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Short supply chain, technical efficiency, and technological change: Insights from cucumber production

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Abstract

This study examines the impact of participation in short supply chains (SSCs) on technical efficiency (TE) and technological change (TC) in cucumber production in China, using data for the period 2011–2016. The meta-frontier model and the two-stage residual inclusion approach are utilized to examine the association between SSC participation, comparable TE, and TC. Accounting for selection bias, we show that SSC participation significantly decreased the comparable TE of cucumber production but accelerated TC. The disaggregated analysis reveals that the comparable TE for SSC participants was generally smaller than that for nonparticipants. Furthermore, comparable TE for nonparticipants consistently increased year-over-year, whereas, for SSC participants, it increased during some years and decreased during others. Last but not least, TC for both SSC participants and nonparticipants increased over time. [EconLit Citations: Q12, D24].

KEYWORDS

cucumber production, short supply chains, technical efficiency, technological change

Abbreviations: 2SRI, two-stage residual inclusion; ATT, average treatment effects on the treated; ESR, endogenous switching regression; IVs, instrumental variables; SSCs, short supply chains; TC, technological change; TE, technical efficiency.

1 | INTRODUCTION

Short supply chains (SSCs) in the fresh-food industry have significantly reduced the number of intermediaries connecting farmers with consumers. The typical SSC includes farm-supermarket docking, you-pick-up operations, community-supported agriculture, and selling directly to supermarkets, restaurants, and canteens. Prior studies have shown that SSCs have several advantages over traditional supply chains (Canfora, 2016; Deppermann et al., 2018; Lioutas & Charatsari, 2020; Migliore et al., 2015; Montalbano & Nenci, 2022; Zhang et al., 2019). For example, Canfora (2016) found that SSCs reduced transportation costs, leading to lower carbon dioxide emissions, thus promoting agricultural sustainability. Santulli et al. (2019) found that SSCs were associated with a lower risk of metabolic syndrome in a population adhering to the Mediterranean diet, and Zhang et al. (2019) showed that SSC participation increased farm profits by reducing market risks, improving farm productivity, and helping farmers expand their operations.

Traditional supply chains spanning large distances deprive farmers of the opportunity to interact with their products' end consumers directly. Thus, farmers cannot build personal relationships with the end consumers, understand their needs and wants, and gain the knowledge necessary to find niche markets and enhance their value proposition. Furthermore, as farmers are positioned towards the end of agricultural supply chains comprising multiple stakeholders, they often receive low prices for their output. The absence of a personal connection with end consumers and the opportunity to charge higher prices may demotivate farmers to improve their products. In contrast, farmers participating in SSCs engage personally with their customers, often building lasting relationships with them. The farmers inform customers about the quality, provenance, and advantages of their products; in return, they receive higher prices for their products. Also, unlike farmers participating in traditional food supply chains, those participating in SSCs may change their production processes in response to food safety and quality requirements (Yadav et al., 2022; Zhang & Yu, 2021). For example, SSC participants may choose to reduce the use of yield-increasing inputs (e.g., chemical fertilizers and pesticides) to meet the increased consumer demand for high-quality and safe food. To compensate for yield losses, SSC participants may adopt advanced agricultural technologies (e.g., precision fertilization technology, biological control technology, and improved seeds resistant to pests and diseases) to improve farm productivity.

Productivity growth among SSC participants may be higher due to their openness to training and adopting different production technologies and inputs. Nevertheless, except for Rao et al. (2012), analyses of this subject are absent in the literature. Using data collected from vegetable farmers in Kenya, Rao et al. (2012) estimated the impacts of farmers' participation in supermarkets, a type of SSC, on farm productivity and efficiency. They found that farmers selling through supermarkets achieved higher productivity, technical efficiency (TE), and scale efficiency than those selling through other channels. Considering the growing importance and popularity of SSC globally, more work is needed to understand the effects of SSC participation.

This study examines the impact of SSC participation and attempts to make two contributions to the literature on fresh-food supply chains. One, we provide the first attempt to explore the impacts of SSC participation on the TE and technological change (TC) in growing cucumbers in greenhouses. Two, we investigate the trends in TE and TC to gain insights into whether and how farmers' decisions to adopt new practices are influenced by their peers. We estimate farm-level panel data collected from cucumber farmers in the province of Jiangsu in China. The data contain detailed input and output information on cucumbers grown in greenhouses. Using panel data allows us to control for trends in the TE and TC in cucumber production over time. The findings of this study may inform policies and programs to promote sustainable agrifood production and the development of SSCs.

China is the world's largest producer of cucumbers. In 2020, it produced 72.83 million tons of cucumbers (80% of the global output) on 1.28 million hectares of land (56.61% of the land allocated to cucumber production globally (FAOSTAT).[1] Despite the magnitude of cucumber production in China, its yield was relatively low: 62.71 tons/ha (FAOSTAT). This is significantly lower than the cucumber yield in other high-productivity countries, such as the

[1]FAOSTAT refers to the Food and Agriculture Organization Statistical Database, and it is available at https://www.fao.org/faostat/en/#data.

