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Does migration network matter in driving internal migration in Indonesia?

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Abstract: Migration theory has developed a framework that considers factors influencing migration, including the pursuit of better economic opportunities in the destination area, which is a crucial pull factor. However, the internal migration literature, especially in Indonesia, currently lacks empirical evidence to show the role of migration networks as a mediating element in this mechanism. To address this research gap, we conducted a case study in Indonesia to examine the role of the migration network on the decision process of internal migrants. Our findings show that migration networks matter in driving internal migration with a moderate size effect, implying informational factors beyond those provided by networks also play a crucial role in migration decisions. These results indicate the importance of exploring additional avenues to enhance the positive impact of migration networks, such as creating designated social media applications to facilitate connections among potential migrants or exploring alternative means of meaningful engagement. Further research should examine the efficacy of such interventions and their potential to augment the influence of migration networks on migration decisions.

Keywords: Migration; Migration Network; Internal Migration; OLS; Indonesia
JEL Classification: J61; R23; O15; C13

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Introduction

Migration has become an essential strategy in economic development, especially in developing countries. In 2020, approximately 3 percent of the world's population (281 million) lived outside their countries (UN DESA, 2020). The decision to migrate internally within one country or across borders between countries is influenced by complex factors. Lee (1966) explained that the reasons people migrate are influenced by what is known as pull and push factors or Lee's theory of migration. Push factors are conditions forcing people to leave their current areas, such as unavailability of job opportunities, poverty, political instability, racial discrimination, poor healthcare, and natural disasters. In contrast, pull factors attract people to certain areas, such as wide employment opportunities, better education, better transportation facilities, and security. Those factors do not influence absolutely because each individual's decision to migrate will never be entirely rational (Lee, 1966).

Furthermore, continuous migration leads to the formation of migration networks (de Haas, 2010). These migration networks can benefit migrants

by providing information, temporary accommodation in destination areas, and financial assistance to go to migration areas (Karamba et al., 2011; Dolfin & Genicot, 2010). The migration network is also widely used as an instrument variable in several studies considering the endogeneity of migrant status, such as Nguyen and Winters (2011) and Karamba et al. (2011). Nevertheless, empirical works exploring the role of networks as mediating factors in the pull factor theory of internal migration have been limited. At the same time, many studies in the international migration context have discussed the migration network and its role in driving migration (Nowotny & Pennerstorfer, 2017; McKenzie & Rapoport, 2010; McKenzie and Sasin, 2007; Winters et al., 2001). Ultimately, migration networks can increase the probability of migration by lowering migration costs (Stark & Taylor, 1991) and increasing opportunities to find work or reducing job search time (Winters et al., 2001).

Indonesia presents an intriguing context for studying the role of migration networks due to the longstanding history of internal migration spanning several centuries, resulting in the formation of extensive migration networks. Numerous research studies have explored internal migration within the Indonesian context (Pardede et al., 2020; Auwalin, 2020; Marta et al., 2020; Farré & Fasani, 2011). Pardede et al. (2020) examined the influence of individual and household characteristics on internal migration in Indonesia. They proved that gender and family structure are significant in migration decision-making. Furthermore, Marta et al. (2020) studied migration motives and their impact on household welfare and found that migration positively impacted household welfare based on investment motivation.

Meanwhile, Farré and Fasani (2011) investigated the impact of media exposure on internal migration and showed that an increase in television channels reduces inter- and intra-provincial migration. However, research studying the role of migration networks at the district level in Indonesia's context remains underexplored. A previous study explores the role of networks but in a narrower form, namely, ethnic identity, in influencing internal migration decisions in Indonesia (Auwalin, 2020). The social norms belonging to a particular ethnicity provide a sense of identity and belonging for its members so that they tend to influence individual decisions within that ethnic group (Auwalin, 2020). Our study advances from existing empirical work, such as Auwalin (2020). In this study, the authors did not account for the influence of the regional origin of the ethnicity-based induced migration. Indeed, Indonesia is not only culturally diverse but also characterized by unique regional identities, each possessing the potential to foster the development of strong regional networks. The networks formed through migration processes can subsequently evolve into migration networks, assessed through similarities in the areas of origin. To the best of our knowledge, there has been no examination of the role of migration networks at the district level as pull factors for internal migration in Indonesia.

