Welfare Impacts of Modern Peanut Varieties in China

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Abstract

This article provides some first evidence of the welfare impacts of modern peanut varieties in China using a nationally representative survey. Propensity score matching is employed to address the choice nature of adoption and identify its impacts on peanut yield and multiple sources of income. Impact on income inequality is further simulated by comparing inequality measures using observed and counterfactual income distributions. It is found that adoption of modern peanut varieties significantly boosts peanut income and total household income, but increases income inequality. Therefore, household-level welfare improvement with agricultural technology adoption may not meet the governmental goals such as inequality reduction, and complementary policies are called for.

Keywords: peanut, adoption, welfare impact, China
JEL: O13, O33, Q12, Q16

1 Introduction

Technological change is a key driver of modern agricultural growth. As a major line of agricultural technology development, crop research has led to thousands of modern varieties and long-term agricultural growth in the developing world (EVENSON and GOLLIN, 2003; RENKOW and BYERLEE, 2010). As a result, the socioeconomic implications of crop technologies are receiving increasing attention. Existing studies focus on the welfare impacts of modern crop varieties in a wide range of developing countries across Sub-Saharan Africa, South Asia and Latin America (MATUSCHKE et al., 2007; MENDOLA, 2007; BECERRIL and ABDULAI, 2010; KASSIE et al., 2011). However, much less is known about such impacts in China, a major crop producer of the world.

This gap needs to be filled as China feeds 20% of world population using 8% of world's arable land (BRÄUTIGAM, 2009), whose experience is extremely policy-relevant for many other developing economies faced by chronical food insecurity as well as related issues such as poverty and malnutrition.

Agricultural growth in China largely benefits from domestic crop research since the 1970s (YUAN, 1998). Unlike the rest of the world where crop research is mainly financed by private companies or international organizations, the Chinese government is the funder of almost all crop research in the country (HUANG et al., 2000). Crop research in China has received substantial investment which accounts for more than half of the total research expenditure in the developing world, and modern varieties of major crops such as rice, wheat, maize, peanut, cotton and soybean are aggressively adopted by smallholders (HUANG et al., 2002). Despite the prominence of crop research in reshaping China's agriculture, literature on its welfare impacts is rather limited. Existing studies mainly focus on either cotton or rice (PRAY et al., 2001; HUANG et al., 2002; HUANG et al., 2005; WU et al., 2010; DING et al., 2011). While more evidence is needed for other important crops whose impacts are almost unknown.

This article helps bridge these gaps by evaluating the welfare impacts of modern peanut varieties (MPVs). This study employs a nationwide survey of peanut farmers and use propensity score matching (PSM) techniques to address the choice nature of farmers' adoption decisions. In addition to yield effect, impacts of MPVs on peanut income, other agricultural income, off-farm income and household income are further disentangled through multiple PSM identifications. The impact on income inequality is finally estimated as the differences of inequality measures of observed income distribution (with MPVs) and counterfactual income distribution (without MPVs) simulated using treatment effect estimates (DING et al., 2011; ZENG et al., 2015). It is found that the MPV adoption significantly boosts peanut income and total household income, but increases income inequality.

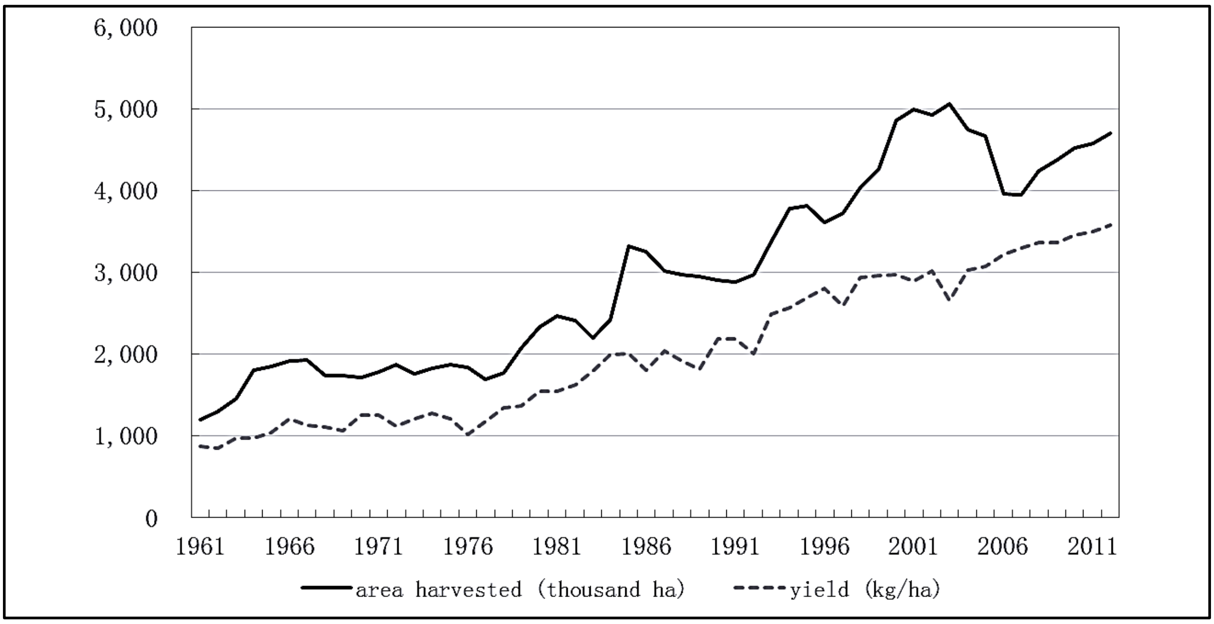
Our contribution is twofold. First, we provide some first evidence of the welfare impacts of peanut technologies in China, the most important industrial and oilseed crop of the largest producer in the world (USDA-FAS, 2012), and complement the growing impact analysis literature of crop technologies worldwide. Second, we apply innovative control for certain unobserved characteristics, differentiate possible impacts that occur through multiple income sources, and further disentangle the impacts on income and inequality, thereby obtaining more accurate impact estimates as well as multidimensional policy implications.