Netherlands (777.35 tons/ha), Iceland (664.33 tons/ha), and the United Kingdom (585.33 tons/ha). Improving crop yields can be achieved by either using higher inputs or increasing the TE of farm production (DeLay et al., 2022; Koirala et al., 2016; Ma et al., 2018; McFadden et al., 2022; Zheng, Ma, Wang, et al., 2021). Increasing inputs increases production costs, whereas increasing TE only requires reallocating existing resources. Increasing the TE of cucumber production is critical to farm productivity and the global competitiveness of China's cucumber industry.

The remainder of this paper is organized as follows. Section 2 presents the methodology. Section 3 presents the data and descriptive statistics. Empirical results are discussed in Section 4, and Section 5 concludes the study.

2 | METHODOLOGY

2.1 | Meta-frontier production function

SSC participants and nonparticipants may adopt different production technologies targeting different customers and production requirements. Thus, SSC participants and nonparticipants may have different production frontiers in farm production. If this is the case, estimating a single production function for the pooled sample may generate biased results, leading to incorrect conclusions. To overcome this concern, following previous studies (Alem et al., 2019; Battese et al., 2004; Bravo-Ureta et al., 2020; O'Donnell, 2008), we employ the meta-frontier production function to estimate the impact of SSC participation on TE and TC.

Mathematical programming techniques and stochastic frontier frameworks have been applied to estimate meta-frontiers (Battese et al., 2004; Chang et al., 2015; Huang et al., 2014; O'Donnell, Rao, et al., 2008). For example, Battese et al. (2004) and O'Donnell (2008) estimated the meta-frontier production function based on a mathematical programming technique. However, Huang et al. (2014) pointed out that the mathematical programming technique does not provide a meaningful statistical interpretation. They proposed a new two-step estimation approach based on the stochastic frontier framework. In this study, we estimated the meta-frontier production function based on stochastic frontier regression techniques to investigate how SSC participation affected TE and TC.

First, we estimated separate production frontiers for both SSC participants and nonparticipants as follows:

$$\ln Y_{it}^{S} = \alpha_0 + \sum_{m=1}^{4} \alpha_m \ln I_{itm} + 0.5 \sum_{m=1}^{4} \sum_{k=1}^{4} \alpha_{mk} \ln(I_{itm}) \ln(I_{itk}) + \sum_{m=1}^{4} \alpha_{mt} \ln(I_{imt}) t + \alpha_t t + 0.5 \alpha_{tt} t^2 + \varepsilon_{it} - \mu_{it}, \tag{1}$$

where $\ln Y_{it}^{S}$ denotes the logarithm of cucumber yield per mu of farm i for SSC participants ($S = 1$) and nonparticipants ($S = 2$) in year t. α_0 is a constant. $\ln I_{itm}$ denotes the logarithm of the input vector for farm i in year t. The inputs considered in this study included seed costs, labor, fertilizer quantity, and other intermediate inputs, measured in mu (1 mu = 1/15 ha). Seed and other input costs were deflated using the input price index and 2011 as the base year. $\ln(I_{itm})\ln(I_{itk})$ refers to the squared terms of inputs when $m = k$, while it refers to the interaction terms between two inputs when $m \neq k$. $\ln(I_{imt})t$ refers to the interaction term between input m and the time-trend variable t. The time-trend variable (t) was included to capture possible TC. α_m, α_{mk}, α_{mt}, α_t, and α_{tt} are parameters to be estimated. The error term, ε_{it}, is independently and identically distributed as $N(0, \sigma^2)$. μ_{it} refers to technical inefficiency and is independently and identically distributed as $N^{+}\left(\mu, \sigma_{\mu}^{2}\right)$.

After estimating Equation (1), the technical efficiencies (TE_{it}^{S}) were predicted as follows:

$$TE_{it}^{S} = \frac{\ln Y_{it}^{S}}{\ln Y_{it}^{S*}} = e^{-u_i}, \tag{2}$$

where $\ln Y_{it}^{S}$ refers to the observed cucumber yield for SSC participants (S = 1) and nonparticipants (S = 2), while $\ln Y_{it}^{S*}$ refers to the "optimal" level of cucumber yield when all inputs have been used most efficiently. Because $\ln Y_{it}^{S} \le \ln Y_{it}^{S*}$, this suggests that $0 < TE_{it}^{S} \le 1$.

The meta-frontier production function is a smooth envelope corresponding to the production frontier for both SSC participants and nonparticipants. After estimating Equation (1), we predicted cucumber yield for SSC participants and nonparticipants based on the estimated coefficients to calculate the meta–technology gap. The predicted yield Y_{it}' was used to estimate the meta-frontier production function using a pooled sample as follows[2]:

$$\ln Y_{it}' = \beta_0 + \sum_{m=1}^{4} \beta_m \ln I_{itm} + 0.5 \sum_{m=1}^{4} \sum_{k=1}^{4} \beta_{mk} \ln(I_{itm}) \ln(I_{itk}) + \sum_{m=1}^{4} \beta_t \ln(I_{imt}) t + \beta_t t + 0.5 \beta_{tt} t^2 + \epsilon_{it} - \mu_{it}^{M}. \tag{3}$$

