agriculture

MDPI

Article

Impact of Farmer Participation in Production Chain Outsourcing Services on Agricultural Output Level and Output Risk: Evidence from the Guanzhong Plain, China

Shouhong Xie [1], Jizhou Zhang [1], Xiaojing Li [2], Zhe Chen [3], Xiaoning Zhang [1,*] and Xianli Xia [1]

1 School of Economics and Management, Northwest A&F University, Xianyang 712100, China; xnxsh0224@nwafu.edu.cn (S.X.); zjz611@nwafu.edu.cn (J.Z.); xnxxli@163.com (X.X.)
2 School of Economics and Management, Yantai University, Yantai 264005, China; ydlxj@ytu.edu.cn
3 School of Economics and Management, China Agricultural University, Beijing 100083, China; xncz@nwafu.edu.cn
* Correspondence: xiaoningzhang@nwafu.edu.cn

Abstract: Shifting from a land-scale operation to a service-scale operation of agricultural production chain outsourcing services (APOS) is crucial to achieving innovation in agricultural-scale operation techniques. Using propensity score matching (PSM) and data from 1027 farm households in Guanzhong Plain, Shaanxi Province, we empirically assessed the impact of APOS on agricultural output level and output risk. First, age, gender, health, education, training, number of outworkers, land tenure, land contiguity, and subsidy satisfaction had a substantial beneficial influence on the involvement of farm families in APOS. Second, involvement in APOS may greatly increase the amount of agricultural production and lower the risk associated with farm families' agricultural output. Moreover, the participation in outsourcing services for agricultural machinery use and field management significantly increased agricultural output and decreased output risk, but the participation in agricultural machinery use outsourcing services increased yield and reduced risks more significantly.

Keywords: outsourcing services; agricultural output; output risk; propensity score matching

check for updates

Citation: Xie, S.; Zhang, J.; Li, X.; Chen, Z.; Zhang, X.; Xia, X. Impact of Farmer Participation in Production Chain Outsourcing Services on Agricultural Output Level and Output Risk: Evidence from the Guanzhong Plain, China. *Agriculture* **2023**, *13*, 2263. https://doi.org/10.3390/agriculture13122263

Academic Editor: Gijs A. Kleter

Received: 18 September 2023
Revised: 3 December 2023
Accepted: 5 December 2023
Published: 12 December 2023

1. Introduction

Ensuring food security and promoting sustainable agricultural growth are pressing concerns for the global community [1]. The Chinese government has placed significant emphasis on enhancing food security and stabilizing grain production capacity, as evidenced in official publications over many years [2]. Advancements in agricultural technology and significant chemical inputs have contributed substantially to China's steadily increasing grain production, reducing global hunger [3]. However, the long-standing dependence of the agricultural production model on chemical inputs and unsophisticated production and management approaches has led to constraints in its development. These constraints include massive resource overconsumption, frequent food safety incidents, rising agricultural pollution, and increased risk in achieving sustainable agricultural development [4–6]. The agricultural sector also faces structural labour shortages due to the vast urban employment environment that depletes rural labour resources, leading to a reduction in agricultural production labour [7]. Additionally, the comparative returns from growing food crops have decreased due to falling grain storage prices and rising cultivation expenditures, leading to decreased motivation among farmers to produce grain [8]. To ensure China's food security, it is crucial to break the resource and environmental constraints of agricultural production, overcome growth bottlenecks, reduce the risk of agricultural output, and achieve a steady increase in agricultural output levels.

China's agricultural sector is characterized by the presence of small-scale farmers in a vast country. The implementation of the household contract responsibility system following China's reform and opening-up has led to the separation of land ownership and usage rights. This has enabled small-scale households to manage land and become the cornerstone of China's agricultural management. The Chinese government increasingly recognizes that the current demonetization of the labour force's employment renders the conventional agricultural production model, reinforced by chemical factor inputs, unsustainable [9]. To achieve long-term improvements in agricultural output levels, it necessitates extensive, intensive, and sophisticated agricultural production processes [10]. In response, the government has advocated for operators to shift towards centralized large-scale land management by land transfer. However, successful land transfer without significantly impacting agricultural expansion remains challenging due to farmers' high demand for land's social security function and the inadequate institutional mechanism for land transfer [11]. At this juncture, service-scale operations such as APOS have emerged, resolving the scale dilemma and offering a new avenue for agricultural-scale operations [12].

Since the 1950s, the agricultural service system in developed countries like those of the European Union has been comprehensive, and agricultural modernisation has been progressively achieved through mechanisation, large-scale, and specialised production [13]. Agricultural cooperatives and farmer associations have become ubiquitous in all aspects of agriculture and have a crucial role in the promotion of agricultural breeding, technology research and development, production, processing, trade, training services, and more. For instance, agricultural cooperatives in the United States, Japan, and various European countries are crucial providers of full-chain agricultural services that facilitate the development of agricultural services trade [14,15]. In light of China's distinctive interface between humans and land, alongside fragmented agricultural land and small-scale concerns, outsourcing within the agricultural production chain has the potential to fulfil the farmers' control of land contract rights and redress the shortfalls of labour and machinery in small farmers' households, leading to economies of scale within agricultural production [16,17]. APOS is the process by which, depending on the household's internal and external resource endowments and environmental conditions, farmers outsource some or all aspects of agricultural production to other specialised farmers and production service providers [18,19]. Numerous productive service organizations have entered the agricultural production sector, offering specialized outsourcing services that compensate for farmers' deficiencies in the agricultural production process, achieve a division of labour and specialization, and boost agricultural output levels. Specifically, APOS has introduced novel ideas to resolve the challenge of "how to grow land and how to grow land appropriately" [20].

Scholars have analysed the link between farmers' involvement in agricultural production outsourcing services (APOS) and agricultural output levels. Research has found that such participation enhances the farmers' yield per unit area and overall yield, which positively impacts agricultural production levels [21]. Furthermore, APOS membership reduces agricultural production expenses, improves product quality and agricultural technology, and leads to augmented agricultural output for the farmers [22]. However, some experts argue that the relationship between APOS and agricultural productivity remains ambiguous. Although outsourcing services available in various agricultural production segments have improved, the involvement in APOS in some regions did not significantly enhance the farmers' agricultural output. Yang [23] found significant heterogeneity in the impact of APOS involvement on agricultural revenue, with the income effect being greater in field management than in other production links, but not in sowing. Gillespie et al. [24] observed that the involvement in agricultural supply chain outsourcing did not result in significant gains in farm output levels and may have even led to output level declines. Previous research has shown that when farmers participate in APOS, outsourcing service providers may benefit from information asymmetries when performing labour activities. Technical services are not entirely delegated and are negotiated to reduce operational expenses, which generates apparent moral hazard issues and significantly affects returns on agricultural produce [25]. Therefore, the impact of APOS on agricultural output varies under different circumstances and in different locations, with either positive or negative effects. The tightened management of agricultural land in China, rural–urban migration for non-farm vocations, and the escalating abandonment of rural land could seriously endanger the food supply [26].

Four contributions are derived from this study. Firstly, the empirical findings offer vital support for the growth of service outsourcing in Chinese agricultural production. Our results support the potential division of labour in agricultural production and the outsourcing of the agricultural production link, thereby disproving the Marshallian theory that the agricultural production chain is indivisible and finite, and that the agricultural division of labour and economies of scale are inherently incompatible [27].

Secondly, to the best of our knowledge, most academics have primarily focused on yield and income analyses in quantifying agricultural output returns of farm families, and the outcomes have yet to reach consistent conclusions. Conversely, Huang et al. [28] have incorporated agricultural production risk in their research on the influence of climate change on agricultural output. Presently, moment estimate-based methodologies are frequently utilized in agricultural economics research to quantify agricultural production risk in a flexible manner. Despite this, agricultural output risk still needs to be studied in conjunction with the entire framework of farm household agricultural output. In most studies, agricultural production risk has only been used as a control variable. However, only a few studies have examined the impact of APOS membership on farm household agricultural production from the perspective of farm household agricultural output level and output risk. We utilized an econometric model to explore the dual effect of APOS participation on agricultural output risk and output, enabling us to gain a better comprehension of the effect of APOS participation on agricultural output.

Thirdly, the farmers' participation in APOS is largely influenced by their noticed personal and household characteristics, including age, gender, education, ability, household size, and farm size. Currently, the farmers' participation in APOS is a "self-selected" behaviour of the farmers' households. Utilizing an OLS model to solve the endogeneity of the self-selection effect may result in biased estimation outcomes. To address the bias caused by self-selection, we adopted a propensity score matching method to tackle the inherent selection bias in the outsourcing process and quantify the causal impact of outsourcing on agricultural output.

