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Migrating for Children's Better Future: Intergenerational Mobility of Internal Migrants' Children in Indonesia

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Abstract

Internal migration dominates population mobility in Indonesia; according to the 2010 census, there were almost 30 million permanent migrants, around 12.5 percent of the population. The effects of this internal migration on the second generation continue to be under-explored. This paper investigates the long-term impact of parents' migration on their children's intergenerational per capita expenditure when adults. We argue that parental migration affects the human capital investment on their children, which has a direct impact on the children's outcomes when adults and on their deviation from the parents' economic status, hence their intergenerational mobility. We pooled the data of five waves of the Indonesian Family Life Survey, and we tackled the self-selection of parents' migration using linear regression with endogenous treatment. Our findings show that despite the fact that parental migration increases the education level of children and their per capita expenditure, it increases intergenerational mobility only when grown-up children live in urban areas, come from the poorest parents, and migrated themselves in their childhood. The left-behind children have more intergenerational mobility only if their father migrated, while there is no significant impact on intergenerational mobility if their mother migrated. The results are consistent with the persistence of individual inequality in Indonesia.

JEL classification: J13, O15

Keywords: Migration, intergenerational mobility, children

1 Introduction

Internal migration represents a significant share of population mobility in Indonesia, involving almost 30 million lifetime migrants (Handiyatmo, 2012). In comparison, international out-migration from Indonesia is relatively smaller as it involved around only 349 thousand people in 2017 (UNDESA, 2017). Approximately 3.3 million of these internal lifetime migrants are children age 0-14 years old (Handiyatmo, 2012). These children are affected by this migration both in the short and long run and have no say in their parents' migration. Suwandinata (2012) suggest that, when it comes to household choices, whilst parents are the main decision makers on food and consumption within the household children are often seen by the parents as influencers. Moreover, some children are left behind when their parents migrate. Beazley et al. (2018) argue that despite their strong feelings about their parents' migration, the left-behind children in Lombok have no choice, whether they 'like it or don't like it'. Lam and Yeoh (2018) suggest similar finding that children have lack of voice, although some of them succeed to persuade their parents to come back home. This paper inquires whether past parental migration during the children's childhood benefits those children when they reach adulthood and whether there is less inter-generational per capita expenditure persistence among the children of the migrants. These questions are scarcely explored in the current literature.

The impact of parents' migration on children depends predominantly on how mi- grant and non-migrant parents invest in their children's human capital. Perceived improved access to higher-quality schooling can be a driver of parents' migration. Klein (2011) suggests that investment in children's human capital can be a key driver of migration, besides the rural-urban wage differential. If parents aspire to move for better investment in their children's education, then parent's migration may benefit children in the future. Also, Long (1972) shows that the number and age of the children influence US parents' decisions to migrate. The parents are more mobile when children are under six years old, indicating that once children enter school, the family is less likely to migrate. These findings indicate that human capital investment is a determinant of parental migration and that parents' choice to migrate has a positive impact on children's welfare when adults.

In this paper, we investigate the long-term impact of parents' migration during their children's childhood on the future outcomes of their children when adults. In particular, we examine how parents' migration affects their children's per capita expenditure as an indicator of intergenerational mobility. We also explore the mechanisms that might explain this relationship, in particular, education. In this paper, 'children' refers to children of migrants and non-migrants at the time of their adulthood.

This paper contributes to the scarce literature on the impact parent's migration has on children's future outcomes. Notably, in a developing country setting, these studies are rare, which is in part due to limited data availability. This paper fills the gap in the literature exploring the long-term impacts of migration of the previous generation. It differs from earlier studies that compared the migrants' social-economic status with their non-migrant parents (Long and Ferrie, 2013) and the non-migrant siblings (Beegle et al., 2011) in rural areas.

The paper is organised as follows: section two provides an overview of Indonesia's inequality and migration. Section three examines the literature of intergenerational mobility and

migration, followed by a theoretical framework and overview of the data in section four and the empirical strategy in section five. Section six describes our findings, section seven explores the mechanisms, and section eight describes the robustness checks. The last section concludes, providing suggestions for future research.

2 Background: Indonesia's Individual Inequality and Migration Profile

Over 24 years from 1994 to 2018, Indonesia's Gini coefficient remained between 0.3 and 0.4 points (see figure 1). The Gini coefficient showed a steady increase during the 1990s before dropping to 0.31 over 2001 and 2002 following a period of financial and political instability. However, inequality increased to 0.39 in 2003, just higher than the previous level high of 0.37 in 2000. Since then, individual inequality stayed reasonably constant over the following 15 years.

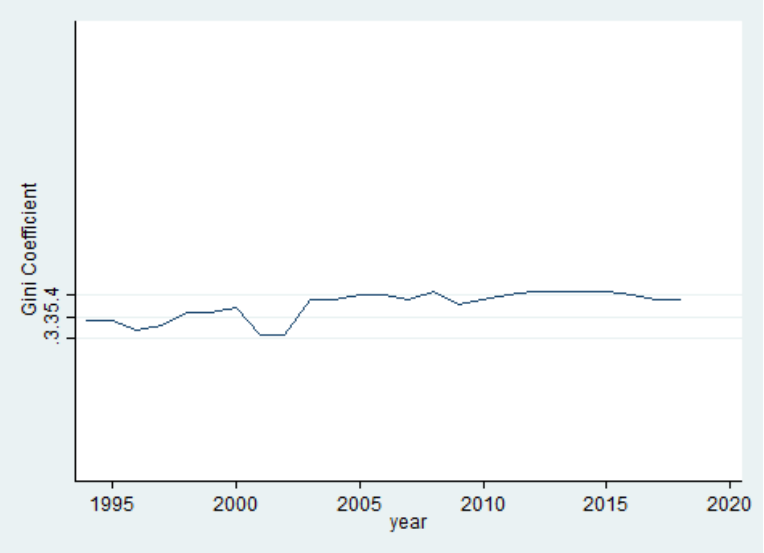

Figure 1: Gini Coefficient in Indonesia, 1994-2018
Source: We retrieved Gini coefficients for the year 1994 to 2011 from Kuncoro and Murbarani (2016) who refer to BPS in their paper. The rest of the years, we use official data from BPS. Gini coefficient is calculated by BPS using the annual SUSENAS data.

The relationship between inequality and intergenerational mobility is famously captured by Corak (2013) and described as the "Great Gatsby Curve". Using cross- sectional data across 22 countries, he finds that those countries with higher income inequality have more intergenerational persistence and less intergenerational mobility. If Indonesia follows a similar pattern as this curve, then the persistence of this level of individual inequality indicates that there may be intergenerational persistence rather than intergenerational mobility.

Ravenstein's law of migration that most migration is short-distance holds for Indonesia. When we divided Indonesia into its seven major islands, population mobility in Indonesia predominantly occurs within the same island rather than between islands. Using the 2014 National Socioeconomic Survey (SUSENAS), we show migration flows between and within the major islands. Table 1 shows the share of lifetime migrants, people who were born in different districts (Kabupaten) to those where they currently live, in the seven major Indonesian islands.

In Table 1, the diagonal highlights that lifetime migration between districts happens within the islands. About 80 per cent of people born in Sumatra undertake intra- island migration

between districts in Sumatra. When they migrate to other regions, they migrate to neighbouring islands. Sumatra has the second highest intra-island migration after Kalimantan at 82.4

Table 1 also shows that Java is still a major destination for many people from other islands. This is also in line with Ravenstein's law of migration that the economic and industrial centres are the primary destination for long-distance migrants. If we look at inter-island migration, the highest percentage of non-Java migrants migrate out of their island to Java, with Sulawesi and Maluku as exceptions. More migrants inter- regionally migrate to Kalimantan if they were born in Sulawesi, and to Papua if they were born in Maluku.