Based on the aforementioned review of the empirical evidence, the primary objective of this study is to quantitatively measure the migration network at the district/city level and provide a descriptive overview of its characteristics. Moreover, the study seeks to investigate the influence of migration networks on the decision-making process behind internal migration in Indonesia. We posit that migration networks significantly influence

an individual's or household's decision to migrate, leading them to prefer areas with stronger migration networks.

The contribution of this research is twofold. First, migration research in Indonesia is still scarce and pays attention to the power of migration networks in influencing migration flows. Therefore, this study seeks to fill this research gap to add to the literature on migration, especially in the Indonesian context. Second, the measurement of migration networks is rarely the focus of research in Indonesia. Accordingly, this research presents how to measure migration networks and portrait migration network patterns at Indonesia's district/city level. Thus, it can be a starting point for further migration network research in Indonesia.

This study uses data from the Indonesian Population Census 2010 to construct the migration network variable and the Susenas 2019-2021 for other variables. We employ the ordinary least squares (OLS) approach supplemented with a coefficient stability testing analysis considering omitted variable problems to analyze the link between migration networks and internal migration decisions. The results of the study show that the migration network matters in migration decisions. The migration percentage tends to be higher in areas with higher migration networks. We perform heterogeneity analysis by the island to examine various effects across the Indonesian archipelago. This research finding is expected to add empirical evidence that the migration network is essential in determining Indonesia's migration flows.

Research Method

The concept of migration used in this study leads to lifetime migration. A lifetime migrant is someone whose current district/city of residence differs from the district/city of birth (BPS-Statistics Indonesia, 2022). This definition of migrant status is similar to that proposed by Nowotny and Pennerstorfer (2017), using country of birth boundaries. Migration status information in our study was taken from Susenas 2019-2021, in which we define individuals as migrants if their hosting district differs from their born district. Moreover, the Susenas data are cross-sectional, with different samples between survey periods, so we used the repeated cross-section or pooled dataset setup. This research utilized Susenas due to its extensive coverage, encompassing all provinces in Indonesia. This wide scope enables the capture of migration patterns and networks across the country rather than being limited to specific provinces. In contrast, the Indonesian Family Life Survey (IFLS) has limited coverage, focusing on only a few provinces. Consequently, it can only analyze the impact of migration networks on household migration decisions within those specific provinces. Hence, we contend that utilizing Susenas data is more suitable for addressing the research questions in this study both due to the availability to define migration status and origin as well as the completeness of province coverage.

Migration decisions are usually joint decisions within a household. Therefore, the focus of this research is the status of migrants at the household level. The dependent variable in this study is household migrant status, a binary variable. This dependent variable is 1 if

there are one or more individuals in the household with migrant status and 0 if none. Migrant households consist of mixed households (migrant and nonmigrant members) and pure migrants (all members are migrants). Meanwhile, non-migrant households are households where all members are not migrants or born and domiciled currently in the same district/city.

However, no information is available when individuals/households migrated, so we cannot precisely build a migration network variable in the year before the migration decision. Therefore, we used a proxy migration network with a lag a few years ago using the Indonesian Population Census 2010. This strategy follows Mora-Rivera and van Gameren (2021), who employed a historic migration rate variable with a few years lag. This migration network variable is the primary independent variable in this study. The household's socioeconomic condition and head are considered control variables in the model. In addition, adding a control variable in the model can also reduce the potential for omitted variable bias.