Lastly, aside from calculating the effect of APOS participation on agricultural production for the whole sample, the existing literature disregards the variety of outsourced service types and farm household groups. This outcome creates ambiguity about the effect of APOS involvement on agricultural production level and output risk for farm families. The participation in APOS significantly influences the agricultural production level and output risk of farms of all sizes, and engagement in different forms of APOS has a substantial impact on agricultural output level and output risk. Interestingly, the involvement in agricultural machinery usage outsourcing services has a more significant influence on boosting agricultural production levels and reducing agricultural output uncertainty. Moreover, the participation in APOS substantially increases agricultural output and decreases agricultural output risk for small-scale farmers.

The remainder of the paper has the following structure. The next section presents the theoretical analysis and research hypotheses. Then, Section 3 describes the data, variables, and models. After that, Section 4 presents the empirical results of the estimations. Finally, Section 5 discusses the findings, and Section 6 concludes the paper.

2. Theoretical Analysis and Research Hypotheses

2.1. Conceptual Framework and Hypothesis Development

2.1.1. Impact of Farmers' Participation in APOS on Agricultural Output Levels

To guarantee an increase in agricultural output returns under limited conditions, a farmer may adopt business management strategies such as reducing production costs, continuously refining agricultural production strategies, and enhancing the quality of agricultural products. The crux of APOS is that farmers utilize the resources of outsourcing service providers for agricultural production instead of relying solely on internal family factors, signifying the specialized division of labour in agricultural production [29]. According to Babbage [30], the division of labour not only helps producers to rapidly acquire specialized skills through externally obtained technical information but also saves time by introducing novel machines and improving flexibility in the application of technology. Moreover, the outsourcing service providers' more standardized and specialized service provision can reduce the farmers' time cost, agricultural labour intensity, and average cost per unit of output [31]. Concurrently, APOS can ensure the stability and elasticity of agricultural production inputs, mitigate the adverse effects of insufficient production factors and seasonal labour shortages, and thus enhance the farmers' agricultural output while ensuring the quality of production materials and without interfering with farming schedules [32].

As a result of the farmers' involvement in APOS, some agricultural production process will be outsourced to providers possessing a production advantage and having access to the resources and innovative agricultural production technology [33]. Furthermore, the farmers can interact with outsourcing service providers during the provision of services, allowing them to exchange technical information and acquire more expertise with production technology and efficacy in production processes [34]. This could enhance the farmers' capacity to produce food and increase overall yields. Therefore, we assume the following:

H1: *Farmer participation in APOS can significantly increase the level of agricultural output.*

2.1.2. Impact of Participation in APOS on Agricultural Output Risk

Farmers' operations exhibit relative fragmentation and weakness when juxtaposed with service organizations and outsourced service providers who wield technical management advantages. Additionally, these farmers are exposed to higher operational and natural disaster risks in agricultural production, which can cause a reduction in agricultural output [35,36]. Nevertheless, it is evident that agricultural production entails a conspicuous seasonal demand for labour, and thus, farmer participation in APOS can satiate the labour requirements of agricultural production through specialized services. Concurrently, this can diminish their reliance on labour and agronomic technology [37]. Participating in APOS can also aid farmers in concentrating their production on the segment in which they excel, thereby amplifying their comparative advantage in that specific segment and elevating their existing business potential [38]. This aspect can assist farmers in ameliorating their output per unit of time and area, thereby mitigating the risk of output loss due to farming delays and factor shortages [29].

Furthermore, it is noteworthy that outsourced service providers possess exceptional capabilities for information screening and searching, as well as sophisticated fertilizers, application tools, and harvesting machinery, which not only facilitates a more accurate grasp of crop application timing and frequency [39], but also helps address issues such as yield loss resulting from excessive fertilizer application by farmers during the production process [40]. By harvesting the crop post rice maturity, the outsourcing service provider can steer clear of yield losses resulting from manual harvesting and untimely harvesting on a large scale, thus effectively mitigating the risk associated with agricultural output [41]. In fact, Qu et al. [25] evinced that crop harvest loss inflates during the harvesting stage due to weather and a paucity of labour, and in the event of severe pest infestation during this stage, crop harvest loss considerably augments. Nonetheless, by participating in APOS, agricultural producers can significantly reduce the rate of harvest loss using specialized and more advanced agricultural machinery. Therefore, we assume the following:

H2: *Farmer participation in APOS can significantly reduce the risk of agricultural output.*

3. Data, Variables, and Models

3.1. Data Collection

The investigation's data originated from a household survey of wheat cultivators in Shaanxi Province's Guanzhong Plain executed between July and August 2020. The sample achieved representativeness given that the Guanzhong Plain serves as an important wheat production region and the primary wheat-producing area in Shaanxi Province. The wheat crop yield is high due to the flat and fertile terrain, making it ideal for mechanized farming operations and aiding the development of agricultural social services. Utilizing a combination of typical and random sampling methods, Weinan, Xi'an, and Xianyang cities were selected in the Guanzhong Plain region. Firstly, we opted for Weinan, Xi'an, and Xianyang to form a first-tier sampling frame, meticulously considering the grain production and regional economic levels. Secondly, we picked secondary sampling units in Jing Yang and Xing Ping cities in Xianyang, Lintong and Yan Liang districts in Xi'an, as well as Pucheng and Fuping counties in Weinan, based on intra-city grain production status and research feasibility. Eventually, we established a numbered list of households in each village and anonymously chose 15–20 households at random to provide an overview of the region's characteristics. Our survey employed questionnaires to gather primary data, primarily on farm production and agricultural social services, without compromising personal ethics and privacy. The questionnaire can be found in the Supplementary Materials. Ultimately, we disseminated 1200 questionnaires and collected 1086, and after eliminating samples containing missing essential information and inconsistencies, we acquired 1027 valid questionnaires, yielding an effective rate of 94.57%. The study area is illustrated in Figure 1.

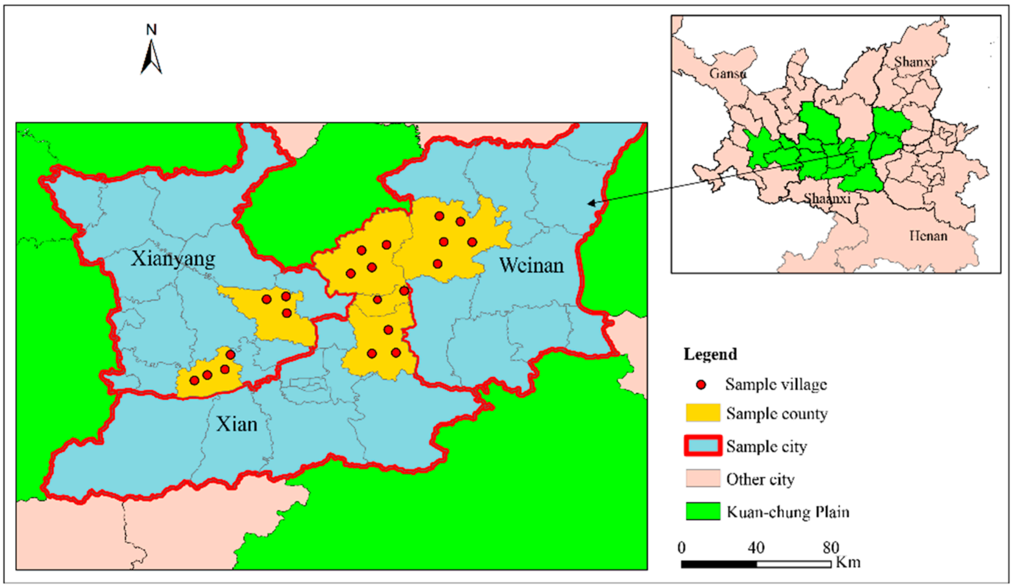

Figure 1. Study area map.

3.2. Variable Settings

3.2.1. Dependent Variables: AOL and AOR

The monitoring of agricultural yield is primarily determined through the agricultural output level (AOL) and agricultural output risk (AOR). Since market prices may affect the agricultural output returns, this manuscript prefers using yield indicators instead of output value indicators to evaluate the agricultural output returns, and then selects average yield per acre to represent AOL. To effectively quantify the agricultural output risk, the output variance is estimated with the method of moment to measure the AOR of farm households. According to past studies [28,42], the larger the number, the more extensive the agricultural output risk.