Table 1: Lifetime Inter-District Migration Flows in Major Islands of Indonesia

Birth Island	Current Island							Total
	Suma-tra	Java	Bali & Nusra	Kali-mantan	Sulawesi	Maluku	Papua	
Sumatra	80.39	17.73	0.30	0.95	0.40	0.04	0.20	100
Java	13.53	76.48	1.65	5.80	1.40	0.29	0.85	100
Bali & Nusra	5.87	9.81	67.84	5.34	8.94	0.38	1.82	100
Kalimantan	1.51	13.27	0.52	82.41	2.03	0.08	0.17	100
Sulawesi	2.49	6.16	1.12	12.17	70.02	2.23	5.80	100
Maluku	1.05	9.35	1.29	0.89	12.63	59.79	15.01	100
Papua	1.57	10.67	1.04	1.14	6.80	2.92	75.85	100
Total	27.81	48.78	3.95	9.05	7.43	1.13	1.84	100

Source: Authors' calculations using National Socioeconomic Survey (SUSENAS) 2014
Source: Nusra refers to West and East Nusa Tenggara
Note: Percentage of total lifetime migrants' population of 45,354,892 people

3 Relevant Literature

3.1. Intergenerational Mobility and Migration

The concept of intergenerational mobility is closely related to the concept of social mobility. While social mobility looks at the differences in the socio-economic status of one generation, intergenerational mobility looks at two or more generations. In economics, intergenerational mobility is defined as the transmission of earning from one generation to the next (Borjas, 1992; Peters, 1992). In addition, occupation (Borjas, 2006; Long and Ferrie, 2013) and consumption (Beegle et al., 2011) can also be used to measure intergenerational mobility. Becker and Tomes (1979) explain how the mechanism of the transmission of parents' income to the children's earning is through human capital investment.

The available literature on both social and intergenerational mobility focuses on international migration rather than internal migration. This is due particularly to developed countries having more data available and because South-North immigration is both economically and politically a critical issue. Some of these studies focused more on assimilation and acculturation of immigrants in destination communities.

A number of papers have explored intergenerational mobility in the USA, in particular, on differentials across immigrants' ethnicity. Borjas (1992) studied second-generation migrants in the USA and how ethnicity impacted skills transmission and intergenerational mobility. He founds that the differences in income and education persist across generations. This persistence has been shown to relate not only to ethnicity but also to parents' occupation. Kim (2006) looked at children of Korean immigrants in the US, finding that being a child of Korean entrepreneur immigrants limited education and occupational choices, leading to downward intergenerational mobility. The direction of intergenerational and social mobility for international migrants can also depend on structural economic change in the destination country (Borjas, 2006; Dribe et al., 2015) and on the investment in skills and education of the migrants (Heckman and Mosso, 2014).

In Europe, using German socio-economic panel data, Dustmann (2008) studied the relationship between return migration, intergenerational earning mobility and in- vestment in the education of immigrants' children. The study found that immigrant's children have lower intergenerational mobility than native children. Hammarstedt and Palme (2012) studied the earnings of second-generation immigrants in Sweden and found that there is overall higher intergenerational mobility. However, different groups of migrants have different rates of intergenerational mobility depending on differences in their group human capital transmission. Nielsen and Rangvid (2012) and Smith et al. (2016) investigated the relationship between the length of the duration of the parent's stay in Denmark and Sweden and their children's educational achievements respectively, in both cases finding a positive impact reflecting the importance of the linguistic ability of the immigrants' parents.

Few studies have investigated the impact of internal migration on intergenerational mobility. Long and Ferrie (2013) examined 19th-century rural-urban migration in Great Britain when the industrial revolution saw labour from agricultural jobs in the rural areas move to manufacturing jobs in cities. The study found that there was upward intergenerational occupational mobility among migrants in 1881, compared with their father's occupations in 1851. They also found that there was a positive selection of migrants to urban areas and a

negative selection of migrants to rural areas. On average, people from all socio-economic strata who moved to the city were substantially more successful in improving their socio-economic status than they would have been had they remained in rural areas, and they were more likely to experience an upward intergenerational occupational mobility. In another study, Krishna (2013) found that children in 14 Bangalore slums experienced intergenerational persistence as they followed their father's occupations. As residents of the slums are mainly migrants, the study implies that the migration of poor parents may result in intergenerational persistence instead of upward intergenerational mobility.

The current literature finds that internal migration has a positive impact on the social mobility of the migrants. Beegle et al. (2011) evaluated the impact of rural to urban migration in Tanzania, using siblings and relatives as counterfactuals for measuring the effects of people's decision to migrate. They found that per capita consumption increased 36 per cent for migrants in comparison with rural stayers, implying upward social mobility of the migrants. They also found that the destination mattered; migrants who moved to a more connected area have higher returns than those in less connected areas. However, even moving to the less connected areas resulted in higher growth in consumption. A study of rural-urban migration in Vietnam confirms a similar positive relationship between migration and social mobility. Nguyen et al. (2013) found that the resulting higher income growth both helps the migrants out from poverty, as well as improving the poverty situation of rural stayers.

The literature on internal migration suggests that migrating leads to higher consumption growth and that migrant parents have more resources and can invest more in their children than those who stay. It also shows that investment in human capital can be a mechanism through which the impact of migration on intergenerational mobility is channeled.

3.2. Intergenerational Mobility and Migration: Indonesia

There are only a limited number of empirical studies that can help us to build an initial hypothesis of the relationship between migration and intergenerational mobility in Indonesia. Intergenerational persistence is evident for children from more impoverished families across the country, although there is no information on whether poor migrants' children are better off than non-poor migrants' children (Pakpahan et al., 2009). Sumner et al. (2014) show that rural Indonesians who work in agriculture have a 90 per cent probability of remaining poor. However, in general, there is a decline in the intergenerational correlation of education for the cohort groups born in 1943-1956 and 1976-1980 due to the benefits of widespread investment in education during the Soeharto era (Levine and Jellema, 2007).

Studies have also shown that migration can play a role in breaking intergenerational persistence. Resosudarmo et al. (2009) show that urban migrants' households have a higher income and lower probability of falling into absolute poverty than local urban residents. In another study, higher social status of the migrants results in a higher propensity to climb the social ladder, as the poor migrants have fewer opportunities than more prosperous migrants to experience upward mobility (McCulloch et al., 2007). Resosudarmo and Suryadarma (2014) also find that migrants' children in urban areas spend on average three more years at school than similar children in rural areas. The study shows that migrants' children have more human capital investment than non-migrants' children, which may result in a less intergenerational persistence.

However, the left-behind children of migrants have lower educational attainment than those who live with their parents. Although, (Lu, 2014) suggests a better height-for- age of children left-behind of internal migrants.

All of these studies suggest that migration can be a way to promote upward social mobility both for the migrants as well as for their children.

3.3. Migration and Human Capital: Intergenerational Mobility mechanism

The theory on intergenerational mobility is closely related to the theory of human capital investment, as past human capital investments of the previous generation have an impact on the earnings of the current generation. Becker et al. (2015) suggest that intergenerational income elasticity is equal to the intergenerational transmission of human capital. They argue that persistence in intergenerational mobility in the top income group is due to the fact that they invest more in human capital on average than their poorer counterparts.