In Equation (3), all symbols have the same meanings as in Equation (1). ϵ_{it} is the error term and is independently and identically distributed as $N\left(0, \sigma_M^2\right)$. μ_{it}^{M} measures the distances of the separated production frontiers of both SSC participants and nonparticipants to the meta-frontier, respectively. μ_{it}^{M} is independently and identically distributed as $N^{+}\left(\mu^{M}, \sigma_{\mu^M}^{2}\right)$. The meta–technology gap for both SSC participants and nonparticipants can be calculated as $TE_{it}^{M} = e^{-\mu_{it}^{M}}$.[3]

Following Huang et al. (2014), the comparable TEs for both SSC participants and nonparticipants were calculated as

$$Comparable \;\; TE_{it} = TE_{it}^{S} \times TE_{it}^{M}. \tag{4}$$

The comparable TE specifically accounts for the potential differences in production technologies between SSC participants and nonparticipants. Finally, the TC was measured using the derivative of Equation (1) with respect to the time-trend variable (Kumbhakar et al., 2000). It was specified as follows:

$$TC = \partial \ln Y_{it}^{S} / \partial t = \sum_{m=1}^{4} \alpha_{mt} \ln(I_{imt}) + \alpha_t + \alpha_{tt} t. \tag{5}$$

2.2 | The two-stage residual inclusion (2SRI) approach

Because farmers choose to participate or not participate in SSCs, SSC participants and nonparticipants may be systematically different in observed and unobserved factors—SSC participation is not random. As a result, the comparable TE and TC, estimated using Equations (4) and (5) for SSC participants and nonparticipants, may not truly reflect the effects of SSC participation. The selection bias inherent in SSC participation should not be neglected.

In this study, we employed the 2SRI approach to examine the impacts of SSC participation on the TE and TC in cucumber production. The pooled sample was estimated to this end. The 2SRI approach enabled us to address the selection bias arising from both observed and unobserved factors; this approach has been widely applied in empirical studies (Ma & Zheng, 2021; Ma & Zhu, 2021; Terza, 2018; Zhu et al., 2021).

The first stage of the 2SRI approach estimates the probability of a farmer participating in SSC based on the following logit model:

[2]Equation (1) is utilized to estimate two separate production frontiers: one for SSC participants (S = 1) and another for nonparticipants (S = 2). Afterwards, the predicted cucumber yield from those two estimations is used to synthesize a pooled sample for meta-frontier analysis.

[3]TE estimated using the meta-frontier model is also called meta–technology ratio or gap in some studies (e.g., Chiu et al., 2012; Rao et al., 2012).

$$Chain_i^* = \lambda_0 + \lambda_1 X_i + \lambda_2 Location_i + \lambda_3 t + \lambda_4 IV_i + \omega_i,$$

$$Chain_i = \begin{cases} 1 \text{ if } Chain_i^* > 0, \\ 0 \text{ otherwise,} \end{cases} \tag{6}$$

where $Chain_i^*$ refers to the probability that a farmer i participates in SSC; this is observable and captured by $Chain_i$. In particular, $Chain_i = 1$ if a farmer is an SSC participant, and 0 otherwise. IV_i refers to a vector of instrumental variables (IVs). X_i is a vector of control variables (e.g., demographic characteristics, inputs of labor, and fertilizer). To control for location and time fixed effects, we also included a regional variable $Location_i$ and a time variable t in our model. λ_0 is a constant. λ_1, λ_2, λ_3, and λ_4 are parameters to be estimated. ω_i is the error term.

We utilized two variables representing the distance from farmers' residential location to Shanghai and the urbanization level of each county as IVs. Shanghai is the most populous city in China and borders Jiangsu province. Jiangsu's counties close to Shanghai have relatively high levels of urbanization. Farmers in these areas are more likely to participate in SSC to respond to consumers' demand for high-quality products. Although urbanization and distance to Shanghai may influence SSC participation, they are not correlated with farm performance indicators, such as TE and TC. The proximity of farmers to Shanghai is unrelated to the spillover effects of TC since the development and deployment of technologies fall under the remit of the local Academy of Agricultural Sciences in Jiangsu province. In addition, it is reasonable to regard distance and urbanization level as exogenous to any given farm.

The second stage of the 2SRI approach estimates the impacts of SSC participation on comparable TE and TC, using Equations (4) and (5). In this study, the comparable TE is a continuous variable scaled between 0 and 1, while TC is measured as an unrestricted continuous variable. On the basis of the nature of the two dependent variables, we employed the fractional response model to estimate the impact of SSC participation on comparable TE and a multiple linear regression model to estimate the impact of SSC participation on TC. The two empirical specifications are specified as follows:

$$Comparable\ \ TE_i = \gamma_0 + \gamma_1 Chain_i + \gamma_2 X_i + \gamma_3 t + \gamma_4 Location_i + \gamma_5 Residual_i + e_i, \tag{7a}$$

$$TC_i = \psi_0 + \psi_1 Chain_i + \psi_2 X_i + \psi_3 t + \psi_4 Location_i + \psi_5 Residual_i + \theta_i, \tag{7b}$$

where $Comparable\ TE_i$ refers to comparable technical efficiency of farm i. TC_i represents the technological change of farm i. γ_0 and ψ_0 are constants. $Chain_{it}$, X_i, t, and $Location_i$ are the same as defined above. $Residual_{it}$ is the residual term obtained from Equation (6), and is included in Equations (7a) and (7b) to account for unobserved heterogeneities that could bias the technical performance variables. γ_1, γ_2, γ_3, γ_4, and γ_5 in Equation (7a), and ψ_1, ψ_2, ψ_3, ψ_4, and ψ_5 in Equation (7b) are parameters to be estimated. e_i and θ_i are the error terms.

