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Internal Migration Behavior and Income in Indonesia

Jalu Tri Atmojo
Master Program in Development Economics, Faculty of Economics and Business, Gadjah Mada University, Indonesia

Eny Sulistyaningrum
Master Program in Development Economics, Faculty of Economics and Business, Gadjah Mada University, Indonesia
Corresponding author: eny@ugm.ac.id

Abstract

This study analyzes the impact of internal migration behavior on individual income in Indonesia. The study uses longitudinal data from the Indonesian Family Life Survey (IFLS) waves 4 and 5 and considers individuals of working age between the ages of 15 and 64 who migrate for reasons of work or are looking for work. Using a combination of propensity score matching and difference in differences approaches (PSM with DiD) and controlling for individual, household, and regional characteristics, the results show that some migration patterns are welfare increasing. Migrating for work once (never move again) and migrating for work repeatedly have significant positive impacts on individual income. In contrast, migrating once and then returning to one's place of origin does not have a significant impact on individual income.

Keywords: internal migration, income distribution, PSM with DiD, IFLS

1. Introduction

Inequality between regions within a country is still a strategic issue for national development today. Fast economic growth, if not balanced with equal distribution, will lead to regional inequality. One classic problem observed in the nation of Indonesian is the imbalance between Eastern Indonesia and Western Indonesia. An addition problem is that of income inequality between rural and urban areas.

Uneven regional development policies make the phenomenon of migration a necessity. The process of migration taking place between regions within a country (internal migration) is considered a natural process that distributes surplus labor in the regions to the modern industrial sector in other cities or regions that are more capable of absorbing labor. Development inequality between regions is a major issue in Indonesia's national development. Indonesia's Gini index, used as a proxy for regional inequality in September 2014, is at 0.414. This figure is an increase compared to the inequality index in 2007 at 0.376. On the other hand, Indonesia's economic growth for the period 2007 to 2014 continued to increase with an average growth rate of 5.8% per year. Despite Indonesia experiencing economic growth, it is concurrently experiencing increased inequality, driving laborers to migrate internally.

The priority of the national development program focuses on efforts to develop regions to reduce inequality and ensure equity. Several government policies to reduce inequality between regions include development from the periphery, provision of adequate infrastructure, development of new growth centers, efforts to reduce gaps in disadvantaged areas and borders, improving basic services, utilizing the potential of the digital economy to encourage regional development, strengthening Indonesia's connectivity as an archipelago country, innovation in local government governance, and optimizing development funding sources. Despite the government's policy focus, inequality between regions remains a reality. The unequal economic development between regions encourages residents to look for new areas that promise a better life than their place of origin. Borjas (2016) explains that the probability of someone migrating is sensitive to the difference in income between the destination and origin. Another supporting theory is put forward in the migration approach which can be done in two ways, namely the labor force adjustment and human capital investment approaches (Brown & Lawson, 1985). The labor force adjustment approach sees migration as a response to differences in wages and job opportunities between regions, while the human capital investment approach sees migration as a form of investment in individual human resources. Costs incurred by a person to migrate are considered investment costs that will benefit them in the future.

According to data from the Central Bureau of Statistics in the 2015 Inter-Census Population Survey (SUPAS), the number of Indonesians who have permanently migrated in the last five years is 27,086,983, while the population who has recently migrated is 4,813,397 people. Recent migration is migration in which the province where a person lives at the time of the census is different from the province where he lived five years ago. Recent migration is more representative of the recent population movement phenomenon. Looking further, the main reason for recent migration, as many as 1,905,409 people or around 39.59% of the population, is because of work or looking for work. The phenomenon of migration flow to growth areas and income inequality are two issues facing many developing countries. Inequality of development between regions in Indonesia impacts economic disparities between regions. The difference in the ability of a region to provide employment for its inhabitants is one of the reasons a person or population migrates to another area. On this premise, it is necessary to conduct research related to a person's decision to migrate and subsequent impact on their income.

Several previous studies have supported efforts to analyze the impact of migration behavior on income. The results of the study by Nguyen et al. (2015) show that migration has a positive effect on increasing the income of individual migrants in Vietnam. Subsequent research conducted by Roth and Tiberti (2017) concluded that migration reduces both the poverty rate by 3–7% and the depth of poverty. Poverty is an indicator of household welfare that can be a proxy for low levels of household income. These findings are in line with Bertholi and Marchetta (2014) who found a significant negative effect of migration on poverty in migrant households in Ecuador.

In contrast to previous studies, Garip (2012) examined, with high prevalence, groups of migration households and found that the difference in the amount of money sent by repeat migrants was greater than one-time migrants. Households with repeat migrants also had on average a larger number of rooms than households with one-time migrants and non-migrants. Meanwhile, Liebensteiner's (2014) study found that the income level of seasonal male labor migration was higher relative to the counterfactual income of male non-migrant workers. This study also found that workers who performed repeated migration tended to earn relatively higher incomes than their fellow workers who only migrated once.

The ease of access to information about the destination affects the success of migration. Research conducted by Rashid (2009) on four groups of immigrants found different results. Refugee-immigrant families who undertook internal migration within a relatively short time period after their arrival in Sweden received a higher family income compared to similar families who did not migrate or families who migrated after staying in the host country for a longer time. Similar results were not found in immigrant families from the other three groups. This can be explained by the fact that immigrants from Nordic, European, and Asian countries are better informed about the destination country, thus increasing their chances of finding a job that matches their skills upon first arrival.

Farjana et al. (2019) in their research evaluated the results of internal migration on household welfare with the results that migrant households had higher income, built more assets, and reduced the poverty gap more than non-migrant households. Different conditions can be seen in a study conducted by Zanker and Azzarri (2010). Although internal migration has an impact on improving income, consumption expenditure is growing due to the high living costs in cities. In addition, migrant households in urban areas reside in poor living conditions and have irregular and unstable jobs.

