Did the Digital Push Last? E-Commerce and Rural Agricultural Earnings in Indonesia During and After COVID-19, Evidence from Sakernas

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Abstract. This paper examines the impact of e-commerce adoption on earnings and income distribution among rural agricultural employers in Indonesia, both during and after the COVID-19 pandemic. Using microdata from the National Labour Force Survey/Sakernas (2018–2024) and applying probit, OLS, Propensity Score Matching, and quantile regression models, we identify the determinants of adoption and its impact on earnings. Adoption was strongly driven by education, training, and enterprise characteristics, while older age and reliance on unpaid household labor constrained uptake. Results show that e-commerce adopters earned substantially higher than non-adopters (more than 30 percent) both during and after the pandemic, confirming sustained income gains beyond the crisis. Quantile regressions reveal that the lowest-income employers benefited most, with earnings gains exceeding 50 percent at the bottom quantile during the pandemic. Although relative advantages shifted toward higher earners after the pandemic, large and significant effects remained for the lowest-income groups. These findings indicate that e-commerce not only enhances market access but also contributes to improving income distribution. Policy interventions to strengthen digital literacy, rural infrastructure, and financial access are essential to preserve its inclusive role and ensure that vulnerable agricultural employers continue to benefit disproportionately.
Keyword: e-commerce, earning distribution, pandemic, rural development.

1. Introduction

The COVID-19 pandemic created profound challenges for rural populations in developing countries, where agriculture remains central to employment and income. In Indonesia, agricultural employers in rural regions were hit especially hard [1], [2]. Restrictions on mobility, disrupted supply chains, and reduced access to traditional markets constrained their ability to sell outputs and maintain stable earnings [3], [4]. These disruptions revealed the vulnerabilities of rural producers to shocks, especially in contexts with limited formal market access and weak coping mechanisms [5], [6].

At the same time, the crisis accelerated digital adoption, with e-commerce platforms emerging as an alternative mechanism for sustaining livelihoods. E-commerce in rural settings covers a wide spectrum of activities that connect agricultural producers and rural communities to broader markets [7], [8], [9]. These activities range from the distribution of industrial goods to rural households to the marketing of agricultural outputs in urban centers, as well as online transactions for agricultural inputs and the delivery of digital services that support poverty reduction and rural development [10], [11]. In this study, e-commerce adoption refers to the uptake of processes involving the purchase, sale, transfer, or exchange of goods, services, and information through digital networks, primarily the internet [12].

At the individual level, the decision to adopt e-commerce is shaped by a variety of factors, including personal attributes such as gender, age, education, marital status, working hours, and employment status; household factors such as family size; as well as broader contextual conditions such as geographic location, digital skills, prior exposure to technology, infrastructure availability, and sectoral specialization [13], [14], [15], [16], [17].

By enabling direct connections between producers and consumers, reducing reliance on intermediaries, and expanding access to geographically dispersed markets, e-commerce offered rural employers both a resilience tool during the pandemic and a potential pathway for longer-term structural transformation. In Indonesia, rapid growth in digital platforms and mobile penetration created opportunities, but adoption remained uneven due to disparities in infrastructure, literacy, and financial access. These dynamics raise pressing questions: to what extent did e-commerce adoption help rural agricultural employers sustain earnings during the pandemic, did these effects persist afterward, and were the benefits evenly distributed across different segments of the rural economy?

Existing evidence highlights the transformative potential of e-commerce. Studies in China [18], India [19], and Latin America [20] show improvements in sales and income among adopters, though often concentrated in urban or peri-urban settings. Evidence from rural Southeast Asia remains scarce, and little is known about how agricultural employers in Indonesia—who provide livelihoods for large segments of the rural population—engage with e-commerce and benefit from it. Moreover, most research focuses on average treatment effects, overlooking heterogeneity across the income distribution. This is a critical omission, as rural employers vary widely in resources and capacity: some operate larger farms and have internet access, while others are small-scale and digitally excluded. Understanding not only whether e-commerce adoption "works on average," but also for whom it works, is essential for both research and policy.

This paper addresses these gaps by pursuing four objectives. First, it estimates the resilience effect of e-commerce adoption during the pandemic, testing whether adopters maintained earnings better than non-adopters. Second, it evaluates the sustainability effect in the post-pandemic period, asking whether benefits persisted beyond the crisis. Third, it examines the distributional impacts of adoption across the earnings spectrum, inquiring whether low-income employers benefit disproportionately, thereby reducing inequality, or whether higher-income employers capture the majority of the gains. Fourth, it identifies the determinants of adoption, clarifying which factors—such as education, farm size, and digital access—influence participation in the digital economy.

To achieve these aims, the study employs a set of complementary econometric methods. Probit models are used to examine adoption decisions, highlighting patterns of digital inclusion and exclusion. Ordinary Least Squares (OLS) provides baseline estimates of the adoption's effect on earnings. To address selection on observables, we applied Propensity Score Matching (PSM). PSM constructs counterfactuals by matching adopters to similar non-adopters. Finally, quantile regressions estimate heterogeneous effects across the earnings distribution, capturing whether adoption disproportionately benefits certain groups. By triangulating results across these methods, the study provides both credible and nuanced evidence.

The paper makes three contributions. First, it offers one of the first systematic studies of e-commerce adoption among rural agricultural employers in Indonesia, a group central to rural livelihoods yet underexplored in the digital economy literature. Second, it develops the conceptual distinction between resilience (short-term coping during crisis) and sustainability (longer-term structural transformation), providing empirical evidence on both. Third, by analyzing heterogeneity through quantile regressions, it contributes to debates on digital inequality, clarifying whether digital adoption narrows or reinforces disparities in rural earnings.

In sum, this study seeks to answer four research questions: What observable characteristics determine the likelihood of adopting e-commerce in rural Indonesia? To what extent did e-commerce adoption affect the earnings of rural agricultural employers during the COVID-19 pandemic? Did these effects persist in the post-pandemic period? Are impacts heterogeneous across the earnings distribution, and which groups benefit the most?

