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Digital Finance and Agricultural Productivity Growth: Comparative Evidence from China and Kazakhstan

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ABSTRACT

The digital transformation of the agricultural sector strengthens the role of digital infrastructure and financial inclusion as factors of productivity growth in agriculture in the context of structural modernization of the economy. The aim of the study is to assess the impact of digital infrastructure on agricultural productivity and to identify the cross—country heterogeneity of effects in economies with different levels of digitalization and institutional development. A balanced panel for 2011-2023 (26 observations) based on data from the World Bank and the International Labour Organisation was used. In the combined model, digital infrastructure demonstrates a positive and statistically significant relationship with performance ($\beta = 0.7626$; $p < 0.01$), with a high quality of fit ($r2 = 0.946$). The exclusion of pandemic years confirms the stability of the effect ($\beta = 0.744$; $p < 0.01$; $r2 = 0.937$). The cross-country analysis revealed heterogeneity: in China, the effect of digital infrastructure is positive and significant ($\beta = 0.421$; $p < 0.01$), while in Kazakhstan the coefficient is negative and weakly significant at the level of 10% ($\beta = -0.483$; $p = 0.092$), indicating differences in institutional readiness and the level of digital maturity. The results obtained confirm the importance of digital infrastructure in improving the efficiency of the agricultural sector, but demonstrate that the institutional and structural environment determines the scale and direction of this impact.

KEYWORDS: Digital Economy, Digital Finance, Digital Infrastructure, Economic Growth, Agricultural Productivity, Kazakhstan, China

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Цифровые финансы и рост производительности сельского хозяйства: сравнительный анализ Китая и Казахстана

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АННОТАЦИЯ

Цифровая трансформация аграрного сектора усиливает роль цифровой инфраструктуры и финансовой инклюзии как факторов роста производительности в сельском хозяйстве в условиях структурной модернизации экономики. Цель исследования — оценить влияние цифровой инфраструктуры на производительность сельского хозяйства и выявить межстрановую гетерогенность эффектов в экономиках с различным уровнем цифровизации и институционального развития. Использована сбалансированная панель за 2011–2023 гг. (26 наблюдений) на основе данных Всемирного банка и Международной организации труда. В объединенной модели цифровая инфраструктура демонстрирует положительную и статистически значимую связь с производительностью ($\beta = 0{,}7626$; $p < 0{,}01$), при высоком качестве подгонки ($r^2 = 0{,}946$). Исключение пандемийных лет подтверждает устойчивость эффекта ($\beta = 0{,}744$; $p < 0{,}01$; $r^2 = 0{,}937$). Межстрановой анализ выявил гетерогенность: в Китае эффект цифровой инфраструктуры положителен и значим ($\beta = 0{,}421$; $p < 0{,}01$), тогда как в Казахстане коэффициент отрицателен и слабо значим на уровне 10% ($\beta = -0{,}483$; $p = 0{,}092$), что указывает на различия в институциональной готовности и уровне цифровой зрелости. Полученные результаты подтверждают значимость цифровой инфраструктуры как фактора повышения эффективности аграрного сектора, однако демонстрируют, что институциональная и структурная среда определяет масштаб и направленность этого воздействия.

КЛЮЧЕВЫЕ СЛОВА: цифровая экономика, цифровые финансы, цифровая инфраструктура, экономический рост, продуктивность сельского хозяйства, Казахстан, Китай

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INTRODUCTION

Over the past decade, the development of the digital economy has transformed resource allocation and production processes in agriculture. From a production factor perspective, the relationship between digital infrastructure and agricultural productivity has become a key issue in agricultural economics. This is particularly important for major agricultural countries such as China and Kazakhstan, which are seeking to modernize their agriculture and increase farmers' incomes while addressing land and water scarcity.