3.2.2. Independent Variable of Interest: APOS

APOS was centred on two distinct types of outsourcing services, namely, agricultural machinery utilization services (tillage, planting, and harvesting), in addition to field management services (fertilization and pest control) within the agricultural production chain. If a farmer neglects to avail themselves of any of these outsourcing services, they are not deemed to have participated in APOS and are consequently assigned a value of 0. Conversely, if a farmer acquires one or a combination of these services, they are regarded as participants in APOS and are assigned a value of 1. Ultimately, the farmer's engagement in APOS is envisaged as a dummy variable for analysis.

3.2.3. Control Variables

With reference to established research findings, this paper selected three aspects of household head characteristics, household characteristics, and village characteristics as control variables. The household head characteristics encompass age, health, gender, and education [43,44]. The advanced age of the household head statistically weakens their ability to operate agricultural machinery and subsequently reduces their competence in managing agricultural production, thereby fostering an inclination towards reluctance in being involved in APOS [45]. Prior research has also inferred that having a female household head considerably enhances the willingness of farmers to partake in APOS. This is because women, having lower productivity levels than men, exhibit greater enthusiasm towards participating in outsourcing activities to reduce the physical strain and labour required in agriculture [46]. The household characteristics incorporate the status of agrotechnical training, the number of seniors, the number of outworkers, land size, land tenure, land contiguity, social networks, land adjustment, and subsidy satisfaction [47,48]. Prior studies have revealed that farming households are more likely to partake in APOS due to the larger cultivation scale, the increased level of labour, and the greater capital investments required to complete agricultural production [18]. The village characteristics comprise village distance, machinery subsidy, and mechanized road [49]. Table 1 presents specific variable assignments and the corresponding descriptive statistics. The mean and standard deviation are used to depict all variables in Table 1, which facilitates a complete comprehension of the data, allowing for comparisons and analysis, as well as assisting in potential pattern identification in categorical variables.

Table 1. Definition and measurement of major variables.

Variable	Variable Definition	Mean	S.D.
AOL	Unit area yield (pounds[1]/mu[2])	1169.4	207.2
AOR	Actual agricultural output risk	4.5	9.0
APOS	1 = participation; 0 = no participation	0.6	0.5
Age	Age of farmer (years)	59.8	9.7
Gender	Whether gender of farmer is male: 0 = no; 1 = yes	0.9	0.2
Health	Actual health status: 1 = very poor; 2 = poor; 3 = fair; 4 = good; 5 = very good	3.9	1.2
Education	1 = illiterate; 2 = elementary school; 3 = junior high school; 4= high school and junior college; 5 = college and above	3.0	1.1
Agrotechnical training	1 = participation; 0 = no participation	0.1	0.3
Number of seniors	Number of people over 65 years old in the household (persons)	1.1	0.9
Number of outworkers	Number of families working outside the home (persons)	1.5	0.9
Land size	Cultivated land area operated by families (mu)	5.9	4.0
Land tenure	Whether the family has tenure of land: 1 = yes; 0 = no	0.8	0.4
Land contiguity	Average household plot size (acres)	3.0	3.1
Social network	Percentage of family names in the village (%)	50.0	32.9
Land adjustment	Whether the household has experienced arable land adjustment: 1 = yes; 0 = no	0.2	0.4
Subsidy satisfaction	Household satisfaction with food subsidies: 1 = very dissatisfied; 2 = relatively dissatisfied; 3 = fair; 4 = relatively satisfied; 5 = very satisfied	2.9	1.4

Table 1. *Cont.*

Variable	Variable Definition	Mean	S.D.
Village distance	Distance of the village from the township (Km)	2.5	1.3
Machinery subsidy	Whether the household's village has machinery subsidies: 1 = yes; 0 = no	0.4	0.5
Mechanized road	Whether the village builds roads between agricultural machinery and farmland: 1 = yes, 0 = no	0.8	0.4

Note: 1 pound = 500g; 1 mu = 1/15 ha. Data source: calculations based on survey data.

3.3. Research Methodology

Collecting reliable estimates of the counterfactual—specifically, what would have happened had farmers not participated—constitutes the most challenging aspect of evaluating any choice behaviour. Therefore, identifying the counterfactual is critical to ensure a valid impact evaluation. To assess the effect of membership in APOS on the farm output of farm households, we opted for the propensity score matching (PSM) method based on existing research [50]. As participation in APOS by farmers is voluntary and non-random, their involvement translates into an uneven distribution of participating and non-participating farmers in the sample data. While the sample selection is not random, selection bias may impair the accuracy of estimation results [51]. Propensity score matching (PSM) is a widely used technique to address the "self-selection" conundrum by constructing a counterfactual analysis framework through matching [52]. This approach eliminates the selection bias associated with self-selection and ensures the reliability of results concerning the relationship between participation in APOS and agricultural output. The PSM model takes the following form.

(1) Farmers were divided into treatment and control groups, and a logit model was applied to calculate the conditional probability fit values (i.e., propensity scores) for each farmer's participation in APOS.

$$P(X_i) = Pr[D = 1|X_i] = exp(\beta X_i)/[1 + exp(\beta X_i)] \quad (1)$$

where D is the treatment variable (D = 1, indicating that the farmer participates in APOS; D = 0, indicating no participation in APOS); X_i is the matched covariates, such as the variables of household head characteristics, household characteristics, and farming land characteristics; P is the estimated propensity score value; and β is the vector of coefficients to be estimated.

(2) A control group was matched with the closest propensity score for each sample farmer participating in APOS [52]. To guarantee the robustness of the matching results, four matching methods were used in this paper (nearest neighbor matching (1–2 matching), caliper matching (r = 0.05), kernel matching (window width = 0.06), and local linear regression), and if the results of these four matching methods did not change significantly, the matching results were shown to be valid [53].

(3) The average treatment effect (ATT) for the treatment group was calculated and the net effect of participation in APOS on the agricultural output of farm households was assessed.

$$ATT = E(Y_1|D = 1) - E(Y_0|D = 1) = E(Y_1 - Y_0|D = 1) \quad (2)$$

where Y_1 is the agricultural output when the farmer participates in APOS, and Y_0 is the agricultural output when the farmer does not participate in APOS.

4. Results and Analysis

4.1. Descriptive Evidence

Stata MP 18.0 (Copyright © StataCorp LLC, located at 4905 Lakeway Drive, College Station, TX, USA) was used for data analysis. Table 2 illustrates two distinct groups of APOS participants and non-participants. Comparing the pivotal outcome variables and distinguishing characteristics between these two groups can offer further discernment. Firstly, with regard to agricultural output levels, the APOS participating farmers demonstrated an average grain yield of 1239.243 pounds/mu, a stark contrast to the non-participating farmers' agricultural output level of 1066.353 pounds/mu, an observation that was deemed significant at the 1% level of significance. This finding presents evidence that the APOS participating farmers exhibit a greater agricultural production capacity than the non-participating farmers. Secondly, the APOS participating farmers have a lower agricultural output risk compared to their non-participating counterparts, and the variation between the two groups is statistically significant at the 1% level of significance. The mean value of the agricultural output risk of the APOS participating farmers was 2.260, while the mean value of the variance of the agricultural output risk of the non-participating farmers was 7.666. Thirdly, there are noteworthy disparities in gender, education, health, and agricultural training experience between the APOS participating and non-participating farmers. Factors such as the number of elderly individuals, the number of outside workers and social networks of the land, as well as other factors vary significantly. It is essential to note that there are substantial disparities in village characteristics. For example, the APOS participating farmers tend to be more educated, healthier, and have more training experience than the non-participating farmers. The APOS participating farmers have fewer elderly individuals, more migrant workers, more titled land, more contiguity, and greater household social networks. In addition, the APOS participating farmers are located further away from the municipality, report higher subsidy satisfaction, and receive more favourable machinery subsidies. These discrepancies merely indicate differences in descriptive statistical conclusions based on the evidence provided; therefore, establishing causality requires further testing.

Table 2. Mean differences in characteristics between APOS participating and non-participating farmers.