Answering these questions is critical for both research and policy. For scholars, the paper extends evidence on digital adoption in rural, developing-country contexts where constraints and heterogeneity are especially pronounced. For policymakers, the findings highlight how e-commerce can strengthen rural resilience during shocks, support sustainable recovery, and potentially reduce inequality. By combining rigorous econometric methods with a clear conceptual framing, the study provides timely insights into digital inclusion and rural development in Indonesia.

2. Research Method

2.1. Data

This study uses microdata from the National Labour Force Survey (Sakernas), a biannual household survey conducted by BPS–Statistics Indonesia. We analyze data from the August rounds between 2020 and 2024, focusing on rural agricultural employers. The pooled cross-sectional dataset includes 364,239 rural agricultural employers. In this context, "employer" refers to individuals who are self-employed with or without assistance from unpaid/temporary or paid/permanent labor. A detailed description of the survey variables used is provided in Table 1.

Table 1. Description of research variables

Variable	Definition
Earning	Real earnings per week in rupiahs adjusted for rural inflation
Log (Earning)	The natural logarithm of weekly real earnings
E-commerce	E-commerce adoption in doing workplace: 0 for non-adopters (reference category) 1 for adopters
Female	Gender of an individual: 0 for male (reference category) 1 for female
Married	Marital status: 0 unmarried (reference category) 1 married
Household members	Number of household members to which an individual belongs (person)
Household members 15+	Number of household members who are 15 years old and above, in which an individual belongs (person)
Education completed	The highest education level completed by an individual: 1- no education/elementary school (reference category) 2- junior high school

ICDSOS
The 3rd International Conference on Data Science and Official Statistics
November 27 - 28, 2025

Variable	Definition
	3- senior high school 4- vocational 5- diploma 1/2/3 6- university
Years of schooling	Years of schooling are approached with the highest educational attainment converted into years of schooling.
Age	Age of an individual: 1- 15-34 years old (reference category) 2- 35-44 years old 3- 45-54 years old 4- 55-64 years old 5- 65 years old and above
Experience	Working experience of an individual (years). It is a potential experience in years calculated by the formula: age minus years of schooling minus six years.
Tenure	The length of time an individual has been employed at their current job (years).
Working hours	The average working hours per week.
Full Employment	Employment status of an individual based on average working hours per week: 0- underemployed (reference category) 1- fully employed
Trained	Participation of an individual in work training (general): 0- untrained (reference category) 1- trained
Employer	Employment status of employers based on the kind of work: 1-self-employed (reference category) 2-assisted by unpaid/temporary labour 3-assisted by paid/permanent labour
Formal	Formality status of employment: 0- informal (reference category) 1-formal
Pandemic (temporal dummy)	Pandemic periods: 1- pandemic (2020-2022) (reference category) 2- post-pandemic (2023-2024)
Regional Dummy	Regional dummy: 0 for outside Jawa (reference category) 1 for Jawa.

2.2. Empirical model

We utilized econometric models to analyze the factors influencing e-commerce adoption among rural agricultural employers, assess its effect on actual earnings, and explore its contribution to the earnings distribution. To strengthen the causal inference of adoption's impact, we also applied a counterfactual analysis through Propensity Score Matching (PSM) and quantile regression techniques.

2.2.1 Determinant of e-commerce adoption

To examine the determinants of e-commerce adoption among rural agricultural employers, we estimate a probit model as denoted in Equation (1) below

$$p(X_i) = pr(D_i = 1 | X_i) = \Phi(X_i'\beta) \quad (1)$$

where $D_i \in \{0,1\}$ denotes a dummy variable indicating whether the individual i adopts e-commerce in their work or not, as defined by Rainer and Cegielski [21], X_i denotes observable characteristics influencing the decision of an individual to adopt e-commerce consisting of individual characteristics, household characteristics, employment characteristics, and temporal and spatial dummy variables; $\Phi(.)$ is the cumulative distribution function (CDF) of the standard normal distribution; and β is a vector of coefficients to be estimated. We assume that the propensity of workers to adopt e-commerce in their work is represented by a latent variable that is a function of observable characteristics and can be denoted as follows

$$D_i^* = X_i'\beta + \varepsilon_i \quad (2)$$

$$D_i = \begin{cases} 1 \; if \; D_i^* > 0 \\ 0 \; otherwise \end{cases}$$

where D_i^* is an unobserved variable representing the propensity to adopt e-commerce and ε_i is a normally distributed error term.

Building on the random utility maximization framework by Marschak [22], Equation (2) posits that an individual adopts e-commerce when their latent utility D_i^* exceeds a certain threshold (normalized to zero), with the observed binary outcome D_i reflecting this decision. We estimated Equation (1) separately for the period during and after the pandemic.

2.2.2 Causality Impact Estimation
To gauge the magnitude of the impact of e-commerce adoption on earnings, we estimated the Ordinary Least Squares Regression (OLS) models denoted in Equation (3) below

$$Y_i = \gamma_0 + \gamma_1 D_i + \textstyle\sum_j \gamma_j X_{ij} + \varepsilon_i \quad (3)$$

where Y_i denotes the real earning adjusted for rural inflation of the ith individual in logarithmic term, D_i denotes e-commerce adoption dummy variable, X_{ij} denotes the j control variables (socio-demographic characteristic, employment characteristics, and temporal and spatial dummy variables) of the *i*-th individual, γ_0 denotes the intercept of the model, γ_1 the regression coefficient of the e-commerce adoption, and ε_i denotes the error term that follow a normal distribution. Since the dependent variable in the logarithmic term, γ_1 can be interpreted as the percentage change of real earning due to participating as an adopter. Following Halvorsen & Palmquist [23], the impact estimation is corrected using $(e^{\gamma_1} - 1) \times 100\%$. We also estimate Equation (3) separately for the period during and after the pandemic.