Existing research has shown that digital infrastructure can improve agricultural productivity by reducing transaction costs and increasing efficiency. However, most empirical evidence is based on country-specific analyses, and systematic comparisons of countries at different stages of economic development are lacking. Furthermore, the literature has not adequately explained whether the relationship between digital infrastructure and agricultural productivity varies across institutional and structural contexts. Therefore, this study examines whether there is a link between national-level digital infrastructure and agricultural productivity, and whether this relationship differs between China and Kazakhstan.

Beyond digital infrastructure, digital financial inclusion has emerged as a complementary driver of agricultural transformation. By expanding access to credit, insurance, and mobile payment systems, digital finance can alleviate liquidity constraints faced by rural households, reduce information asymmetries, and enhance investment in modern agricultural inputs and technologies. In developing and transition economies, where traditional financial systems often underserve rural areas, digital financial services may play a particularly significant role in facilitating productivity-enhancing investments and stabilizing farm incomes.

At the same time, the effectiveness of digital finance in promoting agricultural productivity may depend on national institutional capacity, regulatory frameworks, and the level of digital literacy. Differences in financial market development, rural infrastructure, and policy support between China and Kazakhstan provide a valuable comparative setting for examining heterogeneous impacts. By integrating digital infrastructure and digital financial inclusion into a unified analytical framework, this study contributes to a deeper understanding of how digital transformation influences agricultural productivity growth under diverse development conditions.

This study uses balanced panel data from 2011 to 2023 to examine this relationship using panel regression models and country-specific estimation methods. Digital infrastructure is measured by internet penetration, which reflects the degree of digital connectivity within a country using a uniform international metric. Empirical results show a positive correlation across the entire sample, but country-level estimates show differences between China and Kazakhstan. This paper provides comparable evidence on the role of digital infrastructure in agricultural productivity across different development contexts.

The purpose of this article is to examine whether digital financial inclusion improves agricultural productivity and compare its impact in countries with different levels of digitalization and economic development.

LITERATURE REVIEW

According to the definition of the Organization for Economic Cooperation and Development, digital infrastructure refers to communications and information systems that support the generation, transmission, and processing of data (OECD, 2019). Digital infrastructure includes fixed and mobile broadband networks, fibre optic transmission systems, data centres, and cloud computing services. The International Telecommunication Union points out that internet usage, broadband subscriber numbers, and network coverage are key indicators of the level of digital connectivity (ITU, 2022). From an economic perspective, Greenstein (2021) argued that digital infrastructure is not a single device or technology but rather a multi-layered connectivity architecture comprising application, transport, internet, and connectivity layers. Its structural characteristics enable the efficient transmission of information and resources between individuals, businesses, and governments. Based on this definition, this paper defines national-level digital infrastructure as the level of digital connectivity and uses individual internet usage as a proxy variable. Given that agricultural production is spatially dispersed and subject to information asymmetry, improving digital connectivity may affect agricultural labor productivity.

This paper focuses on China and Kazakhstan to examine the correlation between each country's digital connectivity and agricultural labor productivity at the macro level.

Gollin (2023) argued that differences in agricultural productivity are important in explaining differences in income and structural transformation across countries, showing that spatial resource allocation and cropping patterns influence outcomes. Macours (2019) conducted a literature survey on the diffusion of agricultural innovations and argued that technology adoption depends not only on yield improvements but also on the characteristics, complexity, and availability of information. Hjort et al. (2019) examined variations in the deployment of submarine internet cables in Africa and used a difference-in-differences approach to estimate that faster internet access is associated with increased employment, which, in turn, leads to firm entry and productivity growth. Aker et al. (2015) used market-year data from Niger from 1999 to 2008 to show that the introduction of mobile phones reduced the spatial dispersion of prices for the semi-perishable crop cowpea, but the effects on millet and sorghum were statistically insignificant. All these studies suggest that increased digital connectivity can improve information efficiency and increase market integration, which in turn can affect resource allocation and agricultural labor productivity.