We employed the Ordinary Least Square (OLS) model to address the research question. We acknowledge that the independent variable might not be strictly exogenous, leading to a potential bias point of estimate. To address this issue, we introduced a set of battery control variables in Equation 1 represented by vector X_{hjt}. Moreover, to limit the potential bias considering the omitted data, we conducted coefficient stability testing introduced by Oster (2017).

$$Y_{hjt} = \alpha + \beta(LnMigrationNetwork)_{hij,2010} + \sum_k \theta_1^k X_{hjt}^k + \delta_r + \gamma_t + \varepsilon_{hjt} \quad \text{..... (1)}$$

The subscripts *h*, *t*, and *r* in model (1) denote the household, year, and region, respectively. The index *j* refers to the hosting district, and index *i* refers to the origin district, which we assume from the born district of an individual in the Susenas data. $LnMigrationNetwork_{hij,2010}$ is the main independent variable whose relationship is observed with the migration status of the household. Furthermore, variable X_{hjt} is a set of control variables at the household level. The control variables consist of information on the head of the household, namely, age, gender, education, type of main job, marital status, and household information, including rural–urban residences, house ownership status, and land ownership status. The characteristics of the head of the household are important to consider in the model because, usually, the head of the household is the main decision-maker. Moreover, we included regional fixed effects/FE (δ_r) at island levels to control the time-invariant characteristics of unobserved heterogeneity in the region, such as the perception of the destination area. We also considered the year-fixed effect/FE γ_t to control for time-varying unobserved heterogeneity. Finally, we clustered all standard errors at the district level.

Constructing Migration Network

We measured migration networks by adopting the research of McKenzie and Rapoport (2010) and Massey et al. (1994). These studies calculated the migration network with the proportion of all individuals aged at least 15 in a given community who have previously

migrated. Adopting this measurement, we defined migration network as the share of the number of migrants coming from the origin district *i* and living in hosting region *j* to the number of populations in the origin district *i*. In this case, the migration network is a pull factor for workers to migrate. Access to these networks strongly impacts migration even though it has a diminishing effect (Karamba et al., 2011).

$$m_{ij,2010} = \left(\frac{total\ of\ migrants\ living\ in\ district\ j\ coming\ from\ origin\ districts\ i\ in\ 2010}{total\ of\ populations\ in\ origin\ districts\ i\ in\ 2010}\right) \times 100 \ldots \quad (2)$$

Then, we perform the natural logarithm of the value as follows.

$$Ln(migration\ network) = Ln(m_{ij,2010} + 0.0001) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

where m is the migration network in percent. The natural logarithmic specification describes the assumption of decreasing marginal utility from the migration network variable (Nowotny & Pennerstorfer, 2017). Thus, increasing m has a smaller effect on the probability of selecting a migration destination as the network size increases. Adding 0.0001 to the m value aims to avoid losing observations because the value 0 is not defined in logarithms.

We performed a robustness check by measuring the migration network using the stock of previous migrants adopted from Nowotny and Pennerstorfer (2017) research. To distinguish the migration network variable from equation (3), we then mentioned it as a Network.

$$Network = Ln(mig_{ij,2010} + 1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

where mig is the number of migrants in the origin districts. The purpose of adding number 1 to equation (4) is the same as the previous equation to anticipate the loss of observations because there are no migrants in the original districts.

Results and Discussion

Before conducting an empirical analysis of the relationship between migration networks and household migration status, we explored the data to study household characteristics and migration networks. After data cleaning of Susenas 2019-2021, the total households analyzed were 988,876 households in 34 provinces. Table 1 provides the mean differences between the two groups of analysis: migrant and non-migrant households. The null hypothesis of this mean-comparison test is that the mean between the two groups is statistically equal. The null hypothesis should be rejected if the p-value is lower than 0.05, meaning the mean between the two groups is significantly different.

The average migration network of migrant households is 1.5 times larger than that of non-migrant households, and this difference is statistically significant. This could be an early signal that the migration network tends to influence the intensity of household migration.

Of all sample households, 37.88 percent (374,549) are migrant households, with 84.54 percent of the sample households headed by men and the rest headed by women. Migrant households tend to have household heads with higher education than non-migrant households. This may indicate that people with higher education have more bargaining power to migrate.

