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Adoption of Sustainable Practices for Improving Agricultural Productivity in Viet Nam

Huong-Giang PHAM[#§]
Faculty of International Economics, Foreign Trade University, Viet Nam

Tuong-Anh T. NGUYEN
Faculty of International Economics, Foreign Trade University, Viet Nam

Hoang-Nam VU
Faculty of International Economics, Foreign Trade University, Viet Nam

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Abstract: Conventional agricultural methods are putting considerable strain on developing countries' environments. This problem can be ameliorated through the adoption of Sustainable Agricultural Practices (SAPs), which can bring economic, ecological and social benefits for farmers, consumers and the overall economy. However, the adoption rates of SAPs remain low in many developing countries. It is therefore vital to provide empirical evidence on the improvement of agricultural productivity as it may assist policymakers in designing suitable policy as well as encourage farmers to adopt SAPs on their farms. This study analyses the impacts of different SAP adoption packages on land productivity and labour productivity in Viet Nam. This is the first attempt in the context of Viet Nam to investigate the economic effects of adopting different SAP packages including crop diversification (CD), conservation agriculture practices (CA) and a combination of those. Using panel Viet Nam Access to Resources Household Survey (VARHS) data with multinomial endogenous switching regressions and an instrumental variable helps reduce potential biases in impact evaluation that previous studies have not fully addressed. Results confirm that if a farmer adopts SAPs, it may raise his net profit per hectare by about 4 million Vietnamese Dong (D)/ha/year, whereas the agricultural income per hectare increases by about 4–6 million D/ha/year. Moreover, the joint adoption of multiple SAPs brings higher benefits (of about 2–4 more million D/ha/year) than single SAP adoption. These findings suggest that policymakers and related stakeholders should focus on promoting the adoption of a combination of crop diversification and conservation practices.

Keywords: sustainable agricultural practices, multinomial endogenous switching regressions, household production, Viet Nam.

JEL Classification: D13, O13, Q12

[#] Corresponding author. Huong-Giang Pham, address: Faculty of International Economics – Foreign Trade University, 91 Chua Lang Street, Dong Da District, Ha Noi, Viet Nam. Phone: 84-933-523-468. E-mail: giang.pham@ftu.edu.vn

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1. Introduction

Agriculture is an important sector of any economy that contributes to growth and creates employment opportunities (World Bank, 2021). It helps end extreme poverty as 65% of poor working adults in Viet Nam make their living from it (Castaneda, 2016). The world's population may reach 10 billion by 2050 (Fisher, 2019), making sustainable agricultural development a critical issue. Current conventional farming practices, however, put agricultural growth, food security and poverty reduction at risk. The overuse of chemicals and over-exploitation of natural resources are causing soil degradation, deforestation, water scarcity and climate change (Fisher, 2019). FAO (2017) stated that the agricultural sector contributes to about 20% of global greenhouse gas emissions.

To meet global demand for agricultural commodities and address multiple issues caused by conventional farming, FAO suggests transforming current farming practices to Sustainable Agricultural Practices (SAPs) (Pimentel, 2005). SAPs are systems that use alternative techniques and technologies such as integrated pest management, intercropping, crop rotation (Pham, 2021), vermiculture (Sinha, 2011), adoption of biopesticides (Sharma, 2020), and genetically engineered crops (Zhang, 2011) as a substitute for conventional farming methods. SAPs are a win-win strategy since they can improve food security while addressing environmental issues.

Several attempts have been made to investigate the impact of multiple SAP adoption on different welfare indices (Khonje, 2018). Studies conducted in Asia focus only on the effects of adopting high-yield varieties. There are still significant knowledge gaps regarding the economic returns of SAPs. Some studies only focus on the impacts of single practice adoption, such as conservation agriculture (A.N. Abdulai, 2016) and minimum tillage (Jaleta, 2016), and household welfare.

There is limited evidence regarding the impact of SAPs adoption on agricultural productivity in Asia. Viet Nam is one of the largest exporters of agricultural commodities such as rice, coffee and pepper (IMF 2021). Its agriculture sector employs approximately 40% of the Vietnamese labour force, contributing an average of 15.3% to GDP in 2017, making it the industry with the lowest output per worker (World Bank, 2019a). Viet Nam is amongst the top 20 countries with the highest chemical fertiliser application rate (FAO,

2018) and amongst the top five countries most vulnerable to climate change (Trinh, 2018). Agricultural productivity depends on chemical inputs (FAO, 2018; Trinh, 2018). Arable land is shrinking while farm labour is migrating to the industrial sector (Phan and Coxhead, 2018). Food security is another concern as the population is increasing (GSO, 2019).

Viet Nam has a strong business case to transfer from conventional farming to sustainable farming. It has become one of the biggest exporters of high value-added agricultural commodities, especially rice, rubber, coffee and tropical fruits (IMF, 2021). Such products are in high demand in the developed world and consumers in developing countries are willing to pay more for environmentally-friendly agricultural products such as organic and fair-trade certified ones (Hainmueller, 2015). If Vietnamese farmers adopt SAPs on their farms, their products can meet the requirements of certified organisations and can thus be exported to developed countries at higher value.

The adoption of SAPs is, however, still limited in Viet Nam. Information on SAP adoption as well as studies on this topic, have been sporadic and piecemeal in the country. Limited studies exist related to the application of Viet Nam Good Agriculture Practice (VietGap), organic farming, rice intensification, and traditional practices (e.g. crop rotation, intercropping (IC)) (Huong, 2013; Ngo, 2007; D.T. Nguyen, 2005; Oxfam America, 2007). VietGap was enacted in 2008 by the Ministry of Agriculture and Rural Development (MARD), which covers food safety, product quality, environmental impacts, and the health, safety, and welfare of Vietnamese workers (MARD, 2008). In 2016, households that applied VietGap accounted for only 0.16% of total farm households in Viet Nam (GSO, 2017). Of all SAPs, organic farming has been applied the most sporadically. The Viet Nam Organic Agriculture Association (VOAA) estimates that organic agricultural production is worth about US$12–14 million (V.B. Nguyen and Dam, 2012). Willer (2016) stated that Viet Nam has over 65,000 hectares of land managed using organic agriculture (OA). That includes arable land, aquaculture, forestry and non-agricultural land; however, only approximately 43,000 hectares are available for cultivation.

Given the potential benefits that SAP adoption may bring to Viet Nam's agricultural sector, it is necessary to examine the reasons associated with the current state of SAP adoption in Viet Nam as well as the economic impacts of SAP adoption. While the determinants of SAPs adoption in the country were well-explained in Pham (2021), there is still limited evidence about the impacts of SAPs adoption on agricultural productivity. Providing such information can help: (1) farmers acquire knowledge and a better understanding of the benefits of SAPs, and (2) policymakers to design strategies to promote the adoption of SAPs in Viet Nam.

Thus, this study aims to fill this gap by exploring the impacts of adopting different SAPs on agricultural productivity in Viet Nam. It contributes to the existing literature by calculating the gain in household outcomes resulting from adopting different SAP packages. Potential biases caused by reverse causality and selection bias are significant challenges for impact evaluation studies. Thus, this paper uses multinomial endogenous switching regressions (MESRs) with instrumental variables for panel data analysis to deal with those issues, then calculates the average treatment by the treated (ATT) (i.e. the gap between actual and counterfactual outcomes if potential SAPs households do not adopt SAPs). This study confirms the economic benefits (the increase of land and labour productivity) of SAP adoption, which will contribute to literature and policy implications in Vietnam. Specifically, if farmers adopt SAPs, net profit per hectare increases by about D4 million per year, whereas agricultural income per hectare increases by about D4–6 million per year. Moreover, the joint adoption of multiple SAPs brings higher benefits (of an additional D2–4 more million per ha per year) relative to single SAP adoption. These findings suggest that policymakers and related stakeholders should focus on promoting the adoption of a combination of SAPs.

2. Literature Review

SAPs can solve multiple issues like agricultural challenges (such as low productivity growth) and environmental degradation (such as soil degradation or water scarcity) – 'nên có trích dẫn'. Yet, the economic benefits of SAP adoption for farmers are often debated. Impacts seem to be context-specific, which are especially relevant in the small farm sector with its large degree of heterogeneity related to agro-ecological and socio-economic factors. Clear evidence on the effects of SAP adoption may encourage farmers to adopt, as well as assist policymakers to establish policies to promote SAP adoption.

The adoption of SAPs investigated in previous studies can be divided into different groups in terms of: (1) economics impacts, (2) labour demand impacts, (3) poverty impacts, and (4) education and health impacts.