2 Peanut Production and Research in China

Peanut is the most important industrial and oilseed crop in China. Modern peanut is known to be of South American origin and introduced in the last few centuries. Peanut is grown for both domestic consumption and exports in most agro-ecological zones, and is usually rotated other crops to improve soil fertility through nitrogen fixation. Chinese farmers utilize peanut in a variety of ways, including using peanut seeds for direct consumption, oil extraction and peanut butter manufacturing, while using stalks and leaves for animal feed and peanut shell for fuel (YAO, 2004). Peanut is generally considered a cash crop in many parts of China.

China is the largest peanut producer of the world, accounting for 21.1% of total cropping area and 43.4% of total production worldwide in 2010-2011 (USDA-FAS, 2012). From 1961 to 2011, peanut production in China has increased from 1.05 million metric tons to 16.05 million metric tons (FAO, 2014). Peanut cultivation area in China observes steady expansion since the 1960s, while it is not until the late 1970s have tremendous yield increases been observed (Figure 1), largely due to the adoption of MPVs (YAO, 2004).

Figure 1. Trends of total peanut area and yield in China: 1961-2011



Source: FAO (2014)

Peanut research in China started in the 1950s from farmers' own breeding practices (HUANG et al., 2002). Almost all MPVs in China are developed and released domestically, by either the Oil Crops Research Institute, a research sector of the

Chinese Academy of Agricultural Science, or numerous provincial academies of agricultural science. In fact, provincial academies are major contributors of MPV research, where most of them are developed with traits that meet local agro-ecological conditions (YU, 2008). Unlike key staples (e.g. rice) where yield is the major concern in crop research, peanut research in China largely focuses on alternative traits such as disease resistance, pest resistance, drought tolerance, as well as oil and protein content enhancement in seeds (YU, 2008).

In 2007, China's Ministry of Agriculture has initiated the building of the Modern Agricultural Technology System to promote sustainable agricultural growth and improve rural welfare. As a result, the National Peanut Research System was established in 2008, which consists of 25 experimental stations located in various agro-ecological zones across the country. Since then, peanut research has been implemented in a more systematic manner, with an increasing number of MPVs released each year. Although MPVs released previously and proved successful are still commonly adopted, most MPVs identified in our study are released after the 2000s. The only existing study of modern peanut production in China focuses on technical efficiency (ZHOU et al., 2013), and we are aware of no empirical assessment of the welfare impacts of MPVs, which directly motivates the current study.

3 Analytical Framework

PSM techniques are employed to estimate treatment effects of interest, where the treatment is the adoption decision of MPVs. The basic idea is to compare the outcomes of the treated (adopters) and the untreated (dis-adopters) with the most similar characteristics, matched by the propensity score, or the estimated probability of adoption. Firstly developed in ROSENBAUM and RUBIN (1983), PSM is increasingly applied to empirical impact evaluation (MENDOLA, 2007; BECERRIL and ABDULAI, 2010; WU et al., 2010; KASSIE et al., 2011).

Treatment effects are identified using the standard potential outcome framework (RUBIN, 1974). Suppose a total of N households (indexed by i) are observed, including N_1 adopters and N_0 dis-adopters. Each household observes the outcome of either $Y_i(1)$ if treated (adopting), or $Y_i(0)$ if untreated (dis-adopting). The treatment effect can be naively computed as the difference of expected outcomes:

$$D = E[Y_i(1)|X_i, T_i = 1] - E[Y_i(0)|X_i, T_i = 0] \quad (1)$$

where X_i is a vector of observed characteristics. However, such characteristics of the adopters and dis-adopters may not be similar prior to the treatment, and selection bias occurs. To see this, Equation (1) can be rewritten as:

$$D = ATT + \{E[Y_i(0)|X_i, T_i = 1] - E[Y_i(0)|X_i, T_i = 0]\} \tag{2}$$

where ATT is the average treatment effect on the treated, which is equal to $E[Y_i(1)|X_i, T_i = 1] - E[Y_i(0)|X_i, T_i = 1]$. It is obvious that D does not equal to ATT in general given possible selection bias expressed as the last term in Equation (2). Also, ATT is not directly estimable given that the second term of its expression, $E[Y_i(0)|X_i, T_i = 1]$, is unobservable. Thus, empiricists focus on the elimination of the selection bias so as to obtain ATT estimates as D which is directly computable.