In addition, migrant households work more in the non-agricultural sector, probably because it is relatively easier to mobilize than in agriculture, with only 28.48 percent of the heads of migrant households working in the non-agricultural sector. In comparison, the heads of non-migrant households account for almost half of all non-migrant households working in the agricultural sector (46.00 percent). More migrant households prefer to migrate to urban areas (55.51 percent) than rural areas, implying that urban areas are more attractive as migration destinations. This preference stems from the generally superior infrastructure standards in urban areas, encompassing better educational facilities, healthcare services, communication networks, and transportation systems. Additionally, urban centers offer more comprehensive job opportunities, thereby expanding the prospects for enhancing household economic well-being. Conversely, households established in regions characterized by property ownership, such as houses or land, are less inclined to migrate or opt to remain in their current location. However, it is essential to acknowledge that this study did not include various unobservable factors that could influence an individual's migration decision, such as the perceived comfort of residing in their original area, proximity to parents and family members, and the absence of social conflicts.

Table 1 The Mean Difference Between Migrant Households and Non-migrant Households

Variables	Nonmigrant households		Migrant households		Mean differences
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	
Migration network	18.7295	15.1977	27.2173	21.5181	-8.4878***
Household Head's characteristics:					
Age	49.3415	13.6341	47.5857	13.2946	1.7558***
Age squared	2620.47	1418.81	2441.15	1334.17	179.33***
Gender (male=1)	0.8286	0.3769	0.8731	0.3329	-0.0445***
Marital status (married=1)	0.7810	0.4136	0.8310	0.3748	-0.0500***
Years of schooling	7.4445	4.2169	9.5492	4.2500	-2.1047***
Sector (agriculture=1)	0.4600	0.4984	0.2848	0.4513	0.1752***
Household's characteristics:					
Number of members	3.7050	1.7055	3.8978	1.7261	-0.1928***
Land ownership (yes=1)	0.7804	0.4140	0.7078	0.4548	0.0726***
House ownership (yes=1)	0.8848	0.3193	0.7306	0.4437	0.1542***
Rural–urban status (urban=1)	0.3310	0.4706	0.5551	0.4970	-0.2241***
Observations	614,327		374,549		

Source: Migration network from the Indonesian Population Census 2010 and other variables from Susenas 2019-2021 (processed by author). ***, **, * indicate statistical significance at 1%, 5%, and 10%.