3 | DATA AND DESCRIPTIVE STATISTICS

The data used in the present study were collected from a survey of farmers who used greenhouses to produce cucumbers. The Price Bureau of Jiangsu conducted the survey from 2011 to 2016. Jiangsu, located in eastern China, is one of the most advanced provinces in China, with well-developed agricultural and nonagricultural sectors. A multistage sampling procedure was used to choose sample counties, townships, and smallholder farmers. First, the survey organizer sorted all the counties from 13 cities according to the harvest areas. Counties with harvest areas larger than the median harvest areas were shortlisted as the candidate counties, and then one to three counties from each city were surveyed. Our sample included 19 counties. Second, two townships from each surveyed county were randomly selected; only the townships whose cucumber output exceeded the median cucumber output were eligible for selection. Third, six to eight

TABLE 1 Mean differences in the variables

	SSC participants	Nonparticipants	Mean differences
Variables used in the production function			
Yield (1000 kg/mu)[a]	3.70 (1.35)	5.70 (2.26)	−2.00*** (0.24)
Seed (100 yuan/mu)[b]	2.55 (2.01)	2.04 (1.33)	0.51** (0.30)
Labor (100 days/mu)	0.38 (0.20)	0.60 (0.28)	−0.22*** (0.03)
Fertilizer (100 kg/mu)	0.34 (0.27)	0.65 (0.53)	−0.31*** (0.05)
Others (1000 yuan/mu)	2.83 (0.83)	3.91 (2.04)	−1.08*** (2.06)
Variables used in the technical efficiency function			
Age (years)	48.97 (8.97)	52.80 (9.00)	−3.83*** (1.05)
Illiteracy and primary school (1 = yes)	0.11 (0.03)	0.12 (0.02)	−0.01 (0.04)
Junior high school (1 = yes)	0.57 (0.05)	0.59 (0.03)	−0.03 (0.06)
Senior school (1 = yes)	0.23 (0.04)	0.28 (0.03)	−0.05 (0.05)
College and above (1 = yes)	0.09 (0.29)	0.01 (0.00)	0.08*** (0.02)
Farm size (mu)	5.15 (11.96)	2.10 (1.76)	3.05*** (0.79)
Sample size	105	241	

Note: Standard deviation is presented in parentheses.
Abbreviation: SSC, short supply chain.
[a]1 mu = 1/15 ha.
[b]Yuan is the Chinese currency (1 USD = 6.64 yuan).
**$p < 0.05$.
***$p < 0.01$.

farmers were randomly selected from each township, given different farm sizes. The final dataset comprised 346 observations, including 105 SSC participants and 241 nonparticipants.[4]

The survey collected information on production inputs, cucumber yield, and farmers' marketing preferences (i.e., whether they sold their products through SSCs or traditional channels). Most of the SSC participants sold their cucumbers directly to catering services at public institutions, such as schools and hospitals. Some of them also sold to local supermarkets and community households. In addition, SSC participants had the option to sell cucumbers through a traditional supply chain at higher prices. With all these scenarios in mind, we defined SSC participation as a dichotomous variable equal to one if a farmer sold more than 50% of her products through SSC channels (i.e., SSC participants) and zero otherwise (nonparticipants).

Table 1 describes the mean differences between SSC participants and nonparticipants apropos different variables. It shows that the cucumber yield of SSC participants was lower than that of nonparticipants, and the mean difference was statistically significant at the 1% level, suggesting that SSC participation reduced cucumber yield. On average, SSC participants spent more on seeds but less on labor and fertilizer than nonparticipants; they were also younger than nonparticipants. Relative to nonparticipants, SSC participants were more likely to attend college-and-above education. SSC participants were more likely to attend college-and-above education and cultivate larger farms than nonparticipants. On average, the farm size for SSC participants was 5.15 mu, which was 3.05 mu larger than for nonparticipants.

[4]Unbalanced panel data were used in this study.

Because simply comparing means does not account for confounding factors affecting farmers' decisions to participate in SSC, one cannot draw meaningful conclusions from these comparisons. In fact, the results discussed above show that SSC participants and nonparticipants were systematically different in personal- and farm-level characteristics. Therefore, it is important to estimate the impacts of SSC participation on TE and TC in cucumber production while controlling for other confounding factors.

4 | EMPIRICAL RESULTS

4.1 | Results of the production frontier models

The results estimated for the production functions are presented in Table A1 in the appendix. Columns (2) and (3) present the separate production frontiers estimates for SSC participants and nonparticipants using Equation (1), and the last column comprises the meta-frontier estimates derived using Equation (3). In the interest of brevity, we do not explain these results in detail, as they are mainly used to calculate TE for SSC participants and nonparticipants.

The TE estimates are presented in Table 2. The results show that the TEs for SSC participants and nonparticipants, estimated from the separate production frontiers (column 2), were 0.830 and 0.903, respectively. The findings suggest that SSC participants and nonparticipants lost approximately 17% and 10% of the attainable cucumber yield, respectively.