Researchers consider it necessary to conduct research related to the impact of migration behavior on income in Indonesia during the 2007-2014 period as an effort to analyze the role of each migration behavior in individual migrant efforts to improve welfare, of which one is an indicator measured based on the amount of income received. Previous research has mostly focused on rural-urban migration, along with the unit of observation being carried out at the household level. The difference between this research and previous research lies in the area, period, and variables of interest using three migration categories. This research contributes to adding scientific references by further analyzing the impact of the three migration behaviors on individual success in maximizing opportunities in the migration destination area. The findings of this study can subsequently be used both as input for the Indonesian government to strengthen the role of institutions related to internal migration issues and as a reference for policy formulation in migration and population distribution.

2. Methods

This study analyzes the relationship between migration behavior for reasons of employment and job search and individual income. The outcome variable in this study is a continuous variable, namely the individual income earned during the last 12 months in units of thousand Rupiah. The research was conducted on individuals included within the population of productive age. The Central Bureau of Statistics determines that the population of productive age is the population aged 15–64 years (Tjiptoherijanto, 2001). The study was conducted using individual-level data from the survey results of the Indonesian Family Life Survey / IFLS wave 4 (2007) and wave 5 (2014-2015). The study sample consisted of 12,566 individuals who are residents of productive age, namely aged 15-64 years, are already working, and have income. Then, further selected based on their migration status after 2007, there were samples of 1,758 people who migrated for work reasons and looking for work and 6,423 people who stayed. The 6,423 individuals were a sample group of productive age and had income but did not migrate during the 2007-2014 period.

In addition to the migration behavior variables, the researcher also uses several control variables that represent the characteristics of the respondents who migrate. Variables that represent individual characteristics are marital status, work status, length of education, age, and gender. Household characteristics include number of household members, farm household status, and well-to-do household status. Regional characteristics are obtained in the household status of origin variable. In addition, this study adds control variables in the form of time-fixed effects and regional-fixed effects to the DiD analysis. The use of IFLS longitudinal data allows researchers to combine the Propensity Score Matching (PSM) and Difference in Difference (DiD) methods. The combination of the two methods can overcome the problem of selection bias and unobserved constants over time.

The data used in this paper is defined in Table 1. The variable of interest in this study is the migration status of individuals after 2007, denoted by the migration dummy variable. The migration variable is worth 1 if the individual has migrated after 2007 and 0 for individuals who have not migrated/settled. Migration variable data was obtained from the IFLS-5 questionnaire book 3B in the MG (migration) section, question MG18e as follows: "Since 2007 have you ever moved across the village/kelurahan boundary and stayed at the destination for six months or more?" The results of the selection are seen by the number of moves if only one move is included in the category of one_time _migration. The sample with the number of displacements more than once was then compared with the residential address in the 2007 interview to the last residential address at the time of the 2014 interview. The sample includes the return migration group if there is a similarity of residence in 2007 and 2014. The sample of the repeat migration group includes those who have a different place of residence between 2007 and the last interview in 2014. In addition, the outcome variable in this study is the income received by individuals in the last 12 months, measured in nominal terms.

Table 1: Variable Definitions

Variable name	Type	Definition	According to Literature
one_time_migration	Dummy	Equal to 1 if only one-time migrated and 0 for non-migrate	-
return_migration	Dummy	Equal to 1 if return migrated to the origin and 0 for non-migrate	-
repeat_migration	Dummy	Equal to 1 if doing repeated migration and 0 for non-migrate	-
Income	Nominal	Previous year income (last year income)	
Household Size (HH_Size)	Nominal	Number of family members	Nguyen et al. (2015), Roth dan Tiberti (2017), Bertoli & Marchetta (2014)
Farmer_family	Dummy	Equal to 1 if Farmer_family and 0 otherwise	Nguyen et al. (2015)
Rich_family	Dummy	Equal to 1 if Rich_family and 0 otherwise	Borjas (2016), Du et al. (2005)
Urban	Dummy	Equal to 1 if from urban area and 0 otherwise	Borjas (2016), Roth dan Tiberti (2017), Liebensteiner (2014)
Married	Dummy	Equal to 1 if married and 0 otherwise	Borjas (2016), Liebensteiner (2014)
Works	Dummy	Equal to 1 if works and 0 otherwise	Borjas (2016), Liebensteiner (2014)
D_Educ	Dummy	Equal to 1 if highest level education is junior high school or less and 0 if senior high school or above.	Borjas (2016), Roth dan Tiberti (2017), Liebensteiner (2014)
Age	Nominal	Age of individual	Borjas (2016), Bertoli & Marchetta (2014)
Male	Dummy	Equal to 1 if male and 0 otherwise	Nguyen et al. (2015), Roth dan Tiberti (2017)

Source: Authors' compilation.

The descriptive statistics for the three types of migrants are reported in Table 2, Table 3, and Table 4.

Table 2: Summary Statistics for One-time Migration

Variable		Baseline (2007)		Endline (2014)	
		never move	once_move	never move	once_move
Outcome					
Income	Mean	9,393.81	10,537.83	21,921.41	28,940.98
	Std. Dev	12,126.15	13,626.85	40,102.80	40,364.48
Individual characteristics control variables					
married	Mean	0.861	0.663	0.883	0.904
	Std. Dev	0.346	0.473	0.321	0.295
works	Mean	0.981	0.963	0.980	0.963
	Std. Dev	0.137	0.188	0.141	0.190
education	Mean	0.388	0.604	0.392	0.607
	Std. Dev	0.487	0.489	0.488	0.489
age	Mean	37.685	30.490	44.526	37.519
	Std. Dev	10.402	8.817	10.405	8.838
male	Mean	0.704	0.721	0.704	0.721
	Std. Dev	0.457	0.449	0.457	0.449
Household characteristics control variables					
HH_Size	Mean	7.194	7.337	7.945	8.233
	Std. Dev	3.278	3.306	3.515	3.494
Farmer_fam	Mean	0.364	0.300	0.366	0.295
	Std. Dev	0.481	0.459	0.482	0.456
Rich_fam	Mean	0.885	0.893	0.775	0.808
	Std. Dev	0.319	0.309	0.417	0.394
Area control					
urban	Mean	0.497	0.583	0.584	0.647
	Std. Dev	0.500	0.493	0.493	0.478
Observations		6,423	1,123	6,423	1,123

Source: Authors' calculations from the fourth and fifth rounds of the Indonesian Family Life Survey.

