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RESEARCH ARTICLE OPEN ACCESS

Does Contract Farming Reduce Pesticide Use? Panel Data Evidence From Smallholder Farmers in China

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Received: 28 October 2025 | **Revised:** 19 August 2026 | **Accepted:** 9 September 2026

Funding: National Natural Science Foundation of China, Grant/Award Number: 72403254; China Postdoctoral Science Foundation, Grant/Award Number: GZC20233142; Postdoctoral Project of Hubei Province, Grant/Award Number: 2024HBBHCXB099

Keywords: commodity contract | contract farming | pesticide reduction | pesticide use | smallholders

ABSTRACT

The inappropriate and excessive use of pesticides poses a major threat to human and ecosystem health in the agri-food sector. While existing studies have examined the potential of contract farming to address this issue, most have focused on large-scale farms and relied on small or transactional datasets, often leaving the role of crop-specific characteristics underexplored. Consequently, the generalizability and policy applicability of these findings remain limited in the context of diverse, smallholder-dominated agricultural systems. To address this knowledge gap, the current study uses panel data collected at fixed rural observation points across 31 provincial regions in China between 2009 and 2017 ($N = 158{,}850$) to examine the impact of contract farming on pesticide use among smallholder farmers, both overall and by crop type. The results show that farmers who are engaged in commodity contracts for agricultural product sales use significantly less pesticide than those who are not, suggesting a net positive effect of contract farming on pesticide reduction. Further analysis reveals heterogeneous impacts across crop types: participation in contract farming is consistently associated with reduced pesticide use for rice, wheat, and corn, but not for fruits and vegetables. We discuss possible reasons for the crop-specific variations in the effects of commodity contracts on pesticide reduction and provide policy implications for optimizing the use of such contracts as part of a national pesticide reduction strategy.

JEL Classification: Q12, Q18, Q56

1 | Introduction

Inappropriate and excessive use of pesticides is a substantial problem which can have serious, negative effects on human and ecosystem health (European Environment Agency 2023). In particular, overuse kills soil microbes, reducing soil health, and harms beneficial insects, like bees and butterflies, disrupting pollination, as well as non-target species such as birds and fish, distorting complete food chains (UNEP 2022). Runoff from overuse can contaminate rivers and groundwater, negatively affecting aquatic life and drinking water supplies (European Environment Agency 2024). Furthermore, overuse leads to pests developing resistance, potentially locking farmers into a pesticide treadmill whereby they need to use ever increasing applications (Brown 2018). Inappropriate use is also a threat to human health, especially for those applying the chemicals, but also for food consumers (European Environment Agency 2023). Consequently, reducing inappropriate and overuse of pesticides is an important policy objective (Food and Agriculture Organization of the United Nations, and World Health Organization. 2021b; United Nations Environment Programme 2022).

A large body of literature explores farmers' pesticide use and pesticide reduction behaviors. This identifies individual characteristics that affect farmers' pesticide use, sometimes termed "internal factors," including socio-demographic status, psychological traits (e.g., risk attitudes, institutional trust, and pro-environmental attitudes), and capabilities, knowledge and perceptions related to pesticides and their alternatives (Gesesew et al. 2016; Li et al. 2023; Pan et al. 2021; Tan et al. 2022). For example, limited action capacity and cognitive ability, as well as the perceived risk of reducing pesticide use, act as barriers to farmers' adherence to standardized pesticide application practices (Bakker et al. 2021; Bjørnåvold et al. 2022; Chèze et al. 2020). Research has also examined how contextual factors, such as farm and agronomic conditions, and the social, market, and policy environment, influence farmers' pesticide use, often in connection with their individual characteristics (Jallow et al. 2017; Kaiser et al. 2024; Li et al. 2023; Pan et al. 2021). For instance, farmers operating on a smaller scale tend to be more risk-averse, leading to increased pesticide use (Gong et al. 2016).

In addressing the problem of inappropriate and overuse of pesticides, one potential solution is stricter government regulation and penalties for non-compliance (Food and Agriculture Organization of the United Nations, and World Health Organization 2021a). However, this depends on effective enforcement and monitoring procedures, which may be lacking in some countries (Benaboud et al. 2021; Islam et al. 2017; Straw et al. 2023; Yan et al. 2016). Better education and training can contribute to reducing the problem, but effectiveness depends on suitable extension staff and facilities, which again may be lacking in some countries and can be expensive to provide (Goeb and Lupi 2021; Grimbuhler and Viel 2025; Sharifzadeh and Abdollahzadeh 2021). While government regulations and agricultural extension services are necessary for reducing inappropriate and overuse of pesticides, their efficacy can be hindered by high monitoring costs and fiscal constraints, particularly in fragmented smallholder economies (Antwi-Agyei and Stringer 2021; Sun et al. 2025; Xia et al. 2024). Consequently, contract farming emerges as a market-led alternative by internalizing these supervision costs through a multi-dimensional incentive structure (Weituschat et al. 2023). If contracts stipulate appropriate integrated pest management practices, with incentives for farmers to adhere to the terms stipulated and penalties if they do not, private vertical coordination systems may contribute positively to addressing inappropriate and overuse of pesticides (Rehber 2018).

Despite the documented potential of contract farming, the literature remains inconclusive, with inconsistent and sometimes contradictory findings regarding its impact on the adoption of sustainable practices (e.g., see Dubbert et al. 2023; Goodhue 2011; Goodhue and Simon 2016; Mishra et al. 2018). Because existing studies are often conducted across disparate national contexts, they present a significant identification challenge: it becomes nearly impossible to disentangle whether divergent results stem from unique institutional environments or from crop-specific heterogeneity. This lack of comparative clarity risks the formulation of "one-size-fits-all" policies that fail to account for the varying technical requirements of different crop systems. Furthermore, current research either focuses on large-scale operations, which are generally less risk-averse, or relies on small-sample, regionally specific transactional data when investigating smallholders (Dubbert et al. 2023; Goodhue and Simon 2016; Mishra et al. 2018). This reliance on localized data limits the generalizability of findings where smallholder farming is the predominant agricultural model.