PSM assumes that selection, or the endogenous adoption decision, is based on observed characteristics, and constructs a statistical comparison group by matching each adopter with one or several dis-adopters with the most similar observed characteristics. Identification of ATT is then facilitated as the average difference of outcomes between each adopter and matched dis-adopter(s). As there are multiple observed characteristics, matching in all dimensions is difficult. However, ROSENBAUM and RUBIN (1983) show that matching with the propensity score, or the estimated probability of adoption, is equivalent to directly matching observed characteristics in all their dimensions. The propensity score is defined as:

$$p(X_i) \equiv \Pr(T_i = 1|X_i) = E[T_i|X_i] \tag{3}$$

PSM eliminates selection bias under two assumptions. First, the unconfoundedness assumption suggests that conditioned on observed characteristics, the outcome in the absence of adoption is independent of the adoption decision. Intuitively, as adoption is a self-made decision which should not be treated as random, only random "left-outs" are needed, while arbitrary correlation between adoption decision and outcome is allowed for adopters. Second, the common support assumption further suggests that there exists substantial overlap in covariates between adopters and dis-adopters so that the propensity scores of both groups can be similar. These assumptions can be mathematically represented as:

$$E[Y_i(0)|p(X_i), T_i = 1] = E[Y_i(0)|p(X_i), T_i = 0] \tag{4}$$

With these assumptions satisfied, and given the equivalence between matching with all observed characteristics and matching with propensity score, the ATT estimator can be expressed as the difference of expected outcomes between adopters and matched dis-adopters with balanced propensity score on the common support:

$$ATT = E[Y_i(1)|p(X_i), T_i = 1] - E[Y_i(0)|p(X_i), T_i = 0] \tag{5}$$

Using a surveyed sample, empirical PSM procedure computes the ATT estimator as:

$$ATT = \frac{1}{N_1}\left[\sum_{i \in N_1} Y_i(1) - \sum_{j \in N_0} \omega(i,j) Y_i(0)\right] \tag{6}$$

where $\omega(i,j)$ is the weight applied to outcomes of matched dis-adopters. The final step is to estimate the standard error of ATT, which is obtained through bootstrapping.

The advantages of PSM as compared with alternative strategies that deal with selection bias are that it requires no distributional and functional form assumptions which, however, are critical to procedures such as instrumental variable regression and HECKMAN (1979) selection model. Such assumptions are rather restrictive and hardly testable, the relaxation of which can potentially reduce selection bias (HECKMAN et al., 1998). PSM avoids these issues by assuming no function forms while all covariates can be endogenous (HECKMAN and VYTLACIL, 2007).

A major concern of PSM lies in the assumption that selection, or the adoption decision, is based on observables. It is arguable that unobservable factors such as the farmer's attitude, experience, motivation, risk preference and ability would affect adoption decision making, producing hidden bias that threats the estimated ATT (ROSENBAUM, 2002). Two strategies are implemented to address this concern. First, beyond traditional explanatory variables, we aim to minimize hidden bias by explicitly including additional covariates to partially control for unobservables, a strategy also implemented in TAKAHASHI and BARRETT (2013). Second, as it is impossible to fully control for unobserved factors, ROSENBAUM's (2002) bounds are also computed to check the sensitivity of estimated ATT to hidden bias, which reveals the magnitude of unobservables' effect needed to reverse the estimation results (critical levels of hidden bias).

Multiple ATTs are estimated using PSM, including peanut yield, peanut income, other agricultural income and total household income. Investigation of the impact on income inequality then proceeds through counterfactual simulation (DING et al., 2011; ZENG et al., 2015). Specifically, we subtract the estimated ATT of total household income from observed total household income, while keep the total household income the same for dis-adopters, and a counterfactual income distribution is derived. Gini coefficients are then twice computed using observed and counterfactual income distributions, respectively, and the impacts of MPVs on income inequality are obtained as the differences of these Gini coefficients.

4 Data Description

This study is facilitated by a household survey of peanut farmers implemented in 2012. The survey was organized by the National Peanut Research System and data were collected by multiple experimental stations of the System, which provides information of the 2011-2012 cropping year. Stratification strategy is undertaken where counties are first randomly selected by experimental stations within provinces where they are located, and farm households are then randomly surveyed within each selected county. The data cover 19 provinces which jointly accounted for 97.37% of total peanut acreage and 98.26% of total peanut production in China in 2011. 748 farm households from 115 counties were originally included in the analysis, while 712 from 98 counties grew peanuts in the surveyed period with all needed information available.