Table 3: Summary Statistics for Return Migration

Variable		Baseline (2007)		Endline (2014)	
		return migration=0	return migration=1	return migration=0	return migration=1
		Outcome			
Income	Mean	9,393.81	7,671.88	21,921.41	20,532.97
	St. Dev	12,126.15	9,138.91	40,102.8	24,063.22
		Individual characteristics control variables			
married	Mean	0.861	0.619	0.883	0.853
	St. Dev	0.346	0.486	0.321	0.355
works	Mean	0.981	0.964	0.980	0.955
	St. Dev	0.137	0.187	0.141	0.208
education	Mean	0.388	0.502	0.392	0.508
	St. Dev	0.487	0.501	0.488	0.501
age	Mean	37.685	28.871	44.526	35.826
	St. Dev	10.402	8.206	10.405	8.353
male	Mean	0.704	0.760	0.704	0.760
	St. Dev	0.457	0.428	0.457	0.428
		Household characteristics control variables			
HH_Size	Mean	7.194	7.700	7.945	8.471
	St. Dev	3.782	3.202	3.515	3.395
Farmer_fam	Mean	0.364	0.324	0.366	0.294
	St. Dev	0.481	0.469	0.482	0.456
Rich_fam	Mean	0.885	0.856	0.775	0.769
	St. Dev	0.319	0.352	0.417	0.422
		Area control			
urban	Mean	0.497	0.562	0.584	0.661
	St. Dev	0.500	0.497	0.493	0.474
Observations		6,423	333	6,423	333

Source: Authors' calculations from the fourth and fifth rounds of the Indonesian Family Life Survey.

Table 4. Summary Statistics for Repeat Migration

Variable		Baseline (2007)		Endline(2014)	
		repeat migration =0	repeat migration =1	repeat migration=0	repeat migration=1
		Outcome			
income	Mean	9,393.81	9,363.77	21,921.41	33,035.4
	St. Dev	12,126.15	12,584.75	40,102.8	71,773.35
		Individual characteristics control variables			
married	Mean	0.861	0.434	0.883	0.851
	St. Dev	0.346	0.496	0.321	0.357
works	Mean	0.981	0.977	0.980	0.974
	St. Dev	0.137	0.151	0.141	0.161
education	Mean	0.388	0.613	0.392	0.646
	St. Dev	0.487	0.488	0.488	0.479
age	Mean	37.685	26.248	44.526	33.308
	St. Dev	10.402	6.991	10.405	6.934
male	Mean	0.704	0.768	0.704	0.768
	St. Dev	0.457	0.423	0.457	0.423
		Household characteristics control variables			
HH_Size	Mean	7.194	7.487	7.945	8.361
	St. Dev	3.278	3.334	3.515	3.504
Farmer_fam	Mean	0.364	0.325	0.366	0.328
	St. Dev	0.481	0.469	0.482	0.470
Rich_fam	Mean	0.885	0.874	0.775	0.772
	St. Dev	0.319	0.332	0.417	0.421
		Area control			
urban	Mean	0.497	0.540	0.584	0.613
	St. Dev	0.500	0.499	0.493	0.488
Observations		6,423	302	6,423	302

Source: Authors' calculations from the fourth and fifth rounds of the Indonesian Family Life Survey.

This study uses the Propensity Score Matching (PSM) method combined with a difference in differences (DiD) approach. When the baseline data on outcomes are available, the PSM method can be combined with the DiD method to reduce the risk of bias in estimation (Gertler et al., 2016). The simple PSM method cannot capture unobserved characteristics that explain why individuals or units of observation decide to join the program, but these characteristics may also influence the results. The PSM method controls sample selection on observable variables but cannot account for unobserved variables and their simultaneous effects on migration probability and outcome variables (Rosenbaum & Rubin, 1983). Therefore, a combination of the DiD method with the PSM method was used to eliminate the effect of unobserved variable (time invariant) on the outcome variable (Smith & Todd, 2005). The PSM with DiD approach also addresses the endogeneity problem that usually hinders identification of the effects of migration outcomes (Nguyen et al., 2015).

This study uses Propensity Score Matching because it is the best method to build a valid comparison group. A valid comparison group, according to Gertler et al. (2016), must have at least the three following characteristics: the group has the same characteristics, on average, as the treatment group without a program; the treatment group does not affect the comparison group either directly or indirectly; and the comparison group will react to the program in the same way as the treatment group if given the program.

PSM builds a comparison group based on a person's probability value (propensity score) to receive treatment. PSM has assumptions that must be met to get a comparison group that has the same characteristics as the group receiving treatment (Sianesi, 2001). There are two assumptions that determine the validity of the PSM estimation results, namely the Conditional Independence Assumption (CIA) and the existence of common support. Propensity Score Matching (PSM), according to Sulistyaningrum (2016), is carried out through five steps including estimating the propensity score, selecting the matching algorithm, checking common support, assessing quality of matching and estimating standard errors and sensitivity analysis.