Therefore, the present study is intended to evaluate how farmers' participation in contract farming affects their pesticide use in China, where smallholder farms make up over 98% of all agricultural operations. China, as the world's largest user of pesticides, has an urgent need to reduce pesticide use in its agricultural production (Cai et al. 2021). Although pesticides contributed substantially to China's growth in agricultural output in recent decades (Gao et al. 2021), pesticide use often exceeds the maximum allowable level for optimal environmental security and economic efficiency (Cai et al. 2021). Consumer concerns regarding pesticide use and residues on food are growing. In response, the Chinese government unveiled its *National Plan for Agricultural Green Development in the 14th 5-year Period* in 2021, including the goal of improving pesticide utilization efficiency (The National Development and Reform Commission 2021). In 2022, the Ministry of Agriculture and Rural Affairs launched an *Action Program for Chemical Pesticide Reduction*, aiming to further promote pesticide reduction and improve utilization efficiency, thereby advancing green agricultural development (MARA 2022). These government-led initiatives have contributed to an overall decline in pesticide use within agricultural production in recent years. However, the pace of pesticide reduction remains relatively slow. In certain sectors—such as fruit and vegetable production—inappropriate and overuse of pesticides remains persistent (Shao et al. 2024). Government efforts to reduce pesticide overuse are hampered by the fragmented nature of production in China, driven by the predominance of smallholder farms, which contributes to higher levels of risk aversion among Chinese farmers compared to countries with a greater proportion of large-scale farms (Gong et al. 2016).

Our study makes three main contributions to the existing literature and policymaking. First, we provide a large-scale empirical test of whether formal contracts can serve as a scalable mechanism for promoting sustainable agricultural practices. Moving beyond localized case studies, we employ national-level panel data covering 31 provinces (2009–2017). The use of a two-way fixed effects model and an instrumental variable strategy allows us to address endogeneity concerns, offering more robust results on the impact of contract participation. Second, we extend the current understanding of vertical coordination by reconciling the inconsistent effects of contract participation on pesticide use within a unified institutional context. This allows us to further explore behavioral drivers that were previously confounded by disparate national settings. Third, our findings challenge the one-size-fits-all chemical reduction targets of current frameworks—such as the *National Plan for Agricultural Green Development* (NDRC 2021)—by demonstrating that intervention strategies must be tailored by crop type. Specifically, contract farming should be broadly promoted and strengthened to reduce pesticide use in staple crops, while policy support for cash crops must pivot toward public-private synergies that enforce strict traceability and residue monitoring. Strategically decoupling these interventions can avoid misallocating resources and ultimately enhance the environmental sustainability of smallholder agri-food supply chains.

The next section outlines the conceptual framework and economic model employed in this study, and the third section the data and the variables included in the analysis. The fourth section presents the empirical results, and the final section provides the conclusions and policy implications.

2 | Conceptual Framework and Econometric Model

2.1 | Conceptual Framework

Agricultural products are classified as credence goods because some of their critical quality attributes, such as safety, quality, and production methods (e.g., pesticide use or organic practices) cannot easily be verified by consumers through sight, smell, or taste, even after the products have been consumed (Schrobback et al. 2023; Sheldon 2017). This creates a "market for lemons" (Akerlof 1970), where high-quality, low-pesticide products cannot be easily distinguished from lower-quality alternatives. Consequently, high-quality products may fail to command a price premium, disincentivizing chemical reduction (Hong et al. 2023).

Commodity contracts can serve as a useful mechanism that bridges the information gap by establishing vertical coordination between farmers and downstream buyers, reducing transaction uncertainty and facilitating the transmission of quality-related information (Eccles and Williamson 1987). Farmers outside of commodity contracts lack access to the institutional mechanism that bridges the information gap; even if they were to adopt similar production methods, the absence of a credible certifier or enforceable quality commitment prevents them from reliably signaling low-pesticide attributes to distant buyers (Schrobback et al. 2023). If such an information asymmetry does not exist in an agricultural product market, pesticide input will not differ significantly between farmers with and without commodity contracts. This is because farmers are able to sell high-quality agricultural products at the same premium price regardless of contractual arrangements (Rehber 2018). However, in the presence of quality-related information costs, farmers without commodity contracts are decoupled from the vertical information channels that link producers to quality-conscious consumers. Consequently, they are unable to capture a premium for high-quality attributes. Simultaneously, the opportunity cost of intensive pesticide use remains low for non-contracted farmers, as in the absence of appropriate testing, they face no market-based penalties for high residue levels. In the absence of a price signal for safety, these farmers are incentivized to increase pesticide inputs as a "production insurance" to guarantee yield stability (Schrobback et al. 2023).

For farmers participating in contract farming, contracts may drive behavioral changes to reduced pesticide use through three interlinked mechanisms. First, monitoring and penalties mitigate information asymmetry; the use of field inspections and residue testing creates a credible threat of contract termination, thereby raising the "cost of non-compliance" for the farmer (Rehber 2018). Second, technical assistance may lower the barrier to sustainable transitions by bundling specialized "green" inputs with training in technologies and practices (Minot and Sawyer 2016). Finally, the provision of a price premium, guaranteed upon successful compliance, transforms the unobservable "credence attribute" of low-pesticide produce into a tangible economic reward (Rehber 2018). By aligning the farmer's profit motive with obligatory safety standards, this vertical coordination system functions as a self-enforcing mechanism in environments where public enforcement and extension reach are limited (Minot and Sawyer 2016; Rehber 2018; Shrimali 2021).

However, an increase in pesticide use could also emerge among farmers who have entered commodity contracts. First, commodity contracts inherently introduce a principal–agent relationship characterized by conflicting incentives. The principal's capacity to detect non-compliance diminishes when the transaction costs of oversight, such as laboratory residue testing and field inspections, become prohibitively high (Sgroi and Sciancalepore 2022; Vishnu and Chengappa 2023). This persistent information asymmetry could facilitate opportunistic behavior, whereby agents prioritize yield stability via intensified pesticide application over the unobservable credence attributes stipulated in the contract (Popovic et al. 2012; Steinle et al. 2014; Tang et al. 2022). Second, the severity of this principal-agent problem varies by crop type. For perishable, high-value products like fruits and vegetables, the technical difficulty of storage and rapid quality verification makes production practices harder to observe (He et al. 2018; Peterson et al. 2018). This increases the risk of moral hazard, potentially attenuating the incentive effect of quality premiums and resulting in higher pesticide use. In contrast, staple crops such as wheat and corn are more easily standardized and monitored, which reduces information asymmetry and constrains opportunism. Therefore, an increase in pesticide use is more likely to occur among contract farmers cultivating perishable, high-value crops than among those growing staple crops. Third, low trust in agribusiness firms coupled with strong peer influence within farming communities can drive increases in pesticide use (Suwannadi et al. 2026). Smallholder farmers often harbor skepticism toward corporate extension advice, viewing recommendations to reduce chemical inputs as a risk-shifting strategy that places the burden of potential crop failure entirely on farmers. In the absence of trust, farmers rely heavily on localized peer networks. When a farmer observes neighbors applying intensive chemical treatments to secure their yields, social pressure and the fear of crop failure create a powerful imitation effect. This community-level peer influence can easily override formal training and contract requirements, motivating contract farmers to maintain or even escalate their pesticide use to match local village norms. Consequently, given these countervailing mechanisms operate simultaneously in opposite directions, the net impact of contract farming on pesticide use remains theoretically ambiguous, rendering it an empirical question that requires rigorous quantitative evaluation.