In terms of economic impacts, scholars are interested in the change of yield of main crop (A.N. Abdulai, 2016; Manda et al., 2016), crop production per hectare (for main crops only) (Kassie et al., 2008), household income (i.e. gross income per consumption unit) (Mendola, 2007) and reduction in the input used (Teklewold, Kassie, and Shiferaw, 2013; Zeng et al., 2015). Overall, by applying a high yield variety, farmers in different regions always experience an increase in the yield of main crops, such as maize in South Africa (Bezu et al., 2014; Di Falco et al., 2011; Manda et al., 2016) and rice in Asia (Mendola, 2007; Takahashi and Barrett, 2014). Most studies measure yield or production by the quantity produced per hectare. There is no study that has measured the productivity of multiple crops at a time. Some studies found significant improvement in reducing crop production costs when applying soil conservation practices (Michler et al., 2019; Teklewold, Kassie and Shiferaw, 2013; Zeng et al., 2015). The measurement for production costs is the quantity of input per hectare, such as the number of kilograms of nitrogen applied per hectare, or the number of pesticides by litre per hectare.

Another economic impact is change in household income. It is improved when the combination of improved varieties and conservation agriculture is applied (Khonje, 2018; Teklewold, Kassie, and Shiferaw, 2013). However, Takahashi and Barrett (2013) found when Indonesian farmers apply only rice intensification practices, there is no significant change to household income. Regarding the measurement of income, most studies use household income per unit of land (income per hectare) (Teklewold, Kassie, and Shiferaw, 2013) and gross income per capita (i.e. dividing total income by the total number of household members) (Manda 2016; Mendola, 2007). Bezu (2014) used consumption/income per adult equivalent, which seems to be more reasonable as the consumption of adults will be higher compared to children. The studies use measure per adult equivalent, where a child is treated as half of an adult. There is no study investigating the economic impacts of SAP adoption using agricultural income per farm worker although it is important to explore the change in terms of agricultural labour productivity.

Labour demand impacts are also discussed in studies (Montt and Luu, 2019; Teklewold, Kassie and Shiferaw, 2013) where significant change in the demand for labour occurs, perhaps to compensate for less frequent use of chemical inputs. Also, SAPs application, especially the adoption of a package of SAPs, will increase workloads for women (Montt and Luu, 2019).

Many scholars estimate the impact of SAP adoption on poverty reduction. SAP application (both single and combination) is found to reduce poverty significantly, especially in developing regions such as South Africa (A.N. Abdulai, 2016; Khonje, 2018; Zeng, 2015) and South Asia (Mendola, 2007).

Education and health impacts on children have also been examined by previous studies. Applying SAPs may increase demand for labour, leading children to participate in the agricultural sector and a reduction in child schooling (Montt and Luu, 2019). However, Takahashi and Barrett (2014) find no evidence of any side effect of rice intensification labour demands on child school enrolment in Bangladesh.

Regarding the benefits of applying SAP packages, studies (Kassie et al., 2018; Khonje et al., 2018; Manda et al., 2016; Teklewold, Kassie, and Shiferaw, 2013) find that adopting a combination of SAPs brings higher benefits in terms of household income (i.e. economic impacts) and poverty reduction, compared to adopting a single one. However, few studies have addressed the cumulative impact of SAP adoption between single and multiple packages.

Studies focused on the productivity impacts of SAP adoption including land productivity and labour productivity are still limited. The measurement of land productivity in previous studies also poses some concern. Most studies measure the economic impact of SAP adoption using household income per capita but given SAPs are applied for cultivation, it would be more informative if the impact evaluation focused on the impacts on agricultural income.

Choosing the estimation method is important in impact evaluation. Selection bias is one of the key challenges in non-experimental studies on SAP adoption and impacts of adoption. Farmers' adoption of SAPs may endogenously self-select. They may be chosen to participate in SAP adoption programmes because they are poorer than other households, or their adoption decisions are likely to be influenced by unobserved factors that may be correlated with outcome variables (Khonje et al., 2018). Other issues, such as the potential inverse causality between adoption status and the outcome variable (household welfare) and the heterogeneity of unobserved factors, make impact evaluation studies of SAP adoption more challenging (Kassie et al., 2018). In studies using observational cross-sectional data, propensity score matching (PSM) is commonly used to control for selection bias, but this potential bias is observable. Basically, at the first stage, the probit model at the plot-level or household-level data is estimated (with or without the Mundlak approach to control for FE) to calculate the probability of adoption for each observation. Then, at the second stage, each adopter is matched to a non-adopter with similar propensity score values to estimate the average treatment effects for the treated (ATTs) (Kassie et al., 2011). Thus, the propensity score value used in PSM is based only on observational factors that we modelled at stage 1. Therefore, the PSM method cannot control for the biases related to unobserved factors (A. Abdulai and Huffman, 2014; Jaleta et al., 2016).

To overcome the disadvantages of using PSM, Lokshin and Sajaia (2004) developed the endogenous switching regressions (ESR) model, which accounts for both observable and unobservable factors in impact evaluation studies. The ESR framework is modelled simultaneously in two stages. In the first stage, a farmer's choice of SAP is estimated using MNL (multinomial endogenous switching regression (MESR)) or logit/probit models, using adoption status as the dependent variable. In this model, one can account for unobserved heterogeneity by using the Mundlak approach (i.e. adding the mean of time-varying factors as explanatory variables besides other variables). Then, the invert mill ratios (IMRs) are calculated from the estimated probabilities in the model at the first stage. In the second stage, the impacts of the combination of SAPs are evaluated using the ordinary least squares (OLS) approach with IMRs as additional covariates to account for selection bias from time-varying unobserved heterogeneity. Other empirical studies (e.g. Di Falco, 2014; Kassie et al., 2015) have also applied ESR in impact evaluation. After estimating ESR, the average treatment effects are computed by comparing the expected outcomes of adopters with and without adoption. The ESR is suitable for continuously expected welfare indices, such as output and poverty gap, but not for binary outcome variables, such as poverty headcount. If one wants to apply this estimation technique for a binary outcome variable, they should use the recursive bivariate probit (RBP) model or multinomial endogenous treatment effects (Khonje et al., 2018).

Impact evaluation studies also face the endogeneity issue, because there may exist a reverse causality between SAP adoption and outcome measures. For example, higher profitability may encourage households to adopt SAP, and by adopting SAP, household profits may in turn increase. Thus, controlling for this endogeneity is important. To address this issue, some studies add instrumental variables to the first stage of the analysis above. Examples of instrumental variables that have been used are distance to the main market, distance to the cooperative office, number of contacts with extension agents, information on agricultural technologies and group membership (Khonje et al., 2018), as well as population density and SAP adoption rate at village level (Katungi et al., 2018). The simple falsification test is used to check the validity of the instrumental variable. In conclusion, studies of the impacts of SAP adoption should consider heterogeneity and endogeneity issues to avoid potential biases. Using panel data with ESR analysis and instrumental variables is ideal.

3. Data and Methodology

3.1. Data

The study utilises the Viet Nam Access to Resources Household Survey (VARHS) which is the most comprehensive survey of agricultural activities in Viet Nam (Tarp, 2017). It has been conducted every two years between 2006 and 2018 in 12 provinces across the five main regions of Vietnam. VARHS 2006 surveyed 2,324 households (randomly chosen from VARHS) that are representative of the rural areas in the 12 provinces in 2006. Later, each year the sample was expanded to ensure a representative data. Specifically, about 1,000 new households were added to VARHS 2008 that made the sample size increase to 3,200. They were interviewed for both 2008 and 2010 waves. The 2012 survey interviewed an extra 553 households. The reason for this extension of households is that the sample in VARHS was older than the representative sample in the Viet Nam Household Living Standards Survey (VHLSS) because a large share of the VARHS households is limited to households that were present in 2006.

Information about SAPs can be extracted from VARHS 2008 – 2016 as in 2006 there was not enough information regarding the application of SAPs while the data for 2018 is not available yet. To employ as much as possible the information regarding impacts of SAPs adoption on land productivity and labour productivity, this study will use the unbalanced panel data between 2008 and 2016. This longitudinal data allows us to control for unobserved factors in analyses associated with the impacts of the adoption on productivity.

The five most common SAPs applied are examined are crop rotation (CR), intercropping (IC), soil and water conservation (SWC) practices, organic fertiliser (OF) and land fallow (LF) because they are most adopted in Viet Nam as well as satisfying the definition of SAPs mentioned above. Adoption of CR and IC can improve productivity of land through nitrogen fixation (Kim et al., 2000; Teklewold, Kassie, and Shiferaw, 2013) and reduce the appearance of pests and diseases. Whereas, the SWC, OF and LF are found to improve the productive capacity of the land without chemical inputs, hence maintain or enhance the productive capacity of the land. In Viet Nam, a farm household can adopt one or more than one practice at a time (Pham et al., 2021), thus an evaluation of the impact of the practices on land productivity should consider multiple adoptions.