Bocean (2024) reviewed EU countries to show that the adoption of digital technology through ICT improves the productivity of agricultural labour but does not necessarily improve the productivity of agricultural land. The authors, Rajkhowa and Baumüller (2024), used panel data from 86 countries and found that ICT levels correlate with both agricultural labour and agricultural land productivity; however, labour productivity shows a stronger correlation. Bai et al. (2022) conducted research in the U.S. and indicated that areas with broadband coverage have experienced greater growth in farm sales. LoPiccalo (2021) indicates a statistically significant relationship between higher penetration rates of high-speed broadband access and improvements in crop yields and decreases in operating costs. Suroso et al. (2022) conducted a study using a panel dataset of 126 countries and identified statistically significant relationships between fixed broadband penetration, internet penetration, and farm value-added. Similarly, Oyelami et al. (2022) analysed data from sub-Saharan Africa and showed evidence of a long-run statistically significant relationship between mobile telecommunication utilisation, internet usage, and agricultural output. In general, the studies highlighted above show that digital infrastructure (i.e., fixed broadband networks, mobile telecommunication networks, and internet penetration) is consistently linked to agricultural labour productivity, agricultural land productivity, and farm value-added across multiple economic contexts.

Most research on the relationship between digital infrastructure and agricultural productivity in China has focused on how digital infrastructure can enhance productivity. Research by Rahman and Mamun (2017) has shown that there is a statistically significant positive relationship between telephone infrastructure and total agricultural output. Qiubo et al. (2020) found a statistically significant relationship between total factor productivity in agriculture and ICT indicators (internet and mobile network coverage). At the farm level, Li et al. (2024) found that internet use for agricultural production was associated with higher technical efficiency, whereas mere internet access was not an unequivocal indicator of technical efficiency. Additionally, Deng et al. (2024) identified a statistically significant relationship between internet usage and increased land productivity. Wang and Cai (2025) and Zhao et al. (2025) both found statistically significant relationships between levels of digital infrastructure and total agricultural productivity. Thus, the use of various digital infrastructure indicators shows statistically significant relationships with agricultural productivity in many instances.

In Kazakhstan, while relatively little first-hand empirical data exists regarding the impact that growth in digital infrastructure has on growth in agricultural productivity, Kushzhanov and Aliyev (2018) noted significant improvement in access to fixed broadband and mobile networks as a result of evaluating the implementation of the "Digital Kazakhstan" strategy; however, rural residents continue to have lower quality of access than urban residents. Gaysina et al. (2023) note that with the development of digitalization, the role of farms is changing: opportunities for online marketing of agricultural products through marketplaces and social media, as well as the use of digital agricultural advisory services, electronic government subsidies, and support programs are emerging. On a sector-by-sector basis, Aldashev and Batkeyev (2021) found that rural broadband expansion had a positive impact on sectors beyond agriculture, such as trade and retail, but no statistically significant impact on agricultural productivity. Similarly, Bekbossinova and Doszhan (2025) found no statistically significant relationship between growth in the level of internet penetration and growth in gross agricultural output when analyzing panel data for the period from 2010 through 2023. Overall, the existing body of evidence does not provide substantial support for establishing a systematic relationship between increasing levels of digital infrastructure and agricultural productivity. However, certain digital platforms, including Qoldau.kz and the e-APK ecosystem, are improving the efficiency with which farmers receive agricultural subsidies and integrating agricultural records, thereby contributing to the evolution of digital infrastructure for agriculture at the institutional level.