MPVs are categorized as those primarily identified by the National Peanut Research System (YU, 2008), and subsequent releases of the same genealogy after 2008. Adopters are defined as those who grew MPVs in the previous cropping season, and dis-adopters are those who only grew traditional varieties in that season. As peanut is a self-pollinating crop, farmers can recycle seeds for a number of seasons without significant yield reduction. Thus, concerns on estimation bias due to seed recycling should be minimized. Accounting for sampling weights, our data suggest an adoption rate of 63.23% by area.

Basic household characteristics, including those of the household head, and plot features are recorded in the survey. Varietal information and details of peanut production in the last cropping season, such as acreage, inputs and yields are recalled by the farmer. Various types of income are reported by the farmer on an annual basis. The data also include variables that may partially capture unobserved factors in peanut variety selection. Specifically included are indicators of peanut growing experience, self-reported health condition of household head, village social network (existence of a village cadre in the household and farmer's cooperative membership), ability (pilot household status in peanut production[1]), social learning (number of field training attended) as well as risk attitude (the length of peanut seed recycling period and the number of stated concerns in adoption[2]). In addition to these observed covariates, provincial dummies are also included to capture any unobserved heterogeneity across different agroecological and macroeconomic landscapes (alternative inclusion of county fixed effects yields very similar coefficient estimates of major covariates).

1 A pilot household of peanut production is a selected attendant of peanut field schools, who is supposed to learn new peanut technologies first during intensive training and then communicate these technologies to other farmers.

2 Farmers were asked to make multiple choices among factors that potentially discourage their adoption of MPVs. These factors include: 1) lack of labor, 2) peanut price instability, 3) lack of harvesting machinery, 4) pest outbreaks, 5) lower profitability than other crops, and 6) high production costs. The number of selected concerns are included as an explanatory variable in the adoption decision modeling.

Table 1 presents summary statistics. As a major cash crop, peanut provides nearly one half of total agricultural income for both adopters and dis-adopters. Peanut yield and peanut income of adopters are significantly higher than those of dis-adopters, while this is not the case for total input costs. Off-farm income is slightly lower for adopters, but such difference is small and insignificant. As a result, total household income is significantly higher for adopters.

Table 1. Summary of selected characteristics[1]

	Adopter (n=441)	**Dis-adopter (n=271)**
Landscape (1=hill, 0=plain)	.557 (.497)	.681 (.466)***
Soil type (1=sandy loam; 0=other)	.705 (.459)	.728 (.446)
Household size	4.296 (1.474)	4.436 (1.509)
Total land holding (mu)[2]	17.53 (28.58)	16.49 (20.72)
Peanut area (mu)	10.05 (22.82)	8.117 (12.65)
Village cadre in household (1=yes; 0=no)	.187 (.391)	.213 (.410)
Head gender (1=M; 0=F)	.958 (.199)	.930 (.255)*
Head age (years)	50.02 (9.463)	49.77 (9.081)
Head education (years)	9.336 (2.640)	9.471 (3.407)
Head health (1=good; 0=average or poor)	.903 (.297)	.873 (.332)
Peanut growing experience (years)	16.45 (9.83)	17.42 (10.02)
Pilot peanut household (1=yes; 0=no)	.468 (.500)	.423 (.495)
Number of peanut trainings attended	1.297 (1.293)	1.040 (1.073)***
Cooperative membership (1=yes; 0=no)	.346 (.476)	.299 (.458)
Recycling seed >3 years (1=yes; 0=no)	.345 (.277)	.505 (.301)***
Number of concerns in adoption	1.599 (.879)	1.771 (.951)**
Peanut yield (kg/mu)	574.1 (191.3)	483.2 (152.5)***
Total input cost (yuan/mu)[3]	226.73 (301.12)	212.04 (293.34)
Total peanut income (yuan)[4]	14,764 (20,366)	10,898 (15,131)***
Other agricultural income (yuan)	15,666 (14,380)	14,310 (19,412)
Off-farm income (yuan)	4,835 (15,573)	5,858 (14,333)
Total household income (yuan)	35,265 (34,322)	31,066 (30,291)*

1 Standard deviations are reported in parentheses. *, **, *** indicate significant mean difference between adopters and dis-adopters at 10%, 5% and 1% levels, respectively.
2 1 mu = 0.067 hectare.
3 the aggregate monetary value of all physical inputs excluding labor
4 Daily average exchange rate in 2011 is 1 RMB yuan = 0.157 US dollar.

Source: authors' survey

5 Results

Empirical analysis starts with MPV adoption decision modeling. This is implemented using a logit model (probit model yields extremely similar results). Table 2 presents the results.