Five practices can be divided into two groups based on their key characteristics/benefits. The first one is crop diversification practices (CD practices), which include CR and IC, while the second group is called conservation agricultural practices (CA practices), which is made up of SWC, OF and LF. While CD practices focus on diversifying sources of income from cultivation, CA practices aim to improve soil and land quality in the long-term. Farmers can adopt CD or CA or a combination of both. The joint adoption of SAPs results in three combinations of SAP adoption and one non-adoption option, which are represented by the variable hhMSAP. This variable equals 0 if the household is a non-adopter, 1 if the household adopts at least one CD practice, 2 if the household adopts at least one CA practice and 3 if the household adopts both CD and CA practices. The summary statistics of multiple SAP adoption are presented in Table 1. Overall, more than 50% of the households surveyed in VARHS adopted CA practices, followed by a combination of both CD and CA practices, which account for about 25% of the sample. The non-adopters accounted for less than 10% of the survey sample, while about 3% were CD adopters.[1]

Table 1: Statistics on the Adoption of Multiple Agricultural Practices by Survey Year

hhMSAP	Frequency (%)					
	2008 (n=2,118)	2010 (n=1,598)	2012 (n=2,060)	2014 (n=1,604)	2016 (n=1,891)	Full Sample (N=9,271)
Non-adopters (0)	10.01	3.19	12.67	3.30	3.01	6.84
CD adopters only (1)	5.57	1.13	2.62	1.56	0.69	2.46
CA adopters only (2)	63.88	55.69	55.73	72.32	72.5	63.88
CDCA adopters (3)	20.54	39.99	28.98	22.82	23.8	26.83

hhMSAP = SAP package adoption scenario; n = sample size.

Source: Authors' compilation from VARHS 2008–2016.

[1] CD adopters, CA adopters and CDCA adopters are three discrete sets, so that amongst households, the number of CD adopters = CD adopters only + CDCA adopters, CA adopters = CA adopters only + CDCA adopters.

Table 2 presents the description of variables used in the analysis, while Table 3 presents summary statistics. To minimise the influence of outliers, following Khonje et al. (2018) and Bauchet, Morduch and Ravi (2015), data on the household outcome variables were winsorised with the largest 5% and smallest 5% of the three household outcomes[2]; and the log of the three outcomes used as the main dependent variables. Summary statistics for original household outcomes and winsorised outcomes are presented in Table 3. Three outcomes are examined, namely land profitability, agricultural productivity and labor productivity. Land profitability is calculated as total revenue from cultivation minus the total costs of cultivation, divided by cultivated land area. Agricultural income used to calculate agricultural productivity and labour productivity includes profit from cultivation activities and income from agriculture-related activities such as income from household members being hired to perform agricultural activities. On average, agricultural income per hectare (i.e. agricultural productivity) is twice as high as agricultural profitability (as shown in Table 3). Labour productivity is calculated by dividing the agricultural income by the number of household members who participated in agricultural activities.

[2] Winsorising or winsorisation is the transformation of statistics by limiting extreme values in the statistical data to reduce the effect of possibly spurious outliers. Statistics such as the mean and variance are very susceptible to outliers; winsorisation can be an effective way to deal with this problem, improve statistical efficiency and increase the robustness of statistical inferences (Stephany, no date)

Table 2: List of the Variables Used in the Impact Evaluation Analysis

Variables	Measurement
Dependent variables*	
Land productivity (mill D/ha)	(Total revenue from cultivation – Total cost from cultivation)/total farm size under cultivation[3]
Agricultural productivity (million D/ha)	Total income from agricultural activities /total farm size under cultivation
Labour productivity (million D/capita)	Total agricultural net income/ household agricultural labor
Independent variables	
hhMSAP	Household adopted one of four SAP combination: 0 = Non-adopters; 1 = Adopted crop diversification (CD[4]); 2 = Adopted conservation agricultural (CA) practices[5]; 3 = Adopted both CD and CA.
Gender	Gender of household head (1=Male/0=Female)
Age of household head	Age of the household head (in 10 years)
Education of head	Education of household head (in years)
Education of spouse	Education of household head's spouse (in years)
Household size	Number of household members (number)
Agricultural labour	Number of household members participating in agricultural production (number)

[3] See (Alexander, 2018) for the measurement of net farm profit suggested by Department of Primary Industries and Regional Development – Western Australia.
[4] at least one of two practices: CR and IC
[5] at least one of three practices: SWC, LF, OF

Table 2: ***Continued***

Variables	Measurement
Total farm size	Total size of all plots that household is managing (ha)
Other income	Household earns other income and transfers (1=Yes; 0=No)
TLU (log)	Tropical livestock unit (TLU) is livestock index converted from numbers of different livestock
Credit constraint	Household was rejected for the loan application (1=Yes; 0=No)
Political connection	Household has a political connection [6] (i.e. connection to someone in local authority not living inside their house. (1=Yes; 0=No)
Relatives	Number of relatives in and outside the village (number)
Agricultural groups	Number of agricultural groups that household is member of in village (number)
Sharing with peers	Household obtained assistance or sharing information regarding agricultural production with peers (1=Yes; 0=No)
Contacting extension agents	Household has access to extension agent in the last 1 year (1=Yes; 0=No)
Commune adoption rate	Ratio of total household in a commune adopted SAP and the total number of households in commune under this survey (ratio)

Note: *All household outcomes variables are converted to constant 2010 price using Consumer Price Index (CPI).
Source: Authors' compilation and calculation from VARHS 2008 – 2016.

[6] We follow Markussen and Tarp (2014) in generating a political connections variable that is equal to 1 if a household has relatives outside the household holding any office or other trusted positions in the commune or higher levels of government, and 0 otherwise. The connection excludes (1) members of household hold official positions, or (2) friends holding official positions at least at the lowest administrative level in Vietnam (i.e. commune) is to avoid the potential endogeneity. Whether a household has a member holding official position or non-relative holding official position in government is simultaneously determined with our main outcome variable land productivity and labor productivity. According to Markussen and Tarp (2014) 'Connections with relatives outside the household are arguably more exogenous. A household's investment decisions do little to affect the probability of relatives in other households taking up positions as officials'. The unobserved family characteristics (entrepreneurial spirit, risk and time preferences, etc.) may affect SAPs investment and the probability of having a relative in the local government. These factors could be control by using household fixed effects in the regressions.

Table 3: Summary Statistics of Variables Used in the Impact Evaluation Analysis by Survey Year

	2008		2010		2012		2014		2016		Total	
Variables	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Household outcomes												
Land productivity (mill D/ha)	28.84	32.67	20.77	47.79	20.17	29.61	25.80	319.28	23.95	105.97	23.88	155.62
Agricultural productivity (mill D/ha)	32.61	82.13	65.71	321.29	62.52	619.75	50.98	455.66	59.90	532.99	53.25	445.36
Labour productivity (mill D/person/year)	7.29	13.71	8.68	16.30	7.97	16.29	7.98	15.65	9.25	19.71	8.21	16.46
Household outcomes – 5% winsorised												
Land productivity (log)	3.11	0.79	2.74	0.86	2.71	0.81	2.67	0.86	2.70	0.87	2.78	0.85
Agricultural productivity (log)	2.80	1.30	3.16	1.44	2.70	1.54	2.67	1.46	2.60	1.61	2.76	1.49
Labour productivity (log)	1.66	0.87	1.82	0.88	1.61	0.99	1.66	0.95	1.72	1.03	1.69	0.95
Independent variables												
Gender (=1 if male)	0.82	0.38	0.78	0.41	0.82	0.39	0.81	0.40	0.79	0.41	0.81	0.40
Age of household head (years)	48.85	14.20	53.13	13.39	49.65	14.29	51.28	14.13	52.67	13.85	50.98	14.11
Education of head (years)	5.62	3.79	6.71	3.63	6.31	3.91	6.25	3.96	7.03	3.96	6.37	3.90
Education of spouse (years)	4.85	3.81	6.31	3.70	5.62	4.04	5.66	4.06	6.40	4.18	5.73	4.02
Household size (number)	2.99	1.03	2.91	1.04	3.04	1.16	3.12	1.25	3.21	1.33	3.07	1.18
Total farm size (log)	0.52	0.46	0.51	0.45	0.49	0.47	0.47	0.46	0.47	0.46	0.49	0.46
Agricultural labor (number)	2.78	1.63	2.51	1.57	2.49	1.58	2.53	1.64	2.41	1.66	2.54	1.63
Other income (=1 if yes)	0.91	0.28	0.96	0.20	0.96	0.20	0.96	0.19	0.97	0.16	0.95	0.21
TLU (log)	0.03	0.21	0.03	0.25	0.02	0.02	0.82	0.83	0.93	0.76	0.38	0.68
Household has credit constraint (=1 if loan application is rejected)	0.07	0.26	0.04	0.20	0.01	0.12	0.02	0.15	0.01	0.09	0.03	0.17
Political connection (=1 if yes)	0.14	0.35	0.12	0.33	0.09	0.29	0.08	0.27	0.07	0.26	0.10	0.30

Table 3: ***Continued***

Variables	2008		2010		2012		2014		2016		Total	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Relatives (number)	1.17	1.00	1.44	1.03	1.48	1.05	1.59	1.14	1.39	1.07	1.42	1.07
Sharing with peers (=1 if yes)	1.00	0.00	0.22	0.41	0.20	0.40	0.20	0.40	0.28	0.45	0.33	0.47
Agricultural groups (=1 if household joined agricultural group)	0.88	0.33	0.86	0.34	0.89	0.31	0.88	0.33	0.86	0.34	0.88	0.33
Contacting extension agents (=1 if yes)	0.04	0.20	0.45	0.50	0.47	0.50	0.52	0.50	0.44	0.50	0.38	0.49
Commune adoption rate (%)	72.29	25.63	62.71	29.30	61.57	29.72	64.73	26.01	60.13	31.64	64.09	29.01

Notes: SD = standard deviation.
Source: Authors' compilation from VARHS 2008 – 2016.

