IMPACT OF MIGRATION ON THE VULNERABILITY OF POVERTY:
A CASE STUDY ON THE AGRICULTURAL HOUSEHOLDS IN WEST JAVA PROVINCE, INDONESIA

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ABSTRACT

Rural area in Indonesia relies heavily on the activity in agricultural sectors, while the source of income from the rural households is considerably obtained by the effort of cultivating the agricultural products or commodities. Nevertheless, several problems arise from the issue among agricultural households, as one of them is migration. Indeed, most migrants come to rural areas due to livelihood and poverty alleviation motives. Hence, the objectives of the study are to identify the determinants for agricultural households involving family members in rural-urban migration and measure the impact of migration on vulnerability to poverty. The study focuses on observing primary data with a face-to-face interview of 400 agricultural households in the area of West Java, Indonesia as a sample size. Then, the analysis uses the model of Propensity Score Matching (PSM), which is estimated by using the Probit Model. The empirical evidence from a Probit model indicates that the variables of the household head's age, education level, household size, house ownership and per capita expenditure significantly determines the propensity of agricultural households to be involved in migration movement. Meanwhile, migration activity has a positive impact on decreasing vulnerability to poverty by the agricultural households in West Java, Indonesia.

Keywords: *migration, vulnerability, poverty, agricultural households, Probit model.*

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1. INTRODUCTION

Unpredictable events are common phenomena faced by rural households in developing countries. These challenges, for example, in the form of natural disasters, market failures, and horizontal conflicts, are often shocks for their livelihoods. The impact of this shock will worsen the condition of their economy because, in general, rural communities do not have adequate social security and insurance. To anticipate such situations, they have to adjust strategies to become their general behavior, for example setting aside some economic benefits to save or diversify their income in various economic activities (Ellis, 1998).

The strategy for sustaining livelihoods carried out by rural households is migration. Migration can produce alternative livelihoods as a way out for them to minimize the impact of various shocks on their economic sustainability. In this case, migration is considered to have a high possibility for rural households to increase income through remittances generated by the migration (Ellis et al., 2006; Stark & Lucas, 1988). Indeed, migration opens the only way out for rural households to get out of the economic downturn and uncertainty, and they can diversify their income without having to leave their homes in the village through agricultural intensification and engagement on rural non-agricultural activities (World Bank, 2007). Furthermore, the potential for migration to generate significant increases in income has been proven (Xing, 2018).

In various theoretical perspectives that have been proposed, migration carried out by a person or a household is always accompanied by consideration of the type of business, location, and incentives that enable them to increase their income. Various factors influence the success to increase income from the migration process undertaken, for example, character and skills, economic and social networking, capital ownership, and experience.

Migration is determined by the push and the pull factors. The driving factor is a condition in the place of origin that causes individuals or households to migrate to other potential locations. This factor can be exemplified by aspects of political and social insecurity, limited job opportunities, and limited ownership of factors of production. Meanwhile, pull factors are defined as incentives that are available at the destination and have the potential to provide better economic and social benefits. Besides, in its postulate, migration is also determined by the surplus of labor at the origin location and the deficit of the labor of the destination location (Stark, 2005).

Migration, according to the New Economics of Labor Migration (NELM) theory postulated by Stark and Bloom (1985), is a collective decision taken by a household to maximize income, guarantee the smooth payment they must bear, ensure the sustainability of livelihoods through migration labor allocation. Although migration is a collective decision, it does not mean that migration is always carried out by all members of the household and involves all the resources they have, because, essentially, migration is an effort to diversify livelihoods.

As in other developing countries, rural households in Indonesia depend on their livelihood in the agricultural sector. However, most agricultural households in Indonesia are small farmers. The number of smallholder households in Indonesia is 14,250,000 households or 55.53% of the total agricultural households in Indonesia (Bappenas, 2014). For small farmers, high-risk agriculture encourages them to look for alternative sources of income despite low wages and high-risk

activities, and migration is one of them (Barrett et al., 2001). This opinion is confirmed by data that states that the phenomenon of rural-urban migration in Indonesia has been massive since the 1970s until the present when the secondary sector began to grow rapidly and became a significant source of national income. The rate of rural-urban migration in Indonesia experiences a trend that is always increasing, although not as dramatic as during the 1990s. Migration in Indonesia has always been dominated by migrants with livelihood and poverty alleviation motives (Resosudarmo & Kuncoro, 2006).