He et al. (2025) and several other studies examining country-specific contexts have also noted that, while the connection between digital infrastructure and agricultural performance has been an important topic of investigation, many structural limitations remain. First, most of the available literature focuses on a single country, particularly China, limiting the ability to conduct systematic comparative analyses across multiple economies at different levels of agricultural development. Second, while Patel et al. (2025) utilised cross-country data, their primary focus was on the digitisation of agriculture and sustainability rather than on agricultural productivity, and did not treat agricultural productivity as the primary outcome variable, nor did they systematically compare differences in development levels across countries. Lastly, while most studies have shown a statistically significant correlation between digital connectivity measures and agricultural productivity, there has been little explanation for why these relationships are stronger in some countries than in others or absent in many. This gap is particularly relevant in comparative studies between China and Kazakhstan. Therefore, there is a need to conduct cross-national, longitudinal studies to systematically analyse the impact of national digital infrastructure development on agricultural productivity growth across different structural and institutional environments.

RESEARCH METHODS

This study constructs a balanced panel dataset for China and Kazakhstan spanning 2011–2023. All data are primarily obtained from reputable international databases, such as the World Bank and the International Labour Organisation. Using international sources ensures comparability of statistical indicators and consistency in calculation methodologies. At the time of data collection (i.e., the 2025 World Development Indicators update), 2023 was the last period for which complete data were available for both countries.

Therefore, data for 2024 were excluded from the analysis to maintain a balanced panel structure. The dependent variable is agricultural productivity, measured as value added per worker in the agriculture, forestry, and fisheries sectors (in constant 2015 US dollars), reflecting the level of labor efficiency in the agricultural sector. This indicator is widely used in empirical studies to measure production intensity and technological development in agriculture. The main explanatory variable is internet penetration, which is used as a cross-country indicator of national digital infrastructure development. This indicator reflects the degree of digital connectivity of the economy, the availability of information and communications technologies, and the potential for the dissemination of digital services in rural areas.

The model includes three control variables:

(1) the share of employment in agriculture, reflecting the structure of labor force utilization;

(2) gross capital formation as a percentage of GDP, characterizing overall investment activity and the potential for upgrading production assets;

(3) the share of agricultural raw material exports in merchandise exports, reflecting the degree of openness of the agricultural sector and its orientation toward external demand. Including these variables reduces the problem of omitted variable bias and more accurately isolates the impact of digital infrastructure on productivity.

The natural logarithmic transformation of all variables produces stabilised data, which becomes easier to interpret in economic terms. To examine the effect of digital infrastructure on agricultural productivity, the following OLS baseline model is established (1):

$$\ln(agri\_it) = \alpha + \beta_1 \ln(digi\_it) + \beta_2 \ln(employ\_it) + \beta_3 \ln(capital\_it) + \beta_4 \ln(export\_it) + \varepsilon\_it \quad (1)$$

where:

ln(agri_it) – agricultural labour productivity;

ln(digi_it) – national digital infrastructure (internet penetration rate);

ln(employ_it) – agricultural employment share;

ln(capital_it) – gross capital formation (% of GDP);

ln(export_it) – agricultural raw materials exports (% of merchandise exports);

ε_it – the random error term.

Table 1 presents the descriptive statistics for the key variables over the period 2011-2023.

Table 1. Descriptive statistics of main variables

Variable	Mean	SD	Min	Max
ln_agri	8.6119	0.3340	8.0265	9.1372
ln_digi	4.1797	0.2553	3.6455	4.5313
ln_employ	3.0577	0.3287	2.4956	3.5496
ln_capital	3.5222	0.2609	3.1354	3.8345
ln_export	-1.2103	0.4269	-2.2046	-0.5975

Note: compiled by the authors

It can be seen that agricultural productivity (ln_agri) has a mean of 8.61 and a standard deviation of 0.33, indicating a relatively moderate level of variation in agricultural efficiency across these two countries, though some disparities remain. The mean of digitalisation (ln_digi) is 4.18, and a standard deviation of 0.26, this reflects the variation in the level of digitalisation over the sample period. China's penetration of the Internet has been rapidly expanding, whereas Kazakhstan's has been developing more slowly.