2.2.3 Robustness check of causality impact estimation
The causal estimates in Equations (3) may be biased due to selection on unobserved factors and potential endogeneity, such as reverse causality—where higher earners are more likely to adopt e-commerce [24]. Adopters may systematically differ from non-adopters in ways that also affect income, such as digital

skills, asset ownership, or infrastructure access. To address these issues and improve causal inference, we use PSM, which creates a statistically comparable group of non-adopters based on their likelihood of adopting e-commerce.

To match adopters with comparable non-adopters based on observable characteristics, we estimate propensity scores using a probit model (Equation 1). For robust matching, we apply two algorithms—Nearest-Neighbour Matching (n = 5) with Caliper (radius = 0.005) and Kernel Matching. Using the matched samples, we estimate the impact of e-commerce adoption on real earnings by calculating the Average Treatment Effect on the Treated (ATT), which captures the mean difference in earnings between adopters and their counterfactual outcomes had they not adopted e-commerce.

$$ATT = E\left(Y_{1_i} \mid D_i = 1, p(X_i)\right) - E\left(Y_{0_i} \mid D_i = 1, p(X_i)\right) \tag{4}$$

where Y_{1_i} is the real earnings of an e-commerce adopters and vice versa, Y_{0_i} is the real earnings of an individual for non-adopters. We also estimated equations (4) for both periods.

To further assess the robustness of the causal impact, we examine the heterogeneous effects of e-commerce adoption across the earnings distribution using quantile regression. Unlike OLS, which captures average effects, quantile regression estimates conditional impacts at different points of the income distribution, offering a more nuanced view of how adoption affects low-, middle-, and high-income earners. This approach also helps evaluate the potential of rural e-commerce to reduce income inequality among rural households.

The conditional quantile regression for the τ-th quantile of log earnings Y_i given a vector of covariates X_i is specified as:

$$Q_{Y_i}(\tau \mid X_i) = \gamma_0(\tau) + \gamma_1(\tau)D_i + X_i'\boldsymbol{\gamma}(\tau) + \varepsilon_i(\tau) \tag{5}$$

where $Q_{Y_i}(\tau \mid X_i)$ is the conditional quantile of the log earnings given X_i; $\tau \in (0,1)$ represents the quantile level ($\tau = 0.1, 0.3, 0.5, 0.7, 0.9$); $\gamma_0(\tau)$ is the model intersept at each quantile; $\gamma_1(\tau)$ denotes the impact of e-commerce adoption at each quantile level; X_i includes independent control variables, and $\boldsymbol{\gamma}(\tau)$ is the vector of quantile-specific parameters of control variables to be estimated; and $\varepsilon_i(\tau)$ is error term at each quantile.

Estimating Equation (5) allows the impact of e-commerce adoption to vary across the income distribution, revealing whether gains are concentrated among lower-, middle-, or higher-income earners.

3. Result and Discussion

3.1. E-commerce adoption among rural employers

Table 2 provides a descriptive statistic of the adoption pattern during and after the pandemic. The profile of rural agricultural employers adopting e-commerce reveals a distinct socio-economic and demographic pattern compared to non-adopters, both during and after the pandemic. Adopters consistently reported higher weekly real earnings, averaging Rp 2.57 million during the pandemic and Rp 3.08 million post-pandemic, compared to Rp 1.38 million and Rp 1.72 million for non-adopters. They were notably younger (around 41 years versus 49 years), with less overall work experience but longer tenure in their current activity after the pandemic, suggesting a shift toward more stable enterprise engagement [25], [26]. Adopters also worked longer hours and attained substantially higher education levels, with secondary and tertiary education being far more common than among non-adopters, who were concentrated in primary schooling or below.

A larger share of adopters were male, younger (15–44 years), and unmarried, highlighting a demographic orientation toward more digitally responsive cohorts. Training participation was markedly higher among adopters (16–17 percent versus 4–6 percent), as was engagement with paid labor and formal sector arrangements, whereas non-adopters remained predominantly informal and reliant on unpaid labor. Regionally, adopters were more likely to operate outside Java relative to non-adopters, who were concentrated on the island. Taken together, these characteristics underscore that e-commerce adopters represent a younger, more educated, digitally active, and relatively formalized segment of rural employers, capable of leveraging technology for higher and more stable earnings.

Table 2. Distribution of employers during and after pandemics by adoption status

Variables	Pandemics		Post-pandemics	
	Adopters	Non-adopters	Adopters	Non-adopters
Continuous variable (mean)				
Earnings	2,570,019	1,375,695	3,077,490	1,717,342
Age	41.12	48.90	41.80	49.17
Experience	25.25	35.31	26.03	35.48
Tenure	10.62	18.06	31.23	36.45
Working hours	32.54	28.81	33.16	29.50
Years of schooling	9.81	7.58	9.72	7.67
Number of households	3.84	3.72	3.74	3.56
Number of households 15+	2.76	2.78	2.71	2.71
Dummy variable (%)				
E-commerce	98.93	1.07	98.20	1.80
Married	15.05	18.96	14.86	19.97
Not Married	84.95	81.04	85.14	80.03
Male	90.78	78.92	88.10	78.37
Female	9.22	21.08	11.90	21.63
15-34 years old	29.48	15.12	26.20	14.56
35-44 years old	34.50	23.14	35.04	23.00
45-54 years old	23.65	26.36	26.10	26.79
55-64 years old	9.70	22.25	10.38	22.17
65+ years old	2.68	13.13	2.27	13.48
No Education/Elementary School	34.50	67.32	33.39	65.90
Junior High School	22.07	15.92	24.13	15.95
Senior High School	27.09	12.02	27.46	13.72
Vocational	7.74	3.11	7.84	2.66
Diploma	1.58	0.43	1.45	0.41
University	7.02	1.19	5.74	1.35
Not trained	83.56	95.62	82.70	93.82
Trained	16.44	4.38	17.30	6.18
Under employment	41,61	50,61	39,58	49.10
Full employment	58,39	49,39	60,42	50.90
Self employed	45.82	48.66	42.49	43.14
Assisted by unpaid workers	41.57	48.48	45.52	52.98
Assisted by paid workers	12.61	2.86	12.00	3.88
Informal	87.39	97.14	93.11	98.08
Formal	12.61	2.86	6.89	1.92
Jawa	71.86	85.04	80.82	89.34