2.2 | Econometric Model

2.2.1 | Two-Way Fixed-Effect Model

In this study, the effect of commodity contracts on farmers' pesticide use is estimated by using a two-way fixed-effect model (TWFE). Pooled OLS may produce biased estimates due to time-invariant unobserved heterogeneity, such as cultural customs, risk preferences, or soil texture. The inclusion of household fixed effects removes all time-constant unobserved factors. Year fixed effects further control for common shocks, including macroeconomic conditions, policy changes, and weather fluctuations (de Chaisemartin and D'Haultfœuille 2020; Wooldridge 2020). This within-household identification strategy allows us to isolate the effect of contract participation by comparing changes in pesticide use for the same household farmer before and after contracting. The empirical specification is presented as follows:

$$\begin{aligned} \text{lnPesticide}_{i,h,v,t} = \pi + \varphi \text{Contract}_{i,h,v,t} + X_i'\gamma \\ + X_h'\omega + X_v'\tau + \rho_h + \sigma_t + \varepsilon_{i,h,v,t}, \end{aligned} \quad (1)$$

where, $\text{lnPesticide}_{i,h,v,t}$ denotes the natural logarithm of pesticide use by the farmer i of the household h in the village v in the t-th period; $\text{Contract}_{i,h,v,t}$ denotes a commodity contract; ρ_h denotes the household farmer-fixed effect, controlling for unobservable and non-time-varying household heterogeneity; and σ_t denotes the time-fixed effect, measuring the common shock faced by all farmer households in a given year. π is a constant term. φ, γ, ω, and τ are parameters to be estimated; specifically, φ is the core coefficient in this study, measuring the percentage change in pesticide use by farmers entering into commodity contracts compared with farmers not entering into commodity contracts. $\varepsilon_{i,h,v,t}$ is the random error term. Since farmers within the same village tend to face similar agroecological conditions, market environments, and social interactions, their pesticide application behaviors may exhibit intra-village correlation. Neglecting this dependence could lead to downward-biased standard errors and over-rejection of the null hypothesis. Therefore, following the standard practice in applied econometrics, standard errors are clustered at the village level to allow for arbitrary correlation within villages (Colin Cameron and Miller 2015).

The baseline model also introduces other factors that may affect farmers' decisions associated with commodity contracts and pesticide use (see Table 1). X_i' denotes the individual characteristics of a household head, including gender, age, quadratic term of age, education, agricultural technology training, and self-rated health. These variables serve as proxy variables for farmer households' human capital (Burke et al. 2019). To control for the effect of labor endowment, this study introduces the variables such as the off-farm time and off-farm place of a household head (Ma et al. 2018). X_h' denotes a set of farmer household characteristics, including five-guarantee household, farm size, number of plots, land transfer, and source of agricultural materials. X_v' denotes a set of village characteristics, including the non-agricultural employed labor ratio, labor force ratio, pesticide price, whether villages are located in suburbs or mining areas, and village terrain, providing control for the effect of geographic location. While the control variables X_i', X_h' and X_v' may influence contract participation, our baseline specification does not include interaction terms between the contract variable and these controls. This is because the primary objective of this study is to estimate the average (total) effect of commodity contracts on pesticide use, rather than to fully characterize heterogeneous treatment effects. Introducing multiple interaction terms without strong theoretical guidance may lead to overfitting and complicate the interpretation of the estimated coefficients (Rimpler et al. 2025).

Other variables (e.g., fertilizer and machinery input, and household income) are excluded from the model to avoid selectivity bias. From an identification perspective, these variables are likely to be endogenous outcomes of commodity contracts rather than pre-determined covariates. Commodity contracts typically affect farmers' production decisions by altering input provision, technology adoption, and income through price guarantees, credit access, and technical assistance (Liang and Ma 2025; Ma et al. 2018; Michelson et al. 2023; Miyata et al. 2009). Controlling for such post-treatment variables would block part of the total effect and lead to biased estimates of the parameters of interest, a problem commonly referred to in the empirical literature as "bad control" or post-treatment bias (Angrist and Pischke 2009). Hence, excluding these variables allows us to capture the total effect of commodity contracts on pesticide use, rather than a partial effect conditional on intermediate outcomes (Cinelli et al. 2024).

2.2.2 | Two-Stage Least Square Method

The confounding effect of omitted non-time-varying factors can be overcome using the aforementioned two-way fixed-effect model. However, omitted-variable bias will be caused if the omitted unobservable variables vary by time. Moreover, farmers' conclusion of commodity contracts is self-selective (Khonje et al. 2018). This means that farmers' decision on whether to sell agricultural products through commodity contracts is related to observable (e.g., age, gender, and education level) and unobservable factors (e.g., risk preference and business capacity) (Ma et al. 2018). Furthermore, reverse causality may exist between commodity contracts and pesticide use. For example, farmers may adjust their pesticide use to win commodity contracts. These potential endogeneity problems pose a challenge to the credibility of estimation results of the baseline model. Therefore, we select an effective instrumental variable for commodity contracts, and then adopt the two-stage least squares (TSLS) method to perform parameter estimation.

The selected instrumental variable must be highly related to commodity contracts without directly affecting farmers' pesticide use behaviors. In this study, the annual number of civil disputes in a village is used as an instrumental variable (IV) for commodity contracts. Theoretically, the prevalence of civil disputes reflects the quality of the local institutional and social environment. A higher incidence of disputes is typically associated with weaker contract enforcement, lower interpersonal trust, and higher transaction costs, including bargaining, monitoring, and enforcement costs (North 2012). As a result, farmers are more likely to engage in non-market (personified) contracts (e.g., verbal agreements) rather than formal contracts. These informal arrangements can be sustained through

TABLE 1 | Variable definitions and descriptive statistics.