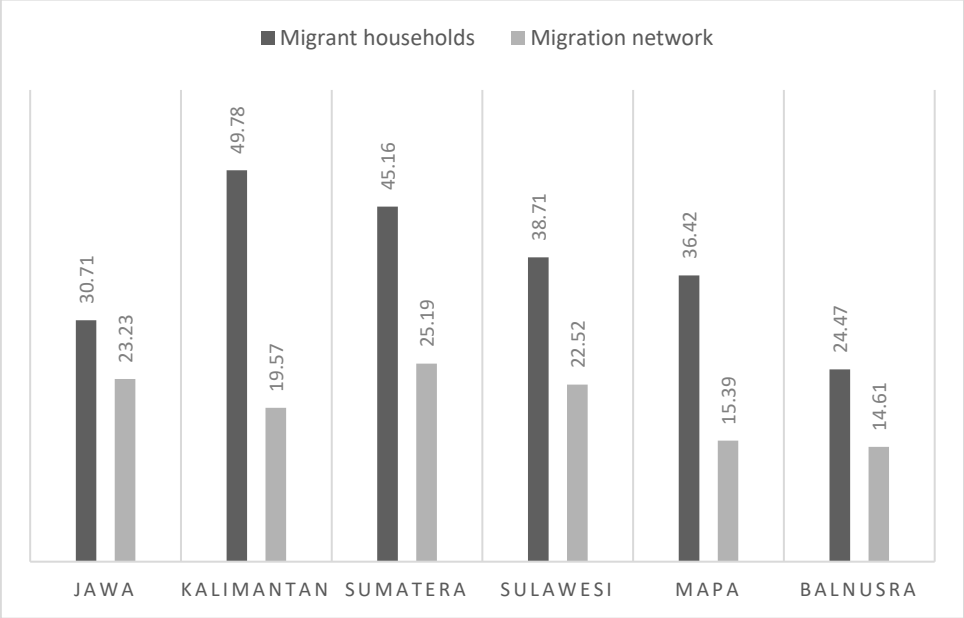

Figure 1 Percentage of Migrant Households and Migration Network by Islands

Figure 1 presents the percentage of migrant households calculated using the Susenas 2019-2021 data and the migration network formed from the Indonesian Population Census 2010 data by island group. Mapa shows a group of islands in Maluku, North Maluku, Papua, and West Papua. Meanwhile, Balnusra is a group of Bali and Nusa Tenggara islands. Figure 1 illustrates a positive correlation pattern between the size of the migration network and the percentage of migrant households on the islands of Sumatra, Sulawesi, Mapa, and Balnusra compared to the number of households on each island. A higher percentage of migrant households in the four island groups seems to be associated with an increasing migration network.

Moreover, Kalimantan Island has the largest percentage of migrant households compared to the population of all households in Kalimantan. Mostly, half of the household population is made up of migrant households, either pure or mixed migrants. However, Kalimantan has a smaller migration network size than Jawa. In absolute terms, the number of migrant households in Jawa is greater than that in Kalimantan. The findings of Table 1 and Figure 1 indicate the necessity for further analysis to examine the impact of the migration network on household migration status.

Main Estimation

Table 2 presents the estimation results of the effects of the migration network on household migrant status in several specifications. Specification (1), without including any control variables, shows that the relationship between the migration network and the status of migrant households is positive and statistically significant, meaning that an increase in the migration network can increase the probability of a household migrating. Furthermore, in specifications (2), (3), and (4), we included island-fixed effects/FE, year-

fixed effects/FE, and the interaction of both. In specification (2), when considering the control in the form of the characteristics of the head of the household, the migration network still has a positive effect on the probability of household migration, although with a smaller magnitude. These results underscore the importance of considering the characteristics of the household head in migration decisions.

Table 2 Regression Estimation of Migration Network on Household Migrant Status

Variables	Household migrant status			
	(1)	**(2)**	**(3)**	**(4)**
Ln (Migration Network)	0.1553***	0.1405***	0.1328***	0.1239***
	(0.0103)	(0.0104)	(0.0103)	(0.0102)
Ln (Migration Network) from Oster Test	-	-	-	[0.1149***]
R-squared	0.0598	0.1393	0.1499	0.1717
Age	-	-0.0020**	-	-0.0003
		(0.0009)		(0.0008)
Age squared	-	0.0000**	-	0.0000
		(0.0000)		(0.0000)
Gender (male)	-	0.0353***	-	0.0264***
		(0.0037)		(0.0034)
Marital status (married)	-	0.0387***	-	0.0435***
		(0.0045)		(0.0039)
Years of schooling	-	0.0173***	-	0.0137***
		(0.0008)		(0.0006)
Sector (agriculture)	-	-0.0864***	-	-0.0615***
		(0.0055)		(0.0048)
Number of members	-	-	0.0169***	0.0169***
			(0.0012)	(0.0012)
Own land	-	-	0.0398***	0.0398***
			(0.0059)	(0.0059)
Own house	-	-	-0.1935***	-0.1935***
			(0.0075)	(0.0075)
Urban	-	-	0.1920***	0.1920***
			(0.0116)	(0.0116)
Island FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Island*year FE	No	Yes	Yes	Yes
Constant	-0.0575**	-0.0638*	0.0478	-0.0526
	(0.0261)	(0.0384)	(0.0304)	(0.0354)
Observations	988,876	988,876	988,876	988,876

Note: District-level clustered standard error in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%.
The Logit estimate is provided in the **Appendix**.

Meanwhile, specification (3) controls the household characteristics and indicates the same direction as the previous specifications. However, specification (3) produces an even smaller magnitude than specification (2), indicating that the socioeconomic conditions of the household have a more significant influence on the decision of a household to migrate

compared to the characteristics of the head of the household. Finally, the full specification (4) takes into account both the characteristics of the head of the household and the socioeconomic conditions of the household and confirms the results of the three previous specifications. Every one-point increase in the migration network will increase the probability of migration by 0.12 percentage points. This magnitude is equivalent to an implied elasticity of 0.33%. Nevertheless, the magnitude of the migration network is not too large to influence migration decisions. This is because migration is a decision influenced by many complex factors. Furthermore, the R-squared value shows an increase from not including any control variable (specification (1) in Table 2) to specification (4), indicating that explanatory variables have increasing power in explaining the dependent variable.