	Participating (N = 612)	Not Participating (N = 415)	Mean-Diff	t-Value
AOL	1239.243	1066.353	172.890 ***	14.381
AOR	2.260	7.666	−5.406 ***	−9.929
Age	59.458	60.205	−0.747	−1.212
Gender	0.953	0.928	0.025 *	1.684
Health	4.132	3.446	0.687 ***	9.782
Education	3.306	2.518	0.787 ***	11.871
Agrotechnical training	0.175	0.067	0.107 ***	5.054
Number of seniors	1.010	1.133	−0.123 **	−2.207
Number of outworkers	1.596	1.388	0.208 ***	3.491
Land size	5.995	5.724	0.271	1.062
Land tenure	0.891	0.754	0.136 ***	5.872
Land contiguity	3.516	2.156	1.361 ***	7.031
Social network	51.535	47.728	3.806 *	1.822
Land adjustment	0.234	0.253	−0.019	−0.711
Subsidy satisfaction	2.987	2.810	0.177 **	2.033
Village distance	2.606	2.396	0.210 **	2.524
Machinery subsidy	0.440	0.318	0.121 ***	3.941
Mechanized road	0.815	0.848	−0.033	−1.370

Note: Mean-diff indicates the difference in means between participation and non-participation; t-value is a *t*-test for the difference between participation and non-participation; *, **, and *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

4.2. Estimation of the Propensity Score for the Decision to Participate in APOS

Utilizing the propensity score matching method, we initially estimated the logit model regarding the factors that influence farmer participation in APOS. Based on this, we calculated the propensity score values for both the APOS participating and non-participating farmers by analysing the variables' characteristics. After analysing Table 3, we discovered that among the head of household attributes, age, education, and health had a significant and positive impact on the farmers' APOS participation. A higher age can result in decreased physical stamina and energy levels, leading to participation in APOS as a means of reducing physical strain and preserving health [54]. On the other hand, a high level of education and better health would result in longer farming operations and a greater understanding of new agricultural techniques, which increases the possibility of embracing APOS [49]. Additionally, gender also played an affirmative role in APOS participation by positively impacting it at a statistical level of 5% with a coefficient of 0.648. Within the household characteristics group, the engagement in agrotechnical training served as a positive incentive toward the farmers' participation in APOS with a statistical impact of 10%. By strengthening their knowledge of mechanized farming, agrotechnical training can aid farmers in decision making and facilitate learning [55], thus effectively preventing the technical and market risks of APOS engagement and promoting the farmers' willingness to engage. The number of outworkers and older individuals also had a statistically significant effect on APOS participation at a level of 1%, but in opposing directions. Households with a greater number of outworkers engage in APOS to reduce the supply of agricultural labour through machine operations, lessening the labour element constraints in agricultural production. Conversely, when faced with irreversible labour outflow, the older members of households, possessing ample farming experience and operation capacity, can engage in some aspects of agricultural production via experience spillover and assisted production, effectively mitigating the labour shortage issue in agricultural production [56], and often negating the need for APOS participation. Concerning land tenure and land contiguity, these significantly and positively influenced APOS participation at a 1% level. In each region, a higher degree of land contiguity points to more contiguous specialized cultivation, resulting in increased outsourcing service transaction density and market capacity, thus promoting the farmers' likelihood of APOS participation. Land tenure reduces the risk of land expropriation, boosting the farmers' perceived property rights security, which augments the expected returns on investment and prompts productive investment in agriculture [57], thereby elevating the probability of APOS participation. Land size warranted consideration as it negatively impinged upon farmer participation in APOS at a statistical level of 1%, where an expansion in farmer arable land size led to an increase in plots, making machinery transfer costs prohibitively high due to land fragmentation, thus diminishing the probability of farmer APOS participation. Subsidy satisfaction also displayed a statistically significant positive impact on farmer APOS participation, at a level of 10%. Furthermore, higher food subsidy satisfaction elevated the farmers' motivation to cultivate crops [58]. Facilitating food crop production and promoting cultivation mechanization also increased the farmers' affinity towards APOS participation.

4.3. Matching Effect Analysis

4.3.1. Common Support Domain Test

The precondition for carrying out propensity score matching is the presence of shared support or overlap between the intervention and control group's propensity scores. In order to eliminate selectivity bias, it is imperative to administer the common support domain test on the sample, which measures the match quality between the explanatory variables of the APOS participating and non-participating farmers' sample [59]. The nearest neighbor matching technique was used as an illustrative example. Using the logit model, we estimated the propensity score values and plotted the kernel density functions of the propensity scores for both treatment and control groups before and after matching. Figure 2 indicates that the sample propensity scores of both treatment and control groups were closer after matching. Furthermore, the kernel density curves of the propensity scores exhibited a substantial overlap, with most observations falling within the range. This indicates that the PSM-based matching was of superior quality and could satisfy the general domain assumption.

Table 3. Logit estimation results of propensity scores.

Variable	Estimated Coefficient	Std. Err.	Estimated Coefficient	Std. Err.
Age	0.025 ***	0.010	0.005 ***	0.002
Gender	0.648 **	0.314	0.117 **	0.056
Health	0.326 ***	0.068	0.059 ***	0.012
Education	0.514 ***	0.073	0.093 ***	0.012
Agrotechnical training	0.435 *	0.249	0.079 *	0.045
Number of seniors	−0.290 ***	0.105	−0.052 ***	0.019
Number of outworkers	0.256 ***	0.080	0.046 ***	0.014
Land size	−0.095 ***	0.030	−0.017 ***	0.005
Land tenure	0.571 ***	0.198	0.103 ***	0.035
Land contiguity	0.347 ***	0.060	0.063 ***	0.010
Social network	0.002	0.002	0.000	0.000
Land adjustment	−0.022	0.172	−0.004	0.031
Subsidy satisfaction	0.094 *	0.054	0.017 *	0.010
Village distance	0.090	0.058	0.016	0.010
Machinery subsidy	−0.011	0.161	−0.002	0.029
Mechanized road	−0.379 *	0.198	−0.069 *	0.036
Constant	−5.722 ***	0.819		
N	1027		1027	

Note: ***, **, * denote statistical significance at 1%, 5%, and 10%, respectively.

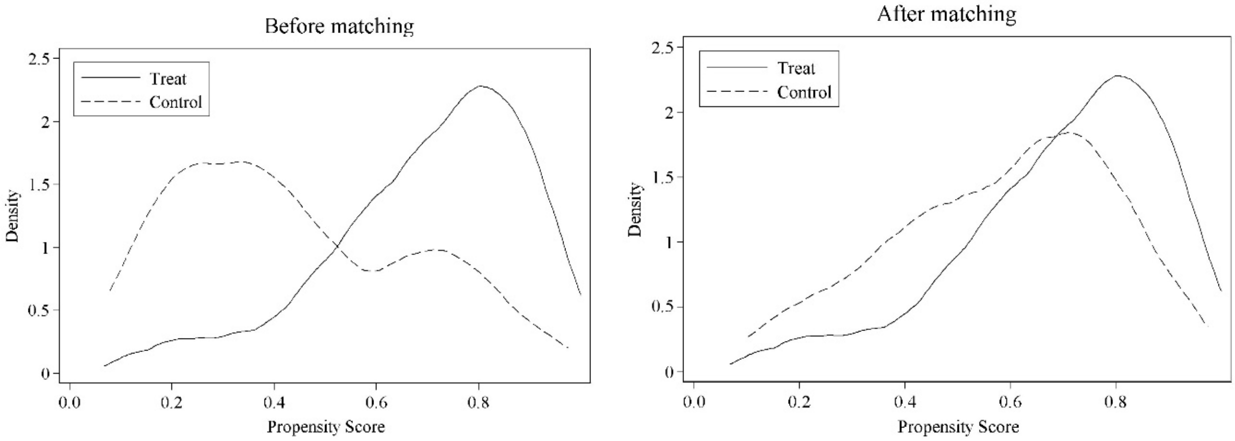

Figure 2. Kernel density before and after matching.

4.3.2. Balancing Test

In order to ensure the validity of matching outcomes, a covariate balance test was conducted to ensure that, apart from agricultural output, there were no significant pre-existing variations in other covariates between the treatment and control groups after matching, thus rendering the matching group a suitable counterfactual [60]. Table 4 illustrates that, with various matching methods, the mean deviation of explanatory variables decreased from 24.6% to 5.6–8.0%, the pseudo-R^2 diminished from 0.199 to 0.0190.029, and the LR statistic decreased from 275.76 to 31.3347.31. All these factors demonstrate a statistically significant reduction, suggesting that the conditional independence assumption has been satisfied post matching, and the distributional differences of explanatory variables between the treatment and control groups have been substantially eliminated. This can effectively eradicate the estimation bias caused by the sample self-selection.