Variable	Definition	Adoption ($n = 78{,}152$) Mean	Non-adoption ($n = 80{,}698$) Mean	Mean diff.
Explained variable				
Pesticide use	Pesticide application per unit area of land (kg/mu)	2.93	9.36	6.42***
Explanatory variable				
Commodity contract	Enter into commodity contracts = 1, Otherwise = 0	1.00	0.00	—
Individual characteristics				
Gender	Household head gender is male = 1, Otherwise = 0	0.90	0.94	−0.04***
Age	Actual age of household head (years)	58.59	57.83	0.76***
Education	Years of education of household head	7.21	7.19	0.03*
Agricultural technical training	Household head received technical training = 1, Otherwise = 0	0.05	0.06	−0.02***
Self-rated health				
Excellent	Household head self-rated health is "Excellent" = 1, Otherwise = 0	0.47	0.51	−0.03***
Good	Household head self-rated health is "Good" = 1, Otherwise = 0	0.28	0.29	−0.01
Fair	Household head self-rated health is "Fair" = 1, Otherwise = 0	0.12	0.11	0.01***
Poor	Household head self-rated health is "Poor" = 1, Otherwise = 0	0.08	0.07	0.01***
Lost labor ability	Household head self-rated health is "Lost labor ability" = 1, Otherwise = 0	0.05	0.03	0.02***
Off-farm time	Days household head worked outside during the year (days)	60.53	42.24	18.29***
Off-farm place				
Outside township within county	Outside township within county = 1, Otherwise = 0	0.12	0.12	0.00
Outside county within province	Outside county within province = 1, Otherwise = 0	0.82	0.84	−0.03***
Outside province	Outside province = 1, Otherwise = 0	0.06	0.04	0.02***
Overseas	Overseas = 1, Otherwise = 0	0.002	0.001	0.001***
Household characteristics				
Five-guarantee household	Indigent rural residents receiving comprehensive government support (food, clothing, housing, medical care, and burial expenses) = 1, Otherwise = 0	0.01	0.01	0.00
Farm size	Actual operating cultivated land area of family (mu)	5.26	9.97	−4.71***
Number of plots	Number of cultivated land plots	2.27	4.96	−2.68***
Land transfer in	Transferred in land = 1, Otherwise = 0	0.03	0.07	−0.05***
Land transfer out	Transferred out land = 1, Otherwise = 0	0.18	0.08	0.11***

(Continues)

TABLE 1 | (Continued)

Variable	Definition	Adoption ($n = 78{,}152$) Mean	Non-adoption ($n = 80{,}698$) Mean	Mean diff.
Source of agricultural materials				
Extension department	Purchased agricultural inputs provided by agricultural technology extension department = 1, Otherwise = 0	0.04	0.28	−0.24***
Village collective	Purchased agricultural inputs provided by village collective = 1, Otherwise = 0	0.06	0.05	0.01***
Other sources	Purchased agricultural inputs provided by entities other than agricultural technology extension department and village collective = 1, Otherwise = 0	0.14	0.05	0.09***
Village characteristics				
Non-agricultural employed labor ratio	Proportion of non-agricultural employment labor force to total labor force in village	0.91	0.90	0.01***
Labor force ratio	Proportion of labor force in village	0.58	0.62	−0.04***
Pesticide price	Market price of pesticide purchases	21.86	18.67	3.20***
Suburb areas	Urban suburb = 1, Otherwise = 0	0.22	0.16	0.06***
Mining areas	Mining suburb = 1, Otherwise = 0	0.07	0.06	0.01***
Terrain				
Plain	Plain = 1, Otherwise = 0	0.43	0.44	−0.01***
Hill	Hill = 1, Otherwise = 0	0.33	0.29	0.04***
Mountain	Mountain = 1, Otherwise = 0	0.24	0.27	−0.03***
Instrumental variable				
Civil disputes	Annual number of civil disputes in a village	4.83	5.97	1.14***

Note: The five guarantee refers to a social welfare program in China, which ensures minimum livelihood security for the most vulnerable rural households.

customs and ethical norms embedded in rural social traditions (MacLeod 2007). This argument is consistent with transaction cost economics, which predicts that weak enforcement environments discourage formal contracting and shift economic exchange toward informal arrangements (Eccles and Williamson 1987). Therefore, the number of civil disputes is expected to be negatively associated with the likelihood of participating in commodity contracts.

Regarding the exclusion restriction, there is no clear theoretical or empirical basis to expect that the incidence of civil disputes directly affects farmers' pesticide use decisions, except through its influence on contractual arrangements. Pesticide use is primarily determined by production conditions, input access, and farming practices, rather than the broader village-level dispute environment. Thus, conditional on observable village characteristics, the incidence of civil disputes can reasonably be assumed to affect pesticide use only indirectly through contract participation. Hence, we examine the relationship between commodity contracts and farmers' pesticide use through the following TSLS method:

$$\mathrm{Contract}_{i,h,v,t} = \pi + \varphi \mathrm{Disputes}_{v,t} + X_i'\gamma + X_h'\omega + X_v'\tau + \rho_h + \sigma_t + \varepsilon_{i,h,v,t}, \quad (2)$$

$$\ln\mathrm{Pesticide}_{i,h,v,t} = \pi + \varphi \widehat{\mathrm{Contract}}_{i,h,v,t} + X_i'\gamma + X_h'\omega + X_v'\tau + \rho_h + \sigma_t + \varepsilon_{i,h,v,t}, \quad (3)$$

where, $\mathrm{Disputes}_{v,t}$ denotes the annual number of civil disputes in a village, $\widehat{\mathrm{Contract}}_{i,h,v,t}$ and is the fitted value of $\mathrm{Contract}_{i,h,v,t}$. The meanings and settings of the remaining variables are the same as those described in Equation (1).

3 | Data and Descriptive Statistics

3.1 | Data

The secondary data herein are sourced from the China-wide rural fixed-observation-point survey conducted by the Research Center for Rural Economy of the Ministry of Agriculture and Rural Affairs of the People's Republic of China. The China-wide rural fixed-observation-point survey provides the largest-scale tracking sample panel data of rural China. Given the large sample size and high representativeness, it provides strong support for examining the effect of commodity contracts on farmers' pesticide use. The survey sample comprised approximately 21,000 rural households from 360 administrative villages distributed across China's 31 provincial regions. Such a survey can help us identify the heterogeneity in the cross-section. Moreover, this survey spans a long period, beginning in 1985. Additionally, the survey covers three levels of respondents—individuals, households, and villages—which allows us to better control for key time-varying factors and exclude confounding variables that may influence both commodity contract participation and pesticide use in the present study.