The investment in human capital is even more critical in the early years of life for shaping and forming skills in later years (Heckman and Mosso, 2014). It is not only human capital investment, but also other events that happen in the early years of the children's lives, health and early education, that have consequences for their lives in adulthood. Almond and Currie (2011) summarise the empirical evidence of the importance of early-life human capital investment, although they do not directly include parental migration as one of the variables having an impact on the early years of the children.

The human capital theory treats migration as an investment, as the decision to migrate is based on income differences and the fact that the income at the destination must be higher than the income at the origin after taking into account the migration cost (Yezer and Thurston, 1976), and suggests that the returns of migration can be a source of investment in children of migrants. Lu (2015) finds that in Indonesia parent's migration has a positive impact on left-behind children's height-for-age, although she found a reverse result in Mexico. These mixed results are in line with Bucheli et al. (2018) who find that in Ecuador remittances have a stronger positive effect to secondary school enrolment on poor urban male children, and a negative effect on poor rural female child while for wealthier children it has negative or non-significant effects.

However, the potential long-term benefits of migration can also be, at least partially offsets by negative impacts on the children who also migrated along with their parents or who were left behind. There is an extensive literature on left-behind children, and it highlights both negative psychological and health impact as well as increases in child labour. Fellmeth et al. (2018) in their systematic review and meta-analysis of 111 studies, of which 91 were conducted in China, show that left-behind children are at higher risk of depression, anxiety, suicide, conduct disorder, substance use, wasting and stunting compared with non-migrants children. They however find no differences in other nutritional outcomes, diarrhea, abuse and unintentional injury.

Children who migrated along with their parents also may experience negative psychological and health impacts due to being uprooted from their support system in the original community (Hagan et al., 1996). Further, Hagan et al. (1996) suggest that these negative impacts are more pronounced for children with uninvolved fathers and unsupportive mothers. The impacts of parental migration are mixed in different locations. In China, left-behind children are more prone to be child labourers as they spend more time on agricultural

and domestic activities when their parents are away. The impact is higher for left-behind girls than left-behind boys (Chang et al., 2011). However, in El-Salvador, parental migration reduces child wage labour upon the receipt of remittances from the parents (Acosta, 2011).

4 Theoretical Framework

The economic literature studies intergenerational mobility and migration separately. The migration literature discusses migration pull and push factors, which explain the self-selection of migrants, while the literature on intergenerational mobility discusses parents' investment in their children. We combine both theories to answer our research questions.

Intergenerational social mobility consists of the transmission of parents' social status to the children's social status. The classic theory of intergenerational mobility in a simple Markov model (Black and Devereux, 2011):

$$Ln(Y_i) = \beta Ln\big(Y_j\big) + \epsilon_i \quad (1)$$

where Y_i is the social status of the children and Y_j is the social status of the parent. Economics literature uses income as a measure of social status; this study uses per capita expenditure as a proxy for income. The coefficient β is the intergenerational elasticity ($0 < \beta < 1$) which means higher intergenerational persistence if the coeffi- cient is closer to 1 and higher intergenerational mobility if the coefficient is closer to zero.

The path and mechanism of this transmission is explained by Becker and Tomes (1979) by suggesting that the wealth of the child as an adult ($Y_{\{i\}}$) is determined by the income of the parents ($Y_{\{j\}}$), the wage level of the children when adults ($w_{\{i\}}$), the children's endowment ($\epsilon_{\{i\}}$), and their luck (ui) in the market. Hence, the parents' demand function of children's income shows:

$$\begin{aligned} Y_{\{i\}} &= \alpha\big(1 + r_j\big)Y_{\{j\}} + \alpha w_{\{i\}} \cdot \epsilon_{\{i\}} + \alpha w_{\{i\}} \cdot u_{\{i\}} \\ &= \beta Y_{\{i\}} + \alpha w_{\{i\}} \cdot \epsilon_{\{i\}} + \alpha w_{\{i\}} \cdot u_{\{i\}} \end{aligned} \quad (2)$$

where, $\beta = \alpha\big(1 + r_j\big)$, showing the intergenerational elasticity as the proportion of what parents spend on their children α and the rate of return per generation $\big(1 + r_j\big)$.

In this paper, we introduce parents' migration ($\mathrm{M_{\{j\}}}$) to the intergenerational mobility framework. We propose that past parental migration affects children's income as adults $Y_{\{i\}}$ and the effect of their own income $Y_{\{j\}}$ on their children's income is conditional on their migration:

$$\mathrm{Y_{\{i\}}} = \beta \mathrm{Y_{\{j\}}} + \gamma \mathrm{M_{\{j\}}} + \delta\, \mathrm{Y_{\{j\}}}.\mathrm{M_{\{j\}}} + \alpha \mathrm{w_{\{i\}}}.\epsilon_{\{i\}} + \alpha \mathrm{w_{\{i\}}}.\mathrm{u_{\{i\}}} \quad (3)$$

The issue is that parents do not migrate randomly. The literature on migration has long discussed the determinants of migration; one of the earliest studies is Raven- stein's law of migration (Ravenstein, 1885), which acknowledges the determinants of migration such as distance and economic opportunities as pull factors. Later, neo- classical economists emphasised the excess of labour in the agricultural sector (Lewis, 1954), and wage differences in rural and urban sectors (Ranis and Fei, 1961; Harris and Todaro, 1970) as the main drivers of rural-urban migration. At the individual level, the non-randomness of the migrants is due to different levels of education (Chiquiar and Hanson, 2005; Kaestner and Malamud, 2014) and skills (Borjas et al., 1992). In section 5.3, we will explain how we deal with the parent's self-selection into migration.

5 Empirical strategy

5.1. Data

The Indonesian Family Life Survey (IFLS) is our primary source of data. The IFLS sampling design is representative both at the national and at the district level. We also use migration data from census and inter-census surveys of Statistics Indonesia and, in addition, weather data from the National Oceanic and Atmospheric Administration in order to explain some aspects of migrants' self-selection.

Besides the quantitative data, we also include in our analysis the qualitative data gathered by the authors in 2017. We conducted semi-structured interviews for this purpose in five different districts, two urban and three rural, with 99 respondents of migrants and non-migrants. This qualitative data informed the quantitative model specification and the interpretation of our results.

The Indonesian Family Life Survey (IFLS) is a longitudinal survey in Indonesia covering 13 out of 27 provinces (in 1993) and collecting information both at the house- hold and at the individual level. It has more than 30,000 respondents, and it represents 83% of the population. IFLS has had five waves (1993, 1997, 2000, 2007, and 2014) with 87.6% of original IFLS 1 households being interviewed in all five waves. In our analysis, we use individual information on migration and individual characteristics and household information on household expenditure.

The IFLS data enable us to match parents with each of their children who have been interviewed in the survey rounds. We observe all adults, who are more than 15 years old and whose parents are interviewed, in each wave of the survey so that we have a data set of adults and their parents from all five waves. The 15 years old benchmark follows the Statistics Bureau of Indonesia, which defines people of working age as 15 years old above. We define parents' migration as migrating out of the district when children were less than 15 years old. Retrospective data on individual migration enable us to trace parents' migration in the year when the children as adults were under 15 years old.