Outside Jawa	28.14	14.96	19.18	10.66

Note: unweighted

3.2. Determinant of e-commerce adoption

The probit regression results in Table 3 identify significant demographic, household, and enterprise-level factors influencing e-commerce adoption among rural agricultural employers. Gender differences are evident: being female reduces the probability of adoption, which is consistent with existing literature documenting gender gaps in digital access and entrepreneurial engagement [27], [28]. Marriage, on the other hand, shows a modest positive effect, suggesting that spousal support and shared household resources may facilitate the transition into digital markets [29], [30]. Household structure is also a crucial determinant. Larger household size reduces adoption likelihood, likely reflecting higher dependency burdens, while the number of adult household members (15+) increases it, indicating that the availability of working-age members contributes positively by easing resource and labor constraints [17], [31].

Table 3. Estimation results of the probit model for e-commerce adoption during and after the pandemic

Variable	Coefficient	dy/dx
Gender (Female)	-0.2664***	-0.0099***
	(0.0264)	(0.0008)
Marital Status (Married)	0.0435*	0.0019*
	(0.0255)	(0.0011)
Number of Household Members	-0.0187***	-0.0008***
	(0.0064)	(0.0003)
Number of Household Members 15+	0.0145***	0.0006***
	(0.0050)	(0.0002)
Age		
35-44	-0.1064***	-0.0077***
	(0.0234)	(0.0017)
45-54	-0.3289***	-0.0197***
	(0.0250)	(0.0017)
55-64	-0.6486***	-0.0301***
	(0.0314)	(0.0017)
65+	-1.0187***	-0.0358***
	(0.0457)	(0.0016)
Education		
Junior High School	0.3063***	0.0128***
	(0.0227)	(0.0011)
Senior High School	0.4244***	0.0201***
	(0.0229)	(0.0013)
Vocational	0.4566***	0.0223***
	(0.0392)	(0.0026)
Diploma	0.6067***	0.0344***
	(0.0759)	(0.0068)
University	0.7046***	0.0440***
	(0.0448)	(0.0045)
Training (trained)	0.2937***	0.0161***
	(0.0290)	(0.0019)

Variable	Coefficient	dy/dx
Employment status by working hours (full employment)	0.0993***	0.0043***
	(0.0173)	(0.0007)
Worker status		
Assisted by unpaid labour	-0.0511***	-0.0021***
	(0.0183)	(0.0008)
Assisted by paid labour	0.4249***	0.0273***
	(0.0595)	(0.0051)
Formality (Formal)	0.1288**	0.0063*
	(0.0654)	(0.0035)
Regional Dummy (Jawa)	0.4459***	0.0225***
	(0.0196)	(0.0012)
Post-Pandemic	0.2608***	0.0114***
	(0.0166)	(0.0008)
Constant	-2.3000***	-
	(0.0365)	
Number of Observations	364,239	364,239
Pseudo R-Squared	0.1380	-

Note: Robust standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1; sampling weight was used in estimation.

Age effects display a strong negative impact, underscoring the generational divide in digital adoption [32], [33]. Compared to younger individuals, older cohorts exhibit progressively lower probabilities of using e-commerce, with the steepest decline observed among those aged 55 and above (more than 3 percent). This pattern suggests that digital literacy and adaptability diminish with age, reinforcing concerns that older farmers may be excluded from the benefits of digital transformation in agriculture. Education, by contrast, exerts a robust and monotonic positive influence. Each higher level of schooling significantly increases the likelihood of adoption, ranging from junior high school (1.28 percent) to university education (4.40 percent) compared to those with no education or only completed primary school. These results highlight the importance of educational attainment in equipping rural entrepreneurs with the skills, confidence, and networks needed to leverage digital platforms for market access.

Work-related characteristics further explain differences in adoption. Training participation significantly raises adoption likelihood by 1.61 percent, suggesting that capacity-building interventions are effective in lowering barriers to entry into e-commerce [34], [35]. Similarly, individuals in full employment are more likely to adopt, which reflects greater economic stability and stronger incentives to expand markets digitally [36], [37]. Labor assistance shows contrasting effects: reliance on unpaid family labor reduces adoption, while employing paid workers substantially increases it by 2.73 percent. This divergence implies that enterprises relying on professionalized labor are more market-oriented and positioned to benefit from e-commerce. Being part of the formal sector is also positively associated, pointing to the advantages of regulatory compliance and visibility in accessing online markets[38], [39].

Spatial and temporal effects provide further insights. Living in Java significantly increases adoption probabilities by 2,25 percent, reflecting the island's superior infrastructure, internet penetration, and logistics networks compared to other regions (reference). Most importantly, the post-pandemic period shows a significant positive effect on e-commerce adoption of 1.14 percent. This indicates that the pandemic acted as a structural shock that accelerated digital diffusion, with momentum persisting beyond the crisis. The results suggest that e-commerce became an essential adaptation strategy for rural employers facing mobility restrictions and shifting consumer behavior, and its role has remained relevant in the recovery phase [40], [41].

3.3. Impact of adoption on earnings

We begin our investigation on the adoption impact on earnings by examining the difference in the log earnings distribution of rural agricultural employers during and after the pandemic. Figures 1 and 2 present the kernel density distributions of log earnings for e-commerce adopters and non-adopters during and after the pandemic. During the pandemic (Figure 1), adopters not only exhibited higher mean earnings but also less dispersion around the mean compared to non-adopters. The distribution for adopters was more peaked and shifted to the right, with a thinner left tail and a longer right tail. This suggests that e-commerce adoption may have provided a resilience effect: adopters appeared better shielded from the most severe income losses and, in some cases, achieved very high earnings. By contrast, non-adopters faced greater volatility, with a larger share clustered at the lower end of the earnings distribution.