A meta-frontier production function is estimated to envelop the two frontier production functions. The results show that the TEs estimated from the meta-frontier model for SSC participants and nonparticipants (column 3 of Table 2) were 0.729 and 0.874, respectively. As a general rule, TE is measured relative to one frontier, and it cannot be compared with another frontier (O'Donnell, Rao, et al., 2008). Thus, it is necessary to calculate comparable TEs to compare the two groups. For this reason, the comparable TE scores for SSC participants and nonparticipants were calculated using Equation (4). A summary of comparable TE is also reported in column (4) of Table 2. The comparable TE is expressed relative to the enveloped meta-frontier for all farms while considering the technological gap between the two groups. On average, the comparable TE of SSC participants was 0.175 lower than that of nonparticipants.

In addition, the first-order conditions for the production function can be interpreted as output elasticities with respect to each input. The output elasticity is a measurement of the potential increase in output due to a 1% increase in an input at a given endowment. We used the estimated parameters for the separate frontiers to calculate the output elasticity with respect to the time trend, which captured TC over time. The results reported in the last column of Table 2 indicate that SSC participants achieved a significantly lower TC than nonparticipants. In fact, the technology used by SSC participants retrogressed, with an annual decline of 0.3%.

The unconditional summary statistics and tests in Tables 1 and 2, in general, suggest that SSC participation decreased comparable TE and hindered TC. But because the participation decision is

TABLE 2 Technical efficiencies and technological change between SSC participants and nonparticipants

	TE (separate production frontier model)	TE (meta-frontier model)	Comparable TE	Technological change
SSC participants	0.830 (0.127)	0.729 (0.169)	0.615 (0.195)	−0.003 (0.147)
Nonparticipants	0.903 (0.032)	0.874 (0.099)	0.790 (0.098)	0.083 (0.048)
Mean differences		−0.144*** (0.015)	−0.174*** (0.017)	−0.086*** (0.011)

Abbreviations: SSC, short supply chain; TE, technical efficiency.
***$p < 0.01$.

endogenous, a simple comparison of the technical performances of SSC participants and nonparticipants has no causal interpretation. That is, the aforementioned differences may not be the result of SSC participation but of other factors, such as differences in household characteristics. Therefore, it is important to evaluate the impacts of SSC participation on technical performances using approaches, such as 2SRI that account for selection bias.

4.2 | Results of 2SRI estimates

4.2.1 | Factors affecting SSC participation

Table 3 presents the results for the impacts of SSC participation on comparable TE and TC using the 2SRI approach. Column (2) of Table 3 shows the first-stage estimates of the 2SRI approach, which is estimated using Equation (6), reporting the factors influencing farmers' decisions to participate in SSCs. The coefficient of age was positive and statistically significant, suggesting that older farmers were more likely to participate in SSCs. Lured by the employment opportunities available in urban China, young individuals are more likely than older ones to migrate from rural to urban regions, leading to systematic urbanization. Consequently, older individuals who remain in rural

TABLE 3 Marginal effects of SSC participation on comparable technical efficiency and technological change: 2SRI model

Variables	First stage	Second stage	
	SSC participation (logit model)	Comparable TE (fractional regression model)	Technological change (OLS)
SSC participation		−0.132*** (0.030)	0.018* (0.010)
Age	0.001*** (0.000)	−0.000*** (0.000)	0.000** (0.000)
Junior high school	0.128* (0.072)	0.049* (0.028)	0.026** (0.011)
Senior school	0.009 (0.097)	−0.012 (0.029)	0.012 (0.010)
College or above	0.244** (0.098)	−0.081 (0.065)	0.031** (0.015)
Farm size	0.029*** (0.007)	0.007*** (0.002)	0.002* (0.001)
Seed costs	0.000 (0.000)	0.000** (0.000)	0.000* (0.000)
Labor input	0.001 (0.001)	−0.000 (0.000)	−0.000* (0.000)
Quantity of fertilizer	−0.001 (0.002)	−0.000 (0.000)	−0.000 (0.000)
Time trend	−0.005 (0.021)	−0.005 (0.004)	0.033*** (0.003)
Region fixed effects	Yes	Yes	Yes
Residual		−0.240*** (0.072)	−0.122*** (0.037)
Distance to Shanghai (IV)	−0.002** (0.001)		
Urbanization level (IV)	0.010* (0.006)		
Sample size	346	346	346

Note: Robust standard errors are presented in parentheses. The reference educational level is primary-school education or less.

Abbreviations: 2SRI, two-stage residual inclusion; IV, instrumental variable; OLS, ordinary least squares; SSC, short supply chain; TE, technical efficiency.

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

areas constitute a significant proportion of farmworkers and stand to benefit from participating in SSCs (Fields & Song, 2020; Zhou et al., 2020). Education was also an important driver of farmers' SSC participation. Relative to illiterate farmers, those who complete junior high school or college education were more likely to participate in SSCs. This stands to reasons as education enhances farmers' abilities to identify markets suited for SSCs and negotiate better prices, increasing their SSC participation. The coefficient of farm size was also positive and significant, suggesting that farmers cultivating large farms were more likely to participate in SSCs. Larger farms enable farmers to achieve economies of scale selling through SSCs; this motivates them to participate in SSCs.