Research on the impact of migration on the poverty status of rural households has been conducted several times by previous researchers, but these studies have not yet come to a compact conclusion. Migration can reduce income inequality in rural areas (Garip, 2013). However, if migrants come from low-income families, then migration tends to result in a greater gap between villages and cities in terms of welfare (Amare et al., 2012) Specifically, in the aspect of poverty, migration is expected to reduce the vulnerability of rural households to poverty through remittance streams. However, the results of the study found that migration by households with high vulnerability will tend to produce low remittances so that poverty traps will remain (de la Fuente, 2010).

In the Indonesian context, research on the impact of migration on the poverty status of rural households has not been much studied. The research that has been done generally measures and compares the wages or living standards of migrants in the migration destination location (Sugiyarto et al., 2019; Rangkuti, 2012; Tjiptoherijanto, 1995). The studies did not examine the impact of migration on the standard of living of households who still live in rural areas but have economic activity in urban areas. Furthermore, studies that specifically involve agricultural households in the study of the impact of migration on their vulnerability to poverty have not been carried out at all. Therefore, this study aims to fill the gap in the area of migration studies that have been carried out previously in Indonesia. Specifically, this study aims to (1) identify the determinants for agricultural households to involve family members in rural-urban migration and (2) measure the impact of such migration on their vulnerability to poverty.

This article is organized into sections. The first part presents the introduction that covers the problem statement, a description of the theory, a brief review of the existing researches, and the objectives and contribution of the research to be achieved. The second part contains an explanation of the research method and data used in this study. Next, the third part narrates the findings based on the results of the analysis and descriptive data. Meanwhile, the last part describes the conclusions of the study

2. METHODOLOGY

2.1. Case Selection

Agriculture is a sector that has a fairly large level of risk. Several studies show that risks in the agricultural sector include production risks, market risks, institutional risks, personal risks, and financial risks (Komarek et al., 2020). The risk forces the majority of households in the agricultural sector to fall below the poverty line (Sricharoen, 2019). Most of the agricultural households carry out risk management measures to reduce the impact arising from each risk

faced by doing income diversification (Danso-Abbeam et al., 2020). Unfortunately, it is often difficult for opportunities to work outside the agricultural sector to be accessed by agricultural households. This encourages them to migrate, either abroad or to the city center in order to obtain income other than income in the agricultural sector (Alobo Loison, 2019). The issue related to the impact of migration on vulnerability to poverty of agricultural households has a high urgency considering that migration is one of the strategies that are widely used to deal with risks. Therefore, this research becomes very relevant to be carried out, so that it can be seen the relationship between the migration of agricultural households and their vulnerability to poverty.

2.2. Data Collection

This research was conducted in 3 different locations in West Java Province, Indonesia. These three locations were selected by purposive sampling method, namely Karawang Regency, Indramayu Regency, and Bekasi Regency. The district was chosen because based on data from the Indonesian Central Statistics Agency, the results of the 2015 population census showed that Karawang, Indramayu and Bekasi districts contributed 53.48 percent of the total migration in West Java in order to find work outside the regency. After the research area is well defined, the next step is the data collection process.

Data were collected by using the direct interview method with research respondents from November 2019 - March 2020. Research respondents were determined using the multistage stage random sampling method. The first stage was selected by respondents who were registered as residents at the village level, thus forming a sampling frame of 18,907 potential respondents. Then from the sampling frame available, the research respondents were selected by simple random sampling method of 1,376 respondents. Of the 1,376 respondents, not all of them have jobs as farmers, so the data needs to be done in a clearing process and to collect as many as 400 respondents of agricultural households. These 400 respondents are respondents used in this study. The 400 respondents consisted of 26 respondents from Bekasi, 172 Karawang, and 202 respondents from Indramayu. From all respondents, this study obtained 147 households with migration and 252 households without migration. Meanwhile, migrant respondents (147) are classified by type of work, namely self-employed, part-time workers, full-time workers, and freelancers

2.3. Data Analysis

In this study, migration is determined by information stating that there are household members who live outside the village for at least one month for work or economic activities in order to earn income. Migrant households are households that have had at least one family member who migrated during this period.