Although the IFLS is a longitudinal survey, we pooled the data as our observations are adults older than 15 years old who matched with at least one of their parents. Past parental migration, in this case, is a time-invariant variable. Hence, for the purpose of our analysis, it is necessary to use a repeated cross-section instead of panel data.

Table 2: Observations Interviewed for x Times

	Times the observations appeared					
Year	1	2	3	4	5	Total
1993	703	444	767	878	1,100	3,892
1997	591	743	1,011	1,228	1,100	4,673
2000	890	1,032	1,691	1,467	1,100	6,180
2007	1,200	1,960	1,222	1,452	1,100	6,934
2014	3,130	1,647	934	995	1,100	7,806
Total	6,514	5,826	5,625	6,020	5,500	29,485

Source: Authors calculation, IFLS 1993-2014

Table 3: Number of Parents - Children Pairs

	All children		Left-behind children	
	Daughter	Son	Daughter	Son
Father	9,507	10,176	628	670
Mother	13,436	13,479	892	879

Source: Authors calculation, IFLS 1993-2014

The IFLS data have some limitations. First, there is some attrition because some observations could not be tracked over time. Table 2 shows how many times the observations appeared in the survey waves. In our sample, 1,100 observations (5,500 in total) repeatedly appear in each wave. We use weights provided by the IFLS to deal with differences in sampling design and attrition.

Second, although the IFLS migration record identifies whether the parents migrated with children, it does not specify which children. However, we assume the children are left behind when the parents migrated without any of their children. Hence, we can differentiate the impact on all the children sampled and the children who were left-behind compared with the children from non-migrant parents. Table 3 shows the number of parents-children pairs for all the children and the left-behind children in all of the IFLS years.

The literature on intergenerational mobility mainly focuses on males, looking at the relationship between son's, father's and grandfather's income (Olivetti, Claudia; Paserman, Daniele; Salisbury, Laura, 2013). The reason why studies on intergener- ational mobility primarily focus on males is due both to the availability of the data and the assumed importance of the father as the main breadwinner in many migrants' households. The longitudinal nature of IFLS data allows us to match mother-child pairs as well as father-child pairs. In this way, we are not missing out the children who only have a mother in the survey. Also, some mothers or fathers have separate migration histories and may have not migrated together.

The IFLS survey covers 21 years observing grown-up children and their parents at five points in time. The period of the survey provides different points in the parents' and children's lifecycles, creating bias. In order to eliminate lifecycle bias, we predict both parents' and children's permanent expenditure fixing their age at 40 years old. In this way, the household per capita expenditure of the children and their parents will be comparable. In the identification strategy section, we explain in more detail how we tackle the lifecycle bias issue.

Table 4 shows a simple mean difference between inflation-adjusted per capita expenditure and the predicted per capita expenditure at age 40 according to their parents' migration status. The table shows that the children and their parents have significantly higher household per capita expenditure (both real and predicted at age 40) if the parents migrated than if the parents stayed. It suggests the selection of migration where migrated parents had more resources than those who stayed. Table 4 also shows possible benefits of parents' migration on children's per capita expenditure.

Figure 2 also shows that children who live in districts with a higher share of mi- grated parents have higher household per capita expenditure at forty years old. The x-axis in figure 2 shows the mean of parental migration at the district level, and mi- grated parents over the total number of parents in that district. Meanwhile, the y-axis shows the mean of children's log household per capita at the district level. Both table 4 and figure 2 indicate that parents' migration is positively correlated with children's per capita expenditure.

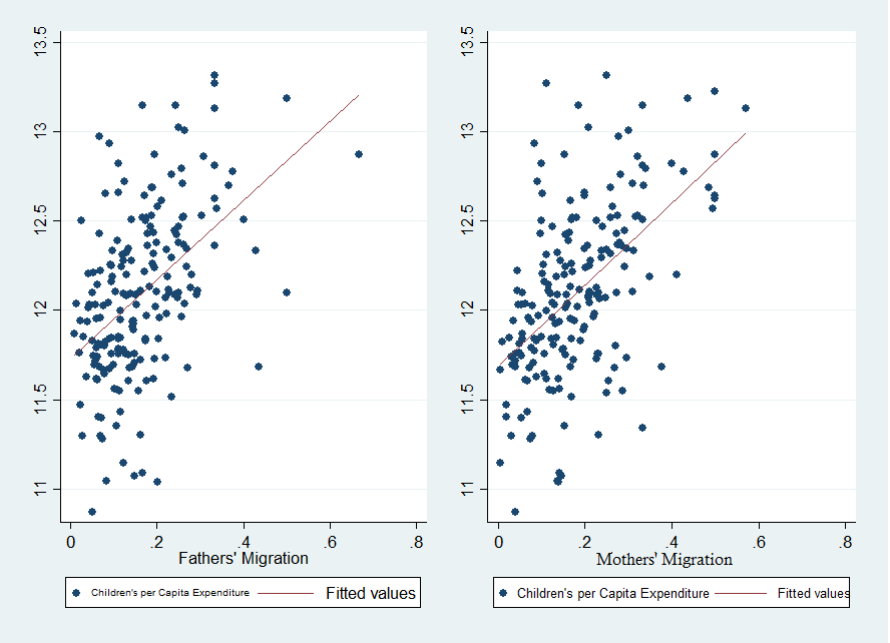

Figure 2: Parents' Migration and Children's Log Household per capita expenditure at The Age of 40 by District

Table 5 shows the mean difference of the covariates in different estimation. We regress the covariates that we use in our regressions on the migration variable to calculate the difference and the associated standard error between the migrants' and stayers' children. The stars refer to significant differences in the covariates between different groups. Table 5 indicates that the parents who migrated are slightly younger than the parents who stayed, from provinces with a higher out-migration rate, from provinces with more negative weather shocks, and migrated parents are more often born in urban areas than parents who stayed.

The covariates for outcome equations relating to children's characteristics are mainly balanced, although children from fathers who migrated are significantly older compared with the children of fathers who stayed. We also can see that the children left behind from mothers who migrated are from a bigger average household size than those from mothers who stayed. Children from migrant parents are currently living more frequently outside Java, and in rural areas compared with children from non-migrant parents. This suggests that there is a heterogeneous effect of the current residency of the children to the outcome.

Table 4: Inflation-adjusted Weekly per Capita Expenditure (in Rupiah) by Migration Status of the Parents in All IFLS Waves

	Obs	Mean
Child's per capita expenditure		
Parents migrated	5,798	96,882
Parents stayed	22,880	76,203
t-stat	-17.5487***	
Child's predicted permanent per capita expenditure at age 40		
Parents migrated	5,798	208,513
Parents stayed	22,880	186,901
t-stat	-18.0775***	
Father's per capita expenditure		
Migrated	5,868	59,940
Stayed	23,617	40,414
t-stat	-21.4356***	
Father's predicted permanent per capita expenditure at age 40		
Migrated	4,354	115,697
Stayed	15,296	99,672
t-stat	-14.1386***	
Mother's per capita expenditure		
Migrated	5,868	71,907
Stayed	23,617	54,608
t-stat	-18.7348***	
Mother's predicted permanent per capita expenditure at age 40		
Migrated	5,439	85,711
Stayed	21,433	71,504
t-stat	-14.6994***	