Agricultural employment (ln_employ) had a standard deviation of 0.33, indicating considerable variation in the structure of labour employed and the process of labour shifting from agriculture to non-agriculture during this period of modernisation. The capital formation (ln_capital) has a standard deviation of 0.26, indicating that the conditions of capital invested in agriculture are again rather stable. The agricultural exports (ln_export) had a standard deviation of 0.43, which is also the highest among the variables considered. This indicates that there is a significant difference in the openness and external orientation of the two countries as far as agriculture is concerned. These results are descriptive statistics that lead up to the regression analysis that follows.

RESULTS

This section presents the results of an empirical assessment of a baseline model designed to identify the impact of digital infrastructure on agricultural productivity in China and Kazakhstan over the period 2011–2023. The resulting estimates allow us to quantify the strength and direction of the relationship between the level of digitalization and agricultural sector performance, taking into account structural and macroeconomic factors. The analysis is based on panel data and ordinary least squares, ensuring comparability of the results across the two countries and forming the basis for further testing of the robustness and cross-country heterogeneity of the identified effects.

The model explains a significant share of the variation in agricultural productivity and is able to characterise the sampled series favourably: $R^2 = 0.946$ and F statistic = 121.01 ($p < 0.01$), indicating that the OLS regressions were statistically significant overall. Internet penetration is used as a proxy for digital infrastructure in this model to capture the broader digital landscape rather than directly measuring digital financial services.

As can be seen from the table, the digital infrastructure variable (ln_digi) shows a value of 0.7626 ($p = 0.000$). Since it is a positive figure with satisfactory statistical significance, this indicates that digital infrastructure is positively associated with agricultural productivity at the 1% level. Possible factors that may explain this relationship include better access to agricultural credit, lower information and transaction costs, and greater adoption of technology in agriculture.

Table 2 presents the OLS results for 2011-2023, using panel data from China and Kazakhstan to examine how digital infrastructure relates to agricultural productivity.

Table 2. Baseline regression results

Variable	Coefficient	Std. Error	t	P>|t|	95% Conf. Interval
ln_digi	0.7626	0.1389	5.49	0.000***	[0.4738, 1.0514]
ln_employ	-0.6640	0.1398	-4.75	0.000***	[-0.9548, -0.3733]
ln_capital	0.6751	0.1343	5.03	0.000***	[0.3958, 0.9545]
ln_export	-0.0438	0.1143	-0.38	0.705	[-0.2815, 0.1939]
cons	5.0238	0.6625	7.58	0.000***	[3.6460, 6.4017]
Obs = 26 R^2 = 0.946 F (4, 21) = 121.01 Prob > F = 0.000 Root MSE = 0.084 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.					

Note: compiled by the authors

The coefficient of agricultural employment share (ln_employ)is -0.6640 (p = 0.000) - negative and statistically significant at the 1% level - suggesting that the transfer of a share of labour out of agriculture into other branches is associated with agricultural labour productivity. The capital formation (ln_capital) estimate is 0.6751 (p = 0.000), implying a clear upward push at the 1% threshold and is positive and significant for agricultural productivity. The coefficient on agricultural export (ln_export) is -0.0438 (p = 0.705), statistically insignificant, suggesting that positive day-to-day export changes are not related to agricultural productivity.

From the VIF tests, it can be seen that multicollinearity among the main explanatory variables is acceptable. In the main, digital infrastructure shows a significant positive relationship with agricultural productivity, as theoretically expected and provides justification for the robustness and heterogeneity tests which follow. The limited observations cover two countries; thus, the high R^2s should be interpreted with caution, as they also reflect broad macroeconomic trends in the sample rather than the actual strong explanatory power.

As indicated in Table 3, to control for the possible influence of the COVID-19 pandemic, we exclude the years 2020-2021 from our estimation.