In carrying out the estimation, there are two things that are taken into consideration, namely the choice of the model and the variables used (Caliendo & Kopeinig, 2008). This study uses three probit models, i.e., for the one-time migration category, return migration, and repeated migration. The probit equation model for the one-time migration category using six covariates is as follows:

$$P(one\_time\_migration = 1/X) = \Phi(\beta_0 + \beta_1 agriculture + \beta_2 rich\_HH + \beta_3 urban + \beta_4 married + \beta_5 education + \beta_6 male + e) \quad (1)$$

The next model is the equation for the return migration category using seven covariates and can be described as follows:

$$P(return\_migration = 1/X) = \Phi(\beta_0 + \beta_1 agriculture + \beta_2 urban + \beta_3 married + \beta_4 works + \beta_5 education + \beta_6 age + \beta_7 male + e) \quad (2)$$

The final probit model, the repeat migration category model, using nine covariates can be written as follows:

$$P(repeat\_migration = 1/X) = \Phi(\beta_0 + \beta_1 agritulture + \beta_2 farmer\_fam + \beta_3 rich\_HH + \beta_4 urban + \beta_5 married + \beta_6 works + \beta_7 education + \beta_8 age + \beta_9 male + e) \quad (3)$$

Several algorithms can be selected to estimate the average treatment effect between two groups. There are no crucial suggestions in choosing a PSM estimator. The data structure owned is more of a consideration in choosing a PSM estimator. Caliendo and Kopeinig (2008) state that in a large sample size, and developing asymptotically, all PSM estimators will give the same results.

The DiD method compares the change in outcome over time (trend) between the population enrolled in the program (group treatment) and the population that is not included (the control group). (Gertler et al., 2016, p. 130). The trend in research is the difference in outcomes in individuals before and after migrating. Individual characteristics or units of observation are reasonably assumed to be constant over time (time invariant).

DiD can be implemented in the regression method by adding an interaction variable between treatment and time after the program / intervention. This study uses panel data and fixed effects because the factors that are not observed have not been accommodated in the regular DiD regression, where it also becomes a robustness check. The addition of control variables time fixed effect, regional fixed effects, and their interaction will accommodate the different characteristics between regions. The results of the impact estimation are presented in two regression models, including a fixed effect model without control variables and a fixed effect model with control variables. The fixed effect model is used to correct heterogeneity in individuals due to the use of longitudinal data (Trivedi, 2003). DiD estimation model in regression according to Khandker et al. (2010) is written as the following equation:

$$Y_{it} = \alpha_0 + \alpha_1 Treatment_{it} + \alpha_2 After_{it} + \alpha_3 Treatment_{it} * After_{it} + \mu_{it} \quad (4)$$

The DiD model with the addition of control variables is written with the equation as follows:

$$Y_{it} = \alpha_0 + \alpha_1 Treatment_{it} + \alpha_2 After_{it} + \alpha_3 Treatment_{it} * After_{it} + \alpha_n C_{(n)it} + \mu_{it} \quad (5)$$

3. Results and Discussion

Appropriate with the migration theory put forward by Borjas (2016, p. 316), migration can be classified into three categories, namely one-time migration (never move again), returned migration, and repeated migration. One-time migration occurs when a worker changes residence to another area and settles in that area. Groups of repeat migrants and return migrants can be classified by looking at the order in which migrants move in the period of observation. Workers who have recently migrated are very likely to move back to their area of origin, resulting in a return migration flow. In addition, it is possible for these migrants to move again to other areas that they consider more profitable, and this results in repeated migration flow. This research attempts to look more deeply at the impact of each of these migration behaviors on income. From a total of 1,758 individual samples of migration, information on the number of times of movement (movenum) during the 2007-2014 period was compared to their residential addresses before migration (2007) and after migration (2014). From this process, the number of samples for each category was obtained, resulting in one-time migration for 1,123 individuals, return migration for 333 individuals, and repeated migration for 302 individuals.

3.1 PSM Estimation Results

The propensity score estimation is carried out in two stages, selecting the model and selecting the variables to be included in the model (Caliendo & Kopeining 2008). In estimating the propensity score, there are two binary models that can be used, either probit or logit (Li et al., 2013). Control variables are selected based on economic theory, previous empirical studies, or the terms of implementing a program. Variables that are thought to influence individual participation and influence the likelihood of outcomes may reduce the confounding factors in the model (Brookhart et al., 2006).

This research on the impact of migration behavior uses the Nearest Neighbor (NN) Matching with replacement estimator for the three models. The selection of this algorithm is based on the assessment of the results of the quality matching which is better than other algorithms. The sample selected is a sample that is included in the common support area (on support); several samples in the treatment group must be excluded because they are not in the support area. According to Sulistyaningrum (2016, p. 45) the NN Matching with replacement method compares treatment and comparison groups that are similar and can be used repeatedly so that a better match is obtained.

The estimation results of NN Matching with replacement for one-time migration and repeated migration groups with the 2014 outcome data show that the average income of each group is higher by IDR 3.096 million and IDR 8.876 million at the 0.1 and 0.05 level of significance. Different results were obtained for the return migration group with the 2014 outcome data showing that the average income of the return migration group was lower at IDR 2.864 million. However, the P-value showed an insignificant impact. The one-time migration and repeat migration increased the individual income significantly on average, but with the individual return migration or back to the original region, it seems that the income is not affected.

Table 5: PSM Estimation Results

Matching Algorithm	NN with replacement				Number of observations
	ATT	SE	BSE	P-Value	
One-time Migration	3,096.58	1,753.07	1,681.04	0.065	7546
Return Migration	-2,864.57	1,990.62	1,977.20	0.147	6756
Repeat Migration	8,876.14	4,425.06	4,398.12	0.046	6725

Notes: SE (Standard Error); BSE (Bootstrapped Standard Error).
Source: Authors' calculations from the fourth and fifth rounds of the Indonesian Family Life Survey.

The estimation results using probit regression in Table 6, Table 7, and Table 8 show that several characteristics influence an individual's decision to migrate, including place of residence, marital status, work status, length of school, age, and sex. Meanwhile, the characteristics of the number of household members, the status of the farm household, and the status of the well-off households did not have a significant effect on the decision to migrate. The results of the balancing test on the three models show a satisfactory balancing score, i.e., the balancing property is satisfied.. This indicates the distribution of the treatment group units has a similarity in score and is proportional to the comparison group so that confounding factors can be resolved while at the same time fulfilling the CIA assumption.