Table 5: Mean Differences of Covariates from Different Estimations

	Father: All samples			Father: The left-behind			Mother: All samples			Mother: The left-behind		
Variables	Stayer	Migrate	Difference	Stayer	Migrate	Difference	Stayer	Migrate	Difference	Stayer	Migrate	Difference
Household size	5.822	5.891	0.068	5.822	6.057	0.235*	5.862	5.908	0.046	5.862	6.090	0.228**
	(2.713)	(3.013)	(0.084)	(2.713)	(3.189)	(0.129)	(2.761)	(2.891)	(0.069)	(2.761)	(2.905)	(0.103)
Children's HH with child age 6-10 y.o	0.429	0.447	0.019	0.429	0.454	0.025	0.434	0.462	0.028*	0.434	0.485	0.051**
	(0.607)	(0.638)	(0.019)	(0.607)	(0.652)	(0.029)	(0.617)	(0.652)	(0.015)	(0.617)	(0.652)	(0.023)
Children's HH with child age 11-14 y.o	0.362	0.400	0.038**	0.362	0.413	0.051*	0.364	0.384	0.019	0.364	0.430	0.066***
	(0.580)	(0.612)	(0.018)	(0.580)	(0.601)	(0.027)	(0.587)	(0.604)	(0.015)	(0.587)	(0.622)	(0.022)
Children being male	0.493	0.531	0.038**	0.493	0.472	-0.020	0.483	0.508	0.025**	0.483	0.458	-0.025
	(0.500)	(0.499)	(0.015)	(0.500)	(0.500)	(0.023)	(0.500)	(0.500)	(0.012)	(0.500)	(0.499)	(0.019)
Children's age	27.047	27.795	0.748***	27.047	27.928	0.881**	29.655	29.839	0.184	29.655	29.551	-0.104
	(8.181)	(8.417)	(0.250)	(8.181)	(8.742)	(0.385)	(9.972)	(9.288)	(0.243)	(9.972)	(9.211)	(0.367)
Children live in urban areas	0.476	0.571	0.095***	0.476	0.524	0.048**	0.483	0.600	0.117***	0.483	0.594	0.110***
	(0.499)	(0.495)	(0.015)	(0.499)	(0.500)	(0.023)	(0.500)	(0.490)	(0.012)	(0.500)	(0.491)	(0.018)
Children live in Java	0.607	0.549	-0.058***	0.607	0.601	-0.005	0.614	0.516	-0.098***	0.614	0.578	-0.036**
	(0.489)	(0.498)	(0.015)	(0.489)	(0.490)	(0.023)	(0.487)	(0.500)	(0.012)	(0.487)	(0.494)	(0.018)
Quintile on children's HH per capita expenditure	3.055	3.323	0.268***	3.055	3.243	0.188***	2.988	3.355	0.367***	2.988	3.290	0.301***
	(1.399)	(1.389)	(0.043)	(1.399)	(1.411)	(0.066)	(1.394)	(1.363)	(0.034)	(1.394)	(1.386)	(0.052)
Parent's birth place, urban areas=1	0.205	0.276	0.071***	0.205	0.241	0.037*	0.213	0.288	0.075***	0.213	0.265	0.052***
	(0.403)	(0.447)	(0.012)	(0.403)	(0.428)	(0.019)	(0.409)	(0.453)	(0.010)	(0.409)	(0.441)	(0.015)
Parent origin district negative precipitation shock	2.238	2.443	0.206***	2.238	2.350	0.112	2.283	2.518	0.235***	2.283	2.490	0.207**
	(2.289)	(2.322)	(0.070)	(2.289)	(2.443)	(0.108)	(2.353)	(2.462)	(0.059)	(2.353)	(2.466)	(0.088)
Parents origin province outmigration rate	21.563	23.732	2.169***	21.563	23.260	1.697**	21.744	23.950	2.207***	21.744	22.638	0.894
	(16.823)	(18.736)	(0.521)	(16.823)	(16.952)	(0.788)	(16.848)	(19.712)	(0.429)	(16.848)	(18.233)	(0.628)
Parents' age	56.936	56.230	-0.706**	56.936	55.611	-1.324**	54.810	53.067	-1.743***	54.810	51.376	-3.434***
	(11.441)	(10.770)	(0.345)	(11.441)	(11.045)	(0.534)	(12.680)	(11.475)	(0.308)	(12.680)	(10.839)	(0.465)
Number of Observations	6,895	1,281	8,176	6,895	489	7,384	9,322	1,989	11,311	9,322	790	10,112

5.2. Estimation Strategy

In order to estimate the impact of parent's migration on their children's intergenerational mobility, we use an endogenous treatment-regression model. Heckman (1976) introduced the sample selection model, which was expanded by Maddala (1986) by deriving both the maximum likelihood and the control function of the model. The model allows both unobservables affecting the treatment and the potential outcome to have a specific correlation structure. The model is a variant of Heckman's selection model which observed both migrants' and stayers' regimes. It addresses self-selection issues and estimates treatment effects as being a migrant or a stayer is non-randomly allocated.

The endogenous treatment-regression model consists of an outcome equation $Y_{\{i\}}$ and an endogenous treatment equation $M_{\{j\}}$, where $M_{\{j\}}$=1 when parents migrated, where $\mathrm{Z}_{\{j\}}$ is a vector of selection variables for parents' migration, j refers to the parents, and i refers to the children.

$$Ln(Y_{\{i\}}) = \beta Ln(Y_{\{j\}}) + \tau M_{\{j\}} + \delta Ln(Y_{\{j\}}) * M_{\{j\}} + \lambda X_{\{i\}} + \epsilon_{\{i\}} \quad (4)$$

$$M_{\{j\}} = \begin{cases} 1, if\ \gamma \mathrm{Z}_{\{j\}} + \mu_{\{j\}} < 0 \\ 0, otherwise \end{cases}$$

$Y_{\{i\}}$ is children's household per capita expenditure and for parents it is $Y_{\{j\}}$; the β is the coefficient which captures intergenerational elasticity while δ represents the difference in intergenerational elasticity between the group of children whose parents migrated and those whose parents stayed. We used the standard practice in development economics, using expenditure, as income is noisy and subject to measurement error. X is a vector of control variables which includes household and individual characteristics of children when adults.

We use the following variables in the selection equation of parents' migration when children are age 0-14 years old: rural-urban information on the parents' birthplace; provincial out-migration rate of the place of the parents' origin (defined as the province where parents were living when they were 12 years old); precipitation shock in the district where parents lived when they were 12 years old; parents' age; and children's gender and age. Table 6 shows the definition of the variables we use for our estimations.

5.3. Identification Strategy

The reason for using per capita expenditure instead of income is because of sample selection bias and reporting bias in income data. Sample selection bias in income data happens when we exclude people who do not have income from the sample. Reporting bias also commonly occurs in income data due to job informality and missing data as some respondents do not agree to report their income.