Table 2. Logit estimation of MPV adoption (n=712)[1, 2]

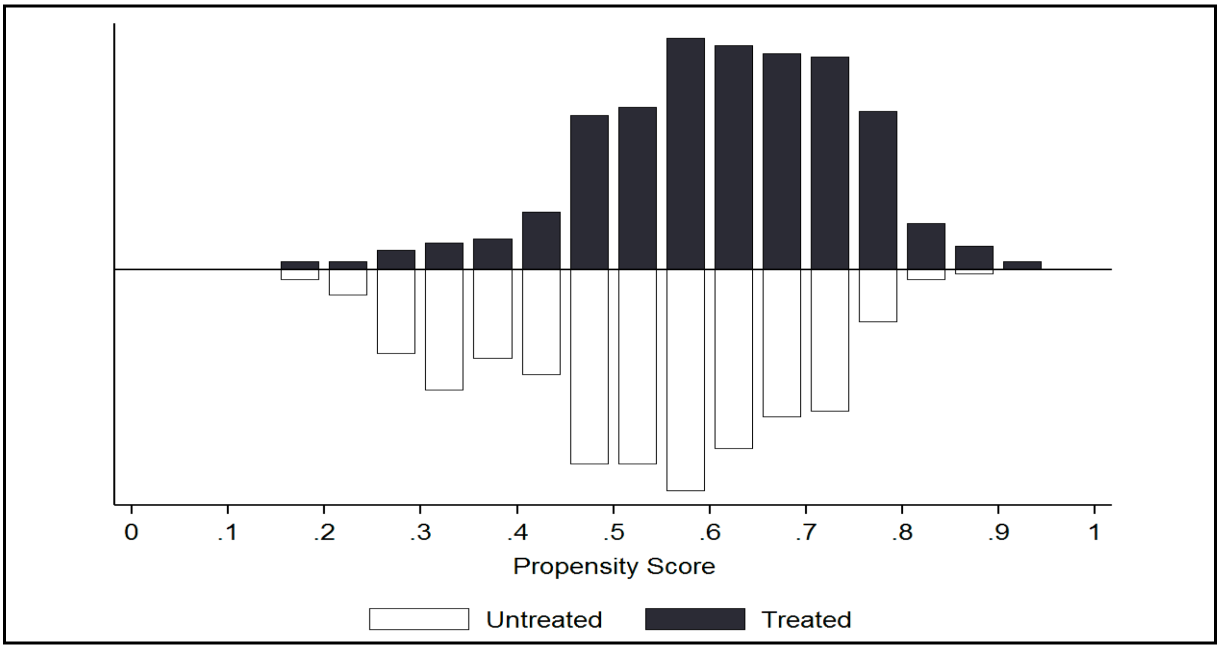
Variable	Coefficient estimate	Marginal effect
Landscape	-0.544 (0.162)***	-0.137 (0.034)***
Soil type	-0.121 (0.168)	-0.024 (0.043)
Household size	0.019 (.034)	0.010 (0.011)
Total land holding	-0.005 (0.004)	-0.001 (0.001)
Village cadre in household	-0.153 (0.173)	-0.059 (0.054)
Head gender	0.356 (0.171)**	0.093 (0.045)**
Head age	-0.050 (0.035)	-0.011 (0.014)
Head age square	0.001 (0.001)	0.000 (0.000)
Head education	0.089 (0.044)**	0.022 (0.009)**
Head health	-0.091 (0.232)	-0.041 (0.060)
Peanut growing experience	-0.005 (0.003)*	-0.001 (0.002)
Pilot peanut household	0.452 (0.197)**	0.110 (0.047)**
Number of peanut trainings attended	0.184 (0.053)***	0.060 (0.018)***
Farmer cooperative membership	0.202 (0.114)*	-0.057 (0.042)
Seed recycling period >3 years	-0.337 (0.121)***	-0.098 (0.048)**
Number of concerns in adoption	-0.194 (0.088)**	-0.046 (0.021)**
Constant	1.073 (1.259)	
Provincial dummies	Included	
Pseudo R^2	0.219	
Log-likelihood	-357.11	
LR chi-square (p-value)	69.45 (0.000)***	
Correct prediction	69.66%	

1 Standard errors are reported in parentheses. *, **, *** indicate significance at 10%, 5% and 1% levels, respectively.
2 Coefficient estimates of provincial dummies are not reported for the interest of space.
Source: authors' own estimation

Households adopting MPVs are more likely to be located in plain areas, headed by male and better educated individuals. Profounder linkages, in terms of marginal effects, appear to be associating adoption decision with those factors we purposely included to partially control for unobservables. Specifically, adoption is positively associated with pilot peanut household status and the number of field training attended, and is negatively associated with the length of peanut seed recycling period and stated number of concerns in adoption. Confirmation of these effects imply that these unobserved characteristics as captured by the latter group of variables may play an even bigger role than commonly observed characteristics in adoption decision making, and that the incorporation of these factors may potentially reduce hidden bias.