In checking the common support, a similarity was found in the distribution of the propensity scores between the treatment group and the comparison group in the three categories of the migration groups. The intersection of the distribution of the treatment group with the comparison group in the three categories of the migration groups, indicated by the overlapping slice areas, indicates similar characteristics between the treatment group and the control group.

Matching quality tests were carried out by performing standard bias tests, average test (t-test), simultaneous test (F-test), and Pseudo-R^2 (Caliendo & Kopeinig, 2008). The results of the matching quality tests for the three categories of the migration groups show no difference in characteristics between the treatment group and the comparison group after matching. From Table 6, the standard bias in each variable decreases after matching one-time migrants with non-migrants. A smaller value after matching indicates good match quality, although there is no definite standard that measures the success of lowering the standard of bias (Caliendo & Kopeinig, 2008). The results of the t-test reveal no significant difference in covariates after matching.

Table 6: Estimated Propensity Score and Matching Quality Test (One-time Migration)

Variable	Probit Regression			Standard Bias		t-test		Hotelling Test (Mean)	
	Coef.	SE.	P.Val	U	M	U	M	Di = 1	Di = 0
agriculture	0.001	0.005	0.842	4.3	2.0	0.180	0.629	7.336	7.269
Rich_HH	0.048	0.058	0.408	2.7	-0.3	0.408	0.935	0.893	0.894
urban	0.086	0.038	0.024	17.3	-0.5	0.000	0.911	0.583	0.585
married	-0.658	0.043	0.000	-47.9	-0.3	0.000	0.950	0.662	0.663
education	0.439	0.037	0.000	44.1	-0.3	0.000	0.952	0.603	0.604
male	0.143	0.041	0.000	3.9	-0.0	0.233	0.992	0.721	0.721
cons	-0.937	0.084	0.000						
Ps. R2	0.0645					0.065	0.000		
Prob > F								0.9996	
Number of obs		7546							

Notes: U (Unmatched); M (Matched); Di=1 (Treatment Group); Di=0 (Control Group).
Source: Authors' calculations from the fourth and fifth rounds of the Indonesian Family Life Survey.

Table 6 shows that the pseudo-R^2 is lower after matching, indicating good match quality and the absence of bias from both groups. The reduced pseudo-R^2 value indicates that there are no differences in characteristics that cause individuals to choose to migrate or not after matching. Furthermore, the Hotelling test was carried out to find the average covariate similarity jointly between the treatment group and the comparison group. The Hotelling test is equal to 0.9996, which is greater than the 0.05 benchmark. That is, collectively, all covariates that are paired in the two groups have similar characteristics.

Tables 7 and 8 report the probit results and the match quality tests for the return migration and repeat migration groups, respectively. Similar to the one-time migration group, the standard bias in all variables decreases after matching. The results of the t-tests reveal no significant differences in the covariates after matching. The pseudo-R^2 score was also significantly reduced after matching, indicating good match quality and an absence of selection bias from the test and control groups. The Hotelling test – used to see whether there is a difference in the average between the treatment group and the comparison group – results in a value of 0.76 for the return migration group and 0.99 for the repeat migration group, which are greater than the test statistic of 0.05. Taken together, these results indicate that all covariates jointly paired across the treatment and control groups have similar characteristics.

Table 7: Estimated Propensity Score and Quality Test Matching (Return Migration)

Variable	Probit Regression			Standard Bias		t-test		Hotelling Test (Mean)	
	Koef.	SE.	P.Val	U	M	U	M	Di = 1	Di = 0
agriculture	0.012	0.008	0.137	15.6	-2.9	0.006	0.725	7.699	7.795
urban	0.131	0.058	0.024	12.9	-2.3	0.022	0.767	0.561	0.572
married	-0.388	0.067	0.000	-57.5	-2.6	0.000	0.774	0.618	0.629
works	-0.297	0.163	0.069	-10.3	1.1	0.032	0.902	0.963	0.962
education	0.087	0.057	0.130	22.9	1.1	0.000	0.889	0.501	0.496
age	-0.039	0.003	0.000	-94.1	-2.0	0.000	0.769	28.87	29.05
male	0.231	0.065	0.000	12.7	-8.3	0.029	0.256	0.759	0.796
cons	-0.114	0.204	0.575						
Ps. R2	0.1169					0.117	0.002		
Prob > F								0.7642	
Number of obs		6,756							

Notes: U (Unmatched); M (Matched); Di=1 (Treatment Group); Di=0 (Control Group).
Source: Authors' calculations from the fourth and fifth rounds of the Indonesian Family Life Survey.

Table 8: Estimated Propensity Score and Quality Test Matching (Repeat Migration)

Variable	Probit Regression			Standard Bias		t-test		Hotelling Test (Mean)	
	Koef.	SE.	P.Val	U	M	U	M	Di = 1	Di = 0
agriculture	0.003	0.009	0.734	8.8	-2.2	0.130	0.791	7.461	7.533
farmer_fam	-0.011	0.073	0.880	-8.3	3.3	0.163	0.681	0.325	0.309
Rich_HH	0.052	0.096	0.584	-3.2	1.9	0.579	0.818	0.873	0.867
urban	0.045	0.072	0.529	8.5	-3.8	0.148	0.641	0.538	0.557
married	-0.659	0.071	0.000	-99.9	0.9	0.000	0.922	0.435	0.431
works	0.039	0.218	0.855	-2.8	-2.5	0.619	0.757	0.976	0.980
education	0.296	0.065	0.000	46.0	0.2	0.000	0.980	0.611	0.610
age	-0.051	0.004	0.000	-129	-1.2	0.000	0.849	26.27	26.38
male	0.296	0.073	0.000	14.7	-1.6	0.016	0.839	0.767	0.774
cons	-0.062	0.270	0.816						
Ps. R2	0.2207					0.221	0.001		
Prob > F								0.9948	
Number of obs		6725							

Notes: U (Unmatched); M (Matched); Di=1 (Treatment Group); Di=0 (Control Group).
Source: Authors' calculations from the fourth and fifth rounds of the Indonesian Family Life Survey.