Table 3. Robust test results (excluding COVID-19 years)

Variable	Coefficient	Std. Error	t-Statistic	p-Value
ln_digi	0.744	0.156	4.76	0.000***
ln_employ	-0.674	0.156	-4.32	0.000***
ln_capital	0.642	0.160	4.00	0.001***
ln_export	-0.029	0.128	-0.23	0.820
_cons	5.267	0.842	6.26	0.000***
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. R^2 = 0.937, F(4, 17) = 82.16, Prob > F = 0.000, Obs = 22.				

Note: compiled by the authors

The results show that the coefficient on digital infrastructure (ln_digi) is 0.7436 (p = 0.000), still positive and at the 1% level, and almost the same as the baseline value of 0.7626 (p = 0.000), indicating the stability of the positive association between digital infrastructure and agricultural productivity. The coefficient on the agricultural employment share (ln_employ) is -0.6737 (p = 0.000), significantly negative at the 1% level, suggesting that labour movement from agriculture to the non-agricultural sectors is associated with agricultural productivity. The coefficient on capital formation (ln_capital) is 0.6415 (p = 0.001), indicating a significant positive relationship, suggesting that capital investment is positively related to agricultural productivity. In contrast, the coefficient of agricultural exports (ln_export) is -0.0295 (p = 0.820) and still insignificant, implying that temporary fluctuations in agricultural exports have a limited impact on agricultural productivity. In general, the model still has very high explanatory power ($R^2 = 0.937$), which is very close to that of the baseline regression ($R^2 = 0.946$), thereby reiterating the stability of the empirical results.

Table 4 presents the results from the regression after standardising the variables using the z-score transformation to further strengthen the regression's robustness.

Table 4. Robust test results (standardised variables)

Variable	Coefficient	Std. Error	t-Statistic	p-Value
z_ln_digi	0.583	0.106	5.49	0.000***
z_ln_employ	-0.654	0.138	-4.75	0.000***
z_ln_capital	0.528	0.105	5.03	0.000***
z_ln_export	-0.056	0.146	-0.38	0.705
_cons	0.000	0.050	0.00	1.000
*** p < 0.01, ** p < 0.05, * p < 0.1. $R^2 = 0.946$, $F(4, 21) = 121.01$, Prob > F = 0.000, Obs = 26.				

Note: compiled by the authors

The differences in measurement scales have been eliminated by standardising all variables using mean-centring and normalisation by the standard deviation. The coefficient of digital infrastructure (z_ln_digi) is 0.583 (p = 0.000). This figure is statistically significant at the 1% level in both the current model and in the base regression and the regression excluding the effects of the COVID variables, suggesting that the positive association between digital infrastructure and agricultural productivity remains stable.

The coefficient of the employment share of agriculture (z_ln_employ) is -0.654 (p = 0.000). This figure is also significant at the 1% level, implying that the transfer of labour from agriculture to non-agriculture is associated with higher productivity. The coefficient of capital formation (z_ln_capital) remains significantly above zero, at 0.528 (p = 0.000), implying a positive association. The coefficient on agriculture's exports (z_ln_export) remains -0.056 (p = 0.705), as in previous models, and is statistically insignificant. In general, the regression reveals strong explanatory power ($R^2 = 0.946$). The direction and significance of the coefficients are exactly the same as in the base regression, thus showing the strong robustness of the findings.

Table 5 displays the results.

Table 5. Cross-country heterogeneity analysis results

Variable	C Coef	C SE	C p	KZ Coef	KZ SE	KZ p
ln_digi	0.4211	0.077	0.001***	-0.4826	0.252	0.092*
ln_employ	-1.4761	0.235	0.000***	-1.6000	0.176	0.000***
ln_capital	0.2038	0.298	0.514	-0.4142	0.204	0.077*
ln_export	0.1096	0.100	0.305	-0.0354	0.038	0.377
_cons	11.0035	0.868	0.000***	16.6035	1.784	0.000***
R^2	0.9975	—	—	0.9907	—	—
*** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors reported, Obs = 13.						