The two IVs had significant coefficients, implying that the IVs relevance condition held. In particular, the negative coefficient of the variable representing the distance to Shanghai suggests that farmers residing farther from Shanghai were less likely to participate in SSCs. The positive coefficient of urbanization level indicates that the higher the urbanization level, the higher the probability of farmers participating in SSCs. Nevertheless, the two IVs are unlikely to have significant impacts on comparable TE and TC.

We employed the underidentification test to check the validity of the IVs (Baum et al., 2007). The Anderson canonical correlation LM statistic is 32.32 with a p value of 0.000. Thus, we rejected the null hypothesis that the equation was underidentified. These results lend credence to the validity of the IVs. In addition, the Sargan–Hansen statistic was 0.067 with a p value of 0.796 for the effect on TC and 1.966 with a p value of 0.161 for the effect on comparable TE. These results further corroborated that the IVs are indeed valid.

4.2.2 | Impacts of SSC participation on comparable TE and TC

Columns (3) and (4) of Table 3 present the second-stage estimates of the 2SRI approach, illustrating how SSC participation and other control variables affect comparable TE and TC. The results were estimated using Equations (7a) and (7b), respectively. The coefficients of the residual terms (see bottom of the table) were statistically significant, suggesting that unobserved factors may have biased the effects of SSC participation on comparable TE and TC. We also used the Hausman test to understand whether SSC participation was endogenous. The null hypotheses that the differences in coefficients of the IV and ordinary least squares estimators were not systematic apropos the effect on TC and comparable TE were rejected,[5] implying that SSC participation was endogenous. Thus, a 2SRI model was applied.

The coefficients of the SSC participation were negative and statistically significant—see column (3) of Table 3. This suggests that SSC participation significantly decreased the TE of cucumber production. To meet the quality and safety standards, SSC participants may use lower levels of agrochemicals. If the existing production inputs and farm management techniques are not appropriately updated or readjusted to compensate for yield losses due to reduced agrochemical use, TE may decline. Our finding is largely consistent with Kumbhakar et al. (2009) but contradicts Rao et al. (2012). Specifically, Kumbhakar et al. (2009) showed that organic dairy farms, due to the implementation of organic standards, had lower TE than conventional farms in Finland, while Rao et al. (2012) found that SSC participants in Kenya (those who sold through supermarket channels) obtained higher TE than nonparticipants.

The results presented in the last column of Table 3 show that SSC participation significantly increased TC, a finding that is consistent with Rao et al. (2012). This is plausible, given that we found a negative relationship between SSC participation and TC. Because SSC participation requires changes in production inputs and technologies, SSC participants adopt better technologies, farm management techniques, or both to avoid or, at least, reduce yield loss.

The comparable TE and TC were also affected by other factors. For example, farmers with junior high school education levels had higher TE scores and TC than illiterate farmers or those with primary school education (i.e., reference group). The positive and significant coefficients of farm size suggest that larger farm sizes increased both TE and TC. Seed quality appears to be an important factor that drives higher levels of TE and TC.

[5]The p value of the Hausman test for the effect on TC was 0.086 and for the effect on comparable TE was 0.024.

4.3 | Robustness check

To confirm the robustness of the results discussed above, we used the endogenous switching regression (ESR) model for estimating the effects of SSC participation on comparable TE and TC. The ESR model is an IV-based approach that can account for both observed and unobserved selection biases (Li et al., 2020; Liu et al., 2021; Takam-Fongang et al., 2019; Zheng, Ma, & Li, 2021). For the sake of simplicity, we only present and discuss the average treatment effects on the treated (ATTs). The results of the ESR model are presented in Tables A2 and A3 in the appendix. Table 4 shows that the estimated ATT was negative and statistically significant for comparable TE and positive and statistically significant for TC. Specifically, SSC participation decreased comparable TE by 27% but increased TC by 80%. In general, the findings of the ESR model confirm the robustness of the results derived using the 2SRI model (Table 3).

4.4 | Disaggregated analysis

An advantage of using panel data is its ability to disaggregate the trends of comparable TE and TC over time. We present the results of the disaggregated analysis in Table 5. Columns (2) and (3) illustrate the changes in the comparable TE scores for SSC participants and nonparticipants from 2011 to 2016. We can draw at least two interesting conclusions from the findings. First, the comparable TEs for SSC participants were generally smaller than those for nonparticipants. Second, the comparable TEs for SSC participants showed year-over-year declines and

TABLE 4 Robustness check using the ESR model

	Mean outcomes			
Outcomes	**SSC participants**	**Nonparticipants**	**ATT**	***t* Value**
Comparable TE	0.576 (0.007)	0.789 (0.004)	−0.213*** (0.007)	−31.728
Technological change	0.149 (0.011)	0.083 (0.003)	0.066*** (0.010)	6.453

Note: Robust standard errors are presented in parentheses. The results of the ESR model are presented in Tables A2 and A3 in the appendix.

Abbreviations: ATT, average treatment effects on the treated; ESR, endogenous switching regression; SSC, short supply chain; TE, technical efficiency.