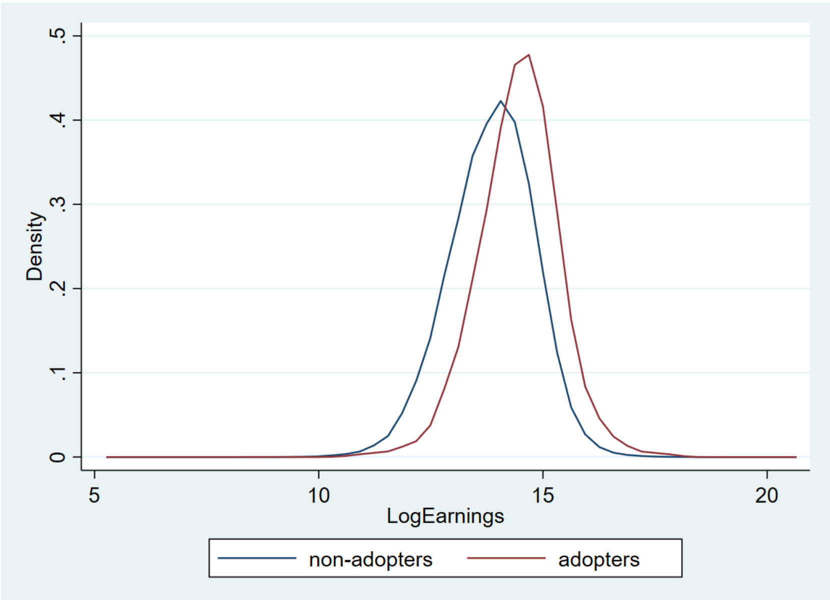

Figure 1. Log earnings distribution during the pandemic

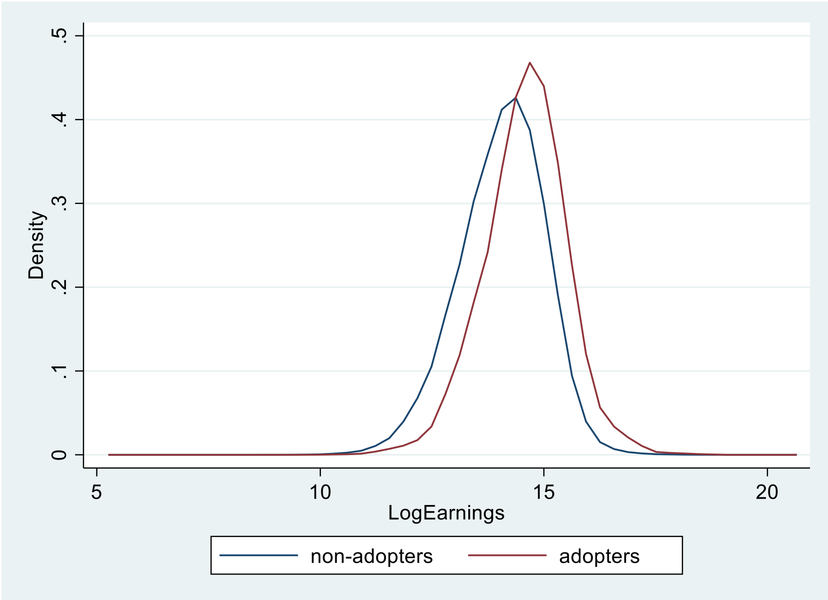

Figure 2. Log earnings distribution after the pandemic

It is important to emphasize that this comparison provides only an indicative assessment of the patterns in the data. Kernel density plots illustrate broad differences in distributions but do not account for confounding characteristics between adopters and non-adopters. To establish whether these apparent differences are statistically significant and causally attributable to e-commerce adoption, further econometric analysis is required. In the subsequent sections, this paper therefore applies OLS, PSM, and quantile regression models to provide a more rigorous test of these indicative findings.

3.3.1 OLS estimation

The OLS results across the pandemic and post-pandemic periods in Table 4 reveal how e-commerce adoption and other determinants shaped rural earnings in Indonesia. During the pandemic years (2020–2022), adopters of e-commerce earned about 82.4 percent $((e^{0.6010} - 1) \times 100\%)$ more than non-adopters in the baseline specification and around 42.7 percent more after controlling for other variables, while in the post-pandemic period (2023–2024), the earnings premium remained sizeable at roughly 69.8 percent without controls and 39.8 percent with controls. This shift suggests that adoption was particularly critical as a resilience mechanism during the crisis, when traditional markets were disrupted, but evolved into a sustainability mechanism in recovery, when digital users continued to enjoy advantages.

Table 4. OLS estimation results of log earnings during pandemic and post-pandemic

Variable	Pandemic		Post-pandemic	
	Basic Model	Full Model	Basic Model	Full Model
E-commerce	0.6010***	0.3557***	0.5294***	0.3348***
	(0.0235)	(0.0228)	(0.0236)	(0.0200)
Female		-0.4322***		-0.4645***
		(0.0090)		(0.0134)
Marital Status (Married)		0.0534***		0.0602***