Table 6: Variables Definition

Variables	Definition
Log of household per capita expenditure	Log of household weekly total per capita expenditure for children when adults, father and mother. Total household expenditure is the inflation-adjusted (based on year 2010) weekly household expenditure on food and non-food items.
Household size	Number of people who live in the household
Male	Dummy variable for gender, male=1 female=0
Number of children age 6-10 years old in the household	total number of children age 6-10 years old in the children's household
Number of children age 11-14 years old in the household	total number of children age 11-14 years old in the children's household
Age	Age at the survey year
Migration	Dummy variable migration=1, when parents migrated across districts at least once when the child was 0-14 years old
Parents' birthplace	Dummy variable urban=1, using the information on whether the birthplace was rural or urban
Negative precipitation shock	The sum of the event of negative precipitation shock at the parents' origin district when the parents were 12 years old
Out-migration rate	Out-migration rate of the province where the parents lived when they were 12 years old. The data is from Statistics Indonesia (BPS), calculation of provincial out-migration from census and inter-census survey

As we are interested in studying the intergenerational expenditure elasticity, we aim at eliminating the lifecycle bias in household per capita expenditure of both children and their parents. As there are age differences between children and parent pairs, comparing their household per capita expenditure at different points of their life results in bias. In order to make them comparable, we predict permanent household per capita expenditure at age 40 years old, following Dustmann (2008). The method is averaging per capita expenditure over several years. It also allows the inclusion of individuals with a minimal number of expenditure data points (Dustmann, 2008).

$$\mathrm{Ln}\left(\mathrm{Y}_{\{1\mathrm{i,t}\}}\right) = \alpha_{\{1\}} + \alpha_{\{2\}\mathrm{Age}_{\{\mathrm{i,t}\}}} + \alpha_{\{3\}\mathrm{Age}^2_{\{\mathrm{i,t}\}}} + \mathrm{v}_{\{\mathrm{i}\}} + \mathrm{u}_{\{\mathrm{i,t}\}} \qquad (5)$$

We then predict equation 5 at the age of 40 years old. Haider and Solon (2006) suggest that current income from the early thirties to mid-forties generally provides an unbiased estimate

of lifetime income. By fixing the age at a certain point, we can compare the children and their parents at the same point in their life.

The endogeneity of the migration comes from the non-randomness of migration. The endogenous treatment regression allows us to capture the self-selection to migrate. The concept of selection variables is similar to instrumental variables, where there should be at least one variable affecting the self-selected decision to migrate but not the outcome variables.

We based the choice of the selection variables on the information we have from our exploratory qualitative survey that we undertook in 2017. The main determinant of the decision to migrate is the network in the destination; more people living outside their districts of origin will pull others to move. This is similar to what Hare (1999) found in her work on migration in China. We used the out-migration rate in the province when parents were 12 years old as a proxy for the peer effect as well as the migration network. The weather in the origin areas is also one of the push factors of migration where people from areas with low precipitations are pushed to migrate. This was true of the migrants interviewed in Bitung. Many had come from the Talaud Islands, where drought had often occurred. We used the number of negative precipitation shocks in the district when the parents were 12 years old. Precipitation shock is a push factor as the weather shock may push people to migrate. We calculate the precipitation shock using the method used by Amare et al. (2018).

Besides external factors such as the weather and migration network, individual differences affect parents' decisions to migrate, such as age (Hare, 1999) and birthplace. Being born in an urban or a rural place correlates with their propensity to migrate. Van Lottum and Marks (2012) highlight the importance of urban primacy as a determinant of internal migration in Indonesia. We rely on parents' reported information in the survey to distinguish the status of their birthplace as rural or urban at the time they were born. We also include the gender of the children and their age in the selection equation as determinants of parents' migration. Children's age contributes to the decision to migrate, since parents, where the family has children of school age, are less likely to migrate (Nivalainen, 2004; Antman, 2012). Having daughters in the household lead to smaller increase of propensity to return to the origin, whilst having a son increase the propensity to stay in the destination (Dustmann, 2003).

The exclusion restriction in selection equation is likely to be valid as the variables we chose do not directly affect the children's household per capita expenditure. Parents' birthplace, weather shock and outmigration rate at parents' origin are not affecting the children's household per capita expenditure in adulthood but affect the parental migration selection. The exclusion restriction of the outcome variables in the selection equation is also valid as children's outcomes should not determine parents' past migration.

6 Results

6.1. All sample

We find that parents' migration has a significant positive impact on their children's future household per capita expenditure for both child-father and child-mother pairs (see table 8). However, we find no significant differences in intergenerational mobility across children of the migrants and the stayers.

Table 7: Average Marginal Effects of Parents' Log per Capita Expenditure and Migration on the Children's Log per Capita Expenditure

	dy/dx	Std. Err.	[95% Conf.	Interval]
Intergenerational Elasticity				
Father's log per capita expenditure	0.586	0.0149	0.557	0.616
Mother's log per capita expenditure	0.607	0.013	0.581	0.632
Migration				
Father migrated=1	0.580	0.086	0.411	0.749
Mother migrated=1	0.709	0.067	0.577	0.841

As we interact the parents' migration variable with their log per capita expenditure, we cannot directly interpret the impact of migration directly from the variables' coefficients in table 8. We use margins to understand the average marginal transmission of parents' log per capita expenditure on their children's log per capita expenditure. The intergenerational elasticity coefficient, regardless of the parents' migration status, shows a slightly higher transmission of household expenditure in child-mother pairs than child-father pairs. The average marginal predictions of intergenerational elasticity for the child-father pairs is 0.586 and for child-mother pairs is 0.607 (see table 7). The numbers are similar to the intergenerational elasticity in the endogenous treatment regression, given that the interaction variable with parental migration is not significant.

Our intergenerational expenditure elasticity coefficient is higher compared with intergenerational earnings elasticity in other countries. The study by Chen et al. (2017) in Canada found an intergenerational elasticity coefficient of 0.29. Solon (1999) listed intergenerational earnings elasticities from previous studies which range from 0.11 in Germany to 0.68 in the UK, whilst the only less developed country listed was Malaysia with a coefficient of 0.26 (table 5, page 1768). The number, however, is not comparable because of different measurements of the earnings. Bruze (2018) suggests that intergenerational persistence from expenditure data is higher than from income data. Using the Danish Expenditure Survey (DES), he shows that intergenerational expenditure elasticity between parents and their children is at 0.418, a higher than intergenerational income elasticity at 0.208.

The OLS result also suggests that parent's migration does not affect children's intergenerational mobility, even if it does not account for parents' self-selection into migration (see table 8). We find that the interaction between the parents' migration dummy and parents' household per capita expenditure is not statistically significant.

In order to understand better, figure 3 shows the average differences in children's log per capita expenditure whose parents migrated and stayed over the distribution of the average

changes in parents' log per capita expenditure. The graphs show that the children whose parents migrated have better per capita expenditure than children whose parents stayed. The parallel slopes, however, showing that both have similar intergenerational elasticity. This suggests that parents' migration is unable to promote intergenerational mobility for all children sample. We found identical patterns both for child-father and child-mother pairs because children of parents who migrated have higher per capita expenditure than those of the parents who stayed.