The matching estimation results are not necessarily robust in the possibility of hidden bias (Caliendo & Kopeinig 2008). Sensitivity analysis is conducted to determine how strong the effect of unobservable characteristics is on changes in the results of program impact estimates (Rosenbaum, 2005). This study used Wilcoxon's signed rank test to obtain the limit value for Rosenbaum bounds.

Table 9: Sensitivity Test Results

Γ	One-time Migration		Return Migration		Repeat Migration	
	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound
1	0.95893	0.95893	0.00007	0.00007	0.72470	0.72470
1.1	0.99911	0.63929	0.00106	<0.00001	0.90585	0.45203

1.2	0.99999	0.18294	0.00834	<0.00001	0.97583	0.21898
1.3	1.00000	0.01944	0.03806	<0.00001	0.99511	0.08386
1.4	1.00000	0.00084	0.11462	<0.00001	0.99919	0.02615
1.5	1.00000	0.00002	0.25083	<0.00001	0.99989	0.00684
1.6	1.00000	<0.00001	0.42997	<0.00001	0.99999	0.00154
1.7	1.00000	<0.00001	0.61362	<0.00001	1.00000	0.00031
1.8	1.00000	<0.00001	0.76658	<0.00001	1.00000	0.00006
1.9	1.00000	<0.00001	0.87354	<0.00001	1.00000	0.00001
2	1.00000	<0.00001	0.93802	<0.00001	1.00000	0.00000
Obs	1,123		333		302	

Notes: N (Matched pairs).
Source: Authors' calculations from the fourth and fifth rounds of the Indonesian Family Life Survey.

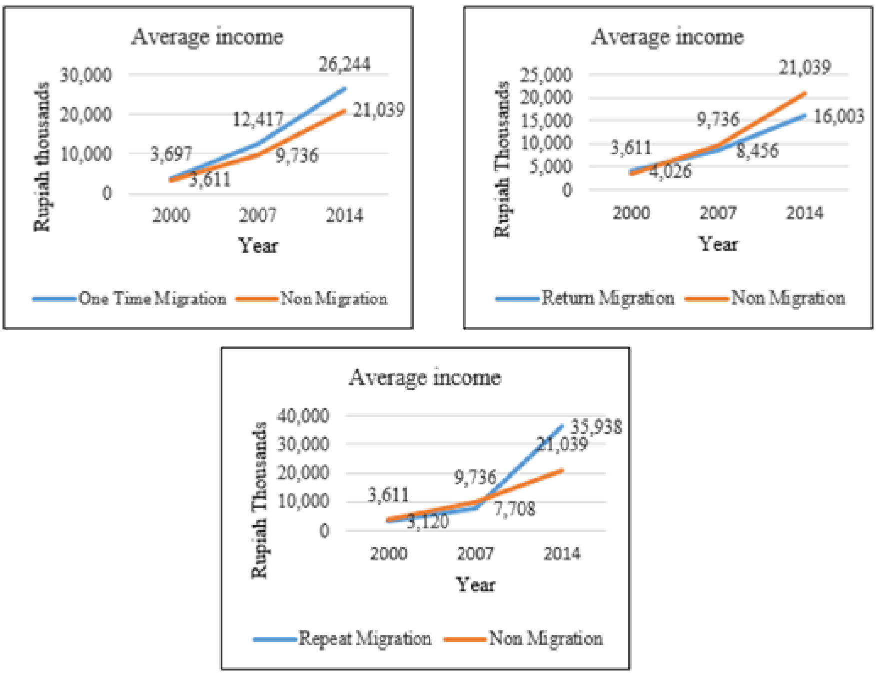
Rosenbaum states that research is considered sensitive if the level of gamma is only slightly greater than 1 and the p-value is no longer significant at the 5% level. Table 5 reveals the three migration groups experienced a change in the level of significance at the lower bound and caused a downward bias. Thus, it can be concluded that this study is still sensitive to the existence of hidden bias. The income level of an individual is likely to be influenced by many things, not only because of the individual's decision to migrate.

3.2 DiD Regression Estimation Results

Before estimating DiD, the two groups must meet the parallel trend assumptions to obtain a valid estimate from the counterfactual. This assumption requires that, in the absence of intervention, the results in the treatment and comparison groups have the same trend movement over time. Based on IFLS 3, 4, and 5 data, change can be observed in the average income in the last 12 months of the two groups in the two time periods before migrating then compared to changes in the results after migration.

In Figure 1 the three graphs show the similarity of trends between the three migration groups and the non-migration groups before the existence of the program / intervention. The similarity of this trend explains that prior to migration (before 2007) in the treatment group, the two groups had the same trend of average income during the last 12 months (equal trend). A gap was discovered in the observation in 2014, possibly due to the effects of migration behavior. From the results of this test, it can be confirmed that the sample used has fulfilled the assumption of a parallel trend.

Figure 1: Average Income of Migration and Non-migration Groups



Source: Authors' calculations from the fourth and fifth rounds of the Indonesian Family Life Survey.