Table 4. Results of the balance tests of explanatory variables before and after propensity score matching.

Matching Estimators	Pseudo R^2	LR Statistic	Mean Deviation (%)	Median Deviation (%)
Before	0.199	275.76	24.6	15.1
Nearest neighbor	0.028	46.66	7.9	6.9
Caliper	0.019	31.57	5.6	3.9
Kernel	0.019	31.33	5.6	3.8
Local linear regression	0.029	47.31	8.0	8.5

4.4. Estimation of Treatment Effect (ATT)

Table 5 depicts the estimation outcomes of the four matching methodologies, which eventually generated the average treatment effect (ATT) of the matched treatment group, reflecting the extent of influence that participation in APOS exerted on the farmers' agricultural output. Though the logit-based four matching algorithms yield slightly distinct quantitative findings, the estimation results are comparable. The ATT coefficients of the impact of APOS participation on agricultural output levels successfully passed the 1% significance level test under all four matching methods, as demonstrated in Table 5. These coefficients were affirmative under all four matching methods, indicating that the farmers' participation in APOS can considerably enhance their agricultural output levels after adjusting for the endogeneity issue arising from the self-selection bias, thus validating hypothesis 1. Without resorting to the application of the PSM model and instead comparing directly the agricultural output levels of farmers participating in APOS with those who do not, the yield increase effects of participation in APOS would be overestimated.

Table 5. Average treatment effect (ATT) of propensity score matching.

Dependent Variables	Matching Method	Treated	Controls	ATT	Std. Err.	t-Value
AOL	Before	1239.243	1066.353	172.890	12.022	14.38
	Nearest neighbor	1240.191	1134.535	105.656	22.469	4.70
	Caliper	1240.191	1118.378	121.813	19.620	6.21
	Kernel	1240.191	1118.776	121.415	19.671	6.17
	Local linear regression	1240.191	1120.365	119.826	22.284	5.38
	Mean	-	-	117.178	-	-
AOR	Before	2.260	7.666	−5.406	0.544	−9.94
	Nearest neighbor	2.225	5.963	−3.738	1.062	−3.52
	Caliper	2.225	6.338	−4.113	1.006	−4.09
	Kernel	2.225	6.333	−4.108	1.009	−4.07
	Local linear regression	2.225	6.385	−4.160	0.758	−5.49
	Mean	-	-	4.030	-	-

Similarly, the ATT of APOS participation's effect on agricultural output risk also passed the 1% significance level test. It was negative, suggesting that the involvement in APOS can significantly diminish the farmers' agricultural output risk after controlling for self-selection bias, thereby affirming Hypothesis 2. Without resorting to the PSM model and merely contrasting the agricultural output risk levels of participating and non-participating farmers, the risk-mitigating effect of APOS participation would have been vastly overestimated.

4.5. Heterogeneity Effects

4.5.1. Heterogeneity Analysis of Different Outsourcing Service Types

Distinct forms of outsourcing services have surfaced in the agricultural production chain owing to variations in the types of services offered by outsourcing service providers. With the nearest-neighbor matching method as our basis, we probed the heterogeneity of the outcomes of participation in outsourcing services for farm machinery and outsourcing services for field management on the agricultural output levels. The outcomes from Table 6 reveal that APOS participants can enhance the agricultural output levels by 105.656 pounds per mu over the entire sample. Conversely, farmers who participate in outsourcing services for farm machinery can raise the agricultural output by 115.025 pounds per mu, while participating in outsourcing services for field management can boost the agricultural output by 105.487 pounds per mu. The observations evince that under identical circumstances, employing agricultural machinery outsourcing services can yield significantly greater increments in the agricultural output levels for farmers.

Table 6. Heterogeneity analysis results of different outsourcing types.

Dependent Variables	Groups	Treated	Controls	ATT	Std. Err.	t-Value
AOL	Total sample	1240.191	1134.535	105.656	22.469	4.70
	Agricultural machinery use outsourcing services	1241.163	1126.138	115.025	20.851	5.52
	Field management outsourcing services	1279.596	1174.109	105.487	16.821	6.27
AOR	Total sample	2.225	5.963	−3.738	1.062	−3.52
	Agricultural machinery use outsourcing services	2.230	5.881	−3.651	−0.974	−3.75
	Field management outsourcing services	2.395	3.784	−1.389	−0.482	−2.88

Note: Nearest neighbor matching is used for estimation.

Similarly, the reduction effect of participating in outsourced agricultural machinery use services on the agricultural output risk is significantly more pronounced than participating in field management outsourcing services. This infers that, all else being equal, taking part in outsourced agricultural machinery use services can mitigate the agricultural output risk for farmers. This could be attributed to the fact that outsourcing services for farm machinery use are more likely to provide standardized service delivery, which is more likely to create economies of scale and enhance the accessibility of services to farmers [12]. In contrast, field management outsourcing services are relatively pricier due to specific gear and management complexities. The variability in production standards among farmers makes it difficult to establish economies of scale in this outsourced service in space. As a result, the accessibility of this outsourced service to farmers is limited, and therefore its impact on the farmers' agricultural output is lower.

4.5.2. Heterogeneity Analysis of Different Land Sizes

Land resources are the foremost production factors for farm households to undertake agricultural production, as well as a significant economic source for farm households to operate [61]. The size of farmland determines the output level of farm households [11,62]. Hence, it is worthwhile to explore how to attain a moderate scale of family operation while preserving the farm households' motivation. This entails examining whether there are discrepancies in the agricultural output levels and outputs risk among APOS participants with various land sizes.

Based on the results of the estimation presented in Table 7, it can be inferred that membership in APOS has a favourable impact on the agricultural output levels of both large- and small-scale farmers, with ATT values of 100.119 and 154.911, respectively. Both these associations pass the test at the 1% level of significance, underscoring the fact that the involvement in APOS raises the bar for agricultural productivity for farmers of all scales. Furthermore, a comparative analysis of coefficients for large- and small-scale farmers reveals that participation in APOS had a greater effect on the level of agricultural productivity for small-scale farmers. According to the results of the regression analysis, the inclusion of APOS had a negative impact on the risk of agricultural output for farmers of both scales, with the respective values of statistical significance being 1% and 5%. This suggests that the exposure of both large- and small-scale farmers to agricultural output risks was reduced to a significant extent by joining APOS. However, when comparing the coefficients of large- and small-scale farmers, it was observed that the participation in APOS led to a significantly greater reduction in the risk of agricultural output for small-scale farmers.

Table 7. Average treatment effect (ATT) of propensity score matching.

Dependent Variable	Groups	Treated	Controls	ATT	Std. Err.	t-Value
AOL	Total Sample	1240.191	1134.535	105.656	22.469	4.70
	Large-scale Farmers	1220.780	1120.661	100.119	26.207	3.82
	Small-scale Farmers	1250.949	1096.038	154.911	45.009	3.44
AOR	Total Sample	2.225	5.963	−3.738	1.062	−3.52
	Large-scale Farmers	2.277	4.259	−1.982	0.700	−2.83
	Small-scale Farmers	2.119	8.223	−6.104	2.508	−2.43

Note: Nearest neighbor matching is used for estimation.

5. Discussion

Participation in APOS is a crucial mechanism that alleviates the existing structural scarcity of agricultural labour for food cultivation and plays a vital role in enhancing the efficiency of agricultural output and augmenting farmers' income. Unlike previous research, our study evaluates the impact of APOS participation on the agricultural output from a dual perspective, encompassing both the level and risk of agricultural output, complementing earlier research that relied on a singular metric to evaluate agricultural output. To address the self-selection problem inherent in observational studies, we employed the propensity score matching (PSM) model as our research methodology. PSM reduces the potential selectivity bias by carefully matching participants in the treatment group with those in the control group based on observable characteristics [63]. Furthermore, PSM minimizes errors associated with ordinary least squares (OLS) regression by meticulously selecting controls, in line with most prior studies that have tackled the issue of self-selection bias [64]. Previous research has also suggested that the PSM method improves the robustness and sensitivity of estimation outcomes compared to other methods [65,66].