Nevertheless, these findings are consistent with the literature showing that migration networks are essential in facilitating migrating opportunities (Beine et al., 2015; McKenzie & Rapoport, 2010; Mckenzie & Sasin, 2007). The result is particularly understandable in Indonesia, given the country's strong emphasis on kinship values. Individuals or households may feel more at ease relocating to areas they perceive as more familiar due to the presence of relatives, friends, or fellow residents from their home region in the destination area.

Coefficient Stability Test

Furthermore, we performed a coefficient stability analysis proposed by Emily Oster (Oster, 2017) or we called it 'Oster test' for migration network and household migration status to examine the coefficient stability of the independent variable and R-squared movements, and the result is shown in Table 3. The implications of the Oster Test are whether the indication of improvement in bias by the control variables is stable and whether the addition of the control variables increases the R-squared (Oster, 2017). The baseline effect (column 1) in Table 3 is the resulting coefficient without including any control variables in the model. Meanwhile, the controlled effect (column 2) is a coefficient that includes all control variables. Adding the control variables to the model reduces the coefficient by 0.0314 points but moves the R-squared by 0.1119 points.

Table 3 The Coefficient Stability Test

Variable	Baseline Effect	Controlled Effect	β if δ=0.545	δ for β=0
	(1)	(2)	(3)	(4)
Ln (Migration Network)	0.1553***	0.1239***	0.1149***	3.7506
	(0.0103)	(0.0102)		
R-squared	0.0598	0.1717	-	-

Note: District-level clustered standard error in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%.

In this coefficient stability test, δ is the relative degree of selection on observed and unobserved variables. Using δ = 0.545, as Oster (2017) suggested, produces a lower bound of the β coefficient of 0.1149. This coefficient does not significantly differ from the final result obtained when including all our controls (0.1239). Therefore, we can infer that

the coefficients we produce are robust. Furthermore, column (4) shows the value of δ or the effect value of Ln (Migration Network) equal to zero with the maximum R-squared (30%) equal to 0.2232. The resulting δ value is 3.7506, meaning that to make the value of β = 0, the unobserved variable needs to consider the Ln (Migration Network) variation, approximately three times more than the observed variables.

Heterogenous Effects

Table 4 Regression Estimation of Migration Network on Migrant Status by Island

Variables	Migrant status					
	Sumatera	**Jawa**	**Kalimantan**	**Sulawesi**	**Balnusra**	**Mapa**
Ln (Migration Network)	0.1503***	0.0856***	0.2111***	0.0884***	0.0544**	0.1632***
	(0.0228)	(0.0133)	(0.0431)	(0.0306)	(0.0234)	(0.0224)
R-squared	0.1094	0.2094	0.2045	0.0699	0.1937	0.3262
Household Head's characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Household's characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Island FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Island*year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.0831	-0.1148*	-0.3145***	0.0116	0.1387**	-0.0846
	(0.0694)	(0.0601)	(0.0957)	(0.0901)	(0.0682)	(0.0742)
Observations	281,386	304,654	97,032	138,387	74,629	92,788

Note: District-level clustered standard error in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%.

In aggregate, it has been proven that migration networks significantly influence the probability of households migrating. However, the effects of the migration network may differ from one region to another due to regional characteristics, such as the region's topography and other economic conditions. Therefore, we estimated by dividing the sample into six groups of islands: Sumatera, Jawa, Kalimantan, Sulawesi, Balnusra, and Mapa. The results of the heterogeneous effect estimation (Table 4) prove that the migration network has a positive and statistically significant path to household opportunities to migrate across the island. Kalimantan Island has an immense migration network magnitude compared to the other four islands. In contrast, the migration network effect on the islands of Balnusra has the least influence on households migrating to these areas. Overall, these results prove that our estimate is valid.