Variable	Pandemic		Post-pandemic	
	Basic Model	Full Model	Basic Model	Full Model
		(0.0102)		(0.0121)
Number of Household Members		-0.0054*		-0.0081***
		(0.0028)		(0.0026)
Number of Household Members 15+		0.0192***		0.0100***
		(0.0042)		(0.0031)
Education				
Junior High School		0.0794***		0.0825***
		(0.0102)		(0.0117)
Senior High School		0.1482***		0.1710***
		(0.0125)		(0.0120)
Vocational		0.1137***		0.1124***
		(0.0145)		(0.0223)
Diploma		0.3343***		0.2515***
		(0.0306)		(0.0514)
University		0.3087***		0.3383***
		(0.0251)		(0.0391)
Experience		0.0176***		0.0191***
		(0.0008)		(0.0011)
Experience squared/100		-0.0295***		-0.0313***
		(0.0011)		(0.0015)
Training (trained)		-0.0055		-0.0283**
		(0.0147)		(0.0134)
Employment status by working hours (full employment)		0.1780***		0.2050***
		(0.0076)		(0.0123)
Worker status				
Assisted by unpaid labour		0.0903***		0.1642***
		(0.0090)		(0.0117)
Assisted by paid labour		0.8328***		0.8031***
		(0.0171)		(0.0184)
Year dummy				
2021		-0.0565***		-
		(0.0114)		
2022		0.1915***		-
		(0.0110)		
2024		-		0.1033***
				(0.0114)
Provincial dummy		yes		yes
Constant		13.5503***		13.7889***
		(0.0341)		(0.0257)
Number of Observations	195,554	195,554	168,685	168,685
R-Squared	0.0060	0.2157	0.0089	0.2254

Note: Robust standard errors in parentheses (clustered at subdistrict level); ***p<0.01, **p<0.05, *p<0.1; sampling weight was used in estimation

Gender disparities persisted throughout, with female agricultural employers earning approximately 35.1–37.2 percent less than their male counterparts in both phases. Being married was consistently associated with a modest 5.5–6.2 percent earnings premium. Household size exerted a small negative effect, reducing income by less than one percent per additional member, whereas the presence of extra working-age household members raised income by 1–2 percent, underscoring the role of adult labor contributions.

Education exhibited a strong and stable gradient: junior and senior high school completion boosted earnings by 8.3–18.6 percent, vocational education by about 12 percent, and diploma or university attainment by 28.6–40.3 percent, highlighting the enduring importance of human capital. Experience showed a 2 percent income increase, but at a diminishing rate, while training yielded no significant benefits during the pandemic and even a small negative effect (approximately –3 percent) afterward, suggesting a mismatch between program content and rural digital needs [42], [43], [44].

Employment conditions and labor inputs also mattered greatly, with full-time work associated with 19.5–22.8 percent higher earnings, assistance by unpaid household members adding 9.7–17.8 percent, and the use of paid labor increasing income by more than 120 percent across both periods, illustrating the central role of productive capacity. Finally, the time effects trace the dynamics of crisis and recovery: relative to 2020, earnings declined by about 5.5 percent in 2021 at the height of the pandemic but rose by 21.1 percent in 2022 as recovery began, while in the post-pandemic phase, earnings in 2024 were 10.9 percent higher than in 2023, reflecting sustained growth.

Taken together, these findings show that e-commerce adoption was decisive for resilience during the pandemic and remained important for sustainability after it, while structural determinants such as gender, education, household composition, and labor inputs consistently shaped rural earnings across both periods.

3.3.2 PSM estimates

The propensity score matching (PSM) estimates in Table 5 reinforce OLS findings that e-commerce adoption delivers substantial earnings benefits for rural agricultural employers. During the pandemic, nearest-neighbor matching (5 neighbors, caliper 0.005) shows that adopters earned on average Rp2,560,936 per week, compared to Rp1,767,921 among matched non-adopters. This gap of Rp 793,015, equivalent to a 31 percent premium, is confirmed by the kernel matching estimator, which produces a similar effect of Rp824,415. After the pandemic, the income premium not only persisted but expanded in absolute terms, with adopters earning Rp3,075,727 weekly versus Rp2,056,746 among controls—a difference of Rp1,018,981 or 33.1 percent. The kernel estimator again supports this result with an estimated treatment effect of Rp935,197.

These findings strongly corroborate the OLS results, which also showed large and statistically significant positive effects of e-commerce adoption on earnings. The similarity across PSM and OLS estimates underscores the robustness of the relationship, demonstrating that the observed income premium is not merely an artifact of selection bias on observables.

Table 5. Impact of e-commerce adoption on weekly real earnings using PSM

PSM Method	Earnings (rupiahs)		Average treatment effect	
	Treated (adopters)	Control (non-adopters)	Rupiahs	% difference
During the pandemic				
Neighbour (5),	2,560,936	1,767,921	793,015***	30.97

Calliper (0.005)				
Kernel (Bootstrap with 1,000 iterations)	-	-	824,415***	-
After the pandemic				
Neighbour (5), Calliper (0.005)	3,075,727	1,968,768	1,106,959	33.13
Kernel (Bootstrap with 1,000 iterations)	-	-	935,197***	-

Note: ***p<0.01, **p<0.05. Sampling weights were used in estimation.

3.3.3 Quantile regression estimates

The quantile regression estimates, transformed into percentage effects on earnings and visualized in the plots, in Tables 6 and 7, reveal that e-commerce adoption significantly improves income among rural agricultural employers, with important implications for income distribution. During the pandemic, adopters at the lowest quantile (Q1) earned approximately 54.1 percent more than non-adopters, while the effect declined gradually toward the top, with gains of 45.4 percent at Q3, 39.9 percent at Q5, 40.6 percent at Q7, and 34.4 percent at Q9. The downward-sloping pattern in Figure 3 corroborates these estimates, showing that e-commerce adoption disproportionately benefited the lower end of the earnings distribution during the crisis, thereby narrowing income disparities at a time when rural markets faced unprecedented disruption. In this sense, e-commerce functioned as a powerful equalizer by expanding opportunities for small and vulnerable employers [45].