Note: compiled by the authors

To investigate the different influences of digital infrastructure on agricultural productivity across countries, we employed Ordinary Least Squares (OLS) estimation on the samples from China and Kazakhstan separately. For China, the estimate of digital infrastructure (ln_digi) is 0.421 (p = 0.001), which holds at the 1% mark and suggests that digital infrastructure is positively related to agricultural productivity. This may be explained by the increased accessibility of agricultural finance and the efficiency of information, which, in turn, enhances productivity in the agricultural sector.

In the case of Kazakhstan, the coefficient on digital infrastructure is -0.483 (p = 0.092), significant only at the 10% level and indicating that it is not yet a sufficiently strong and stable influence on agricultural productivity. This implies that the foundation of digital infrastructure in Kazakhstan remains weak, while the relatively low level of informatisation of agriculture has not been sufficient to translate digital infrastructure into a factor tending to increase productivity.

The results here indicate that the role of digital infrastructure in agricultural productivity shows a clear cross-country heterogeneity. China's more developed digital infrastructure system is associated with higher agricultural efficiency, while Kazakhstan is still in the early stages of digital transformation. These results indicate cross-country differences in the relationship between digital infrastructure and agricultural productivity and provide a basis for further discussion. However, given the small subsample size for each country, the country-specific estimates should be interpreted cautiously, particularly in the case of Kazakhstan, where the statistical significance is weak.

This chapter examines the impact of digital infrastructure on agricultural productivity in China and Kazakhstan, using balanced panel data from 2011 to 2023. The results of the main regression analysis show that digital infrastructure has a positive relationship with agricultural productivity and highlights its important role in improving the efficiency of the agricultural sector. Data reliability checks, variable normalisation, and the exclusion of pandemic years support the reliability and consistency of these results. The heterogeneity test reveals that while digital infrastructure is positively related to agricultural productivity in China, the effect in Kazakhstan is insignificant or slightly negative. This may be related to differences in development stages between the two countries in terms of digital infrastructure, financial inclusion and agricultural informatisation. In conclusion, the results suggest a positive relationship between digital infrastructure and agricultural productivity, while also indicating cross-country differences in digital development patterns. These empirical results provide a basis for further discussion of policy implications and development recommendations in the following chapter.

DISCUSSION

The empirical results suggest that improvements in digital infrastructure are positively related to agricultural productivity. The regression coefficient for the digital infrastructure variable in the benchmark regression model is 0.7626, statistically significant at the 1% level ($p = 0.000$). This indicates a positive association between digital infrastructure development and agricultural production efficiency. The robustness tests also support this pattern. The regression excluding the pandemic years of 2020 and 2021 (coefficient = 0.7436, $p = 0.000$) produces results similar to the benchmark model. The regression using standardised variables (coefficient = 0.583, $p = 0.000$) also yields comparable coefficient signs and significance levels. These findings support the robustness of the positive relationship between digital infrastructure and agricultural productivity across different model specifications. In general, digital infrastructure is consistently associated with agricultural productivity in the estimated models, providing a basis for further comparative analysis of cross-national differences.

Beyond digital infrastructure, other variables are also statistically significant in relation to agricultural productivity. The agricultural employment variable exhibits a significant negative coefficient in the overall models ($p = 0.000$), suggesting that a lower share of agricultural employment is associated with higher agricultural labour productivity. This pattern is consistent with structural transformation, where labour reallocation may coincide with improvements in average labour efficiency. The capital formation variable is significantly positive in all models ($p \leq 0.001$), indicating a positive association between capital accumulation and agricultural productivity. This may reflect the role of investment in mechanisation and agricultural infrastructure. In contrast, the coefficient of agricultural exports is negative and statistically insignificant ($p \geq 0.70$), suggesting that short-term fluctuations in agricultural exports are not systematically related to agricultural productivity in the sample. Overall, labour structure and capital accumulation appear more closely associated with agricultural productivity than with export performance.

