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Original Article

Impact of the Input Subsidy on Farming Productivity of Maize Farmers in Son La and Hoa Binh provinces, Vietnam

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Abstract: Developing the agricultural system has been an urgent issue of the Vietnamese government recently. A wide range of subsiding and restructuring policies have been legislated, such as applying new technologies, agricultural materials, and hybrid seeds to improve the farming productivity of agriculture production. This article examines the outcome of the government agricultural subsidy policies for a drought-and-disease-tolerant maize variety in two north-west provinces of Vietnam. We apply the Difference in Difference (DID) model to analyze data of 255 Vietnamese maize farming households in 2016 and 2017. By combining all assumptions of the DID method, we assess the result by using three statistical estimation methods: (i) without covariates, (ii) with covariates, and (iii) propensity score matching. Our main finding is that maize farmers who received the subsidized seed variety in the two provinces had lower production compared to those who did not by approximately 1.895 tons/ha. The study therefore recommends that the government should consider other types of subsidy such as extension training programs to improve the productivity of the farmers.

Keywords: Maize, subsidy, difference in difference, Kernel matching.

1. Introduction

Vietnam is one of the fastest developing countries with great advantages of natural resources. Agriculture is one of the leading economic sectors which contributes mainly to the economic development of the country. However, the share of agriculture sector in the economy has declined in recent years, while that of other economic sectors have increased. Recently in Vietnam, agricultural autarky or urban agriculture - a form of domestic, self-sufficient producing - has been existing in parallel with traditional agricultural production, agricultural commodities, and modern

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technology. Agricultural autarky is flexible and changing according to agriculture commodities. In fact, the characteristics of this economic form are small-scale and scattered production using traditional working tools, family labors with low farming productivity. This type of production is popular in many regions in Vietnam, especially in mountainous areas.

In 2017, the Vietnam Prime Minister authorized Decision No. 899/QD-TTg on restructuring agriculture industry to improve value added and sustainability. Agriculture is oriented towards commodity production with industrial processing and agricultural services. By applying intensive cultivation and specialization, agricultural performance will have a strong foundation to improve its productivity and materials during both the pre-harvest and post-harvest phases [1, 2].

Hoa Binh and Son La provinces have issued similar legal documents with the aim of restructuring their agricultural sector. Specifically, Son La People’s Committee has enacted Decision No. 3528/QD on approving the project on developing and improving agricultural production efficiency in Son La province [3]. On the same note, Hoa Binh People's Committee has legislated Decision No. 1604/QD with similar contents [4]. By combining the advantages of growing livestock maize on steep lands with the subsidy of maize seed from the Decision No. 899/QD-TTg, the People’s Committees of Hoa Binh and Son La assisted their farmers with the hybrid maize seed with the characteristic of good disease and drought resistance. After one year applying the new seed in two provinces, maize output varied greatly between the two provinces although the terrain of Son La province is quite similar to that of Hoa Binh province.

The most common type of direct subsidy from government is for agricultural production extension courses [7]. The content of extension schemes includes additional skills and knowledge in not only production but also in marketing products. The analysis of To-The and Nguyen-Anh (2021) indicated the initial benefit of training programs for maize farmers’ production efficiency; meanwhile, the efficiency of guidance for market access for maize farmers as another vital part of the extension program was unlikely to be accounted [6].

Therefore, to evaluate the efficiency of using a hybrid maize variety as well as the subsidy policies, our study focused on estimating the change in farming productivity and the difference between the two studied provinces in hybrid maize farming productivity during 2015-2016. However, a limitation of benchmarking is that it can be only used for cross-sectional data. Evaluating impacts of a supportive policy generally employs panel or repeated cross-sectional data to cope with the before- or after-intervention difference, as well as treated and non-treated groups. Thereby, an advanced version of benchmarking is applied for panel data which is called Difference in difference (DID).

DID is, by principle, a quasi-experimental design that employs longitudinal data from treatment and control groups to estimate an appropriate counterfactual to obtain the causal effect. Ashenfelter and Card (1985) underlined the impact evaluation of any policies [8]. DID is one of the most widely adopted methods to estimate the treatment effects caused by observing “control” and “treatment” groups in different time periods, which is the core of policy research.

Based on the principles of the theory and assumptions discussed by Angrist and Pischke (2008) [7], our decision was to employ the DID method. The following sections interpret the principal understanding of the DID method and how we apply the method in our study. Specifically, section 2 systemizes generally the methodology of DID. Consequently, section 3 describes the data that we collected ourselves in the two provinces. Next, section 4 presents the results of the empirical DID model with different approaches and discussion of the outcome. Eventually, section 5 concludes the study and proposes some policy implications.