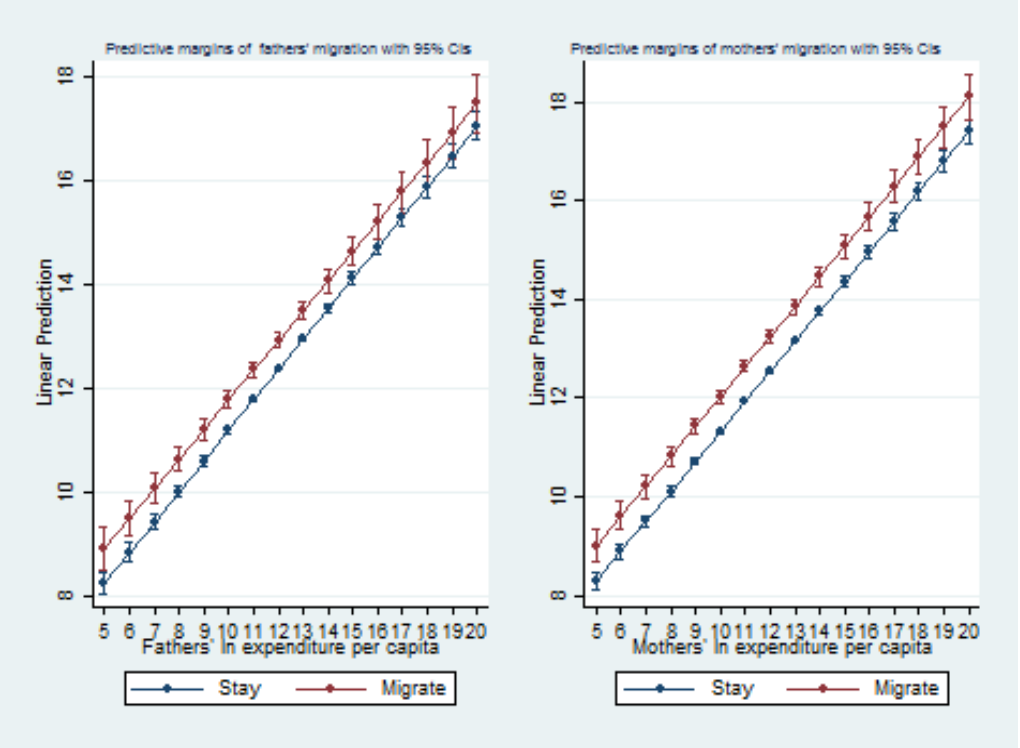

Figure 3: Predictive margins of parents' migration on children log per capita expenditure, averaged over distribution of parents' log per capita expenditure

Table 8: Impact of Parents' Migration on Children's per Capita Expenditure and Intergenerational Expenditure Elasticity: Endogenous Treatment Estimations on Child-Father Pairs and Child-Mother Pairs

	(1)	(2)	(3)	(4)
	OLS		Selection	
Dep. var: Children's ln household per capita expenditure	Father	Mother	Father	Mother
Parents' ln household per capita expenditure (excap)	0.597***	0.613***	0.589***	0.608***
	(0.015)	(0.012)	(0.016)	(0.014)
Parents' migration	0.380	-0.028	0.759*	0.722**
	(0.366)	(0.299)	(0.404)	(0.337)
Interaction: parents migration and excap	-0.023	0.014	-0.016	-0.001
	(0.031)	(0.026)	(0.035)	(0.029)
Household size	-0.117***	-0.113***	-0.119***	-0.113***
	(0.004)	(0.004)	(0.005)	(0.004)
Household with child age 6-10 years old	0.066***	0.065***	0.068***	0.065***
	(0.011)	(0.009)	(0.013)	(0.010)
Household with child age 11-14 years old	0.073***	0.076***	0.068***	0.071***
	(0.011)	(0.009)	(0.012)	(0.010)
Male	0.003	-0.010	-0.011	-0.029*
	(0.016)	(0.014)	(0.018)	(0.016)
Age	-0.017***	-0.029***	-0.019***	-0.032***
	(0.004)	(0.003)	(0.005)	(0.003)
Age2	-0.000	0.000**	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	6.079***	6.287***	6.152***	6.312***
	(0.189)	(0.149)	(0.214)	(0.175)
Selection to migration				
Parents' birth place, urban==1			0.229***	0.279***
			(0.058)	(0.046)
Negative weather shocks when parents' 12 y.o			0.023**	0.008
			(0.011)	(0.009)
Out migration rate when parents' 12 y.o			0.002	0.002**
			(0.001)	(0.001)
Parents' age			0.037*	-0.012
			(0.022)	(0.015)
Parents' age^2			-0.000**	-0.000
			(0.000)	(0.000)
Male			0.106**	0.043
			(0.054)	(0.046)
Age			-0.007	0.049***
			(0.018)	(0.013)
Age^2			0.000	-0.000*
			(0.000)	(0.000)
Constant			-2.004***	-1.255***
			(0.508)	(0.327)
/athrho			-0.429***	-0.580***
			(0.088)	(0.077)
/lnsigma			-0.470***	-0.460***
			(0.016)	(0.016)
Year effects	yes	yes	yes	yes
Province effects	yes	yes	yes	yes
Observations	10,768	14,900	8,211	11,377
R-squared	0.555	0.581		
F	150.6	383.5	123.9	173.9
lambda			-0.253	-0.330
converged			1	1

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
all estimation standard errors are clustered at household level and all samples are weighted.
Variables definition refer to table 6

6.2. Left-Behind Children

In this section, we use a sub-sample from the observations in our main regression. The sub-sample is the children whose parent migrated at least once without any of the children and the children whose parent stayed. We exclude the observations where parents are recorded as having migrated with children. In this case, we compare the left-behind children with the children whose parent did not migrate. We assume that the children are left behind if their father or mother migrated alone. This assumption is because IFLS provides information if the father or the mother migrate with children but does not give any specific information on which children. Table 9 shows the endogenous treatment regression results of child-father and child-mother pairs.

We find that fathers' migration has a significant impact on the children left behind but not mothers' migration. Further, the fathers' migration promotes intergenerational mobility for the children left behind. This is shown by the significant negative coefficient of interaction variable between parents' migration and parents' log per capita expenditure in child-father pairs. The intergenerational elasticity is the same in the sub-sample and the full sample for child-father pairs, whilst slightly less in the sub-sample of left-behind children for child-mother pairs.

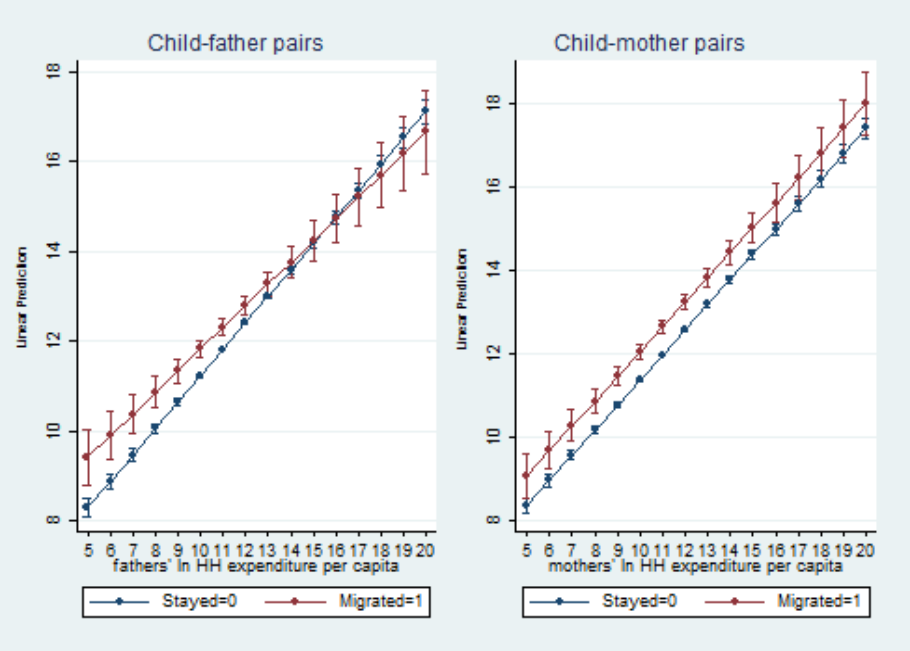

Figure 4: Left-behind children: Predictive margins of parents' migration on children's log per capita expenditure, averaged over distribution of parents' log per capita expenditure

Figure 4 shows more clearly the different intergenerational mobility for the children left behind when their father migrated and the children whose father stayed. It also shows that the left-behind children of a father with a lower household per capita expenditure benefited from migration but not the children of a father with a higher household per capita expenditure. Meanwhile, the parallel slopes for child-mother pairs show no significant

impact of migration on intergenerational mobility, but it does show that the left-behind child from the migrated mother has better log household per capita expenditure.