Table 6. Impact of e-commerce adoption on earnings at different quantiles during the pandemic

	Q1	Q3	Q5	Q7	Q9
Ecommerce	0.4324**	0.3746**	0.3356**	0.3404**	0.2953**
	(0.0462)	(0.0265)	(0.0315)	(0.0216)	(0.0370)
Married	0.0949**	0.0985**	0.0867**	0.0732**	0.0565**
	(0.0125)	(0.0092)	(0.0088)	(0.0083)	(0.0094)
Female	-0.4086**	-0.4617**	-0.4648**	-0.4448**	-0.3804**
	(0.0112)	(0.0088)	(0.0078)	(0.0083)	(0.0098)
Proportion of 15+ in the household	0.2086**	0.1498**	0.0872**	0.0619**	0.0244
	(0.0246)	(0.0184)	(0.0160)	(0.0151)	(0.0185)
Age	0.0217**	0.0283**	0.0294**	0.0278**	0.0260**
	(0.0022)	(0.0017)	(0.0015)	(0.0015)	(0.0018)
Age2	-0.0003**	-0.0004**	-0.0004**	-0.0003**	-0.0003**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log of year of schooling	0.2529**	0.2478**	0.2321**	0.1932**	0.2031**
	(0.0167)	(0.0123)	(0.0108)	(0.0097)	(0.0135)
Log of tenure	0.0623**	0.0603**	0.0526**	0.0442**	0.0235**
	(0.0035)	(0.0024)	(0.0022)	(0.0023)	(0.0031)
Log of working hours	0.1906**	0.1617**	0.1422**	0.1188**	0.0644**
	(0.0057)	(0.0040)	(0.0039)	(0.0038)	(0.0047)
Trained	-0.0285	-0.0394*	-0.0091	0.0305*	0.0569**
	(0.0183)	(0.0178)	(0.0153)	(0.0119)	(0.0208)
Assisted by paid	0.8867**	0.8926**	0.8504**	0.8348**	0.8707**

labour					
	(0.0269)	(0.0198)	(0.0158)	(0.0124)	(0.0319)
Year 2021	-0.0572**	-0.0398**	-0.0171*	-0.0032	-0.0231*
	(0.0136)	(0.0094)	(0.0089)	(0.0084)	(0.0104)
Year 2022	0.1866**	0.2106**	0.2200**	0.1890**	0.1436**
	(0.0136)	(0.0095)	(0.0088)	(0.0083)	(0.0107)
Jawa	-0.2644**	-0.2620**	-0.2396**	-0.1925**	-0.1193**
	(0.0110)	(0.0085)	(0.0075)	(0.0075)	(0.0096)
_cons	11.0836**	11.7419**	12.2746**	12.8655**	13.6368**
	(0.0670)	(0.0515)	(0.0449)	(0.0435)	(0.0548)
Number of Ob	195,554	195,554	195,554	195,554	195,554

Robust standard errors in parentheses. Survey weight was applied in the estimation.
* $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

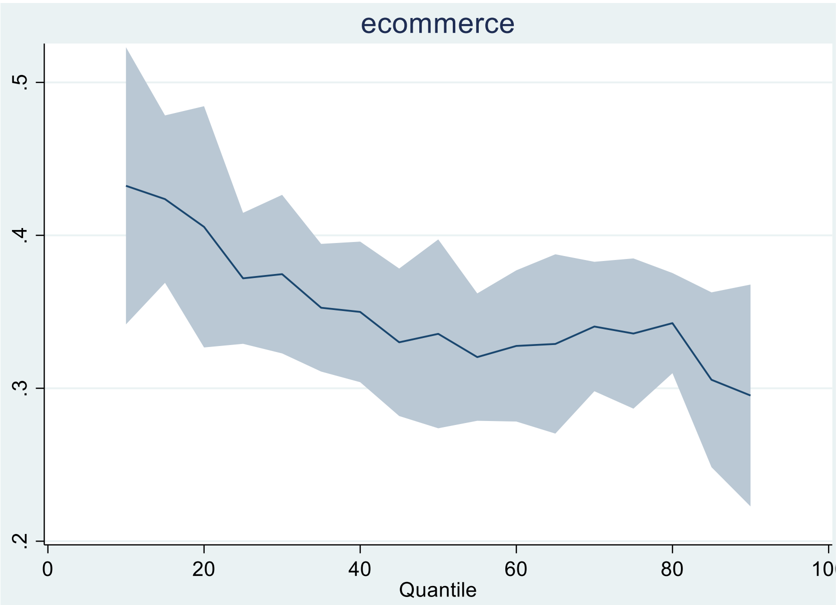

Figure 2. Quantile of e-commerce coefficients during the pandemic with a 95 percent confidence interval

In the post-pandemic period, the earnings premium from e-commerce remained sizeable across all quantiles, though its distribution shifted. At the bottom quantile, adopters continued to earn 49.9 percent more than non-adopters, confirming the sustained inclusiveness of digital platforms for the most vulnerable. However, mid-quantile employers (Q3–Q7) saw somewhat smaller gains relative to the pandemic, ranging from 40.5 percent at Q3 to 30.3 percent at Q7. By contrast, the top quantile (Q9) experienced a rebound to 37.3 percent, a dynamic captured in Figure 4, where the declining trend stabilizes and partially rises toward higher quantiles. This suggests that higher-income employers consolidated their capacity to leverage e-commerce during the recovery [46]. Despite these shifts, the persistence of strong effects at Q1 demonstrates that e-commerce adoption continues to promote equity by bolstering incomes at the bottom of the distribution.

Table 7. Impact of E-commerce Adoption on Earnings at Different Quantiles after the Pandemic