Robustness Test

Table 5 Regression Estimation of Network on Household Migrant Status

Variables	Household migrant status			
	(1)	**(2)**	**(3)**	**(4)**
Network	0.0751***	0.1186***	0.1139***	0.1097***
	(0.0065)	(0.0068)	(0.0069)	(0.0069)
R-squared	0.0486	0.1736	0.1821	0.2038
Age	-	-0.0024***	-	-0.0013*
		(0.0009)		(0.0008)
Age squared	-	0.0000***	-	0.0000***
		(0.0000)		(0.0000)
Gender (female)	-	0.0315***	-	0.0230***
		(0.0039)		(0.0036)
Marital status (married)	-	0.0330***	-	0.0332***
		(0.0047)		(0.0040)
Years of schooling	-	0.0182***	-	0.0146***
		(0.0008)		(0.0007)
Sector (agriculture)	-	-0.1104***	-	-0.0539***
		(0.0075)		(0.0047)
Number of members	-	-	0.0190***	0.0138***
			(0.0011)	(0.0011)
Own land	-	-	0.0398***	0.0288***
			(0.0059)	(0.0055)
Own house	-	-	-0.1868***	-0.1581***
			(0.0073)	(0.0067)
Urban	-	-	0.1854***	0.1345***
			(0.0111)	(0.0093)
Island FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Island*year FE	No	Yes	Yes	Yes
Constant	-0.4564***	-0.9608***	-0.8322***	-0.8945***
	(0.0663)	(0.0755)	(0.0723)	(0.0751)
Observations	988,876	988,876	988,876	988,876

Note: District-level clustered standard error in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%.

Furthermore, we conducted a robustness test (shown in Table 5) using another measurement of the migration network variable, adopting the research of Nowotny and Pennerstorfer (2017). The OLS estimates generate results similar to the main estimates, direction, and significance. The network positively affects the probability of household migrant status, with or without controlling the characteristics of the household head and the socioeconomic conditions of the household. These results suggest that our estimates are relatively robust.

Discussion

Migration is a multifaceted decision influenced by an array of factors. In addition, migration transpires when individuals perceive that the expenses associated with migration are lower than the anticipated benefits, for example, as articulated by Adhisti

(2014) in the context of international migration. Adhisti (2014) revealed that calculating the net value of labor migration benefits can be an alternative framework in individuals' decision-making processes regarding destination country selection. We infer that a similar calculation applies to internal migration. Moreover, migration can also be influenced by migration networks. These networks may impact an individual's or household's decision to migrate by providing potential migrants with various advantages, such as knowledge about migration destination areas. This information encompasses several factors that potential migrants may consider when deciding whether to migrate, including border crossings (Dolfin & Genicot, 2010) and job opportunities (Winter et al., 2001). The primary objective behind the network-to-migration decision we are examining is minimizing economic costs associated with information search.

The migration network measurement can be formed through various perspectives that have the potential to create a network, such as networks based on family (Karamba et al., 2011), community (Karamba et al., 2011), ethnic identity (Auwalin, 2020), or administrative area such as country (Nowotny & Pennerstorfer, 2017). In this research, we measured the migration network using the administrative boundaries of the district or city of origin to see whether the network formed within the region of origin influences migration decisions.

On the other hand, numerous intricate factors influence an individual's decision to migrate, with economic considerations consistently identified as a primary driver for migration across various contexts. For instance, studies conducted in Russia have shown that individuals often relocate from economically disadvantaged regions to more prosperous areas (Andrienko & Guriev, 2004). From an economic standpoint, having access to a migration network can yield economic advantages for potential migrants. This access is often considered a privilege, as previously migrated individuals may gain entry to expanded employment opportunities (Winter et al., 2001) through established networking relationships. Additionally, aspiring migrants who have not yet established themselves in their migration destination may receive temporary shelter assistance and, in some cases, even financial support from the migration networks they are associated with (Karamba et al., 2011; Dolfin & Genicot, 2010). Access to a network can mitigate migration costs, enhancing an individual's prospects for migration.