Based on the logit estimates, propensity scores are obtained for each household as the predicted probability of adoption. Propensity scores of adopters range from 0.179 to 0.928 and those of dis-adopters range from 0.154 to 0.854, suggesting the common support of 0.179 to 0.854. Only a trivial portion of observations out of this common support are dropped (9 out of 712). Figure 2 presents the histograms of propensity scores of adopters and dis-adopters, where the common support condition is visually satisfied.

Figure 2. Propensity score distribution and common support



Source: authors' own estimation

Formal balancing tests are further implemented to check if covariates are distributed similarly between adopters and dis-adopters after matching. ROSENBAUM and RUBIN (1985) propose to check the mean absolute standardized bias of covariates, where a standardized difference is suggested not to exceed 20% after successful matching. Alternatively, SIANESI (2004) suggests the comparison of pseudo R^2 and likelihood ratio test of the joint significance of all covariates in the logit model using the samples before and after matching. Hypothesizing no systematic differences of covariate distribution between adopters and dis-adopters after matching, the pseudo R^2 is expected to be lower and the joint insignificance of covariates should not be rejected.

Detailed results of these tests are presented in Table 3. The mean standardized biases of all covariates are reduced to 2.98%-3.93% after PSM. Pseudo R2 also observes decrease with PSM. Moreover, the null hypothesis that all covariates are zero cannot be rejected using the after-matching sample, meaning the observed characteristics of adopters and dis-adopters are similar enough and are thus not able to jointly predict adoption. Therefore, our PSM procedure has fairly successfully balanced covariates distribution between adopters and dis-adopters.

Table 3. Balancing tests of matching quality with logit propensity score estimation[1]

Matching algorithm[1]	NNM-1	NNM-5	KM-0.03	KM-0.06
Mean std. bias (before)	13.17	13.17	13.17	13.17
Mean std. bias (after)	3.93	3.55	3.21	2.98
Percentage of bias reduction	68.79	69.78	75.25	76.99
Pseudo R^2 (before)	.217	.217	.217	.217
Pseudo R^2 (after)	.019	.024	.011	.009
LR χ^2 with p-value (before)	61.43 (.000)	61.43 (.000)	61.43 (.000)	61.43 (.000)
LR χ^2 with p-value (after)	20.71 (.189)	20.38 (.205)	21.93 (.147)	23.07 (.112)

[1] NNM-1: single nearest neighbor matching with replacement; NNM-5: five nearest neighbors matching with replacement; KM-0.03: kernel matching with bandwidth 0.03; KM-0.06: kernel matching with bandwidth 0.06

Source: authors' own estimation

PSM procedures are then applied to obtain ATTs on multiple outcomes, namely peanut yield, peanut income, other agricultural income, off-farm income and total household income. Possible impacts on the other income sources are also investigated MPV adoption may lead to relocation of resources such as labor, and so it may affect other agricultural activities and off-farm employment. Several matching algorithms are applied, including nearest neighbor matching with either one nearest neighbor with replacement (NNM-1) or five nearest neighbors with replacement (NNM-5), and Epanechnikov kernel matching with alternative bandwidths of 0.03 (KM-0.03) and 0.06 (KM-0.06). We also check if the estimated ATTs are robust to radius matching (with the radius being either 0.001 or 0.005), and find that they are. Finally, standard errors of ATTs are obtained using bootstrapping with 1,000 replications.

Results are presented in Table 4. The first panel shows the yield ATT of MPVs, estimated as 101.2-118.3 kilogram per mu, a 20.9%-24.5% increase from the average yield of traditional peanut varieties.[3] These results are robust with multiple matching algorithms, all with high statistical significance (at least at 5% level).

As a result of the yield boost, peanut income per mu of an average adopter is increased by 434.0-452.3 RMB yuan (yuan hereafter, see the second panel of Table 4). Although the average peanut area of adopters is slightly larger than that of dis-adopters, such difference is statistically insignificant. Consequently, the total peanut income of an average adopter is increased by 4,511-5,084 yuan at the household level (the third panel of Table 4),[4] a 41.4%-46.7% increase as compared to an average dis-adopter. Such increase is much larger than that of peanut yield (20.9%-24.5%). The difference might be explained by unobserved factors such as better quality and appearance of peanut seeds and related products associated with MPVs which result in higher sale prices. This is of policy significance as it suggests that welfare impacts of MPVs can go way beyond their yield advantages alone.

The impacts of MPV adoption on other agricultural income and off-farm income are reported in the third and fourth panels of Table 4. Although no significant tradeoff is observed between peanut adoption and other cropping activities, there is weak evidence that could associate peanut adoption with decreased off-farm income. This might be explained by resource relocation with MPV adoption especially labor. As our data do not contain information on off-farm labor inputs, such hypothesis is not directly testable. However, it is still partly evidenced by our backstage check that compares labor inputs in peanut production between adopters and dis-adopters using the same PSM algorithms, where peanut labor inputs of adopters appear to be higher than those of dis-adopters (with at least 10% significance). Despite such likely tradeoffs, the magnitude of off-farm income lose is much smaller than the income gain with adoption, suggesting the overall welfare improvement can still be positive.