2. Literature review

Government input subsidies play an important role in supporting Vietnamese farmers to obtain more production capital [6]. In Vietnam, the subsidies are distributed through networks at the provincial, district and communal levels where poor and vulnerable farmers often have limited access to appropriate ecological conditions. The main advantage of hybrid maize is that seeds do not need to be purchased every season, albeit part of the production can be saved in-situ to be used as reserved seeds the following year. Moreover, the characteristics of the varieties are expected to be more resilient to pests, or water and nutrient scarcity, while mitigating the problem of soil erosion effectively. Therefore, our study intentionally applies public extension courses as our intervention to determine the impact of that supportive policy on maize farmer’s productivity by using the DID method.

A benchmarking tool is fundamentally a specific case of the DID method when applying cross-sectional data to evaluate the performance [9]. Indeed, one study conducted by Dinar and Tzouvelekas(2007) integrated non-neutral production frontier and benchmarking methods to evaluate the effects of different sources of extension services on farm outcome [10]. In an extension of benchmarking for longitudinal data, DID is a quasi-experimental design to estimate from treatment and control groups an appropriate counterfactual to obtain the causal effect. Athey and Imbens (2006) synthesized the literature of the DID method as the estimation of the policy interventions effect measuringthe changes in outcome experienced by the group receiving the treatment, adjusted by the change experienced by the group not studied inthe intervention [11]. Furthermore, most policy analysis is based on panel or repeated cross-sectional data in which predicted variables vary across collected data. However, some independent variables, such as personal traits, characteristics of farm location and studied policies, remain constant in values among all individuals in a group [7].

The selection of the targeted households is non-random because of the focus on the ethnic groups in Vietnam. This heterogeneity issue may cause an “estimation bias” of the DID estimator. Propensity score matching (PSM) is one of the most applicable methods to deal with non-random statistics. The matching algorithm such as Kernel can effectively decipher the issues caused by omitted observations, heterogeneity or selection bias. Its application gives more reliable results [13,14]. The mechanism of the matching process that determines a counterfactual of each observation in treatment groups seeks for a best match observation in control groups [15]. Thereby, our estimated outcome will be unbiased to report a significant contribution for policy implication.

3. Methodology

3.1. Difference in Difference concept

DID is a statistical technique used in econometrics and quantitative research in social sciences that attempts to mimic an experimental research design using observational study data, by studying the differential effect of the treatment of a 'treatment group' versus a 'control group' in a natural experiment [16]. Furthermore, DID treatment effects have been widely used when the evaluation of a given intervention entails the collection of panel or repeated cross section data. The DID estimator measures the treatment effect by looking at the difference between the average outcome in the control and treatment groups, before and after treatment. Angrist and Pischke (2008) determined that the DID integrates the advances of the fixed effects estimators with the causal inference analysis when unobserved events or characteristics confound the interpretation [7].

3.2. Modeling the outcome

Athey and Imbens (2006) determined the general model of DID [11]. Suppose that there are two groups indexed by treatment status

T = 0,1 where *0* indicates the farmers who do not receive the hybrid seed subsidy, i.e. the control group, and 1 indicates individuals who do receive the hybrid seed subsidy, i.e. the treatment group. Assume that we observe individuals in two time periods, $t = 0,1$ where *0* indicates a time period before the treatment group receives the subsidy, i.e. pre-treatment, and 1 indicates a time period after the treatment group receives governmental subsidy, i.e. post-treatment. Every observation is indexed by the letter $i = 1,..., N$; individuals will typically have two observations each, one pre-treatment and one post-treatment.

Let $\bar{Y}_0^T$ and $\bar{Y}_1^T$ be the sample averages of the outcome for the treated groups (receiving seed subsidy) before and after treatment, respectively. Similarly, let $\bar{Y}_0^C$ and $\bar{Y}_1^C$ be the corresponding sample averages of the outcome for the control group (counterfactual). In practice, by running the fixed effect regression, we can estimate the DID estimator for the individual *i*, the initial setting performs the following linear regression:

$$Y = \alpha + \gamma t_i + \beta T_i + \delta t_i T_i + e_i$$

Where α is constant term, β is treatment group specific effect, γ is time trend common to control and treatment groups, δ is true effect of the subsidy. On the other hand, we can estimate using the equation:

$$\hat{\delta}_{DD} = (\bar{Y}_1^T - \bar{Y}_0^T) - (\bar{Y}_1^C - \bar{Y}_0^C)$$

