agricultural raw-material export share in either direction.

Third, time-varying omitted variables that are correlated with both digital connectivity and the agricultural raw-material export share cannot be ruled out, even under the two-way fixed-effects specification.

Fourth, the panel contains only 14 country clusters; Driscoll–Kraay inference, while appropriate given the diagnosed serial correlation and cross-sectional dependence, should still be interpreted cautiously with a small number of clusters (Cameron & Miller, 2015).

Fifth, regional heterogeneity between ASEAN and South Asia, and the trajectory of agricultural exports in absolute value, are not resolved by this study; both would require re-estimation under the preferred TWFE specification and are left for future research.

Sixth, the Digital Economy Index is a composite connectivity measure built from four indicators and does not capture every dimension of digital economy development, such as digital skills, platform adoption, or e-commerce penetration specifically among agricultural exporters.

7. CONCLUSION

Using panel data for 14 ASEAN and South Asian economies over 2010–2023, this study finds that a strong negative association between digital economy development and the agricultural raw-material export share, obtained under a one-way country fixed-effects model, is not robust to the inclusion of year fixed effects. In the preferred two-way fixed-effects specification with Driscoll–Kraay standard errors, the coefficient on the Digital Economy Index is positive but statistically insignificant, and this result is stable across Driscoll–Kraay lag lengths of 0 to 3. Alternative first-difference and country-specific-trend specifications also produce positive coefficients. The apparent decline in agriculture's raw-material export share associated with digitalization in simpler specifications is therefore better understood as intertwined with broader common temporal dynamics than as a robust within-country effect of digitalization itself.

These findings suggest that researchers and policymakers should be cautious about drawing conclusions on the digitalization–agricultural trade relationship from panel specifications that do not explicitly test for, and control for, common year effects. Future research extending the sample to additional developing economies, incorporating product-level trade disaggregation, or examining absolute agricultural export values alongside export shares, would help clarify whether the diversification or enabling channel described in this study's theoretical framework better characterizes the relationship once a longer time series or a broader country sample becomes available.

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