Vulnerability to poverty measurement requires some preliminary steps that involve statistical inferencing techniques, namely modelling consumption expenditure, then calculating the opportunity for households to fall into poverty. Regarding statistical inference, statistical inference includes all methods related to the analysis of partial data to produce a forecast or draw conclusions about a population. The basic foundation used to measure vulnerability in this study was adopted from the approach built by Chaudhuri et al. (2002), namely Vulnerability as

Expected Poverty (VEP). Defining vulnerability and procedures for calculating household opportunities for falling into poverty are the same as VEP.

Vulnerability to poverty can be interpreted as the possibility of individuals or households to fall into poverty. Some thresholds are used to separate groups of people who are vulnerable to poverty and not vulnerable to poverty. The determination of the boundary line is based on the possibility of individuals or households to become poor by 50 percent or 0.5. Households that have the possibility of being poor above 50 percent are classified as high vulnerable groups (Haughton & Khandker, 2009).

In this estimation, an indicator of household living standards is denoted by per capita consumption expenditure, the vulnerability of household i at time t is defined as the probability that a household will fall below the poverty line, m,

$$V_{it} = Pr(c_{i,t+1} \leq m) \tag{1}$$

V_{it} represents the vulnerability of household i at time t and $c_{i,t+1}$ is the household's per capita consumption expenditure at $t+1$. Furthermore, household consumption is determined by various household characteristics and unpredicted shocks, so that household consumption can be formulated as follows

$$c_{it} = c(X_i, \alpha_i, \beta_i, \varepsilon_i) \tag{2}$$

where X_i denotes observable household characteristics, while β_t is a vector of parameters of the household characteristics. The α_i and ε_{it} represent, respectively, an unobserved time-invariant effect, and an error term that measures any unobservable factors that contribute to the welfare outcome. Although i's future consumption $c_{i,t+1}$ cannot be observed in time t, estimating the consumption equation based on Equation (2) make it possible to measure household i's vulnerability as

$$V_{it} = Pr(c_{i,t+1} = c(X_i, \beta_{t+1}, \alpha_{t+1}, \varepsilon_{t+1}) \leq m | X_i, \beta_i, \alpha_i, \varepsilon_i) \tag{3}$$

Thus, household vulnerability can be derived from the stochastic feature of intertemporal consumption flows. As explained earlier, our data are cross-sectional. Therefore, this study used VEP size because adjustments are needed for the original VEP estimation. With cross-sectional data, the household consumption function is assumed as follows

$$\ln c_i = X_i \beta + \varepsilon_i \tag{4}$$

In the VEP estimation, it is necessary to establish the assumption that denotes the economic structure is relatively stable over time. Based on this assumption, future consumption is determined by predictable shocks, and characteristics that cannot be observed are accommodated by ε_i, which contributes to various levels of consumption per capita. It is also assumed that the error variants are as follows:

$$\sigma_{\varepsilon,i}^2 = X_i \theta \tag{5}$$

According to this model, β and θ are estimated by using a Three-Step Feasible Generalized Least Square (FGLS) operation (see Chaudhuri et al. (2002) for technical details). Afterward, $\hat{\beta}$ and $\hat{\theta}$ can be utilized for estimating the expected log consumption. Thus, the variance of log consumption for each household as follows

$$\hat{E}[lnc_i|X_i] = X_i\hat{\beta} \tag{6}$$
$$\hat{V}[lnc_i|X_i] = X_i\hat{\theta} \tag{7}$$

With the assumption that denotes lnc_i is normally distributed and employing the estimations above, the probability of poverty in the future is defined by the expression:

$$\hat{V}_i = \widehat{Pr}(ln\,c_i < \ln m\,|X_i) = \Phi\left(\frac{\ln m - X_i\hat{\beta}}{\sqrt{X_i\hat{\theta}}}\right) \tag{8}$$

Equation (8) indicates the presumption that high volatility of consumption reduces vulnerability for households with expected consumption below the poverty line, whereas it increases vulnerability for those whose expected consumption is above the poverty line. Thus, they might have little chance to escape from poverty if the poor are risk-averse.