The impacts on total household income is finally presented in the last panel of Table 4, confirming the positive overall welfare improvement hypothesized above. Specifically, an average adopter observes a total household income increase of 4,365-4,822 yuan, 14.1%-15.5% higher than an average dis-adopter. Again, such results are highly significant and robust across specifications.

3 1 mu equals 0.067 hectare; so these numbers translate into a yield boost of 1,554-1,835 kilogram per hectare.

4 Daily average exchange rate in 2011 is 1 RMB yuan = 0.157 US dollar.

Table 4. PSM estimation of multiple treatment effects

Outcome variable	Matching algorithm[1]	*ATT*[2]	Critical level of selection bias
Peanut yield (kg/mu)[3]	NNM-1	101.2 (46.44)**	1.45
	NNM-5	117.9 (40.32)***	1.75
	KM-0.03	118.3 (37.60)***	1.65
	KM-0.06	102.9 (32.66)***	1.55
Peanut income per area (yuan/mu)[4]	NNM-1	441.6 (202.5)**	1.70
	NNM-5	452.3 (156.2)***	1.65
	KM-0.03	434.0 (177.4)**	1.65
	KM-0.06	440.5 (208.7)**	1.60
Total peanut income (yuan)	NNM-1	4,822 (2,315)**	1.65
	NNM-5	5,084 (1,898)***	1.75
	KM-0.03	4,511 (2,193)**	1.60
	KM-0.06	4,774 (2,156)**	1.60
Other agricultural income (yuan)	NNM-1	885.4 (1,022)	1.45
	NNM-5	707.3 (1,151)	1.50
	KM-0.03	822.9 (954.2)	1.65
	KM-0.06	916.3 (932.4)	1.65
Off-farm income (yuan)	NNM-1	-1,042 (656.4)*	1.45
	NNM-5	-763.5 (697.2)	1.45
	KM-0.03	-836.0 (563.1)	1.55
	KM-0.06	-944.4 (526.8)*	1.60
Total household income (yuan)	NNM-1	4,467 (2,601)*	1.55
	NNM-5	4,822 (2,309)**	1.75
	KM-0.03	4,365 (2,078)**	1.75
	KM-0.06	4,581 (2,184)**	1.70

[1] NNM-1: single nearest neighbor matching with replacement; NNM-5: five nearest neighbors matching with replacement; KM-0.03: kernel matching with bandwidth 0.03; KM-0.06: kernel matching with bandwidth 0.06

[2] Standard errors are reported in parentheses. *, **, *** indicate significance at 10%, 5% and 1% levels, respectively.

[3] 1 mu = 0.067 hectare

[4] Daily average exchange rate in 2011 is 1 RMB yuan = 0.157 US dollar.

Source: authors' own estimation

As a major procedure to check the sensitivity of estimated ATTs to hidden bias and their robustness, ROSENBAUM's (2002) bounds are also computed that reveals the magnitude of unobservables' effect needed to reverse the estimation results. The critical values of selection bias computed in all PSM procedures range from 1.45 to 1.75, suggesting that only if farmers with the same observed characteristics differ in their odds of adoption by a factor of 45%-75% would our ATT estimates be invalid. However, this is very unlikely as we have already controlled for important covariates affecting the adoption decision, including several measures that partially control for unobservable factors. Therefore, the impacts of hidden bias on the ATT estimates discussed above can be reasonably considered as minimal.

Three robustness check procedures are further applied. First, as it is suggested that PSM-estimated ATTs can be sensitive to propensity scores (HECKMAN et al., 1998), we alternatively obtains propensity scores using probit model to re-estimate all ATTs. These results are extremely close to our main estimates, lending credit to the latter.

Second, recent impact studies also carry out robustness checks using alternative definitions of the technology (TAKAHASHI and BARRETT, 2013), which is of practical value in crop impact assessment as varietal features may change overtime with seed recycling. We, therefore, investigate how relative impacts change with a stricter definition of MPVs. Specifically, as farmers are asked about the lengths they recycle peanut seeds, we utilize the information and redefine adopters as those who grew MPVs in the previous cropping season and also who recycle seeds for no more than three years. This narrower definition leads to a decreased number of adopters, with the dis-qualified adopters dropped from our sample. Our results show that the ATT estimates are in general slightly larger than our main estimates, suggesting the latter are rather conservative. Detailed results are available upon request in the interest of space.