As a robustness check assumption of parallel trends, this study conducted a regression analysis of both treatment and comparison groups to see the consistency of the effect of covariates on outcomes in the two periods before the intervention. The regression results can be seen in Table 10 as follows:

Table 10: Regression Results for the Migration Behavior Group and the Control Group

Variable	Groups				
	One time Migration	Return Migration	Repeat Migration	All Treatment	Control
agriculture	-268.19	170.60	-171.23	-166.70	-38.05
farmer_fam	1,871.60	532.70	4,662.03	1,545.58	204.55
Rich_HH	2,653.55	-2,706.10	933.13	1,557.94	2,874.33***
urban	650.09	1,502.15	4,915.98	986.01	1,365.81***
married	2,321.69	3,419.11**	2,061.88	2,354.18**	1,048.00***
works	4,371.87	2,732.65	8,279.42	4,310.16	1,992.82*
education	5,451.14***	3,327.08***	6,790.94**	5,152.89***	6,112.61***
age	-347.99	123.54	681.32	-223.42	459.27***
age_sq	6.56	0.14	-9.85	4.88	-4.80***
male	702.60	3,178.52*	5,104.65	1,190.96	1,254.28***
year	995.02***	374.83*	610.53	830.10***	788.59***
cons	-1,992,892***	-757,961.3*	-1,247,127	-1,664,791***	-1,592,121***
N	422	136	64	622	6690

Notes: Asterisks each indicate significance: ***1%, **5%, *10%.
Source: Authors' calculations from the fourth and fifth rounds of the Indonesian Family Life Survey.

From the regression results of each migration group, the direction of influence (positive / negative) is compared, as seen from the coefficients of each covariate. From Table 10 it can be concluded that the coefficient of the covariate has a significant effect on the treatment group, and the comparison group shows the same effect. Likewise, in the regression of all treatment groups the results showed the same direction of influence on the covariates which had a significant effect.

The DiD assumption assumes that the unobserved characteristic bias can be corrected because it is assumed to be constant over time. However, if there are other variables of observed characteristics that are known to vary over time, then these variables can be included as control variables in the DiD model, and then DiD analysis is carried out using the regression method. The control variable added to the DiD analysis will have a net effect on the treatment variable on the outcome being observed (Khandker, 2010).

This study uses panel data and fixed effects because the factors that are not observed have not been accommodated in the regular DiD regression, and this also becomes a robustness check. The addition of control variable time fixed effect, regional fixed effects, and their interaction will accommodate the different characteristics between regions. The results of the impact estimation are presented in two regression models, including a fixed effect model without control variables and a fixed effect model with control variables.

Based on Table 11, the overall regression results show an impact of one-time and repeat migration on income. This can be observed after taking into account the control variables in the DiD model; statistically the results of the analysis are both at the 1% and 10% significance levels. The behavior of one-time migration and repeated migration has a positive impact, as seen from the increase in the average individual income of Rp3.594 million and Rp8.888 million when compared to before migration.

The increase in average income is greater than the difference in the average Provincial Minimum Wage (UMP) of the original region before migration in 2007-2014. There are as many as 20 provinces from which one-time migration groups originate and 18 provinces which are regions of origin for repeat migration groups. Based on data processing of UMP BPS RI, the average increase in the UMP of the area from the one-time migration group and the repeat migration group from the 2007-2014 period amounted to Rp835,637 and Rp838,011, respectively.

The estimation results of the DiD impact of return migration behavior on income were found in both regression models that, statistically, return migration behavior did not have a significant impact on individual income. The return migration behavior resulted in an increase in income of Rp333 thousand compared to before the program was implemented. The addition of control variables in the DiD analysis resulted in the migration behavior again reducing the impact magnitude to Rp154 thousand on individual income compared to without control variables.

Table 11: DiD Regression Results on the Fixed Effect Impact of Migration Behavior on Income

Outcome	DiD Regression fixed effect	DiD Regression fixed effect
One_time_migration	5,875.55***	3,594.97***
control	N	Y
N	15,092	15,092
R-Sq	0.0516	0.0194
Return_migration	333.5	154.71
control	N	Y
N	13,512	13,512
R-Sq	0.0442	0.0087
Repeat_migration	11,235.6***	8,888.3*
control	N	Y
N	13,448	13,448
R-Sq	0.0450	0.0127

Notes: The variables one_time_migration (never move again), return migration, and repeat migration represent interactions between treatment and year, indicating the magnitude of the estimated impact of each migration behavior. Control variables: number of household members, farm household status, well-off household status, origin of residence, marital status, working status, years of schooling, age, age squared, sex, year, province, and interaction between years and provinces. An asterisk indicates statistical significance: *** 1%, ** 5%, * 10%.
Source: Authors' calculations from the fourth and fifth rounds of the Indonesian Family Life Survey.

3.3 The Impact of Migration Behavior on Income

There are many reasons that motivate a person to decide to migrate; this study limits the phenomenon of migration for reasons of work and looking for work. This study seeks to see the extent of the impact on a person who decides to migrate for the welfare of his life. One of the benchmarks is the increase in income after moving to a migration destination.

The results showed an increase in income for individuals who did both one-time and repeat migration amounting to Rp3.594 million and Rp8.888 million, respectively. The increase in average income was greater than the difference in the average Provincial Minimum Wage (UMP) of the original region before migration in 2007-2014, amounting to Rp835,637 and Rp838,011, respectively. Similar results were also obtained for individuals who did returned migration, except that the increase on income was relatively small, amounting to Rp154,000. The estimation results of one-time migration and repeat migration show an impact on income, while return migration does not show a significant impact. This result also corrects the magnitude of the impact of the three migration behaviors in which the sensitivity analysis shows a downward bias in the PSM estimation results.

This finding is in line with the results of research by Nguyen et al. (2015) which showed that migration has a positive effect on increasing the income of individual migrants in Vietnam. This effect is more pronounced in provinces with fewer employment opportunities. Roth and Tiberti (2017) in their research also found that migration reduces the poverty rate by 3–7% and reduces the depth of poverty. Poverty is an indicator of household welfare that can be a proxy for low levels of household income. Another study conducted by Liebensteiner (2014) in Armenia found that the income level of seasonal male labor migration was higher relative to the counterfactual income of male workers who did not migrate. This study also found that workers who migrated several times in the 2007-2010 period tended to have relatively higher incomes than their fellow workers who only migrated once. Migrants who migrate only once appear to be less successful in their efforts to increase income.