The common weakness that exists in the study measuring the impact of a treatment/decision on the expected outcome is the occurrence of selection bias, where the parties being compared (obtaining treatment or deciding with those who do not) do not have a balance in term of characteristics embed at the control variables. This selection bias problem will generate bias in measuring the impact on outcome variables. One method that can negate the selection bias problem is Propensity score matching (PSM) (Heckman & Leamer, 2007).

The average treatment effect of migration (ATT) of farm households is calculated by the formula in Equation (9). Variables *D* in the equation are indicators of whether agricultural households have migrated members. Meanwhile, *Y* is the index of vulnerability to poverty. The PSM formula for calculating ATT is:

$$\Delta_{ATT} = E(\Delta|D = 1) = E(Y(1)|D = 1) - E(Y(0)|D = 1) \tag{9}$$

Where Δ_{ATT} is the average treatment effect of migration; $E(Y(1)|D = 1)$ is the expected value of vulnerability to poverty index of households with migration, and $E(Y(0)|D = 1)$ is the expected value of vulnerability to poverty index of households without migration.

PSM is employed to build counterfactual relations between households with and without migration. To control selection bias, statistically, the control group (non-migrant) equal to the treated group (migrant), and all observable covariates must be involved and match between the two groups. The propensity score, $p(X)$, as proposed by Rosenbaum and Rubin (1983), is the

probability of particular conditions determined by all covariates, *X*. Furthermore, the conditional independence assumption (CIA) has to be met by supporting variables for identification (Heckman & Leamer, 2007). If this assumption is achieved, the PSM estimator for Δ_{ATT} is formulated as follows:

$$\Delta_{ATT}^{PSM} = E_{(p(X)|D\,=\,1)}\{E[Y(1)|D = 1, p(X)] - \{E[Y(0)|D = 0, p(X)]\} \qquad (10)$$

Equation (10) illustrates the average difference, which is precisely weighted by the propensity score in each group, is the PSM estimator. In this study, PSM is estimated using the Probit Model. PSM explanatory variables (covariate *X*) were determined according to theory and previous empirical studies identifying determinants of the decision to migrate (Amare et al., 2012; Wang et al., 2011; Nghiem, 2010; Naudé, 2010; Brauw, 2009; Stark, 2005; Reardon et al., 1994).

$$Prob(D_i = 1) = F(AgeHH_i, AgeHHsq_i, AgLand_i, LandTen_i, Hsize_i, HHgen_i, HHedu_i, House_i, lnExp_i) \quad (11)$$

In the Probit estimation model indicated in equation (11), the PSM is estimated with explanatory variables, namely age of household head (*AgeHH*, year), occupied agricultural land area (*AgLand*, m^2), agricultural land ownership status (*LandTen*, = 1 if self-owned and = 0 if others), household size (*Hsize*, person), the gender of household head (*HHgen*, = 1 if male and = 0 if female), household head's education level (*HHedu*, = 1 if at least graduated from senior high school and = 0 if under senior-high-school), house ownership status (*House*, = 1 if self-owned and = 0 if others), monthly household's per capita expenditure (IDR). This research uses a natural logarithm of the expenditure (*lnExp*)to standardized the variable value and tightens its variants. This study also tried to capture the nonlinear relationship between migration and age as it introduced the square of age households' head (*AgeHHsq*).

In this study, Kernel Matching was employed in analyzing the PSM model. The Kernel Matching (KM) approach can be seen as a weighted regression of counterfactual results. Weight depends on the distance between each individual from the control group and treated group participants who are estimated to be counterfactual (Caliendo et al., 2005). Both algorithm approaches are very suitable for medium sample sizes, so they are suitable for use in this study.