The heterogeneous regression results indicate cross-country differences in the relationship between digital infrastructure and agricultural productivity. In the Chinese sample, the coefficient of digital infrastructure is 0.4211 and statistically significant at the 1% level ($p = 0.001$), suggesting a positive association between digital infrastructure and agricultural productivity. In contrast, for Kazakhstan, the coefficient of digital infrastructure is

-0.4826 and weakly significant at the 10% level ($p = 0.092$). Given the small subsample size, this estimate should be interpreted with caution. The results do not provide robust evidence of a positive relationship between digital infrastructure and agricultural productivity in Kazakhstan during the sample period.

The coefficients of agricultural employment, capital formation, and agricultural exports display broadly similar patterns across the two countries. In both samples, labour structure and capital accumulation are more consistently associated with agricultural productivity than export performance. However, given the limited sample size, these associations should be interpreted cautiously. Overall, digital infrastructure development appears more advanced in China and is positively associated with agricultural productivity in the Chinese sample.

CONCLUSION

This study conducts a systematic empirical analysis of the relationship between digital infrastructure and agricultural productivity using balanced panel data from China and Kazakhstan during 2011–2023. The empirical results indicate that the main research objectives have been addressed. Digital infrastructure is positively and statistically significantly associated with agricultural productivity in the pooled sample (coefficient = 0.76, $p < 0.01$). This association remains statistically significant after excluding the pandemic years (coefficient = 0.74, $p < 0.01$), suggesting that the results are robust across model specifications. The heterogeneity analysis indicates cross-country differences. In the Chinese sample, digital infrastructure is positively and significantly associated with agricultural productivity (coefficient = 0.42, $p < 0.01$). In contrast, the estimate for Kazakhstan is negative and weakly significant (coefficient = -0.48, $p = 0.09$). Given the limited subsample size, this result should be interpreted cautiously and does not provide robust evidence of a positive relationship in Kazakhstan during the sample period. Overall, the findings suggest a positive association between digital infrastructure and agricultural productivity in the pooled analysis, while also indicating cross-country differences in the estimated relationships.

At the policy level, the findings suggest that continued improvement in rural digital infrastructure may be associated with higher agricultural productivity. For China, this implies the importance of further enhancing digital connectivity in rural areas, strengthening broadband coverage, and improving the integration between digital platforms and agricultural information systems. Ensuring stable and secure digital networks may help sustain the observed positive association within the current institutional framework. For Kazakhstan and other Central Asian countries, the results indicate that strengthening basic digital infrastructure—such as expanding internet access and improving digital connectivity in rural regions—may be a prerequisite for realizing potential productivity gains. Given the limited empirical evidence in the Kazakh sample, policy measures should proceed cautiously and focus on foundational digital development before expecting measurable productivity improvements. More broadly, cross-country cooperation in digital infrastructure standards, data governance, and connectivity frameworks may facilitate knowledge exchange and gradual digital integration in the agricultural sector.

Future research could proceed in at least two directions. First, microdata from agricultural surveys or firm-level panel datasets can be integrated to explore potential mechanisms in the relationship between digital infrastructure and agricultural productivity. This will allow us to more closely examine potential transmission channels. Second, nonlinear specifications and spatial econometric models can be used to examine whether the relationship between digital infrastructure and agricultural productivity varies across regions and levels of development. These methods can help to better understand the heterogeneity and contextual variation in digital development and agricultural outcomes.

AUTHOR CONTRIBUTIONS

Conceptualization and theory: YS, DR and ZC; research design: ZC and NZ; data collection: YS, DR, ZC and NZ; analysis and interpretation: YS, DR, ZC and NZ; writing draft preparation: YS, DR and NZ; supervision: NZ; correction of article: YS, DR and ZC; proofread and final approval of article: YS, ZC and NZ. All authors have read and agreed to the published version of the manuscript.

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