Although the survey spans a long period, stemming from 1985, the analytical sample in this study is restricted to the period 2009–2017 for three main reasons. First, the measurement and statistical definitions of key variables (particularly those related to agricultural inputs, contract participation, and pesticide use) became more standardized and consistent during this period, ensuring comparability across time. Second, China initiated a nationwide rural land titling reform after 2009, which significantly strengthened property rights and reduced tenure insecurity. This reform helps mitigate the confounding influence of land tenure arrangements on farmers' input decisions, thereby allowing for a cleaner identification of the effect of commodity contracts (Xie et al. 2023). Third, and critically from an identification perspective, the post-2009 period corresponds to a stage in which agricultural markets and contract arrangements in rural China became more institutionalized and widespread. Prior to this period, commodity contracts were relatively limited in scope and often informal, making their measurement less reliable and their economic interpretation less clear. After 2009, the increasing formalization of contract farming, alongside improvements in market infrastructure and enforcement mechanisms, allows for a more meaningful and consistent characterization of contract participation. Restricting the sample to this period therefore reduces measurement error and enhances the internal validity of the empirical analysis.

3.2 | Descriptive Statistics

Table 1 presents the descriptive statistics of the variables used in this study. Nearly half of the farmer households (49.20%) have entered into commodity contracts, indicating substantial cross-sectional variation in contract adoption. Crucially, 36.6% of households switch their contract participation status at least once between 2009 and 2017, which confirms that there is sufficient within-household variation over time to robustly support identification in our household fixed-effects framework. On average, households not engaged in commodity contracts apply 6.42 kg/mu more pesticides than those who are, suggesting a potential role of commodity contracts in reducing pesticide use. However, this preliminary observation, based on a *t*-test of bivariate correlation, may not be robust due to the influence of confounding factors. Therefore, a more rigorous empirical analysis is conducted. Significant differences in individual, household, and village characteristics between contract and non-contract farmers support the relevance of the control variables selected for this study.

4 | Results

4.1 | Baseline Results: TWFE Estimates

Table 2 presents the estimation results of the baseline model. Column (1) reports the results with household-fixed and time-fixed effects. Columns (2) to (4) progressively control for individual, household, and village characteristics, respectively. Across all specifications, the estimated coefficients for commodity contracts are consistently negative and statistically significant, indicating a robust association between commodity contract participation and reduced pesticide use. Using the estimation results under the strictest control in Column (4) as the baseline, farmers engaged in commodity contracts exhibit a significant 40.70% reduction in pesticide use compared to non-contract farmers. This demonstrates that the results are

TABLE 2 | Baseline estimation results.

Variable	lnPesticide (1)	(2)	(3)	(4)
Commodity contract	−0.652***	−0.652***	−0.424***	−0.407***
	(0.030)	(0.030)	(0.024)	(0.024)
Individual characteristics	No	Yes	Yes	Yes
Household characteristics	No	No	Yes	Yes
Village characteristics	No	No	No	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Constant	1.411***	1.085***	1.884***	1.772***
	(0.024)	(0.262)	(0.232)	(0.217)
Observations	158,850	158,850	158,850	158,850
R-squared	0.270	0.270	0.440	0.455

Note: ***, ** and * represent significance levels of 1%, 5%, and 10% respectively. Standard errors clustered at the village level are in parentheses.

both statistically and economically significant. Evidently, commodity contracts can significantly reduce pesticide application intensity. This finding preliminarily suggests that the net effect of commodity contracts on pesticide reduction is positive. Specifically, the incentive effect of quality premiums associated with commodity contracts appears to outweigh the inhibitory effect of moral hazard stemming from the principal-agent relationship.

4.2 | TSLS Estimates

Table 3 presents the estimation results using the TSLS method. The first-stage results show that the coefficient of "civil disputes" is significantly negative, indicating that a higher annual number of civil disputes in a village decreases the likelihood of farmers entering into commodity contracts. These findings align with our theoretical expectations. Furthermore, the F-statistic from the first-stage regression substantially exceeds the commonly accepted threshold of 10, allowing us to reject the null hypothesis of a weak instrumental variable. This suggests that the chosen instrument is appropriate and valid. The second-stage results indicate that the variable "commodity contract" continues to exert a significant negative influence on farmers' pesticide use.

The estimates from the FE and TSLS approaches differ in both magnitude and precision. The FE estimate indicates a significant negative association between commodity contracts and pesticide use (− 0.407, s.e. = 0.024), whereas the TSLS estimate suggests a stronger negative association (− 0.807, s.e. = 0.446). Although household and year fixed effects absorb time-invariant unobserved household heterogeneity and common temporal shocks, they cannot fully eliminate concerns arising from time-varying unobservables or endogenous participation decisions. For example, localized pest outbreaks or other time-varying shocks may increase both farmers' incentives to participate in commodity contracts and their pesticide use. Such mechanisms tend to attenuate the estimated FE coefficient toward zero. Consequently, we interpret the FE estimate as a precise and conservative benchmark, which is likely to represent a lower bound (in absolute magnitude) of the average treatment effect for the full sample.

TABLE 3 | Results of TSLS estimates.

	(1)	(2)	(3)
The first stage:	Commodity contract		
Civil disputes	−0.003***	−0.002***	−0.002***
	(0.000)	(0.000)	(0.000)
F-value	223.674	248.360	248.560
The second stage	lnPesticide		
Commodity contract	−1.662***	−0.859**	−0.807*
	(0.368)	(0.385)	(0.446)
Individual characteristics	Yes	Yes	Yes
Household characteristics	No	Yes	Yes
Village characteristics	No	No	Yes
Household fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Constant	1.974***	2.149***	1.997***
	(0.445)	(0.293)	(0.340)
Observations	158,850	158,850	158,850
R-squared	0.270	0.303	0.324

Note: ***, ** and * represent significance levels of 1%, 5%, and 10% respectively. Standard errors clustered at the village level are in parentheses.

The difference between the FE and TSLS estimates may also reflect that the two approaches identify different treatment parameters in the presence of heterogeneous treatment effects. Specifically, the TSLS estimator identifies a Local Average Treatment Effect (LATE) for farmers whose participation decisions are affected by the instrumental variable (i.e., compliers), rather than the average treatment effect for all farmers

(Imbens and Angrist 1994). If these marginal participants experience larger pesticide-reduction effects from commodity contracts than the average farmer, the TSLS estimate may naturally exceed the FE estimate in magnitude. Therefore, the discrepancy between the two estimates should not be interpreted solely as evidence of bias in the FE specification, but may also reflect treatment effect heterogeneity across farmers.