3.2. Estimation Methods

3.2.1. Multinomial Endogenous Switching Regression

This section outlines the estimation strategy used to investigate the impacts of multiple SAP (MSAP) adoption on land productivity and labour productivity. Following previous studies, the impact of MSAP adoption on land productivity and labour productivity modelled using multiple endogenous switching regressions (MESR), are described below.

The utility of a farm household i (U_i^*) adopting any practice j at time t is:

$$U_{jit}^* = X_{jit}'\beta + \bar{X}_{jit}'\omega + \varepsilon_{jit}, \tag{1}$$

Where X_{it} is a vector of observed exogenous covariates that represents household characteristics, social capital, resource constraints, district dummies, and β and ω are vectors of parameters to be estimated; $\bar{X}_{it}'\omega$ is a vector of the means of the time-varying variables which are used to control for fixed effects (FE) under the Mundlak approach. Although U_i^* is a latent variable, we can observe the binary outcome of a farmer's adoption decision $hhMSAP_{it}$, as below:

$$hhMSAP_{jit} = \begin{cases} 0 \; if \; U_{jit}^* > \max(U_{mit}^*) \\ \quad \cdots \\ J \; if \; U_{jit}^* > \max(U_{mit}^*) \end{cases} \tag{2}$$

for all $m \neq j; j = 0,1,2,3 \; for \; different \; SAP \; packages$

The outcome variables for each group of adopters can be expressed as:

$$\begin{cases} Regime\ 0: Y_{0it} = Z_{0it}'\beta + \bar{Z}_{0it}'\vartheta + \mu_{0it} \quad \text{if hhMSAP} = 0 \\ \quad \vdots \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad j = 1,2,3 \\ Regime\ J: Y_{Jit} = Z_{Jit}'\beta + \bar{Z}_{Jit}'\vartheta + \mu_{Jit} \quad \text{if hhMSAP} = \text{J} \end{cases} \tag{3}$$

Where variable Y_{jit} represents a vector of outcome variables of the i farmer in regime j at time t, namely land productivity, agricultural income per hectare (i.e. agricultural productivity) and agricultural income per farm worker. Z_{jit} is a vector of household's characteristics, $\bar{Z}_{jit}'$ is a vector of the means of household's characteristics, $hhMSAP_{it}$ is an indicator of the household SAP adoption status for different SAP packages42F[7] (0, 1, 2, or 3); μ_{jit} is a random error (RE) term, β and ϑ are vectors of parameters to be estimated. $\bar{Z}_{jit}$ is included to control for unobserved time-constant characteristics using the Mundlak approach (Mundlak, 1978). $\bar{Z}_{jit}$ includes time-varying variables only, thus the gender of the household head is excluded from the $\bar{Z}_{jit}$ due to no or very little variation.

The error term μ_{jit} includes unobserved individual effects and a random error term. Therefore, if we estimate (3) using ordinary least squares (OLS), parameter estimates will be biased since unobserved factors in the error term μ_{jit} in equation (3) may be correlated with ε_{jit} in equation (1). Examples of these unobservable effects include farmer risk, managerial abilities, farmer's experience of applying SAPs and his or her innate technical abilities (A. Abdulai & Huffman, 2014; Manda et al., 2016). To obtain a consistent estimate of β and ϑ in equation (3), the inverse mill ratio (IMR) needs to included, which is computed from the estimated probability in equation (2) and which is $\hat{\tau}_{jit}$ in equation (4) below:

$$\begin{cases} Regime\ 0: Y_{0it} = Z'_{0it}\beta + \bar{Z}'_{0it}\vartheta + \hat{\tau}'_{0it}\sigma_0 + \mu_{0it} \quad \text{if hhMSAP} = 0 \\ \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad\quad . \\ \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad\quad . \\ \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad\quad . \\ Regime\ J: Y_{Jit} = Z'_{Jit}\beta + \bar{Z}'_{Jit}\vartheta + \hat{\tau}'_{Jit}\sigma_J + \mu_{Jit} \quad \text{if hhMSAP} = \text{J} \end{cases} \quad j = 1,2,3 \quad (4)$$

$$\hat{\tau}_{jit} = \sum_{m \neq j}^{j} \rho_j \left[\frac{\hat{p}_{mi} \ln(\hat{p}_{mi})}{1-\hat{p}_{mi}} + \ln(\hat{p}_{jit})\right]$$

Where ρ is the correlation between the ε_{jit}'s and μ_{jit}'s. The standard errors in equation (4) are bootstrapped so that we can control for the heteroskedasticity arising from the generated regressors due to the use of two-stage estimation.

Controlling for unobserved factors using observational data is impossible, thus this study acknowledges that there may be some unobserved factors (such as extreme weather events, natural disasters or death of family members) that may cause potential endogeneity given that these shocks influence both adoption status and the outcome variables. Regional dummy variables and credit constraint variables are included to partially control for these shocks.

[7] hhMSAP = 0 for non-adopters; hhMSAP = 1 for CD adopters; hhMSAP = 2 for CA adopters; hhMSAP = 3 for CDCA adopters

The ESR framework involves the simultaneous modelling of two stages. In the first stage, a farmer's choice of SAP is estimated using a multinomial logit (MNL) selection (MNLS) model (using hhMSAP as a dependent variable), accounting for unobserved heterogeneity by using the Mundlak approach. The inverse mill ratios (IMRs) are calculated from the estimated probabilities in the MNLS model. In the second stage, impacts of the combination of SAPs are evaluated using OLS with IMRs as additional covariates in order to account for selection bias from time-varying unobserved heterogeneity. Other empirical studies (e.g. Di Falco, 2014; Kassie et al., 2015) have also applied ESR in their impact evaluations. After estimating the ESR, the average treatment effects are computed by comparing the expected outcomes of adopters with and without adoption. The ESR is suitable for continuous dependent variables. If one wants to apply ESR to binary outcome variables, recursive bivariate probit (RBP) models need to be adopted (Heckman, 1978).

In terms of endogeneity, there may be a reverse causality between SAP adoption and the outcome measures. For example, higher profitability may encourage households to adopt SAPs, and by adopting SAPs, land productivity may in turn increase. Controlling for this endogeneity is important. To achieve this, some studies include instrumental variables to the first stage of the analysis. Examples of instrumental variables that have been used are: distance to the main market; distance to the cooperative office; the number of contacts with extension agents; information on agricultural technologies; and group membership (Khonje et al., 2018), as well as population density and the SAP village adoption rate (Katungi et al., 2018). This chapter uses the commune SAP adoption rate as an instrumental variable. It is reasonable to assume that farmers are more likely to adopt a new agricultural practice if they observe their neighbours doing so. The commune adoption rate is the number of households adopting SAPs over the total number of households in a commune. Thus, commune adoption rate may affect the adoption decision of farmers (farmers are more likely to adopt agricultural practices if they observe their neighbours and friends adopting them (Krishnan and Patnam, 2014), but it is not correlated with the household outcome variables. In Viet Nam, a commune is the lowest administrative level. Following Di Falco, Veronesi, and Yesuf (2011) and Khonje et al.

(2018), we will use a simple falsification test to check the validity of our instrumental variable.

3.2.2. Multinomial Endogenous Switching Regression

Following MESR estimations, the average treatment effect on the treated (ATT) is required which is the difference in the expected values of outcomes on adopters had they not adopted. The framework for this estimation is explained below.