Furthermore, viewed from the perspective of the area of origin, migrants can serve as influencers who attract others from their hometown to move elsewhere in search of a better life. This influence is fostered when migrants share information with individuals who still reside in their area of origin. However, the information the network shares can negatively and positively affect migration decisions. Favorable information may act as a push factor, encouraging individuals to leave their area of origin. Conversely, if the information proves to be disadvantageous, people may choose to remain in their area of origin.

Our estimations indicate that migration networks play a significant role in driving internal migration in Indonesia. Our findings align with earlier studies, such as those conducted by Zhao (2003), although our estimated effect size is somewhat lower than similar studies in

China. Migration in Indonesia typically occurs between cities or districts, and while our results suggest a moderate effect size, it is evident that other informational factors beyond migration networks also influence migration decisions. This less pronounced effect of the network may be attributed to the accessibility of information about destination areas through various digital platforms in today's era of extensive digital development. Access to the migration network concerning destination area information may not be the only benefit prospective migrants hope for. However, this connection to the migration network may still be able to attract potential migrants more strongly if it is linked to assistance in the migration destination area, such as financial assistance or temporary shelter.

Conclusion

This study investigates whether migration networks matter in driving internal migration in Indonesia. The result found that the migration network contributes to driving internal migration in addition to the characteristics of the head of the household and the socioeconomic conditions of the household. The role of the migration network in driving internal migration is moderately significant, implying that informational factors beyond migration networks also influence migration decisions. These results suggest that future research could explore interventions to enhance the positive effects of migration networks, such as developing dedicated social media apps to connect potential migrants or other alternative means. Furthermore, the study reveals that regions with higher migration networks tend to have more migrant households. Data exploration also highlights regional variations, with Bali and Nusa Tenggara islands exhibiting the lowest migration networks compared to other islands, while Sumatra Island has the highest migration network among them.

Although our estimation results are reliable, we acknowledge several limitations of this study. Firstly, we lack information on the timing of household migrations, preventing us from accurately calculating migration networks before making decisions. Secondly, we cannot analyze the short-term and long-term impacts of migration due to data constraints. Additionally, the literature suggests that migration networks extend beyond administrative regions and can encompass family or community networks. Given these limitations, we recommend further research to conduct separate analyses on short-term and long-term migration impacts and to consider other important networks that may influence migration decisions. Furthermore, conducting causal inference analysis could address potential endogeneity issues.

Author Contributions

Conceptualisation, Methodology, Analysis, Original draft preparation, Review and editing, E.N. and R.N.; Visualization, E.N.; Supervision, R.N.

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Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study, in the collection, analyses, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

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Appendix

Table 1 Logit Estimation of Migration Network on Household Migrant Status

Variables	Household migrant status			
	(1)	(2)	(3)	(4)
Ln (Migration Network)	0.1583***	0.1416***	0.1319***	0.1237***
	(0.0109)	(0.0107)	(0.0106)	(0.0105)
Age	-	-0.0023***	-	-0.0007
		(0.0008)		(0.0007)
Age squared	-	0.0000***	-	0.0000*
		(0.0000)		(0.0000)
Gender (male)	-	0.0372***	-	0.0289***
		(0.0037)		(0.0034)
Marital status (married)	-	0.0402***	-	0.0444***
		(0.0045)		(0.0039)
Years of schooling	-	0.0171***	-	0.0136***
		(0.0007)		(0.0006)
Sector (agriculture)	-	-0.1182***	-	-0.0614***
		(0.0079)		(0.0048)
Number of members	-	-	0.0168***	0.0109***
			(0.0012)	(0.0012)
Own land	-	-	0.0409***	0.0299***
			(0.0059)	(0.0055)
Own house	-	-	-0.1797***	-0.1508***
			(0.0069)	(0.0063)
Urban	-	-	0.1806***	0.1296***
			(0.0104)	(0.0084)
Island FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Island*year FE	No	Yes	Yes	Yes
Observations	988,876	988,876	988,876	988,876

The OLS estimation in Table 2, section Results and Discussion, produces a coefficient of 0.1239, while the Logit estimation result has 0.1237, which statistically shows the same direction, magnitude, and significance. Therefore, we prefer to use OLS because the resulting estimation results are efficient and can be directly interpreted.