Finally, we estimate a series of post-matching regressions to further validate our results. In each regression, the dependent variable is one of the outcomes in Table 4, and the independent variables include a binary adoption indicator and the same set of covariates used in propensity score prediction. We estimate these regressions through OLS with county-level clustered standard errors. If our PSM procedures have correctly identified the ATTs of interest (which appropriately account for self-selection bias in adoption), these ATTs would be reproduced using the simple OLS regressions with the post-matching sample. We see that this is the case for all outcomes. Therefore, we conclude from all these robustness check procedures that our main estimates are robust.

We now turn to the investigation of the impacts of MPV adoption on income inequality using the estimated ATT of total household income. This is done through simulating the counterfactual household income were MPVs not adopted (DING et al., 2011; ZENG et al., 2015). Specifically, we subtract the estimated *ATT* of total household income from observed total household income for adopters, while keep observed total household income the same for dis-adopters. The counterfactual distribution of total household income without MPVs is then derived. Gini coefficients are computed separately based on observed and counterfactual total household income distributions, respectively. The differences between these Gini coefficients are the impacts of MPV adoption on income inequality. As the change of total household income already incorporates different impacts on multiple income sources both on-farm and off-farm, our results go beyond any partial-equilibrium analysis and are general enough as an overall measurement of the income inequality impacts of MPVs.

Multiple counterfactual Gini coefficients are simulated using the total income *ATT* estimated through alternative PSM algorithms. Table 5 presents the results. Although one may envision all-round welfare improvement due to increased income, it is seen that, however, MPV adoption has actually widened income inequality, as evidenced by an increase of Gini coefficient by 0.004-0.006.

Table 5. Impacts of MPV adoption on income inequality

Matching algorithm for total income *ATT*	Gini coefficient with observed income	Gini coefficient with counterfactual income
NNM-1	0.424	0.419
NNM-5	0.424	0.418
KM-0.03	0.424	0.420
KM-0.06	0.424	0.420

Source: authors' own estimation

These impacts due to MPVs alone is not trivial. However, it does not necessarily imply welfare deterioration. For example, it can be the case that adopters benefit from MPV adoption, while dis-adopters are left with little welfare change, thereby widening the income gap. In that case, there is still Pareto welfare improvement at the population level which, however, is not captured by the Gini coefficient. Moreover, the Gini coefficient may observe an increase even if all farmers observe household income increases but to different extends (ARNOLD, 2007: 573-581). Given the limitations of this measure, further analysis beyond the support of our data is needed to disentangle the welfare change with MPV adoption. While our results do suggest that, with the mass adoption of MPVs, special attention may be needed from social planners among whose goals is inequality reduction.

6 Conclusion

This study provides some first evidence on the welfare impacts of MPVs in China. Our empirical procedure consists of PSM estimation of treatment effects on multiple outcomes and counterfactual simulation of impacts on income inequality. It is found that MPV adoption significantly increases peanut yield and peanut income. Although it might negatively affect off-farm income due to labor relocation, such impacts are small. As a result, total household income still observes significant increase with adoption. However, it is further found that the adoption of MPVs increases income inequality. Therefore, the diffusion and adoption of MPVs alone may not be able to meet the governmental goal of inequality reduction.

Our policy suggestions are twofold. First, given the positive welfare improvement at the household level, the adoption of MPVs should be consistently encouraged and peanut research should be continuously funded. Future research may focus on labor-saving MPVs which do not negatively affect farmers' off-farm employment, thereby expecting a larger increase in total household income. Also, agricultural extension agencies should continue investment in the diffusion of MPVs. As revealed by our logit estimation, factors like pilot household status, field training, seed recycling habits and concerns are all found important in adoption decision making, where effective extension can make a difference. More efforts are needed in strengthening the effects of training and trained attendants, encouraging frequent seed renewal, and eliminating farmers' concerns that prevent them from adoption.

On the other hand, the positive impacts of MPV adoption on income inequality should not discourage adoption promotion. Our findings simply suggest the benefits of MPVs, though positive and significant, might not have been evenly distributed across households. Thus, it is necessary to identify complementary strategies to improve the welfare status of the disadvantageous group. Policy instruments to encourage MPV adoption among such group may include provisions of seeds, credits and other necessary but expensive inputs, and subsidies. General income transfers from relative governmental funds may also work to reduce inequality, thereby serving as an effective supplement. Moreover, opportunities and mechanisms concerning technology diffusion through formal or informal learning should be enhanced for dis-adopters, which may facilitate wider adoption in the long run. With complementary policies that aim to improve the welfare status of the disadvantaged, Pareto improvement at the social level can be expected.

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Acknowledgements

We wish to thank the National Philosophy and Social Science Foundation of China (13&ZD160) and the Humanities and Social Science Youth Fund of the Ministry of Education of China (12YJC790071) for financial support. We are also grateful to China Agricultural Research System (CARS-14B) for funding the nationwide household survey. The current study is further facilitated by academic resources jointly provided by the Priority Academic Program Development of Jiangsu Higher Education Institutions and China Center for Food Security Studies at Nanjing Agricultural University.

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