Similar findings were obtained by Garip (2012) who examined migratory household groups with high prevalence in Mexico. This study looks at the impact of migration behavior based on several indicators, including remittances per month per capita, the average number of house rooms, and the percentage gap between migrant and non-migrant households. This research examines how individuals' wealth status is linked to their propensity to migrate and remit money. A significant result was obtained in that the difference in the amount of money sent by repeat migrants was greater than that of one-time migrants. This difference can be attributed to the higher earning potential of repeat migrants gained from previous work experience. The results of subsequent studies capture the ratio of average wealth seen from the number of rooms in home ownership among non-migrants, single migrants, and repeat migrants. Households with repeat migrants have a higher average number of rooms than one-time migrant and non-migrant households. This pattern provides further evidence that migration is a mechanism for accumulating wealth and implies a change in the distribution of wealth in society.

Rashid (2009), in his research on four groups of immigrants who settled in Sweden, found slightly different results. Empirical findings show that families of refugees who migrate internally within a relatively short period of time after their arrival in Sweden receive a higher family income compared to similar families who do not migrate and families who migrate after staying in the host country for a longer time. Similar results were not found in immigrant families from the other three groups, namely the Nordic, European, and Asian. A possible explanation is that immigrants from Nordic, European, and Asian countries are better informed about the destination country, which in turn increases their chances of finding a job that matches the skills they had upon first arrival. This will of course be different for immigrants for political reasons who may not have the same opportunities as refugees from the three groups.

Farjana et al. (2019) in their research applied the New Economies of Labor Migration (NELM) theory to analyze panel data at the household level to evaluate the results of internal migration on household welfare. Welfare is analyzed using three variables outcome, i.e., household income, capability to build assets, and poverty gap. The results of this study find evidence that migrant households have higher incomes, build more assets, and reduce the poverty gap more than non-migrant households.

Return migration still frequently occurs in the social dynamics of Indonesian society. The sample in this study was 19% of the return migration group where this behavior has the opportunity to reduce the average income of the individual. However, the return migration behavior is not necessarily concluded as an individual failure in optimizing resources to seize opportunities in the destination area. Groups of workers who return-migrate generally feel that their efforts to maximize opportunities in the destination area have been less successful. If viewed from descriptive statistics, the data shows that the return migration group has a lower average level of education when compared to the one-time migration group and the repeated migration group. This can be an indication that education plays an important role in the success of someone migrating for work reasons and looking for work.

Different migration theories will produce different approaches in looking at a person's decision to migrate again. In neoclassical migration (NE) theory, migration is income or utility-maximizing behavior by individuals. Neoclassical migration theory links migration to failure to integrate in the destination area. In contrast, according to the new economic theory of labor migration (NELM), return migration in developing countries must be understood as a livelihood strategy for households, and migrants will return once they have succeeded in obtaining sufficient knowledge and income to accumulate assets and invest in their home areas. The projected return on investment will then be postponed for a continuous or indefinite period if integration is unsuccessful.

4. Conclusions and Suggestions

Based on the results of the analysis and discussion in this study, it can be concluded that there are differences in the impact among migration behavior on income. The behavior of one-time migration (never move again) and repeat migration have a significant impact on increasing the average income of an individual at a significance level of 1% and 10%. Only the return migration behavior does not impact significantly on the income of individuals. These results are consistent after several experiments combining the PSM and DiD methods with a number of regression models.

One-time migration and repeated migration are relatively advantageous compared to return migration. This study shows that the behavior of one-time migration and repeated migration can increase the opportunity for an individual's income to increase. The one-time migration group is seen as more able to maximize the opportunities at their first opportunity to migrate. This is inseparable from the readiness of individual migration actors and the receipt of better initial information about the destination area. Uncertainty, caused by the lack of initial information obtained or due to changes in the environment of the destination area, makes some migration actors find that the available job opportunities or local facilities in the destination area are much worse than expected. Workers learn that the initial migration decision was a mistake. Thus, the flow of return migration and repeated migration emerges as an attempt by migrants to correct these mistakes. Migration actors will possibly move again to other areas that they consider more profitable, and this results in repeated migration flows.

Some suggestions given regarding the results of the research obtained include the following:

1. Based on the conclusions in this study, the behavior of one-time migration and repeated migration is able to increase the opportunity for an increase in individual income. Therefore, government support is needed to ensure access to quality and equitable education for all levels of society. The success of a person in migrating is not only caused by the better job opportunities available in the destination area, but by the knowledge and skills possessed by migrating actors as factors determining the success of migration. Individual migration actors who have the skills and abilities needed by the world of work will be absorbed more quickly into the workforce. To achieve this, the government can improve the education system so that it is affordable for all levels of society. This is also done by strengthening the role of skills and expertise educational institutions that play a role in preparing a competent workforce in their fields. Other efforts can be made by strengthening cooperation between the private sector and educational institutions so that educational institutions can capture

the workforce needs needed by the business world.

2. Labor force mobility is a natural mechanism that prevents structured unemployment and promotes economic growth. Thus, policymakers must provide relevant information about the regional labor market. Seeing the migration goals that tend to move from rural areas to cities, a synergy between the central and the regional governments is needed to determine plans for new growth points expected to stimulate growth in the surrounding areas. In addition, facilitation for affordable living areas would contribute to the net benefits of migration, mitigating higher costs of living for migrants in urban areas.
3. Future research can continue studying the impact of migration at various regional scales or by considering differences in characteristics between regions to see the impact of migration behavior on income if it is related to the characteristics of the migration destination areas. In addition, further research can look at the impact of migration from a multi-dimensional perspective, including welfare, health, education, quality of life, and happiness. The phenomenon of return migration can be further analyzed regarding the entrepreneurial status of workers after returning to their home regions.

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