To address any potential biases arising from unobservable variables, we conducted robustness tests, and employed five supplementary matching methods with bias adjustments. Our empirical analysis revealed that the participation in APOS increased the quantity of agricultural output and reduced output risks for farm households. This finding is consistent with earlier research that demonstrated how the engagement in APOS can enhance agricultural productivity, reduce production costs, and increase farm household income [21,41]. Our study further emphasizes the importance of urging farmers to participate in APOS and adopt service-scale operations to achieve higher agricultural growth rates in China. Our paper's primary contribution lies in examining the disparities in how participation in APOS affects the agricultural output due to differences in outsourcing models. Specifically, farming equipment outsourcing services tend to increase the agricultural output and reduce the output risks compared to field management outsourcing services. Adu-Baffour et al. [67] explain this disparity by noting that pricing and technological requirements vary across different production segments, leading to variations in the farmers' incentives to participate in APOS. Therefore, it is imperative for the government to develop customized extension strategies and programs to cater to distinct APOS demands.

Undoubtedly, the gradual differentiation context of farm households can be exceedingly diverse due to variations in capital endowments [68]. Given that there exist significant differences in APOS engagement among farm households of varying magnitudes, it is of paramount importance to scrutinize the impact of APOS participation on the agricultural output of farm households possessing different land sizes. We observed that participating in APOS has a more substantial effect on augmenting the agricultural output level of small-scale farmers. This may be attributed to the fact that small-scale farmers possess less arable land and rely chiefly on technological advancements and intensive cultivation per unit area of land to enhance their agricultural output. Moreover, by engaging in APOS to procure agricultural machinery, they can expeditiously attain innovation in production factors [67,69]. Smallholder farmers derive maximum benefits as they can significantly amplify their unit area and profitability. Additionally, we found that participating in APOS had a greater influence on reducing the agricultural output risk for small-scale farmers. This could be explained by the fact that small-scale farmers, who employ traditional production methods and decentralized operations, are primarily risk-averse. They possess a high sensitivity to agricultural production hazards and a limited ability to cope with natural disasters and pests [70]. Despite the advent of new agricultural technologies, smallholders tend to adopt wait-and-see and conservative strategies [71]. The participation in APOS can mitigate such uncertainty, and the farmers only need to ensure that the outsourcing service providers comply with the contracted work standards, instead of grappling with the novel processes and knowledge requisite for agricultural production, which can effectively reduce the risk of agricultural output resulting from a dearth of technological know-how amongst farmers [72]. Compared to small-scale farmers, large-scale farmers possess robust risk management capabilities and can offset yield losses or the dissipation of efficiency through their strong agricultural production and management prowess. Moreover, large farms own many machines, so the impact of APOS participation on their agricultural output risk remains insignificant [73,74].

There exist several limitations to our analysis that warrant a thorough discussion. Firstly, since we have utilized cross-sectional data, we have not accounted for regional development disparities in the studied areas. Additionally, farmer behaviour tends to evolve with time, and this could be ameliorated by integrating long panels of data in future studies to precisely identify causal effects. Secondly, even though the PSM model significantly reduces selection bias, we cannot exclude measurement errors and endogeneity arising from two-way causation. We will employ the instrumental variables method to resolve these issues in subsequent studies. Finally, this study has taken into consideration the adverse impact of the COVID-19 pandemic, which has significantly affected the results, as many farmers are now more hesitant about adopting new processes and technologies owing to the social isolation mechanism caused by COVID-19. Furthermore, several research areas are challenging to investigate due to the COVID-19 pandemic's impact. In the future, advanced research techniques such as internet and telephone research will be utilized.

6. Conclusions and Policy Implications

This study employed the propensity score matching method (PSM) to examine the effects of APOS participation on farm output levels and output risks for farm households using data from field surveys conducted among 1027 farm households situated in the main grain-producing areas of the Guanzhong Plain in Shaanxi Province. The findings indicate that (1) the household head's characteristics, including their age, gender, health status, and education level, as well as the household characteristics like their agricultural training status, number of migrant workers, land tenure, land contiguity, and subsidy satisfaction, have a noteworthy positive impact on farm household participation in APOS. (2) The participation in APOS substantially ameliorated the agricultural output levels and lowered the risk of farm household agricultural output. (3) Upon differentiating between various outsourcing categories, the participation in agricultural machinery usage and field management outsourcing considerably enhanced the agricultural output levels and diminished the agricultural output risk. Nonetheless, the participation in agricultural machinery outsourcing services had a greater effect on augmenting the agricultural output levels and reducing the agricultural output risk. (4) After distinguishing between farmers with different landholdings, evidence revealed that APOS participation had a more significant influence on elevating the agricultural output levels and decreasing the agricultural output risk for small-scale farmers.

The findings bear notable policy implications. (1) The government should persist in augmenting agricultural technology training and elevate the standard of agricultural production grants to cut down on the farmers' outsourcing procurement costs and foster their willingness to partake in production linkage outsourcing by raising awareness of outsourcing and subsidizing outsourcing services. (2) The government ought to investigate innovative APOS models mindful of local conditions, enhance APOS efficiency and specialization, and thoroughly employ APOS's role in heightening the output and lowering the risks. (3) Considering the disparate effects of several types of APOS, we must construct differentiated strategies and supportive policies for promoting APOS, orienting towards guiding service groups to ameliorate the supply of agricultural machinery outsourcing services and advancing the durability and consistency of the farmers' participation in production outsourcing.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agriculture13122263/s1, Survey on Agricultural Household Grain Production.

Author Contributions: Conceptualization, S.X. and J.Z.; methodology, S.X. and J.Z.; software, S.X., X.L., Z.C. and X.Z.; validation, Z.C., X.L., X.X. and J.Z.; formal analysis, S.X., Z.C. and X.L.; investigation, X.L. and X.Z.; resources, J.Z. and Z.C.; data curation, S.X., X.X. and J.Z.; writing—original draft preparation, S.X. and Z.C.; writing—review and editing, S.X., X.X., J.Z. and X.L.; visualization, S.X.; supervision, X.Z.; project administration, X.L. and X.Z.; funding acquisition, X.Z. All authors have read and agreed to the published version of the manuscript.

Funding: The authors are grateful for the financial support by the Key Research and Development Plan of Shandong Province (Soft Science Project) (NOS. 2022RKY06010).

Institutional Review Board Statement: The present study did not require approval or ethical review by any Educational Institution, as the study does not involve any personal data and the respondents were well aware that they can opt out anytime during the data collection phase.

Informed Consent Statement: Prior to participating, participants were clearly informed that their involvement was voluntary, and that they could withdraw at any time without penalty. Their confidentiality was also guaranteed, and they were made aware that their data would only be used for research purposes.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Guo, S.; Lin, L.; Liu, S.; Wei, Y.; Xu, D.; Li, Q.; Su, S. Interactions between Sustainable Livelihood of Rural Household and Agricultural Land Transfer in the Mountainous and Hilly Regions of Sichuan, China. *Sustain. Dev.* **2019**, *27*, 725–742. [CrossRef]
2. Hou, M.; Zhong, S.; Xi, Z.; Yao, S. Does Large-Scale Ecological Restoration Threaten Food Security in China? A Moderated Mediation Model. *Ecol. Indic.* **2022**, *143*, 109372. [CrossRef]
3. Wang, Q.; Liu, X.; Yue, T.; Wang, C.; Wilson, J.P. Using Models and Spatial Analysis to Analyze Spatio-Temporal Variations of Food Provision and Food Potential across China's Agro-Ecosystems. *Ecol. Model.* **2015**, *306*, 152–159. [CrossRef]
4. Khan, S.; Hanjra, M.A.; Mu, J. Water Management and Crop Production for Food Security in China: A Review. *Agric. Water Manag.* **2009**, *96*, 349–360. [CrossRef]
5. Liu, Y.; Zhou, Y. Reflections on China's Food Security and Land Use Policy under Rapid Urbanization. *Land Use Policy* **2021**, *109*, 105699. [CrossRef]
6. Wuepper, D.; Borrelli, P.; Finger, R. Countries and the Global Rate of Soil Erosion. *Nat. Sustain.* **2020**, *3*, 51–55. [CrossRef]
7. Liu, Y.; Fang, F.; Li, Y. Key Issues of Land Use in China and Implications for Policy Making. *Land Use Policy* **2014**, *40*, 6–12. [CrossRef]
8. Pu, M.; Zhong, Y. China's Market-oriented Grain Procurement and Storage System Reform: New Risks and Countermeasures. *Issues Agric. Econ.* **2019**, 10–18.
9. Coronado-Apodaca, K.G.; Martinez-Ruiz, M.; Iqbal, H.M.N.; Sosa-Hernandez, J.E.; Parra-Saldívar, R. Agro-Food Sustainability Transitions: New Frontiers For Food Security. *Curr. Opin. Environ. Sci. Health* **2022**, 100412. [CrossRef]
10. Li, B.; Shen, Y. Effects of Land Transfer Quality on the Application of Organic Fertilizer by Large-Scale Farmers in China. *Land Use Policy* **2021**, *100*, 105124. [CrossRef]