Taking the expectation of this estimator we will see that it is unbiased:

$$E[\hat{\delta}_{DD}] = E[\bar{Y}_1^T] - E[\bar{Y}_0^T] - (E[\bar{Y}_1^C] - E[\bar{Y}_0^C])$$
$$= \alpha + \beta + \gamma + \delta - (\alpha + \beta) - (\alpha + \gamma - \gamma)$$
$$= (\gamma + \delta) - \gamma = (\gamma + \delta) - \gamma = \delta = \delta$$

4. Data collection and analysis

4.1. Study sites and data collection

The data used in this paper was randomly collected from the field surveys conducted in two mountainous provinces of Vietnam from February to June in 2016 and 2017. We collected panel data by interviewing the same households and taking the identity code for each interviewee in 2016. The households were asked about their maize production (e.g. maize varieties, quantity of production, cultivation areas). Other questions related to household characteristics such as: terrain, gender, education, etc. Direct interviews included a quantitative household survey of 255 maize farmers in 2016 and 253 of those farmers in 2017.

Table 1: Definition of variables

Variable name	Definition	Nature
Productivity	Maize productivity of each household	Continuous
Time	Time when conduct the interview: before or after policy	Dummy
Terrain	Households cultivate maize on steep of land or not	Dummy
High education	High education level of the household's head: above high school or not	Dummy
Gender	Gender of household's head: male or female	Dummy

Source: Authors' estimation (2020).

Table 2: Descriptive statistics (n = 508)

Variable	Mean	Std. Dev	Min	Max
Productivity	4.207994	3.608457	1.11	8.01
Time	0.4990177	0.5004909	0	1
Terrain	0.7504912	0.4331545	0	1
High education	0.3772102	0.485165	0	1
Gender	0.6561886	0.4754463	0	1

Source: Authors' estimation (2020).

A definition of variables is available in Table 1 and the summary statistics of variables are reported in Table 2. Our data, obtained from a random sampling procedure, correspond to a small/moderate sample. Due to the research purpose, we estimated the productivity of maize by means of dividing cultivation area by maize production. We would like to represent the productivity of maize instead of the above two variables. Due to the same characteristics of the surveyed households, we describe the collected data in both 2016 and 2017 and there are 508 total observations. Specifically, the mean of maize productivity is 4.2 tons per hectare, however the standard deviation of the productivity is remarkably large at 3.6 tons/ha. The smallest production is 1.11 tons/ha; meanwhile the largest production is 8.01 tons/ha. In addition, the variable "Time" is used to differentiate the surveyed years 2016 and 2017. Similarly, three remain variables are "Terrain", "High education" and "Gender" are also given with the value 0 and 1 which are particularly described in Table 1 and Table 2.

4.2. Identification of dependent and independent variables

According to the theoretical model suggested by Athey and Imbens (2006) in Section 2, we decided to select our dependent variable as the productivity of maize. Besides, two surveyed provinces and the survey time are our independent variables [11]. Furthermore, our regression model would include three more pre-treatment covariates (X_k) into the theoretical model. Therefore, our proposed model has the following form:

$$Y = \alpha + \gamma t_i + \beta T_i + \delta t_i T_i + \beta_k X_{k,i} + e_i$$

$$Y = \alpha + \gamma t_i + \beta T_i + \delta t_i T_i + \beta_k X_{k,i} + e_i$$

with $k = 1, 2, 3$.

where, Y = productivity of new maize seed in 2015 and 2016 (n = 508), t = year after applying new maize variety (1 = year 2016, 0 = year 2015), T = two surveyed provinces (1 = Son La, 0 = Hoa Binh), X_1 = Gender (1 = male, 0 = female), X_2 = High education (1 = above high school education, 0 = under high school education), X_3 = Terrain (1 = steep maize cultivation land, 0 = flat maize cultivation land).

5. Estimation results and discussion

Our survey took place in Hoa Binh and Son La province where maize production accounted for a large amount of the share in total income of the local farmers. However, after one year applying a new maize variety that is drought-tolerant seed subsidized by the government, the production performance of two provinces is increasingly different in term of maize volume. Beside the general production efficiency and the adoption of the new variety of the whole surveyed households, we intend to examine whether the existence of the difference in output of the new type of seed in two provinces is significant by using the DID method. Despite the existence of other plausible methods based on the availability of observational data for quasi-experimental causal inference such as matching methods, instrumental variables, and regression discontinuity, DID estimations offer an alternative for reaching unconfoundedness by controlling for unobserved characteristics and combining it with observed or complementary information. Additionally, the DID is a flexible form of causal inference because it can be combined with some other procedures, such as the Kernel Propensity Score [17, 18].