***$p < 0.01$.

TABLE 5 Changes of comparable technical efficiency and technological change between 2011 and 2016

	Comparable TE		Technological change	
Year	**SSC participants**	**Nonparticipants**	**SSC participants**	**Nonparticipants**
2011	0.639	0.778	0.009	0.011
2012	0.622	0.781	0.016	0.018
2013	0.625	0.784	0.030	0.034
2014	0.612	0.794	0.053	0.059
2015	0.591	0.795	0.106	0.092
2016	0.625	0.796	0.228	0.135

Abbreviations: SSC, short supply chain; TE, technical efficiency.

increases—it decreased from 0.639 in 2011 to 0.591 in 2015. Then, it increased to 0.625 in 2016. On the other hand, the comparable TE scores for nonparticipants consistently increased year-over-year, with the increments ranging from 0.778 in 2011 to 0.796 in 2016.

The last two columns of Table 5 report the changes in TC, showing that TC for both SSC participants and nonparticipants increased from 2011 to 2016. A comparison of the TCs of the two groups of farmers shows that between 2011 and 2014, the TC for SSC participants was smaller than that of nonparticipants. From 2015 to 2016, TC was more apparent in SSC participants than in nonparticipants. One possible explanation is that in the first few years of selling through SSCs, SSC participants may not have found appropriate production technologies and farm management techniques to compensate for yield loss resulting from reducing the use of agrochemicals. As discussed earlier, SSC participants tend to reduce agrochemical use to improve the quality and safety of their products and meet consumers' requirements. It is possible that once SSC participants learn to optimize production, TC ensues. Further research is needed to test this conjecture.

5 | CONCLUSIONS

Recent years have seen a proliferation of initiatives to develop agricultural SSCs in China. By reducing the number of intermediaries, SSCs may benefit farmers and consumers. Selling through SSCs, farmers have the opportunity to build personal connections with their customers, market their products directly, and find niche markets. Furthermore, consumers can learn about where the food comes from, how it is produced, and who produces it. SSCs may also benefit local economies.

In this study, we estimated the effects of SSC participation on TE and TC in farm production. Using a meta-frontier production function, we analyzed panel data collected from cucumber farmers in China's Jiangsu province. In addition, we examined the effects of SSC participation on comparable TE and TC using the 2SRI approach, which addressed the selection bias in SSC participation.

The empirical results showed that the average comparable TEs for SSC participants and nonparticipants were 0.615 and 0.790, respectively. The average TCs for SSC participants and nonparticipants were −0.003 and 0.083, respectively. Accounting for the selection bias, we showed that SSC participation significantly decreased the TE of cucumber production but significantly increased TC. The disaggregated analysis revealed that comparable TE scores for SSC participants registered year-over-year increases and decreases between 2011 and 2016, while those for nonparticipants consistently increased over the same period. The TC for both SSC participants and nonparticipants increased at different rates. Specifically, relative to nonparticipants, TC was lower among SSC participants from 2011 to 2014 but higher between 2015 and 2016.

The findings of this study have important policy implications. Although the TE of cucumber production for SSC participants, on average, was lower than that for nonparticipants, we found that the downward trend was reversed in 2015. We argued that it takes some time for SSC participants to find and then adapt to the appropriate technologies and management techniques to compensate for yield loss arising from reducing the use of agrochemicals. However, the prospects of lower TE during the early stages of SSC adoption may discourage SSC participation, especially if the higher prices do not compensate for yield loss. Therefore, the Chinese government should develop training programs to help SSC participants improve production efficiency and increase farm productivity. To be clear, the data used in this study did not allow us to control for farmers' and farms' characteristics. Nevertheless, our findings provide valuable insights into the associations between SSC participation, comparable TEs, and TC. More studies in this field are needed to deepen our understanding of the impacts of SSC participation on farm performance.

We want to draw attention to three limitations of this study. First, we measured SSC participation as a dichotomous variable, as we had limited data. Future studies should investigate how SSC participation *intensity* (i.e., the share of cucumber sales via SSCs) affects the TE and TC of cucumber production. This would be a useful extension of the present paper, and we hope that data will soon become available to support such research endeavors. Second, our analysis focused only on cucumber production in Jiangsu province. Future studies can build on ours by analyzing data collected for other crops (e.g., tomato, cabbage, carrot, and potato) and other provinces in China. Third, our empirical estimations are based on 5-year panel data with only 346 observations. More analyses with larger sample sizes should be conducted to improve our understanding of the effects of SSCs.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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APPENDIX