11. Cao, Y.; Zou, J.; Fang, X.; Wang, J.; Cao, Y.; Li, G. Effect of Land Tenure Fragmentation on the Decision-Making and Scale of Agricultural Land Transfer in China. *Land Use Policy* **2020**, *99*, 104996. [CrossRef]
12. Qiu, T.; Shi, X.; He, Q.; Luo, B. The Paradox of Developing Agricultural Mechanization Services in China: Supporting or Kicking out Smallholder Farmers? *China Econ. Rev.* **2021**, *69*, 101680. [CrossRef]
13. Luo, J.; Han, H.; Jia, F.; Dong, H. Agricultural Co-Operatives in the Western World: A Bibliometric Analysis. *J. Clean. Prod.* **2020**, *273*, 122945. [CrossRef]
14. Ajates, R. An Integrated Conceptual Framework for the Study of Agricultural Cooperatives: From Repolitisation to Cooperative Sustainability. *J. Rural Stud.* **2020**, *78*, 467–479. [CrossRef]
15. Pokharel, K.P.; Featherstone, A.M. Examining the Productivity Growth of Agricultural Cooperatives: The Biennial Malmquist Index Approach. *J. Co-Oper. Organ. Manag.* **2021**, *9*, 100148. [CrossRef]
16. Harff, Y.; Lamarche, H. Le travail en agriculture: Nouvelles demandes, nouveaux enjeux. *Econ. Rural.* **1998**, *244*, 3–11. [CrossRef]
17. Picazo-Tadeo, A.J.; Reig-Martínez, E. Outsourcing and Efficiency: The Case of Spanish Citrus Farming. *Agric. Econ.* **2006**, *35*, 213–222. [CrossRef]
18. Ji, C.; Guo, H.; Jin, S.; Yang, J. Outsourcing Agricultural Production: Evidence from Rice Farmers in Zhejiang Province. *PLoS ONE* **2017**, *12*, e0170861. [CrossRef] [PubMed]
19. Wang, T.; Huang, L. An Empirical Study on the Relationship between Agricultural Science and Technology Input and Agricultural Economic Growth Based on E-Commerce Model. *Sustainability* **2018**, *10*, 4465. [CrossRef]
20. Zhu, Y.; Deng, J.; Wang, M.; Tan, Y.; Yao, W.; Zhang, Y. Can Agricultural Productive Services Promote Agricultural Environmental Efficiency in China? *Int. J. Environ. Res. Public Health* **2022**, *19*, 9339. [CrossRef] [PubMed]
21. Lyne, M.C.; Jonas, N.; Ortmann, G.F. A Quantitative Assessment of an Outsourced Agricultural Extension Service in the Umzimkhulu District of KwaZulu-Natal, South Africa. *J. Agric. Educ. Ext.* **2018**, *24*, 51–64. [CrossRef]
22. Zang, L.; Wang, Y.; Ke, J.; Su, Y. What Drives Smallholders to Utilize Socialized Agricultural Services for Farmland Scale Management? Insights from the Perspective of Collective Action. *Land* **2022**, *11*, 930. [CrossRef]
23. Yang, Z. Can Outsourcing of Agricultural Production Improve the Welfare of Farm Households? Evidence from Rice Farmers in Yangtze Valley. *Chin. Rural Econ.* **2019**, 73–91.
24. Gillespie, J.M.; Nehring, R.F.; Sandretto, C.L.; Hallahan, C.B. Forage Outsourcing in the Dairy Sector: The Extent of Use and Impact on Farm Profitability. *Agric. Resour. Econ. Rev.* **2010**, *39*, 399–414. [CrossRef]
25. Qu, X.; Kojima, D.; Wu, L.; Ando, M. Impacts of Work Attitude of Outsourcing Services on Food Losses: Evidence from Rice Harvest in China. *Int. Food Agribus. Manag. Rev.* **2022**, *25*, 587–599. [CrossRef]
26. Mulley, B.G.; Unruh, J.D. The Role of Off-Farm Employment in Tropical Forest Conservation: Labor, Migration, and Smallholder Attitudes toward Land in Western Uganda. *J. Environ. Manag.* **2004**, *71*, 193–205. [CrossRef]
27. Alfred, M. *Principles of Economics*; Cosimo Classics: New York, NY, USA, 2009.
28. Huang, J.; Wang, Y.; Wang, J. Farmers' Adaptation to Extreme Weather Events through Farm Management and Its Impacts on the Mean and Risk of Rice Yield in China. *Am. J. Agric. Econ.* **2015**, *97*, 602–617. [CrossRef]
29. Zhang, X.; Yang, J.; Thomas, R. Mechanization Outsourcing Clusters and Division of Labor in Chinese Agriculture. *China Econ. Rev.* **2017**, *43*, 184–195. [CrossRef]
30. Babbage, C. *On the Economy of Machinery and Manufactures*; Cambridge Library Collection—History of Printing, Publishing and Libraries; Cambridge University Press: Cambridge, UK, 2010; ISBN 978-1-108-00910-2.
31. Quélin, B.; Duhamel, F. Bringing Together Strategic Outsourcing and Corporate Strategy:: Outsourcing Motives and Risks. *Eur. Manag. J.* **2003**, *21*, 647–661. [CrossRef]
32. Takeshima, H. *Overview of the Evolution of Agricultural Mechanization in Nepal: A Focus on Tractors and Combine Harvesters*; Elsevier: Amsterdam, The Netherlands, 2017.
33. Qing, Y.; Chen, M.; Sheng, Y.; Huang, J. Mechanization Services, Farm Productivity and Institutional Innovation in China. *China Agric. Econ. Rev.* **2019**, *11*, 536–554. [CrossRef]
34. Sims, B.; Kienzle, J. Making Mechanization Accessible to Smallholder Farmers in Sub-Saharan Africa. *Environments* **2016**, *3*, 11. [CrossRef]
35. Guan, X.; Zang, Y.; Meng, Y.; Liu, Y.; Lv, H.; Yan, D. Study on Spatiotemporal Distribution Characteristics of Flood and Drought Disaster Impacts on Agriculture in China. *Int. J. Disaster Risk Reduct.* **2021**, *64*, 102504. [CrossRef]
36. Lunt, T.; Jones, A.W.; Mulhern, W.S.; Lezaks, D.P.M.; Jahn, M.M. Vulnerabilities to Agricultural Production Shocks: An Extreme, Plausible Scenario for Assessment of Risk for the Insurance Sector. *Clim. Risk Manag.* **2016**, *13*, 1–9. [CrossRef]
37. de Brauw, A.; Kramer, B.; Murphy, M. Migration, Labor and Women's Empowerment: Evidence from an Agricultural Value Chain in Bangladesh. *World Dev.* **2021**, *142*, 105445. [CrossRef] [PubMed]
38. Benin, S. Impact of Ghana's Agricultural Mechanization Services Center Program. *Agric. Econ.* **2015**, *46*, 103–117. [CrossRef]
39. Li, Q.; Wang, J.; Wu, J.; Zhai, Q. The Dual Impacts of Specialized Agricultural Services on Pesticide Application Intensity: Evidence from China. *Pest Manag. Sci.* **2022**, *79*, 76–87. [CrossRef] [PubMed]
40. Chisango, F. Agricultural Mechanization for Sustainable Agriculture and Food Security in Zimbabwe: A Case of Bindura District in Mashonaland Central Province. 2010. Available online: https://www.semanticscholar.org/paper/Agricultural-mechanization-for-sustainable-and-food-Chisango/16d69b706ae7711fa406df1dab67d6243c184659 (accessed on 20 June 2022).