The TSLS results provide additional evidence consistent with a negative effect of commodity contracts on pesticide use, but the magnitude of this effect should be interpreted with caution. Specifically, the 95% confidence interval of the TSLS estimate ranges from approximately −1.68 to 0.07, indicating substantial uncertainty surrounding the estimated effect size and suggesting that the data cannot precisely distinguish between a small and a relatively large effect. Moreover, the TSLS coefficient is only marginally significant at the 10% level and does not achieve conventional statistical significance levels. Therefore, the TSLS results should be interpreted as suggestive evidence rather than a precise estimate of the magnitude of the effect. Nevertheless, the consistency in the direction of the FE and TSLS estimates strengthens the conclusion that commodity contracts are associated with reduced pesticide use.

To further assess the validity of the instrumental variable, we use the zero first-stage approach as a falsification test (Di Falco et al. 2011). If the instrumental variable only affects the dependent variable through the explanatory variable (i.e., commodity contracts), then it should have no significant effect on pesticide use among farmers not engaged in commodity contracts. Table 4 presents the results of this test. Specifically, while the "civil disputes" significantly affects pesticide use in the full sample, it has no significant effect within the subsample of non-contract farmers. This supports the validity of the instrumental variable, or at least provides no evidence to reject the assumption of its validity.

A potential concern is that the instrument may violate the exclusion restriction. In particular, villages with more civil disputes may reflect weaker social norms or governance quality, which could influence farmers' production behavior, including pesticide use. To address this concern, we adopt the plausibly exogenous approach proposed by Klein and Vella (2009) and van Kippersluis and Rietveld (2018), which relaxes the strict exclusion restriction by allowing the instrument to have a bounded direct effect on the outcome. Column (3) of Table 4 reports the results. The estimated effects remain negative and robust, suggesting that our main findings are not sensitive to moderate violations of the exclusion restriction.

4.3 | Robustness Checks

To test the robustness of the above results, we conduct parameter estimation by replacing the core explanatory variable, sample data, and estimation method. First, we use the "percentage of sales under commodity contracts" (i.e., the proportion of agricultural products sold under commodity contracts to total agricultural products) as a substitution variable. Compared with the dichotomous variable indicating whether farmers enter into commodity contracts, the percentage of sales under commodity contracts provides greater variability, allowing for a more nuanced understanding. The binary variable fails to distinguish between farmers with low versus high levels of contract-based sales, yet this variation may significantly influence pesticide use. By contrast, using the percentage of sales under commodity contracts as a substitution variable not only captures the presence of contract engagement but also reflects the intensity of farmers' participation in such arrangements. Table 5 presents the estimation results using this substitute core explanatory variable. The estimated coefficient for the percentage of sales under commodity contracts is both significant and negative, indicating that a higher proportion of sales under commodity contracts is associated with lower levels of pesticide use.

Second, we re-estimate the model parameters by converting the unbalanced panel data into balanced panel data, which serves as a robustness test through subsample selection. While extracting a balanced panel from the unbalanced data reduces the sample size in the cross-sectional dimension, it enables us to fully leverage the advantages of the two-way

TABLE 4 | Validation of the instrumental variable.

	lnPesticide		
Variable	**(1) Total sample**	**(2) Non-adoption sample**	**(3) Plausibly exogenous approach**
Civil disputes	−0.003***	0.005	−0.623*
	(0.001)	(0.007)	(0.367)
Individual characteristics	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Constant	0.551	1.542***	—
	(0.794)	(0.271)	—
Observations	158,850	80,698	158,850
R-squared	0.363	0.234	—

Note: ***, ** and * represent significance levels of 1%, 5%, and 10% respectively. Standard errors clustered at the village level are in parentheses.

fixed effects model and effectively control for unobserved, time-invariant confounding factors. Table 6 presents the parameter estimation results of the balanced panel data model. Columns (1–3) list the estimation results where “commodity contract” is used as an explanatory variable, and Column (4) lists the estimation results where “percentage of sales under commodity contracts” is used as an explanatory variable. Both “commodity contract” and “percentage of sales under commodity contracts” have significant negative effects on farmers' pesticide use under the balanced panel data model.

TABLE 5 | Robustness checks: Replacement variables.

	lnPesticide		
Variable	**(1)**	**(2)**	**(3)**
Percentage of sales under commodity contracts	−0.441**	−0.436**	−0.482***
	(0.205)	(0.176)	(0.168)
Individual characteristics	Yes	Yes	Yes
Household characteristics	No	Yes	Yes
Village characteristics	No	No	Yes
Household fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Constant	0.510*	1.653***	1.543***
	(0.278)	(0.229)	(0.216)
Observations	158,850	158,850	158,850
R-squared	0.186	0.408	0.426

Note: ***, ** and * represent significance levels of 1%, 5%, and 10% respectively. Standard errors clustered at the village level are in parentheses.

Table 7 presents the results of the robustness tests for the estimated relationship by progressively enriching the baseline specification. Household, village, and year fixed effects are maintained throughout, while additional observable controls and province fixed effects are introduced sequentially across specifications. Column (1) presents the model controlling for household, village, and year fixed effects. The estimated coefficient on commodity contracts is negative and statistically significant (− 0.792, s.e. = 0.035), indicating that the baseline result is robust after accounting for time-invariant household- and village-level heterogeneity as well as common time shocks. Adding individual characteristics in Column (2) leaves the estimated coefficient virtually unchanged, suggesting that observable individual heterogeneity explains little of the baseline relationship. In Column (3), the inclusion of province fixed effects together with household characteristics attenuates the estimated coefficient from −0.792 to −0.618 (s.e. = 0.032), indicating that regional variation across provinces and household-level factors account for a portion of the initial estimate. Finally, Column (4) incorporates village-level characteristics, further adjusting the coefficient to −0.579 (s.e. = 0.033). These findings confirm that the negative association between commodity contracts and pesticide use remains highly robust across progressively richer specifications. Similarly, using the proportion of sales under commodity contracts as an alternative measure of contract intensity yields a consistent negative and statistically significant estimate (− 0.546, s.e. = 0.168), reinforcing that greater reliance on commodity contracts reduces pesticide use.