The expected value of different productivities for adopters with adoption (actual adoption) is:

$$E\left(y_{jit} \middle| U = j, Z_{jit}, \bar{Z}_{jit}, \hat{\tau}_{jit}\right) = \beta_j Z_{jit} + \vartheta_j \bar{Z}_{jit} + \sigma_j \hat{\tau}_{jit} \qquad (5a)$$

The expected value of the productivity for adopters had they decided not to adopt (the counterfactual) is:

$$E\left(y_{0it} \middle| U =, Z_{jit}, \bar{Z}_{jit}, \hat{\tau}_{jit}\right) = \beta_0 Z_{jit} + \vartheta_0 \bar{Z}_{jit} + \sigma_0 \hat{\tau}_{jit} \qquad (5b)$$

Estimates from MESR are used to predict the actual outcomes (equation 5a) and counterfactual outcomes (equation 5.5b) for a household that adopted one of three SAP adoption scenarios (CD, CA or CDCA). A t-test is computed to compare the expected outcome in (5.5a) and (5.5b).

$$ATT = E\left(y_{jit} \middle| U = j, Z_{jit}, \bar{Z}_{jit}, \hat{\tau}_{jit}\right) - E\left(y_{0it} \middle| U =, Z_{jit}, \bar{Z}_{jit}, \hat{\tau}_{jit}\right) = Z_{jit}\left(\beta_j - \beta_0\right) + \bar{Z}_{jit}\left(\vartheta_j - \vartheta_0\right) + \hat{\tau}_{jit}\left(\sigma_j - \sigma_0\right) \qquad (6)$$

In equation (6), the ATT is the difference between the mean outcome variables if the adopters had similar characteristics and resources to non-adopters, which is captured in Z_{jit}. ATT is corrected for the potential bias by adding the Mundlak approach (i.e. $\bar{Z}_{jit}$) to control for unobserved time-invariant factors and $\hat{\tau}_{jit}$ to control for selection bias and other endogeneity originating from unobserved heterogeneity. This section outlines the estimation strategy to investigate the impacts of multiple SAP (MSAP) adoption on productivity. The impact of MSAP adoption on productivity is modelled using endogenous switching regressions (ESR). In the first stage, a farmer's choice of SAP is estimated using Multinomial logit model (MNL) or logit/probit models, using adoption status as the dependent variable. Unobserved heterogeneity can be accounted for by using the Mundlak approach. The invert mill ratios (IMRs) are calculated from the estimated probabilities in the first stage.

In the second stage, impacts of the combination of SAPs are evaluated with IMRs as additional covariates (Kassie et al., 2015). After estimating ESR, the average treatment effects are computed by comparing the expected outcomes of adopters with and without adoption. The ESR is suitable for continuously expected welfare indices but not for binary outcome variables. The estimation technique for a binary outcome variable should use the recursive bivariate probit (RBP) model or multinomial endogenous treatment effects (Khonje et al., 2018). We also include instrumental variable(s) to control for the endogeneity and use the simple falsification test to check the validity of the instrumental variable(s).

Following MESR estimations, the average treatment effect on the treated (ATT) is calculated which is the difference in the expected values of outcomes of adopters had they not adopted. From this calculation, we can find the actual impacts of SAP adoption on the agricultural productivity.

3.3. Hypothesis

Based on the analysis strategy mentioned above, we advance the following hypotheses:

H1: Adoption of multiple SAPs especially the land conserving practices may bring higher land productivity

H2: Adoption of crop diversity practices may bring higher labour productivity while the adoption of land conserving practices may reduce the labor productivity.

4. Results

4.1. Factors Affecting the Adoption of Multiple SAPs

Table 4 presents marginal effects from the MNL estimation of equation (5.2). Although coefficients and marginal effects are available, interpreting marginal effects of the individual probability of adoption is straightforward (Khonje et al., 2018; Nguyen-van et al., 2017). The marginal effects of factors associated with the adoption of SAP differ across different SAP combinations. Specifically, household characteristics are not significantly associated with the adoption of SAP packages, which is similar to findings in Pham et al. (2021) for individual adoption. The adoption of only CD or only CA is negatively associated with household size and farm size. Specifically, having one adult equivalent (i.e. one adult or two children aged less than 18 years) reduces the probability of adoption of CA by 1%, whereas managing a 1% larger farm size reduces the probability of adopting CA by 6.5%. CA practices such as conservation practices and OF use require not only labour but also investment. Large farm sizes may discourage farmers to invest in such practices. In contrast, farm size and household agricultural labour significantly encourage the adoption of combinations of CD and CA. This may be because more available land and labour allow farmers to adopt multiple practices at a time and there may be economies of scale in doing so.

An important finding is that social capital plays a role in encouraging the adoption of multiple types of SAPs (i.e. CDCA). Specifically, having relatives outside of the household who hold leadership positions in local authorities encourages the adoption of CDCA by 9%. If a farmer shares information regarding cultivation with his peers (i.e. friends and neighbours), it increases the probability of CDCA adoption by approximately 5%. Therefore, it is important to promote the adoption of multiple SAPs via social capital channels, both formally (via extension agents) and informally (via relatives and peers). Results also suggest that political connections are negatively associated with the adoption of CA practices. This could be explained by households with political connections obtaining knowledge of the benefits of SAPs earlier and therefore becoming early adopters. For some middle- and long-term investments such as SWC practices, farmers do not need to re-invest every year. Therefore, if farmers are early adopters, they are less likely to adopt during the survey period.

Table 4: Marginal Effects of Multinomial Logit Model for Factors Affecting SAP Adoption

Variables	Non-adopters		CD adopters		CA adopters		CDCA adopters	
Gender (=1 if male)	–0.010	(0.012)	–0.011	(0.008)	0.011	(0.038)	0.009	(0.038)
Age of household head (years)	–0.002	(0.002)	0.001	(0.001)	–0.003	(0.005)	0.003	(0.005)
Age of household head squared	0.000	(0.000)	–0.000	(0.000)	0.000	(0.000)	–0.000	(0.000)
Education of head (years)	0.002	(0.002)	0.001	(0.001)	–0.000	(0.005)	–0.003	(0.005)
Education of spouse (years)	0.001	(0.002)	0.002	(0.002)	–0.004	(0.006)	0.001	(0.005)
Household size (number)	–0.003	(0.006)	–0.010**	(0.004)	0.017	(0.016)	–0.004	(0.015)
Total farm size (log)	0.009	(0.012)	0.003	(0.008)	–0.065**	(0.030)	0.053*	(0.029)
Agricultural labour (number)	–0.005	(0.003)	0.001	(0.002)	–0.008	(0.009)	0.012	(0.008)
Other income (=1 if yes)	–0.003	(0.015)	0.011	(0.008)	–0.021	(0.038)	0.014	(0.036)
TLU (log)	–0.009	(0.007)	–0.005	(0.005)	–0.001	(0.013)	0.016	(0.012)
Credit constraint (=1 if Yes)	0.002	(0.018)	–0.005	(0.013)	0.009	(0.047)	–0.007	(0.044)
Political connection (=1 if yes)	–0.005	(0.011)	–0.010	(0.010)	–0.075***	(0.027)	0.090***	(0.026)
Relatives (number)	0.001	(0.003)	–0.004*	(0.002)	–0.002	(0.008)	0.005	(0.008)
Sharing with peers (=1 if yes)	–0.009	(0.009)	–0.008	(0.007)	–0.026	(0.022)	0.043**	(0.021)
Variables	**Non-adopters**		**CD adopters**		**CA adopters**		**CDCA adopters**	
Agricultural groups (=1 if joined)	–0.020	(0.015)	0.007	(0.009)	–0.003	(0.042)	0.016	(0.040)
Contacting extension agents (=1 if yes)	0.021***	(0.007)	–0.006	(0.005)	0.031	(0.019)	–0.004	(0.018)
Regional dummies	YES							
Year FE	YES							
Number of observations	4229							

Notes: Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Non-adopters are the reference category. FE = fixed effects.

Source: Authors' compilation from Stata.

4.2. Economic impact of multiple SAP adoption

The results of the second stage of MESR (estimation of equation (4)) are presented in appendix tables A2, A3 and A4. The commune SAP adoption rate is a good instrumental variable48F[8] as it significantly affects multiple SAP adoption but is not significantly associated with the household outcome measures. Unobserved time-invariant factors are controlled for using the Mundlak approach. The joint significance test in MESR is not statistically significant, indicating that the correlation between the explanatory variables and the unobserved heterogeneity is not important. In this paper, we choose to interpret results of MESR with the Mundlak approach.

The ATTs are calculated by comparing household outcomes of SAPs adopters versus the counterfactual outcomes if they had not adopted. The values of ATTs are presented in Table 5, showing that a household is better off if ATT is positive and worse off if it is negative. The adoption of any SAP scenario brings significantly higher land productivity and agricultural income per hectare than non-adoption. Specifically, households that adopt CD or CA gain, on average, 3.7 million D/hectare/year or 4 million D/hectare/year in profitability compared to the scenario where they had not adopted the practice. The combination of CA and CD can bring a gain of about 5.7 million D/hectare/year in household profit compared to non-adoption. In terms of agricultural productivity, CD adopters can increase productivity by 6.2 million D/hectare/year while CA adopters may gain 4.2 million D/hectare/year compared to their counterfactual. Amongst the three SAP packages, adopting both CD and CA brings the highest welfare to households: D10.3 million higher per hectare per year.