TABLE A1 Estimates for the production frontiers

Coefficient	Separate production frontiers SSC participants	Nonparticipants	Meta-frontier
Seed	2.052 (1.722)	5.477*** (0.947)	5.353*** (0.898)
Labor	−1.362 (1.156)	0.503 (1.353)	0.736 (0.656)
Fertilizer	0.277 (0.944)	−5.343*** (1.694)	−1.465 (1.117)
Intermediate	−5.550 (3.689)	−3.626 (2.552)	−6.259** (2.946)
0.5 ∗ $(Seed)^2$	−0.097 (0.161)	−0.320* (0.175)	−0.190*** (0.046)
0.5 ∗ $(Labor)^2$	−0.338* (0.198)	−0.566** (0.270)	−0.219** (0.096)
0.5 ∗ $(Fertilizer)^2$	0.190** (0.076)	−0.567*** (0.164)	−0.071 (0.053)
0.5 ∗ $(Intermediate)^2$	0.705* (0.400)	0.289 (0.504)	1.280*** (0.434)
Seed ∗ *Labor*	−0.242*** (0.079)	0.375*** (0.091)	0.133*** (0.043)
Seed ∗ *Fertilizer*	0.268*** (0.053)	−0.204* (0.111)	0.069 (0.065)
Seed ∗ *Intermediate*	−0.201 (0.225)	−0.572*** (0.177)	−0.654*** (0.145)
Labor ∗ *Fertilizer*	−0.037 (0.108)	0.247** (0.114)	0.121* (0.064)
Labor ∗ *Intermediate*	0.586*** (0.199)	−0.089 (0.220)	−0.096 (0.103)
Fertilizer ∗ *Intermediate*	−0.327** (0.130)	1.037*** (0.288)	0.121 (0.154)
Seed ∗ *Time*	0.004 (0.022)	−0.010 (0.026)	−0.022** (0.009)
Labor ∗ *Time*	−0.036 (0.044)	−0.026 (0.031)	0.033 (0.026)
Fertilizer ∗ *Time*	0.080*** (0.030)	−0.066* (0.039)	−0.016 (0.031)
Intermediate ∗ *Time*	0.164 (0.131)	0.120 (0.078)	−0.067** (0.027)
Time	−1.681* (0.922)	−0.481 (0.453)	0.486*** (0.142)
0.5 ∗ $(Time)^2$	0.085*** (0.023)	0.016 (0.017)	0.037*** (0.012)
Sample size	105	241	346

Note: Robust standard errors are presented in parentheses.
Abbreviation: SSC, short supply chain.
**p* < 0.10, ***p* < 0.05, and ****p* < 0.01.

TABLE A2 The ESR model estimating the impact of SSC participation on comparable technical efficiency

Variables	First stage SSC participation	Second stage SSC Participants	Nonparticipants
Age	0.002*** (0.000)	−0.000*** (0.000)	−0.002*** (0.001)
Junior high school	0.557 (0.460)	0.067 (0.042)	0.019 (0.019)
Senior school	0.143 (0.467)	−0.004 (0.072)	−0.026 (0.022)
College or above	5.990*** (0.412)	0.074 (0.063)	0.086 (0.083)
Farm size	0.064*** (0.023)	0.003 (0.002)	−0.001 (0.003)
Seed cost	0.000 (0.000)	0.000** (0.000)	−0.000 (0.000)

(Continues)

TABLE A2 (Continued)

Variables	First stage SSC participation	Second stage SSC Participants	 Nonparticipants
Quantity of labor	−0.001 (0.006)	−0.002*** (0.001)	−0.000 (0.001)
Quantity of fertilizer	−0.006 (0.008)	−0.001 (0.001)	0.000 (0.000)
Time trend	−0.109 (0.109)	−0.019 (0.013)	0.005 (0.006)
Region fixed effects	Yes	Yes	Yes
Distance to Shanghai (IV)	−0.008*** (0.001)		
Urbanization level (IV)	0.022** (0.008)		
Constant	−5.061 (1.450)	0.795*** (0.119)	0.902*** (0.062)
$\rho 1$		0.323*** (0.070)	
$\rho 0$			0.962*** (0.068)
Sample size	346	346	346

Note: The reference educational level is primary-school education or less. Robust standard errors are presented in parentheses.
Abbreviations: ESR, endogenous switching regression; IV, instrumental variable; SSC, short supply chain.
***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

TABLE A3 The ESR model estimating the impact of SSC participation on technological change

Variables	First stage SSC participation	Second stage SSC Participants	 Nonparticipants
Age	0.001*** (0.000)	0.000 (0.000)	−0.000 (0.000)
Junior high school	0.267 (0.550)	0.005 (0.019)	−0.014 (0.009)
Senior school	−0.257 (0.570)	−0.013 (0.022)	−0.010 (0.010)
College or above	3.918*** (1.255)	−0.029 (0.027)	−0.035 (0.030)
Farm size	0.105*** (0.040)	−0.000 (0.001)	0.004** (0.002)
Seed cost	0.001 (0.001)	0.000 (0.000)	0.000*** (0.000)
Quantity of labor	−0.005 (0.006)	0.000 (0.000)	0.000*** (0.000)
Quantity of fertilizer	−0.006 (0.007)	0.002*** (0.000)	−0.001*** (0.000)
Time trend	−0.116 (0.073)	0.085*** (0.008)	0.016*** (0.003)
Region fixed effects	Yes	Yes	Yes
Distance to Shanghai (IV)	−0.006** (0.003)		
Urbanization level (IV)	−0.003 (0.016)		
Constant	1.323*** (1.189)	−0.345*** (0.072)	0.044* (0.023)
$\rho 1$		−0.811*** (0.168)	
$\rho 0$			0.432*** (0.179)
Sample size	346	346	346

Note: The reference educational level is primary-school education or less. Robust standard errors are presented in parentheses.
Abbreviations: ESR, endogenous switching regression; IV, instrumental variable; SSC, short supply chain.
***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.