4.4 | Heterogeneity Analysis: Crop-Specific Estimation Results

Table 8 presents the crop-specific estimation results. This approach is econometrically equivalent to estimating a pooled model with interaction terms between the treatment variable and crop-group indicators when testing for differential

TABLE 6 | Robustness checks: Replacement of data.

	lnPesticide				
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Commodity contract	−0.614***	−0.614***	−0.391***	−0.373***	
	(0.034)	(0.034)	(0.026)	(0.028)	
Percentage of sales under commodity contracts					−0.482***
					(0.171)
Individual characteristics	Yes	Yes	Yes	Yes	Yes
Household characteristics	No	Yes	Yes	Yes	Yes
Village characteristics	No	No	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	1.392***	0.724***	1.544***	1.443***	1.261***
	(0.026)	(0.274)	(0.327)	(0.298)	(0.293)
Observations	98,919	98,919	98,919	98,919	98,919
R-squared	0.256	0.256	0.433	0.449	0.424

Note: ***, ** and * represent significance levels of 1%, 5%, and 10% respectively. Standard errors clustered at the village level are in parentheses.

TABLE 7 | Robustness checks: Replacement variables, data and estimation method.

Variable	lnPesticide				
	(1)	(2)	(3)	(4)	(5)
Commodity contract	−0.792***	−0.792***	−0.618***	−0.579***	
	(0.035)	(0.035)	(0.032)	(0.033)	
Proportion of sales under commodity contracts					−0.546***
					(0.168)
Individual characteristics	No	Yes	Yes	Yes	Yes
Household characteristics	No	No	Yes	Yes	Yes
Village characteristics	No	No	No	Yes	Yes
Province fixed effects	No	No	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	98,919	98,919	98,919	98,919	98,919
R-squared	0.735	0.735	0.794	0.801	0.768

Note: ***, ** and * represent significance levels of 1%, 5%, and 10% respectively. Standard errors clustered at the village level are in parentheses.

TABLE 8 | Crop-specific estimation results.

Variable	Wheat		Rice		Corn		Vegetables		Fruit	
	(1) OLS	(2) TSLS	(3) OLS	(4) TSLS	(5) OLS	(6) TSLS	(7) OLS	(8) TSLS	(9) OLS	(10) TSLS
Commodity contract	−0.512***	−0.545***	−0.432***	−0.565***	−0.445***	−0.495***	0.018	0.135	0.045	0.105
	(0.021)	(0.113)	(0.035)	(0.156)	(0.026)	(0.086)	(0.156)	(0.216)	(0.117)	(0.126)
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.541***	1.624***	1.254***	1.362***	1.764***	1.836***	1.672***	1.712***	1.682***	1.701***
	(0.024)	(0.035)	(0.232)	(0.241)	(0.282)	(0.267)	(0.237)	(0.223)	(0.243)	(0.273)
Observations	158,850	158,850	158,850	158,850	158,850	158,850	158,850	158,850	158,850	158,850
R-squared	0.276	0.281	0.260	0.275	0.340	0.390	0.315	0.285	0.285	0.288

Note: ***, ** and * represent significance levels of 1%, 5%, and 10% respectively. Standard errors clustered at the village level are in parentheses.

treatment effects (Angrist and Pischke 2009; Wooldridge 2010), while additionally allowing the effects of other covariates to differ across groups. The effect of commodity contracts on farmers' pesticide use is heterogeneous among different crop types. For famers growing staple food crops (wheat, rice, and corn), the effect coefficients of commodity contracts determined by the OLS and TSLS methods are both negative, and none of their confidence intervals contains the zero value. This suggests that commodity contracts can significantly reduce pesticide use intensity among food crop farmers. For vegetable and fruit farmers, the effect coefficients of commodity contracts are positive, and both of their confidence intervals contain the zero value. This indicates that commodity contracts can positively affect the pesticide use of vegetable and fruit farmers, but not significantly. This means the pesticide reduction effect of commodity contracts does not exist in the subsample of vegetable and fruit farmers, though it does not provide evidence that commodity contracts can significantly increase their pesticide use. Figure 1 demonstrates the estimation results of the crop-specific grouped regressions.

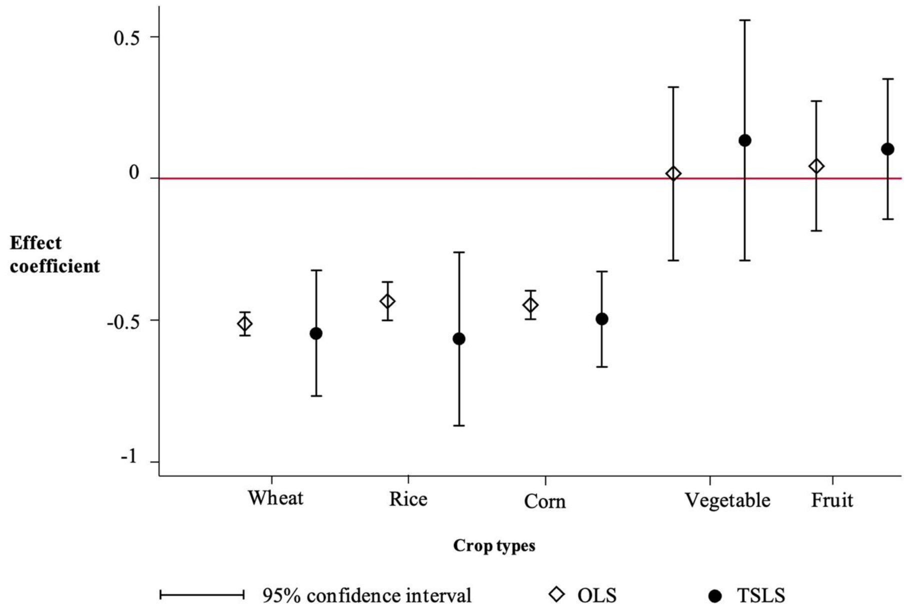

FIGURE 1 | Heterogeneous effect of commodity contracts on pesticide use.

5 | Discussion and Conclusion

Contract farming has an inherently paradoxical role in pesticide use, leading to both increases and reductions in use among farmers. The net impact of contract farming depends on the relative strength of these opposing forces. Using panel data from 2009 to 2017 across 31 provincial regions in China, the baseline regression results in our study indicate that farmers participating in contract farming used significantly less pesticide than those who did not. This aligns with findings from prior studies conducted in China (e.g., see Li and Wang 2024; Ren et al. 2021). To address potential endogeneity in the baseline model, we employed an instrumental variable approach, which confirmed the robustness of the core conclusion. This suggests that, even in the context of smallholder farming, the positive influence of incentive mechanisms embedded in contracts outweighs the negative influence of moral hazard inherent in the principal-agent relationship. Accordingly, as in certain developed countries where large-scale farming is more prevalent (Ahearn et al. 2005; Bryan Endres and Endres 2017; Burns and MacDonald 2018), contract farming appears to be an effective instrument for promoting pesticide reduction in China.