3. RESULTS AND DISCUSSION

3.1. *Household characteristics*

Based on the information presented in Table1, household characteristics can be explored. The age of the household's head (*AgeHH*) in the two groups of households is relatively the same, which is around 41 years old. Besides, in terms of the household size (*Hsize*), the two groups are also relatively similar in which every household possesses five members. Most of those two groups are headed by male household heads (see the *HHgen* value). Education (*HHedu*), which represents the intellectual capacity of household heads, shows the gap between households with migration and without migration. The head of the household with migration who graduated from senior high-school and above is valued to 44%, while one of the households without migration was 33%. At asset ownership, the number of households who possess the self-owned house in the

without-migration group is more than that of the with-migration group. However, in terms of authorized agricultural land, those two groups have a slight difference in it. Also, they generate a similar amount of per capita expenditure

Table 1: Household characteristics

Variable	With migration		Without migration	
	Mean	**S. D.**	**Mean**	**S. D.**
Age of household head (year)	41.238	17.411	41.318	17.969
Household head's education level (= 1 if at least graduated from senior high-school and = 0 if under senior high-school)	0.441	0.497	0.330	0.470
The gender of the household head (= 1 if male and = 0 if female)	0.556	0.497	0.564	0.496
Agricultural land ownership status (= 1 if self-owned and = 0 if others)	0.714	0.452	0.727	0.445
Household size (person)	5.119	2.204	5.063	2.043
House ownership status (= 1 if self-owned and = 0 if others)	0.863	0.343	0.905	0.293
Monthly household's per capita expenditure (IDR)	498,223.8	381,275.3	437,032.7	350,438.7
Observation	148		252	

Source: Data computation, 2021

### 3.2. *Assessing the effect of migration on vulnerability on poverty*

Figure 1 illustrates the blocks of the matching observations with the common support approach. The diagram in the figure indicates that most of the samples are included in the matching process in the treated / household with migration (147) and the untreated / household without migration (252). One observation was not involved in the matching process (off-supported). Moreover, the sample equivalence compared in the PSM specification is presented in Figure 2. Before the matching stage, the recipient group and not the recipient of input subsidies have a prominent difference in the flow distribution of the propensity score and potentially lead to selection bias. Meanwhile, after matching through a covariate balance, the observations involved in the analysis have equal characters. This equality will reduce bias and will localize conclusions that focus only on the impact of migration on the agricultural household's vulnerability to poverty.

Figure 1: Histogram of the distribution of matched groups of households with migration (treated) and households without migration (untreated)
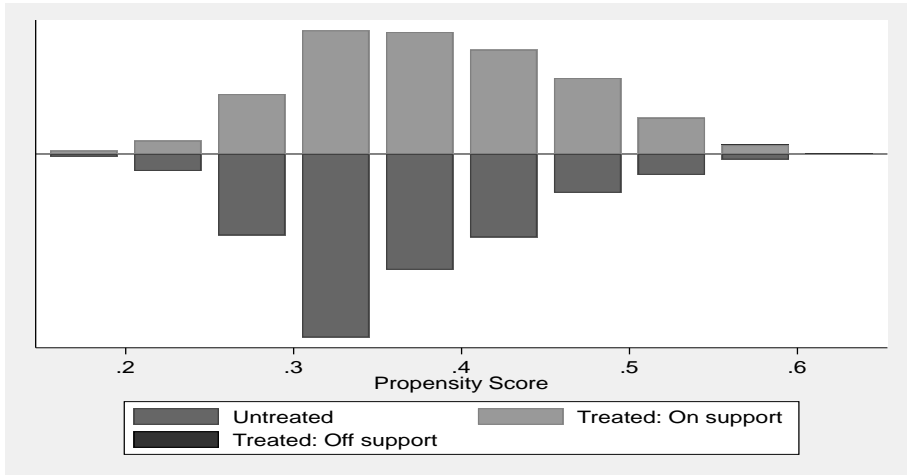
Source: Data computation, 2021

Figure 2: Distribution of Kernel Density propensity score before and after matching
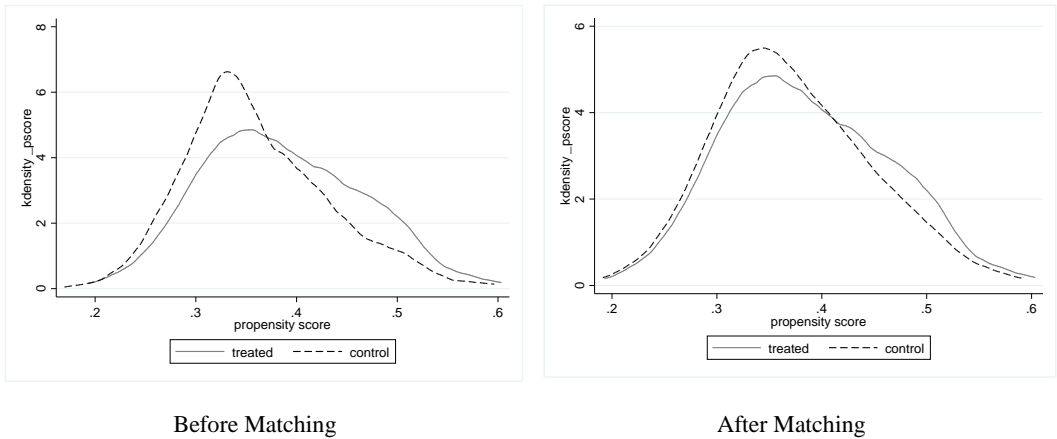
Before Matching   After Matching