[8] The instrumental variable significantly associated with agricultural income per farmer for the CA adopter group, but not CD and CDCA adopter.

Table 5: MESR-based Average Treatment Effects of the SAP Adoption on Economic Outcomes of Farm Households

Outcome Variable	Technology Choice (J)	Adoption Status		Average Treatment Effects on the Treated (ATTs)
		Adopting (J=2,3,4)	Nonadopting (J=1)	
Land productivity (log)	CD_1CA_0	18.61	14.84	3.77**
	CD_0CA_1	14.16	10.17	3.99***
	CD_1CA_1	16.19	10.65	5.54***
Agricultural productivity (log)	CD_1CA_0	27.71	21.50	6.21**
	CD_0CA_1	21.87	17.67	4.20***
	CD_1CA_1	27.27	16.94	10.33***
Labour productivity (log)	CD_1CA_0	13.33	11.69	1.64
	CD_0CA_1	5.80	7.57	–1.77***
	CD_1CA_1	7.28	8.07	–0.79***

Notes: J represents adoption combination of technologies defined above. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' compilation from Stata.

Results also indicate no statistically significant difference in labour productivity between adopters and non-adopters for CD, whereas adopting CA and CDCA may reduce agricultural income per farmer by 1.7 million D/person/year and 0.8 million D/person/year, respectively. Given the average income of the adult equivalent in the studied areas is 7.29 million D/person/year, the reduction represents about 10–20%. This finding can be explained as SAP adoption requiring more labour compared to CA (Montt and Luu, 2019; Teklewold, Kassie, Shiferaw, et al., 2013), so households adopting CA and CDCA may have had to re-allocate their labour from other activities. The findings suggest that the increase in income from adopting CA and CDCA may not fully compensate for labour allocation costs. Given the adoption of CA practices brings long-term environmental benefits such as improved soil quality and more efficient water use via investment in SWC practices, OF and LF, farmers who invest in these practices may be willing to trade short-term benefits (from obtaining higher yields and income) for these long-term benefits (possibly environmental benefits). Therefore, lower average labour productivity is understandable in this context.

4.3. Robustness Checks

Instrument variable fixed effects (IV-FE) regressions are used as the main robustness check. As discussed in the introduction, the unobserved heterogeneity in studies regarding the impacts of agricultural technology adoption on household outcomes can be estimated using FE panel data regressions. However, unlike in MESR, selection bias cannot be controlled for in FE panel data regressions. Results of the IV-FE regressions are presented in Table 6. Overall, the estimated treatment effects (of SAP adoption) are positively and statistically significant for the adoption of CD and CA, but not significant for CDCA. This result confirms the importance of CD and CA adoption for increased land productivity and agricultural income per hectare. However, for agricultural income per farmer, the impact of the different SAP combinations is not statistically significant.

In addition, we estimate the ATUs, which are presented in appendix table A5. This is the counterfactual estimation of household outcomes for non-adopters if they were to adopt. Overall, non-adopters would benefit in terms of agricultural income per farmer, but not in terms of land productivity and agricultural productivity. It can be seen from appendix table A1 that non-adopters have a significantly lower number of household members working in the agricultural sector compared to CD and CDCA adopters. Therefore, if non-adopters adopted SAPs, they may gain more in terms of labour productivity. On the other hand, non-adopters may be worse-off if they adopt CA and CDCA as the ATUs are negatively significant. Previous studies found that farmers can experience a fall in yields (as the result of changing production techniques or crop varieties) and net revenue or income (due to an increase in labour and input costs to compensate for the reduction in chemical inputs) when applying SAPs (Crowder and Reganold, 2015). Findings from Pham (2020) also found that the risk of output loss may discourage farmers from adopting SAPs. These reasons explain why some farmers decide not to adopt SAPs in the context of Viet Nam. SAP adoption is good for the overall economy and society as SAPs bring long-term benefits to the environment and people's health. To encourage non-adopters to adopt SAPs, it is recommended that policymakers should provide financial support to compensate them for any loss they incur.

Table 6: Robustness Checks on Welfare Effects of SAP Adoption Using Panel Regressions

Variables	Land Productivity (log)			Agricultural Productivity (log)			Labour Productivity (log)		
	IV-FE	N of obs	N of hhs	IV-FE	N of obs	N of hhs	IV-FE	N of obs	N of hhs
CD	0.311**	5,205	2,360	0.328*	5,348	2,426	0.103	5,322	2,414
	(0.121)			(0.175)			(0.120)		
CA	0.645***	4,787	2,234	0.556*	4,825	2,254	0.174	4,812	2,246
	(0.238)			(0.321)			(0.217)		
CDCA	–0.004	1,434	1,044	0.171	1,447	1,054	–0.009	1,447	1,053
	(0.319)			(0.420)			(0.336)		

IV=instrumental variable; FE=Fixed effect; hhs=households.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' compilation from Stata.

5. Conclusion

This paper utilised VARHS data to investigate the impacts of SAP adoption (single and multiple) on household-level outcomes in Viet Nam. Impacts of SAP package adoption on three outcomes were explored: impacts on land productivity (i.e. household profit per hectare), agricultural productivity (i.e. agricultural income per hectare), and labour productivity (i.e. household agricultural income per farm worker). An MESR framework was adopted to correct for selection bias and endogeneity that may arise from observed and unobserved heterogeneity. Unobserved heterogeneity was controlled for using the Mundlak approach in the pooled OLS estimation.

Results suggest that the adoption of SAPs significantly increases land productivity and agricultural productivity. In all adoption scenarios (CD only, CA only and both CDCA), households that adopted SAPs would have obtained poorer outcomes had they not adopted. Households achieve the highest benefits when they adopt a combination of CD and CA practices. It suggests that while income falls the costs of adopting SAPs fall to a greater extent, which is why profitability increases. However, when it comes to labour productivity, the adoption of CA or CDCA reduces agricultural income per farm worker. This may be due to the labour intensiveness of SAP adoption and/or households' willingness to trade income for higher environmental and health benefits. Regarding the factors associated with the adoption of different SAPs packages, cultivating larger farms encourages the adoption of CDCA as well as the utilisation of social learning channels, such as sharing information with peers and having political connections. Extension agents also play an important role in encouraging SAP adoption.

Findings on the impact of SAPs packages adoption and factors associated with these adoptions can assist policymakers and related stakeholders encourage the adoption of SAPs by providing empirical evidence on the impacts of SAP adoption on household level outcomes. Overall, the wider adoption of SAPs, especially the combination of CDCA practices, can generate higher benefits for smallholder farmers in Viet Nam in terms of profitability and agricultural income per hectare. There is some evidence, however, that adopting SAPs can reduce the agricultural income per farmer. To encourage farmers to widely use SAPs, there should be an explicit combination of solutions from stakeholders in both government and private sector. Firstly, for local government, social learning channels, agricultural insurance and financial support to compensate for any (potential) loss in agricultural production could be taken into account to educate and encourage farmers to adopt SAPs. Secondly, for pesticide dealers and retailers, as farmers are now paying more attentions to and more interested in SAPs, it is possible to sell simultaneously chemical pesticide and biopesticide products to farmers upon their request. Consultant(s) should also be ready at each store to provide detailed information and instruction about the usage of biopesticide. When farmers find that buying biopesticide products as well as receiving advice about applying them in their farming is quite convenient, the adoption of SAPs would be widely spread. Thirdly, for farmers, the key actors in the deal, it is a must to encourage them to not only change their perceptions to not only buy more biopesticide from other suppliers but also become biopesticide producers themselves. For example, producing vermicompose and using traditional ingredients (ginger, pepper, lemongrass) to prevent pests (Nga, 2022).

By having these policies together, farmers who are willing to trade-off short run gains for long-term environmental benefits (adopting CA and CD-CA) will not be disadvantaged by experiencing a reduction in income.