Furthermore, we would like to import some pre-treatment covariates into the model. From Table 3, among the three covariates "Gender", "High Education" and "Terrain", two of the three covariates have a significant effect on the adoption of the new maize variety of surveyed households. "Gender" is not a significant factor in the probit model of propensity score estimation. Meanwhile, Education has a relatively large impact on the Y (productivity) at a 95% significance level. Lastly, "Terrain" has a tremendous effect on the productivity at a 99% significance level. Indeed, the two provinces have difficult and mountainous terrain that limits the growing of suitable crops for Son La and Hoa

Binh province. Similarly, Aalmo and Baardsen (2014) indicated that terrain hindrance was the only significant factor among his other six environmental factors in the model [19]. By combining all four assumptions of the DID estimation, we estimate the results of three simple DIDs in Table 4.

Table 3: Estimation results of probit model

Province	**Coef.**	**Std. Dev**	**z**
Terrain	-1.157***	0.201	-5.76
High education	-0.393**	0.177	-2.22
Gender	-0.464	0.180	-0.26
Constant	0.796***	0.203	3.93

Note: ***p < 0.01; **p < 0.05; *p < 0.1.
Source: Authors' estimation (2020).

Table 4: Estimation results of empirical model

Parameter	**Without covariates**		**With covariates**			
			No matching		Kernel matching	
	Estimate	t	Estimate	t	Estimate	t
Before (n = 255)						
Control	3.782		3.684		3.712	
Treated	3.333		3.158		3.333	
Diff (T-C)	-0.449	-0.78	-0.526	-0.87	-0.379	-0.63
After (n = 253)						
Control	5.580		5.465		5.954	
Treated)	3.681		3.498		3.681	
Diff (T-C)	-1.899***	3.27	-1.968***	3.17	-2.273***	3.76
Diff-in-Diff	-1.450*	1.77	-1.442*	1.76	-1.895**	2.22
R-square	0.04		0.05		0.07	

Note: ***p < 0.01; **p < 0.05; *p < 0.1.
Source: Authors' estimation (2020).

After one year applying the new variety, the production performance of maize farmers resulted differently. Initially, in 2016, the output of the two provinces was quite similar. Relying on the Diff (T-C) of the t-test statistic, we could not reject the null hypothesis that maize productivity in Hoa Binh province equaled that in Son La. However, after one-year cropping, maize farmers adopting the new variety in Son La province produced at higher productivity of maize compared to those in Hoa Binh province. Accordingly, the Diff (T-C) of the t-test statistic showed us that we were able to reject the null hypothesis that in 2017 the production performance of the two provinces was not different. The DID estimator represented the difference between maize output in 2015 and 2016 existed at different significance levels. Among the three Diff-in-Diff results, the DID method with covariates using kernel matching interpreted two interesting outcomes. As we mentioned in the previous section, the probit model illustrated the estimation of kernel matching with the above three covariates which described the "Terrain" covariate as a significant impact on the output between the two provinces. Specifically, when we account for the different provincial characteristics between adopted and non-adopted new seed variety by farmers in Table 4, in DID estimation, the steep and flat cultivation areas had an effect on the output of the new maize variety. Similarly, Aalmo and Baardsen (2014) indicated that steep terrain has a negative impact on farming productivity in Norway [19].

The DID estimator of kernel matching is more reliable than the two remaining methods. Another study of applying improved maize varieties in Mexico using propensity score matching indicated the kernel-based matching alo resulted in a more robust outcome [21]. Applying the DID estimator with propensity score matching of this method generated better policy implications by using time-series data [22]. Our DID estimator is -1.895, and the p-value was accompanied by two stars, interpreted as the statistical inference at a level of 95 percent. Most of the surveyed respondents believed the quality of seed provision by local government was less likely to be superlative compared to seeds purchased in the market.

6. Conclusion and policy implication

Regarding our estimation, the policy subsidy has a negative effect on the productivity of subsidizing the new maize variety. This implies the inefficient actions of the government for the productivity of the maize farmers in Hoa Binh and Son La provinces. Furthermore, the study indicates the extension's inability in subsidizing free inputs because it may affect the expenditure of government public funds for other sectors in the long term. The government should alternatively develop other types of subsidies such as extensive training programs because the core objective of the reform is to provide effective farming advisory services to farmers. Unlike public subsidies, this support scheme targets a specific group of farmers (i.e. low-income and cultivation in erosion-prone hillsides) to create awareness about erosion and to diminish the transaction costs of pro-environmental agricultural technology adoption with knowledge acquisition on cultivation techniques, inputs, product quality, merchandising and agricultural markets [24-27].

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