Source: Data computation, 2021

In this study, PSM is used to balance the distribution of relevant variables between households with migration and without migration to produce an accurate selection into the treatment group. At this stage, the mean absolute standardized difference between the treatment group and the control group before and after matching is compared. Besides, on the difference of bias calculated for each covariate, as shown in Table 2. For example, in the unmatched sample, around 55% of households with migration are headed by the male household head (*HHgen*), while this proportion was about 56% in the control group. However, after matched, it can be seen that the proportion of male-headed households is around 53% in the control group. So, PSM could balance the standardized difference of the covariate in each group. This issue is vital since the standardized differences could have impacted the treatment probability significantly. This study utilized a similar calculation for all the covariates. Table 2 also shows that a significant

reduction in overall bias was achieved through matching. According to Rosenbaum and Rubin (1983), the Pseudo-R^2 from PSM should be as low as possible. Table 6 shows the Pseudo-R^2 from unmatched and matched propensity scores, which confirmed the ideal result. Moreover, the PSM results in the joint significance of the regressors are always rejected after matching and suggests no systematic difference in the distribution of covariates between treated and control groups. Therefore, through Kernel Matching Algorithm, it was possible to generate a control group that is compatible with the treated group that will be used for the estimation of ATT.

Table 2: Bias Reduction on Operational Variables

Variable	Unmatched (U) / Matched (M)	Mean		Standardized Difference
		Treated (with migration)	Control (without migration)	
AgeHH	U	41.238	41.319	0.081
	M	41.237	40.845	-0.608
AgeHHsq	U	2003.4	2029.9	-26.5
	M	2003.8	1966.9	36.9
HHgen	U	0.5561	0.5640	-0.0079
	M	0.5562	0.5390	0.0172
HHedu	U	0.4408	0.3304	0.1104
	M	0.4397	0.4519	-0.0122
Hsize	U	5.1193	5.0635	0.0558
	M	5.1104	4.8987	0.2117
AgLand	U	0.7139	0.7272	-0.0133
	M	0.7133	0.6981	0.0152
House	U	0.8635	0.9051	-0.0416
	M	0.8642	0.8501	0.0141
lnExp	U	12.862	12.733	0.129
	M	12.859	12.844	0.015

Pseudo-R^2 (unmatched)	= 0.49	Mean absolute bias before matching	= 7.8
Pseudo-R^2 (matched)	= 0.42	Mean absolute bias after matching	= 3.8
P-value of LR (unmatched)	= 0.000	% bias reduction (total)	= 51.28
		Observation	= 400
P-value of LR (matched)	= 0.507		

Source: Data computation, 2021

The impact of migration on the agricultural household's vulnerability on poverty will be analyzed with the PSM model through two phases. The first step in the form of a Probit model analysis is employed to calculate the propensity score of each observation. Explanatory variables are expected to determine the probability of an agricultural household to let its member migrate. In this study, migration is determined by information stating that there are household members

who have lived outside the village for at least one month for work or economic activities in order to earn income. According to the Probit model, the propensity of a household to involve in migration activity is significantly determined by household head's age (*AgeHH*), household head's education level (*HHEdu*), household size (*Hsize*), house ownership (*House*), and per capita expenditure (*lnExp*). This analysis also indicates the nonlinear correlation between migration decisions and age (Table 3).