Although this study is the first to provide empirical evidence about the impact of SAPs adoption on agricultural productivity in Viet Nam, it still has some limitations that future studies should take into consideration. The analysis examined the impacts of SAP adoption on farm household outcomes. Although the combination of the MESRs and instrumental variable approaches helped to control for potential selection bias and endogeneity, it cannot fully take account of ecological and climate factors. Future studies could use natural disaster, rainfall indexes, etc. as control variables in the first stage of MESRs analysis. In our data, we do have information on natural disasters for three waves of the data. However, the information is limited which has led to a significant reduction in observations. Therefore, we decided not to include this variable into our analysis. We assume the ecological and climate information is considered in the fixed-random effect estimation by applying the Mundlak approach in the first stage of MERSs. Extension services regarding the SAPs adoption could be a (potentially) good instrumental variable, yet we do not have such information. The variable contacting extension service in our analysis is mixed information including extension support programmes, new varieties, the use of new fertilisers, etc., thus we cannot use this information as an instrumental variable. In addition, we assumed that a household was an adopter of one practice if it was applied in at least one plot. In reality, each household manages multiple plots at different locations. Plot characteristics are important factors explaining farmers' adoption decisions. However, due to the sporadic distribution of cultivated plots, we could not aggregate information on plot characteristics to put into the MNL model at stage one of the impact evaluation analysis.

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Appendices

Table A1: Summary Statistics of Main Explanatory Variables for Different Groups of SAP Adoption

Variables	CD Adoption			CA Adoption			CDCA Adoption		
	Nonadopters	Adopters	t	Nonadopters	Adopters	t	Nonadopters	Adopters	t
Gender (=1 if male)	0.81	0.86	–6.26***	0.84	0.85	–0.64	0.84	0.87	–2.42**
Age of household head (years)	50.83	50.66	0.62	47.45	50.16	–5.96***	46.89	50.38	–6.02***
Education of head (years)	6.28	6.36	–1.03	6.00	6.19	–1.39	5.85	6.40	–3.27***
Education of spouse (years)	5.56	5.53	0.27	5.01	5.34	–2.20**	4.67	5.51	–4.39***
Household size (number)	3.12	3.21	–3.53***	3.17	3.23	–1.41	3.23	3.27	–0.75
Total farm size (log)	0.50	0.66	–17.94***	0.72	0.57	9.52***	0.65	0.64	0.43
Agricultural labour (number)	2.66	3.07	–13.03***	2.92	3.00	–1.55	2.89	3.20	–4.67***
Other income (=1 if yes)	0.95	0.94	2.04**	0.92	0.94	–2.50**	0.94	0.94	–0.56
TLU (log)	0.40	0.35	3.24***	0.12	0.43	–10.51***	0.13	0.38	–6.64***
Credit constraint (=1 if Yes)	0.03	0.04	–2.80***	0.04	0.03	0.71	0.03	0.03	–0.13
Political connection (=1 if yes)	0.09	0.12	–4.11***	0.09	0.10	–1.42	0.09	0.13	–2.59***
Relatives (number)	1.41	1.45	–1.79*	1.19	1.40	–5.41***	1.23	1.47	–4.75***
Sharing with peers (=1 if yes)	0.33	0.38	–4.58***	0.41	0.37	2.29**	0.39	0.38	0.32
Agricultural groups (=1 if household joined agricultural group)	0.88	0.92	–5.96***	0.89	0.91	–2.53**	0.88	0.93	–3.74***

Table A1: *Continued*

Variables	CD Adoption			CA Adoption			CDCA Adoption		
	Nonadopters	**Adopters**	**t**	**Nonadopters**	**Adopters**	**t**	**Nonadopters**	**Adopters**	**t**
Contacting extension agents (=1 if yes)	0.39	0.46	–6.53***	0.31	0.46	–8.70***	0.33	0.50	–7.80***
Commune adoption rate (%)	58.52	77.56	–34.06***	48.30	75.86	–34.85***	40.34	81.26	–44.63

CD = crop diversification practices, CA = conservation agricultural practices, CDCA = crop diversification and conservation agricultural practices. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' compilation from Stata.

Table A2: Estimation of the Main Equation for Land Productivity (2nd Stage of MESR)

Variables	Land Productivity (log)			
	Nonadopters	CD Adopters	CA Adopters	CDCA Adopters
	(1)	(2)	(3)	(4)
Gender (=1 if male)	0.620	–0.016	0.062	–0.003
	(0.419)	(1.335)	(0.088)	(0.148)
Age of household head (years)	0.057	0.023	–0.004	0.011
	(0.068)	(0.289)	(0.009)	(0.016)
Age of household head squared	–0.000	–0.001	–0.000*	–0.000
	(0.001)	(0.002)	(0.000)	(0.000)
Education of head (years)	0.046	0.044	–0.019**	0.006
	(0.052)	(0.264)	(0.010)	(0.015)
Education of spouse (years)	0.032	0.140	–0.015	0.010
	(0.055)	(0.293)	(0.012)	(0.015)
Household size (number)	–0.026	–0.660	0.001	0.007
	(0.185)	(0.783)	(0.032)	(0.050)
Agricultural labour (number)	0.085	0.035	0.044***	0.055*
	(0.084)	(0.286)	(0.015)	(0.028)
Other income (=1 if yes)	–0.926*	0.598	–0.138*	–0.362***
	(0.498)	(1.344)	(0.081)	(0.105)
TLU (log)	–0.214	–0.660	–0.119***	–0.037
	(0.212)	(1.285)	(0.030)	(0.045)
Credit constraint (=1 Yes)	0.416	–1.291	0.078	0.185
	(0.398)	(2.056)	(0.113)	(0.148)
Political connection (=1 if yes)	0.008	0.433	–0.042	0.021
	(0.389)	(2.157)	(0.061)	(0.078)
Relatives (number)	–0.058	–0.191	0.019	0.022
	(0.100)	(0.343)	(0.016)	(0.024)
Sharing with peers (=1 if yes)	0.374	–0.915	0.103**	0.018
	(0.251)	(0.906)	(0.046)	(0.063)
Agricultural groups (=1 if joined)	–0.154	0.160	0.012	–0.019
	(0.495)	(1.586)	(0.088)	(0.115)
Contact extension agents (=1 if yes)	–0.054	0.583	–0.060	–0.045
	(0.222)	(0.885)	(0.042)	(0.060)
Constant	2.391	3.905	1.957***	2.176***
	(1.480)	(5.674)	(0.243)	(0.488)

Table A2: *Continued*

Variables	Land Productivity (log)			
	Nonadopters	**CD Adopters**	**CA Adopters**	**CDCA Adopters**
	(1)	(2)	(3)	(4)
Joint significance of time varying covariates	chi2(13) = 10.47	chi2(13) = 5.47	chi2(13) = 68.65***	chi2(13) = 16.49
Significance of instruments	F(1, 140) = 3.54	F(1, 49) = 1.39	(1, 2697) = 2.62	F(1, 1260) = 0.95
Ancillary				
Sigma2	0.663	0.752	0.671***	0.618***
	(0.875)	(10.253)	(0.122)	(0.160)
Rho1	-	–1.101	0.479	0.838*
	-	(0.826)	(0.296)	(0.448)
Rho2	–0.097	-	–1.164***	–0.760*
	(0.775)	-	(0.427)	(0.454)
Rho3	0.629	0.216	-	–0.189
	(0.526)	(0.832)	-	(0.307)
Rho4	–0.344	0.386	0.552***	-
	(0.695)	(0.769)	(0.201)	-
Number of observations	152	66	2,730	1,281

Notes: Non-adopter is the reference category. Standard errors were bootstrapped with 100 replications. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' compilation from Stata.

Table A3: Estimation of the Main Equation for Agricultural Income per Hectare (2nd stage of MESR)

Variables	Agricultural Income per ha (log)			
	Nonadopters	**CD Adopters**	**CA Adopters**	**CDCA Adopters**
	(1)	(2)	(3)	(4)
Gender (=1 if male)	0.502	–0.986	0.161	0.006
	(0.505)	(2.199)	(0.119)	(0.176)
Age of household head (years)	0.099	0.033	0.013	–0.019
	(0.075)	(0.355)	(0.013)	(0.019)
Age of household head squared	–0.001	–0.001	–0.000**	0.000
	(0.001)	(0.002)	(0.000)	(0.000)
Education of head (years)	0.063	–0.047	–0.022	–0.008
	(0.081)	(0.309)	(0.015)	(0.024)
Education of spouse (years)	0.084	0.051	–0.011	–0.008
	(0.085)	(0.393)	(0.019)	(0.021)
Household size (number)	–0.233	–0.200	–0.050	0.062
	(0.248)	(0.938)	(0.045)	(0.062)
Agricultural labour (number)	0.055	–0.351	0.051**	0.034
	(0.110)	(0.487)	(0.022)	(0.041)
Other income (=1 if yes)	–1.218**	0.584	–0.157	–0.207
	(0.528)	(2.430)	(0.098)	(0.138)
TLU (log)	0.275	–0.279	0.001	0.008
	(0.244)	(8.193)	(0.045)	(0.056)
Credit constraint (=1 Yes)	–0.196	–1.966	0.069	0.431**
	(0.622)	(4.701)	(0.162)	(0.184)
Political connection (=1 if yes)	–0.980*	–0.014	–0.026	–0.110
	(0.547)	(3.045)	(0.089)	(0.125)
Relatives (number)	–0.088	–0.006	–0.003	0.013
	(0.128)	(0.559)	(0.027)	(0.035)
Sharing with peers (=1 if yes)	0.438	–1.007	–0.160**	–0.148*
	(0.375)	(1.310)	(0.075)	(0.088)
Agricultural groups (=1 if joined)	0.091	0.207	0.205*	–0.154
	(0.590)	(2.328)	(0.124)	(0.169)
Contact extension agents (=1 if yes)	0.350	0.270	–0.030	–0.046
	(0.316)	(1.350)	(0.065)	(0.075)