41. Qu, X.; Kojima, D.; Nishihara, Y.; Wu, L.; Ando, M. Can Harvest Outsourcing Services Reduce Field Harvest Losses of Rice in China? *J. Integr. Agric.* **2021**, *20*, 1396–1406. [CrossRef]
42. Koundouri, P.; Nauges, C.; Tzouvelekas, V. Technology Adoption under Production Uncertainty: Theory and Application to Irrigation Technology. *Am. J. Agric. Econ.* **2006**, *88*, 657–670. [CrossRef]
43. Azadi, H.; Houshyar, E.; Zarafshani, K.; Hosseininia, G.; Witlox, F. Agricultural Outsourcing: A Two-Headed Coin? *Glob. Planet. Chang.* **2013**, *100*, 20–27. [CrossRef]
44. Do, M.H.; Nguyen, T.T.; Grote, U. Land Consolidation, Rice Production, and Agricultural Transformation: Evidence from Household Panel Data for Vietnam. *Econ. Anal. Policy* **2022**, *77*, 157–173. [CrossRef]
45. Qian, L.; Lu, H.; Gao, Q.; Lu, H. Household-Owned Farm Machinery vs. Outsourced Machinery Services: The Impact of Agricultural Mechanization on the Land Leasing Behavior of Relatively Large-Scale Farmers in China. *Land Use Policy* **2022**, *115*, 106008. [CrossRef]
46. Cao, T.; Zhou, J.; Zou, W. Large-Scale Operation and Selection of Agricultural Machanization Services for Farmers. *J. Northwest AF Univ.* **2021**, *31*, 141–149.
47. Dawadi, B.; Shrestha, A.; Acharya, R.H.; Dhital, Y.P.; Devkota, R. Impact of Climate Change on Agricultural Production: A Case of Rasuwa District, Nepal. *Reg. Sustain.* **2022**, *3*, 122–132. [CrossRef]
48. Qiu, T.; Choy, S.T.B.; Luo, B. Is Small Beautiful? Links between Agricultural Mechanization Services and the Productivity of Different-Sized Farms. *Appl. Econ.* **2022**, *54*, 430–442. [CrossRef]
49. Baiyegunhi, L.J.S.; Majokweni, Z.P.; Ferrer, S.R.D. Impact of Outsourced Agricultural Extension Program on Smallholder Farmers' Net Farm Income in Msinga, KwaZulu-Natal, South Africa. *Technol. Soc.* **2019**, *57*, 1–7. [CrossRef]
50. Ngango, J.; Hong, S. Impacts of Land Tenure Security on Yield and Technical Efficiency of Maize Farmers in Rwanda. *Land Use Policy* **2021**, *107*, 105488. [CrossRef]
51. Abdul-Rahaman, A.; Abdulai, A. Do Farmer Groups Impact on Farm Yield and Efficiency of Smallholder Farmers? Evidence from Rice Farmers in Northern Ghana. *Food Policy* **2018**, *81*, 95–105. [CrossRef]
52. Becerril, J.; Abdulai, A. The Impact of Improved Maize Varieties on Poverty in Mexico: A Propensity Score-Matching Approach. *World Dev.* **2010**, *38*, 1024–1035. [CrossRef]
53. Pan, D.; Kong, F.; Zhang, N.; Ying, R. Knowledge Training and the Change of Fertilizer Use Intensity: Evidence from Wheat Farmers in China. *J. Environ. Manag.* **2017**, *197*, 130–139. [CrossRef]
54. Mi, Q.; Li, X.; Gao, J. How to Improve the Welfare of Smallholders through Agricultural Production Outsourcing: Evidence from Cotton Farmers in Xinjiang, Northwest China. *J. Clean. Prod.* **2020**, *256*, 120636. [CrossRef]
55. Mwambi, M.; Depenbusch, L.; Bonnarith, U.; Sotelo-Cardona, P.; Kieu, K.; di Tada, N.; Srinivasan, R.; Schreinemachers, P. Can Phone Text Messages Promote the Use of Integrated Pest Management? A Study of Vegetable Farmers in Cambodia. *Ecol. Econ.* **2023**, *204*, 107650. [CrossRef]
56. Liao, L.; Long, H.; Gao, X.; Ma, E. Effects of Land Use Transitions and Rural Aging on Agricultural Production in China's Farming Area: A Perspective from Changing Labor Employing Quantity in the Planting Industry. *Land Use Policy* **2019**, *88*, 104152. [CrossRef]
57. Zhou, N.; Cheng, W.; Zhang, L. Land Rights and Investment Incentives: Evidence from China's Latest Rural Land Titling Program. *Land Use Policy* **2022**, *117*, 106126. [CrossRef]
58. Lopez, R.A.; He, X.; De Falcis, E. What Drives China's New Agricultural Subsidies? *World Dev.* **2017**, *93*, 279–292. [CrossRef]
59. Schreinemachers, P.; Wu, M.-H.; Uddin, N.; Ahmad, S.; Hanson, P. Farmer Training in Off-Season Vegetables: Effects on Income and Pesticide Use in Bangladesh. *Food Policy* **2016**, *61*, 132–140. [CrossRef]
60. Wanjala, B.M.; Muradian, R. Can Big Push Interventions Take Small-Scale Farmers out of Poverty? Insights from the Sauri Millennium Village in Kenya. *World Dev.* **2013**, *45*, 147–160. [CrossRef]
61. Tran, T.Q.; Vu, H.V. Land Fragmentation and Household Income: First Evidence from Rural Vietnam. *Land Use Policy* **2019**, *89*, 104247. [CrossRef]
62. Ma, W.; Liu, T.; Li, W.; Yang, H. The Role of Agricultural Machinery in Improving Green Grain Productivity in China: Towards Trans-Regional Operation and Low-Carbon Practices. *Heliyon* **2023**, *9*, e20279. [CrossRef]
63. Haglund, E.; Ndjeunga, J.; Snook, L.; Pasternak, D. Dry Land Tree Management for Improved Household Livelihoods: Farmer Managed Natural Regeneration in Niger. *J. Environ. Manag.* **2011**, *92*, 1696–1705. [CrossRef]
64. Tang, K.; Xiong, Q.; Zhang, F. Can the E-Commercialization Improve Residents' Income? --Evidence from "Taobao Counties" in China. *Int. Rev. Econ. Financ.* **2022**, *78*, 540–553. [CrossRef]
65. Fan, L.; Guo, L.; Wang, X.; Xu, L.; Liu, F. Does the Author's Collaboration Mode Lead to Papers' Different Citation Impacts? An Empirical Analysis Based on Propensity Score Matching. *J. Informetr.* **2022**, *16*, 101350. [CrossRef]
66. Zhang, Y.; Li, J.; Tao, W. Does Energy Efficiency Affect Appliance Prices? Empirical Analysis of Air Conditioners in China Based on Propensity Score Matching. *Energy Econ.* **2021**, *101*, 105435. [CrossRef]
67. Adu-Baffour, F.; Daum, T.; Birner, R. Can Small Farms Benefit from Big Companies' Initiatives to Promote Mechanization in Africa? A Case Study from Zambia. *Food Policy* **2019**, *84*, 133–145. [CrossRef]
68. Liu, R.; Yu, C.; Jiang, J.; Huang, Z.; Jiang, Y. Farmer Differentiation, Generational Differences and Farmers' Behaviors to Withdraw from Rural Homesteads: Evidence from Chengdu, China. *Habitat Int.* **2020**, *103*, 102231. [CrossRef]

69. Chen, M.; Heerink, N.; Zhu, X.; Feng, S. Do Small and Equally Distributed Farm Sizes Imply Large Resource Misallocation? Evidence from Wheat-Maize Double-Cropping in the North China Plain. *Food Policy* **2022**, *112*, 102350. [CrossRef]
70. Chèze, B.; David, M.; Martinet, V. Understanding Farmers' Reluctance to Reduce Pesticide Use: A Choice Experiment. *Ecol. Econ.* **2020**, *167*, 106349. [CrossRef]
71. Liu, E.M.; Huang, J. Risk Preferences and Pesticide Use by Cotton Farmers in China. *J. Dev. Econ.* **2013**, *103*, 202–215. [CrossRef]
72. Chen, Z.; Sarkar, A.; Hossain, S.; Li, X.; Xia, X. Household Labour Migration and Farmers' Access to Productive Agricultural Services: A Case Study from Chinese Provinces. *Agriculture* **2021**, *11*, 976. [CrossRef]
73. Foster, A.D.; Rosenzweig, M.R. Are Indian Farms Too Small? Mechanization, Agency Costs, and Farm Efficiency. Manuscript Yale University. 2011. Available online: https://www.bu.edu/econ/files/2009/09/Rosenzweig_Seminar-Paper.pdf (accessed on 6 August 2022).
74. Hornbeck, R.; Naidu, S. When the Levee Breaks: Black Migration and Economic Development in the American South. *Am. Econ. Rev.* **2014**, *104*, 963–990. [CrossRef]