	Q1	Q3	Q5	Q7	Q7
Ecommerce	0.4050**	0.3398**	0.2907**	0.2645**	0.3170**
	(0.0431)	(0.0261)	(0.0197)	(0.0286)	(0.0425)
Married	0.0883**	0.0897**	0.0892**	0.0763**	0.0799**
	(0.0163)	(0.0127)	(0.0107)	(0.0103)	(0.0142)
Female	-0.5061**	-0.5314**	-0.5245**	-0.4723**	-0.3853**
	(0.0153)	(0.0121)	(0.0102)	(0.0101)	(0.0134)
Proportion of 15+ in the household	0.0215	0.0307	0.0295**	0.0285*	0.0215
	(0.0319)	(0.0218)	(0.0033)	(0.0116)	(0.0511)
Age	0.0358**	0.0387**	0.0351**	0.0308**	0.0324**
	(0.0029)	(0.0022)	(0.0020)	(0.0018)	(0.0025)
Age2	-0.0004**	-0.0004**	-0.0004**	-0.0003**	-0.0003**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log of year of schooling	0.2424**	0.2383**	0.2255**	0.2457**	0.2475**
	(0.0220)	(0.0159)	(0.0122)	(0.0124)	(0.0169)
Log of tenure	0.0530**	0.0470**	0.0388**	0.0278**	0.0169**
	(0.0031)	(0.0033)	(0.0029)	(0.0026)	(0.0037)
Log of working hours	0.2637**	0.2151**	0.1685**	0.1292**	0.0751**
	(0.0075)	(0.0067)	(0.0058)	(0.0059)	(0.0066)
Trained	-0.0815**	-0.0631**	-0.0360*	-0.0256	0.0500**
	(0.0227)	(0.0211)	(0.0157)	(0.0179)	(0.0159)
Assisted by paid labour	0.8868**	0.8863**	0.8311**	0.7537**	0.6976**
	(0.0252)	(0.0193)	(0.0137)	(0.0157)	(0.0138)
Jawa	-0.2636**	-0.2328**	-0.2039**	-0.1627**	-0.1015**
	(0.0150)	(0.0122)	(0.0094)	(0.0092)	(0.0128)
_cons	10.8897**	11.6756**	12.3741**	12.9425**	13.5365**
	(0.0886)	(0.0664)	(0.0563)	(0.0548)	(0.0795)
Number of Ob	168,685	168,685	168,685	168,685	168,685

Robust standard errors in parentheses. Survey weight was applied in the estimation.
* $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

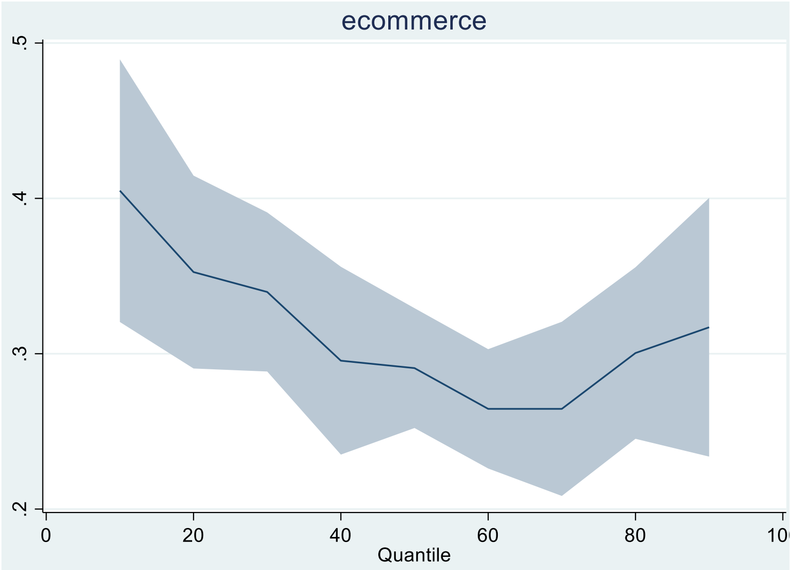

Figure 4. Quantile of e-commerce coefficients after the pandemic with a 95 percent confidence interval

Taken together, the results highlight the dual role of e-commerce adoption: while it boosts earnings across the board, its greatest impact lies in reducing inequality by lifting incomes proportionally more at the lower end. The convergence of earnings effects during the pandemic illustrates that digital platforms can mitigate income disparities among rural agricultural employers, particularly when conventional market channels are restricted [47], [48]. Although the post-pandemic reallocation of benefits toward higher earners signals the risk of stratification, the consistently high returns at Q1 confirm that e-commerce remains a viable tool for improving income distribution in rural economies.

From a policy perspective, these findings insist on the necessity of treating e-commerce adoption not only as an efficiency-enhancing innovation but also as a distributional level [12]. Strengthening access for mid- and low-quantile employers through digital literacy programs, affordable logistics, and credit support would help preserve and expand the inclusive effects observed during the pandemic. By ensuring that the bottom segments of the rural labor market continue to realize disproportionate benefits, policymakers can harness e-commerce to promote a more equitable distribution of earnings and foster inclusive rural development in the long term.

4. Conclusion

This study provides compelling evidence that e-commerce adoption served both as a resilience mechanism during the pandemic and as a sustainability mechanism in the recovery period. By directly linking rural agricultural employers to broader markets, e-commerce adoption significantly raised earnings and cushioned households against the most severe income shocks. The distributional analysis demonstrates that the greatest benefits accrued to the lowest-income groups during the pandemic, narrowing disparities at a critical time. Although the post-pandemic reallocation of gains toward higher-income employers suggests a risk of stratification, the continued large effects at the bottom quantile confirm that digital platforms remain an effective tool for improving income distribution. With respect to the determinants of adoption, this study finds that e-commerce uptake is influenced by demographic, household, enterprise, and spatial factors. Specifically, women, older cohorts, and larger dependent households are less likely to adopt, whereas higher education, participation in training, engagement with paid labor (indicating larger or more commercially oriented operations), and formal sector participation significantly enhance adoption. Regional disparities also play an important role—employers located in Java have higher adoption rates due to better digital infrastructure and market access—while the post-pandemic period shows that external shocks can accelerate digital transformation and sustain adoption momentum.

From a policy perspective, these results highlight the need to treat e-commerce not only as a driver of efficiency and market access but also as a lever for inclusive growth. Expanding rural digital infrastructure, reducing entry barriers, and promoting training tailored to agricultural contexts can ensure that vulnerable employers maintain access to these opportunities. Strengthening credit and logistics support for small-scale employers will further preserve the equalizing role of digital adoption observed during the crisis. In sum, e-commerce holds significant promise for advancing equitable rural development in Indonesia, but its inclusiveness will depend on deliberate policy interventions to ensure that the poorest employers continue to benefit disproportionately.

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