Table A3: ***Continued***

Variables	**Agricultural Income per ha (log)**			
	Nonadopters	**CD adopters**	**CA adopters**	**CDCA adopters**
	(1)	(2)	(3)	(4)
Constant	1.295	3.872	1.919***	3.535***
	(2.022)	(6.724)	(0.344)	(0.695)
Joint significance of time varying covariates	chi2(13) = 2.22	chi2(13) = 1.23	chi2(13) = 43.63***	chi2(13) = 43.23***
Significance of instruments	F(1, 150) = 4.81	F(1, 49) = 0.07	F(1, 2712) = 4.12	F(1, 1263) = 3.86
Ancillary				
Sigma2	1.093	2.446	1.118***	1.097***
	(1.370)	(322.973)	(0.132)	(0.280)
Rho1	-	–1.288	–0.140	–0.060
	-	(0.871)	(0.292)	(0.401)
Rho2	0.518	-	0.447	0.862**
	(0.872)	-	(0.432)	(0.399)
Rho3	0.058	0.330	-	–0.508**
	(0.440)	(0.765)	-	(0.256)
Rho4	–0.349	0.660	–0.183	-
	(0.749)	(0.766)	(0.183)	-
Number of observations	152	66	2,730	1,281

Notes: Non-adopter is the reference category. Standard errors were bootstrapped with 100 replications. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' compilation from Stata.

Table A4: Estimation of the Main Equation for Agricultural Income per Farmer (2nd Stage of MESR)

Variables	Agricultural Income per Farmer (log)			
	Nonadopters	CD Adopters	CA Adopters	CDCA Adopters
	(1)	(2)	(3)	(4)
Gender (=1 if male)	0.238	–0.274	0.141*	0.040
	(0.425)	(1.208)	(0.082)	(0.116)
Age of household head (years)	0.072	0.051	–0.005	–0.004
	(0.053)	(0.222)	(0.008)	(0.015)
Age of household head squared	–0.000	–0.001	–0.000	0.000
	(0.000)	(0.002)	(0.000)	(0.000)
Education of head (years)	0.040	–0.039	–0.010	–0.014
	(0.043)	(0.222)	(0.010)	(0.020)
Education of spouse (years)	0.035	0.158	–0.001	0.013
	(0.063)	(0.248)	(0.012)	(0.018)
Household size (number)	–0.126	–0.541	–0.060*	–0.014
	(0.180)	(0.657)	(0.034)	(0.049)
Total farm size (log)	0.200	1.150	0.584***	0.495***
	(0.415)	(1.432)	(0.068)	(0.121)
Other income (=1 if yes)	–0.894*	0.067	–0.165**	–0.271**
	(0.460)	(0.872)	(0.079)	(0.114)
TLU (log)	0.357*	0.235	0.091***	0.082
	(0.200)	(1.202)	(0.031)	(0.053)
Credit constraint (=1 Yes)	0.026	–0.349	0.059	0.412***
	(0.506)	(1.825)	(0.096)	(0.105)
Political connection (=1 if yes)	–0.781*	0.972	0.009	–0.157**
	(0.411)	(1.597)	(0.064)	(0.078)
Relatives (number)	0.019	–0.171	0.008	0.025
	(0.099)	(0.495)	(0.018)	(0.021)
Sharing with peers (=1 if yes)	0.261	–0.267	–0.093**	–0.117*
	(0.248)	(0.752)	(0.045)	(0.066)
Agricultural groups (=1 if joined)	0.414	–0.087	0.177*	–0.024
	(0.444)	(1.282)	(0.092)	(0.120)
Contact extension agents (=1 if yes)	0.242	0.566	0.051	0.041
	(0.233)	(0.696)	(0.048)	(0.052)

Table A4: *Continued*

Variables	Agricultural Income per Farmer (log)			
	Nonadopters	**CD adopters**	**CA adopters**	**CDCA adopters**
	(1)	(2)	(3)	(4)
Constant	0.597	2.765	1.311***	2.922***
	(1.358)	(4.165)	(0.275)	(0.453)
Joint significance of time varying covariates	chi2(13) = 3.77	chi2(13) = 2.22	chi2(13) = 56.70***	chi2(13) = 25.39***
Significance of instruments	F(1, 150) = 1.98	F(1, 49) = 0.00	F(1, 2704) = 21.94***	F(1, 1263) = 0.36
Ancillary				
Sigma2	0.700	0.902	0.674***	1.192***
	(0.877)	(7.240)	(0.077)	(0.334)
Rho1	-	–1.095	–0.326	–0.459
	-	(0.945)	(0.301)	(0.298)
Rho2	0.156	-	–1.007**	–0.477
	(0.852)	-	(0.483)	(0.321)
Rho3	0.468	0.199	-	0.980***
	(0.550)	(0.754)	-	(0.134)
Rho4	–0.485	0.672	0.644***	-
	(0.676)	(0.677)	(0.195)	-
Number of observations	152	66	2730	1281

Notes: Non-adopter is the reference category. Standard errors were bootstrapped with 100 replications. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' compilation from Stata.

Table A5: MESR based Average Treatment Effects of Adoption of MSAPs on Household Welfare ATU

Outcome Variable	Technology Choice (j)	Adoption Status		Average Treatment Effects on the Untreated (ATU)
		Adopting (J=2,3,4)	Nonadopting (J=1)	
Land productivity (log)	CD_1CA_0	3.20e+08	15.74	3.20e+08
	CD_0CA_1	14.94	15.68	–0.74*
	CD_1CA_1	14.02	15.68	–1.66***
Agricultural productivity (log)	CD_1CA_0	8.49e+08	24.24	8.49e+08
	CD_0CA_1	20.34	24.13	–3.79***
	CD_1CA_1	19.34	24.13	–4.79***
Labour productivity (log)	CD_1CA_0	5026.29	8.84	5017.45***
	CD_0CA_1	9.64	8.84	0.79**
	CD_1CA_1	9.01	8.84	0.16

Notes: j represents adoption combination of technologies defiend above. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' compilation from Stata.

Table A6: MESR based Treatment Effects of the Adoption of MSAPs on Household Welfare – Unconditional Average Effects

Outcome Variable	Technology Choice (j)	Adoption Status		Average Treatment Effects
		Adopting (J=2,3,4)	Nonadopting (J=1)	
Land productivity (log)	$CD_1 CA_0$	9.48e+07	10.64	9.48e+07**
	$CD_0 CA_1$	14.53	10.60	3.93***
	$CD_1 CA_1$	15.95	10.60	5.34***
Agricultural productivity (log)	$CD_1 CA_0$	2.35e+08	17.80	2.35e+08***
	$CD_0 CA_1$	22.20	17.76	4.43***
	$CD_1 CA_1$	25.16	17.76	7.39***
Labour productivity (log)	$CD_1 CA_0$	5720.95	7.84	5713.11***
	$CD_0 CA_1$	6.26	7.84	–1.58***
	$CD_1 CA_1$	6.89	7.84	–0.94***

Notes: j represents adoption combination of technologies defined above. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' compilation from Stata.

Table A7: MESR based Treatment Effects of the Adoption of MSAPs on Household Welfare – Heterogeneity Effects

Outcome Variable	Technology Choice (j)	Adoption Status		Heterogeneity Effects
		Adopting (J=2,3,4)	Nonadopting (J=1)	
Land productivity (log)	$CD_1 CA_0$	17.29	19.37	–2.07***
	$CD_0 CA_1$	15.92	1.03e+08	–1.03e+08*
	$CD_1 CA_1$	15.06	5.37e+07	–5.37e+07*
Agricultural productivity (log)	$CD_1 CA_0$	20.42	19.90	0.52
	$CD_0 CA_1$	24.63	2.38e+08	–2.38e+08***
	$CD_1 CA_1$	23.34	1.59e+08	–1.59e+08**
Labour productivity (log)	$CD_1 CA_0$	11.54	12.33	–0.79**
	$CD_0 CA_1$	6.47	6656.34	–6649.87***
	$CD_1 CA_1$	6.47	4112.14	–4105.66***

Notes: j represents adoption combination of technologies defined above. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' compilation from Stata.

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