The heterogeneity analysis, accounting for crop type, reveals that the positive effect of participation in contract farming on pesticide reduction was evident for food crops (wheat, rice, and corn), but not for cash crops (vegetables and fruits). This suggests that for food crops, the positive influence of the incentive mechanisms embedded in commodity contracts outweighs the negative influence of moral hazard. In contrast, for cash crops, the opposing effects appear to neutralize each other, resulting in no significant net impact on pesticide use. The variation by crop type may be attributed to the perceived greater risk associated with reducing pesticide use in cash crop cultivation, combined with the fact that contracts tend to recommend practices and specific inputs but lack enforcement mechanisms, and that contractors often have limited monitoring capacity. For instance, compared to food crops, reducing pesticide use in cash crop production may be perceived as riskier due to the increased likelihood of crop diseases and pest infections. This is because cash crops generally have higher market value and are not supported by minimum purchase price policies, unlike some staple food crops in China (Hou et al. 2019; Ma and Zheng 2022; Ren et al. 2021). At the same time, fresh and perishable agricultural products (e.g., vegetables and fruits) are not easily storable or divisible for transport, which increases quality supervision costs and poses greater challenges for contractors in enforcing production standards (He et al. 2018; Peterson et al. 2018). As such, moral hazard within the principal–agent relationship is more likely to arise among farmers cultivating perishable cash crops, thereby offsetting, or even outweighing, the influence of incentive mechanisms embedded in commodity contracts. For example, contract farming tends to result in increased pesticide use among cashew farmers in Ghana when sales contracts fail to effectively supervise and enforce product quality (Dubbert et al. 2023).

Our results provide important policy implications regarding pesticide reduction strategies. Given its robust positive impact on pesticide reduction in staple crop production, contract farming should be strategically promoted for the cultivation of rice, wheat, and corn—which together account for the majority of cropland in China—with contracts explicitly incorporating strengthened enforcement of recommended practices and input protocols. Conversely, because contract farming does not currently reduce pesticide use in cash crop production, policy should avoid a blanket expansion of commercial contracting for high-value crops. Instead, policy interventions for cash crops should pivot toward establishing robust supply chain traceability, stringent residue-testing systems, and third-party quality assurance mechanisms. Given the high costs of quality supervision and the greater challenges contractors face in enforcing production standards for certain cash crops such as vegetables and fruits, targeted policy support is essential. Public agricultural extension services could transition into a more collaborative role, partnering with lead enterprises to co-manage quality supervision (Mishra et al. 2018). Such public-private synergies can alleviate the monitoring burden on individual firms, align with consumer safety preferences (Jin et al. 2023), and establish the market discipline needed to reduce chemical reliance in cash crop sectors where commercial contracts alone currently fail.

While our study examined the influence of commodity contracts both generally and across different crop types, several limitations should be acknowledged. First, the relationship between contract participation and pesticide use may involve dynamic adjustments over time. However, our baseline specification adopts a static fixed-effects model, which focuses on identifying contemporaneous (short-run) effects based on within-farmer variation and does not explicitly capture lagged responses. As such, the analysis may overlook potential adjustment processes, which should be further investigated in future research, for example, using dynamic panel models. Second, this study lacks data to explore how farmers' use of specific agricultural extension and advisory services may interact with contract participation to affect pesticide reduction in various cultivation contexts. Future research would benefit from collecting detailed data on farmers' access to and use of various agricultural services, with the aim of identifying service packages that most effectively reinforce the pesticide reduction effects of contract farming. Third, we acknowledge that China's institutional uniqueness, particularly its minimum purchase price policies for staples like wheat and rice, creates a subsidized, low-risk market structure that buffers staple farmers from intense commercial pressures. As such, the observed pattern regarding the divergent impacts of contracts on staple versus cash crops is potentially applicable to developing economies characterized by fragmented smallholder agriculture and state-backed price supports for staples alongside deregulated cash crop markets (e.g., parts of India or South Asia). However, this divergence is unlikely to hold in countries with entirely liberalized free markets, robust agri-environmental subsidies (such as those of the European Union), or large-scale, vertically integrated corporate farming structures (such as the United States), where greater capital resources, mechanization, and direct regulatory compliance reduce reliance on contract integrators for input decisions. The divergence may be more salient in institutional environments where food safety traceability and residue-testing systems remain patchy, as is often the case in developing economies, which causes contract farming structures to inadvertently prioritize volume and aesthetic quality over chemical reduction. Where rigorous, nationwide traceability infrastructure is effectively enforced, such as in Japan, the divergence observed in our study would likely diminish or disappear. More broadly, our core finding—that contract farming reduces overall pesticide use—is likely generalizable to other smallholder-dominated agricultural systems, particularly where contracts act as primary channels for technology transfer, stringent buyer standards, and professionalized technical guidance. Fourth, our analysis focuses on capturing the average treatment effect of commodity contracts on pesticide use. While we explore crop-specific variations, the net impact may still vary across other fine-grained farm or farmer characteristics (such as operator age, education, or land fragmentation). Exhaustively interacting contract participation with all socio-economic controls within our high-dimensional fixed-effects framework introduces a margin of error regarding model over-specification and reduced statistical power. Consequently, our average estimates should be interpreted with the caveat that they may hide differences among individual farmers and farms. Unpacking these complex socio-economic interaction profiles remains a valuable avenue for future research.

Author Contributions

Zhihui Liang: writing – original draft, funding acquisition, visualization, formal analysis, conceptualization, methodology. **Shan Jin:** conceptualization, writing – review and editing, writing – original draft. **Matthew Gorton:** writing – review and editing.

Acknowledgments

This research was supported by the National Natural Science Foundation of China (grant numbers: 72403254), China Postdoctoral Science Foundation (grant number: GZC20233142) and Postdoctoral Project of Hubei Province (grant number: 2024HBBHCXB099). None of the funding bodies were involved in the design of the study, data collection, analysis, interpretation, or writing of this manuscript. The authors would like to thank Alexander Smith for his assistance with proofreading the manuscript.

Ethics Statement

Ethical review and approval were not required for this study because it used secondary, anonymized data supplied by the Research Centre for Rural Economy of the Ministry of Agriculture and Rural Affairs of the People's Republic of China under a data-sharing agreement.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the Research Centre for Rural Economy of the Ministry of Agriculture and Rural Affairs of the People's Republic of China. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of the Research Centre for Rural Economy.

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