The age variable significantly determines the propensity to involve in migration and indicates nonlinear correlations. These results indicate that the tendency for migration will increase with the end. Furthermore, after reaching a certain age, the propensity to migrate will decrease. These results are relatively consistent with previous literature (Pisarevskaya et al., 2020; Alexander & Ward, 2018; Lanari et al., 2018). Another variable that also significantly determines the propensity to migrate is education level. The level of education can be represented by the level of education that has been completed by the head of the household. The study revealed that education level boosts the agricultural household's propensity to involve in migration. Individuals with higher education, such as diplomas and scholars, will have more open opportunities to obtain employment in the non-agricultural sector in urban areas (Park & Kim, 2015).

As presented in Table 3, a greater household size will increase the propensity to migrate. As a common condition, more number of family members increases the requirement of financial resources to meet household needs. If the number of non-productive household members is greater than the number of productive members, then the dependency of household needs will become a burden for productive household members. Thus, they migrate to obtain greater income (Wondimagegnhu & Zeleke, 2017). This result is also in line with the correlation between per capita expenditure and propensity to migrate. Higher per capita expenditure increases the propensity to migrate. Meanwhile, in terms of the asset, an agricultural household that owns a house tends to have a lower propensity to migrate. The asset ownership in the rural area reduces the possibility of a household/an individual to migrate because of social and economic connections

Tabel 3: PSM Probit Estimation

Variable	Coeffiecient	z-probability
AgeHH	0.0174	0.012**
AgeHHsq	-0.0001	0.052*
HHgen	0.0079	0.876
HHedu	0.3325	0.000***
Hsize	0.0219	0.072*
AgLand	-0.0613	0.273
House	-0.2255	0.005***
lnExp	0.1184	0.001***
_cons	-2.2866	0.000***
Prob. Chi^2 = 0.000	Pseudo R^2 = 0.487	
Observation = 400	Log likelihood= -1729.35	

Notes: ***: significant at α=1%; **: significant at α=5%; *: significant at α=10%
Source: Data computation, 2021

The ATT measured to denote the impact of migration on agricultural households' vulnerability to poverty is shown in Table 4. The PSM reveals that the migration could decrease the agricultural households' vulnerability to poverty. This result is in line with Beegle et al. (2011), who discovered that migration is an effective way to escape from poverty. As mentioned by neoclassical theory, migration is a strategy undertaken by rural households to improve their economic status, especially from rural to urban areas. Although their migration requires more expensive living costs and reduce or omits income in the area of origin, overall, the migration can increase household income. This result was also confirmed again by Hagen-Zanker and Azzarri (2010), which proves the same thing where the presence of migratory household members can provide additional financial capabilities for the household. Moreover, since the income increased, households could possess more financial capacity to purchase goods and services. Thus, expenditure increases.

Table 4: The impact of migration on vulnerability on poverty

Number of Treated (with migration)	Number of Control (without migration)	ATT	S.E.	t-prob.
147	252	-0.033***	0.009	0.0002

Note: ***: significant at α=1%
Source: Data computation, 2021

Migration carried out by agricultural households has a positive impact on decreasing vulnerability to poverty. This is related to the increasing diversification of income generated from the migration process. Income diversification needs to be encouraged to agricultural households in the form of providing business fields in the non-agricultural sector as well as encouraging the creation of added value to agricultural products. This triggers an increase in overall household income and leads to a decrease in the vulnerability of agricultural households to poverty (Iqbal et al., 2018; Mat et al., 2012).

4. CONCLUSION

The research uses primary data collected among selected agricultural households in West Java, Indonesia. The results reveal that the tendency to be involved in migration is significantly determined by the variables of age, education, the size of household, house ownership, and per capita expenditure. Non-linear correlation is indicated by the household head's age and the ownership of assets, meaning an increase of these variables would decrease the propensity of migration activity. Conversely, the increment of education level, household size, and expenditure would boost the level of propensity to migrate to the rural area by the households due to a positively coefficient correlation. According to ATT measurement, the activity of migration may impact the decrease of the agricultural households' vulnerability to poverty. Hence, it is concluded that the approach of migration to the rural area can be a feasible strategy to reduce the level of poverty in agricultural households. While the study is also suggested that the proactive campaign and support from the local government to encourage households to migrate to the rural area is urgently needed in order to reduce the vulnerability of poverty among local society

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