Table 9: Impact of Parents' Migration on Left-behind Children's per Capita Expenditure and Intergenerational Expenditure Elasticity: Endogenous Treatment Estimations on Child-Father Pairs and Child-Mother Pairs

	(1)	(2)
Dep. var: Children's ln household per capita expenditure	Father	Mother
Parents' ln household per capita expenditure (excap)	0.589***	0.604***
	(0.016)	(0.014)
Parents' migration	1.641***	0.767
	(0.598)	(0.508)
Interaction: parents migration and excap	-0.105*	-0.008
	(0.054)	(0.045)
Household size	-0.121***	-0.116***
	(0.005)	(0.004)
Household with child age 6-10 years old	0.071***	0.069***
	(0.014)	(0.011)
Household with child age 11-14 years old	0.070***	0.074***
	(0.013)	(0.011)
Male	0.013	-0.015
	(0.019)	(0.017)
Age	-0.019***	-0.031***
	(0.005)	(0.003)
Age^	-0.000	0.000***
	(0.000)	(0.000)
Constant	6.192***	6.709***
	(0.215)	(0.331)
/lnsigma	-0.243***	-0.472***
	(0.077)	(0.081)
/athrho	-0.489***	-0.492***
	(0.016)	(0.014)
Province effects	Yes	Yes
Year effects	Yes	Yes
Selection equation	Yes	Yes
Observations	7,384	10112
F	1547	448.1
lambda	-0.146	-0.269
Converged	1	1

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

All estimation standard errors are clustered at household level and all samples are weighted. Variables definition refer to table 6

7 Heterogeneous Effects

We introduce some heterogeneous effects by interacting parents' migration and parents' per capita expenditure (in logarithm) with dummy variables that define whether children are living in urban areas, are living in Java, belong to different quantiles of household per capita expenditure, working in agricultural or non-agricultural sector, and had different migration status. Table 10 and table 11 show the regression results of each heterogeneous effects.

The results show that being in an urban area benefits child (see table 10 column (1) and (2) and figure 5). In rural areas, we find that both father's and mother's migration benefits children whose parents have lower household per capita expenditure but not children whose parents have higher household per capita expenditure. Conversely, in urban areas, children of parents with lower per capita expenditure benefit less from parent's migration. Being in an urban area instead promotes higher intergenerational mobility for children regardless of parent migration.

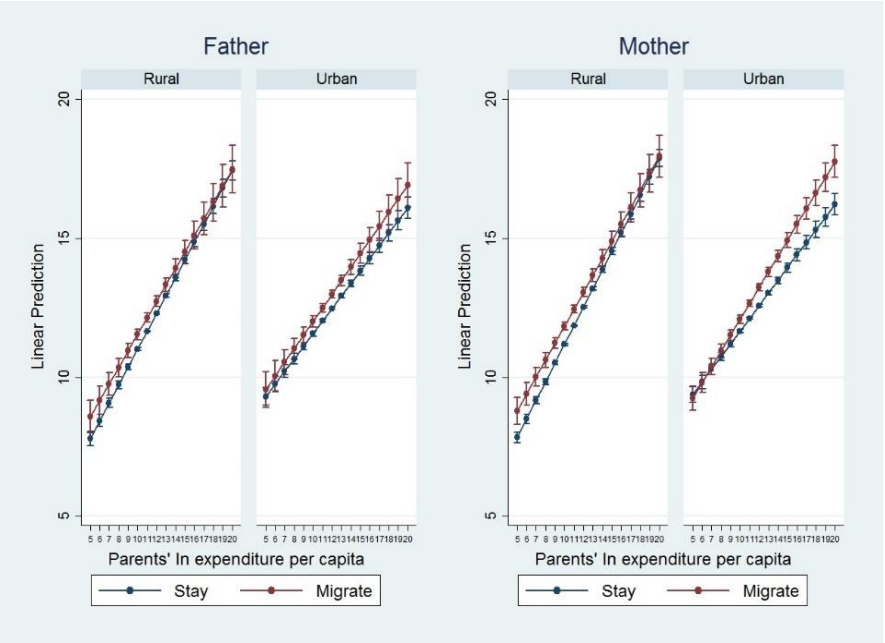

Figure 5: Predictive margins at CI 95% of parents' migration by children being in urban or rural areas on children's log per capita expenditure, averaged over distribution of parents' log per capita expenditure

Similarly, living in Java leads to the children being more intergenerationally mobile than residing outside Java (see table 10 column (3) and (4) of interaction being in Java and parents' household per capita expenditure). However, all the coefficients related to parents' migration are not statistically significant. The figures also show a parallel line between children from parents who migrated and stayed showing that there is no difference in the impact of migration if we take into account the effect of children currently living in Java or outside Java.

We also find that children currently working in the agricultural sector have lower per capita expenditure and lower intergenerational mobility (see table 10 column (5) and (6)). But parental migration does not seem to explain this differential. The result, however, is in line with grown-up children having higher household income when living in an urban area.

Table 10: Heterogeneous Effects – Children's Current Residence and Agriculture Work

	(1)	(2)	(3)	(4)	(5)	(6)
	Urban		Java		Agriculture work	
Dep. var: Children' ln Household per capita expenditure	Father	Mother	Father	Mother	Father	Mother
Parents' ln household per capita expenditure (excap)	0.643***	0.670***	0.640***	0.644***	0.438***	0.474***
	(0.020)	(0.017)	(0.023)	(0.022)	(0.026)	(0.022)
Parents' migration (migration)	1.039*	1.256***	0.671	0.714	1.028	0.568
	(0.578)	(0.483)	(0.556)	(0.483)	(0.658)	(0.563)
Interaction: parents migration and excap	-0.050	-0.060	-0.012	-0.001	-0.037	0.001
	(0.052)	(0.044)	(0.048)	(0.043)	(0.056)	(0.049)
Var of interest	2.381***	2.577***	1.002***	0.732**	-1.636***	-1.562***
	(0.361)	(0.307)	(0.364)	(0.317)	(0.487)	(0.401)
Interaction: var interest and excap	-0.189***	-0.215***	-0.070**	-0.050*	0.119***	0.117***
	(0.031)	(0.028)	(0.031)	(0.028)	(0.043)	(0.037)
Interaction: var interest and migration	-0.959	-1.964***	0.291	0.111	-1.280	0.048
	(0.890)	(0.660)	(0.782)	(0.658)	(1.149)	(0.957)
Interaction: var interest, excap and migration	0.086	0.173***	-0.019	-0.009	0.100	-0.005
	(0.077)	(0.059)	(0.068)	(0.058)	(0.102)	(0.087)
Constant	5.532***	5.626***	5.575***	5.918***	7.981***	7.872***
	(0.248)	(0.192)	(0.288)	(0.255)	(0.341)	(0.268)
/athrho	-0.373***	-0.481***	-0.437***	-0.584***	-0.403***	-0.438***
	(0.088)	(0.079)	(0.088)	(0.077)	(0.106)	(0.099)
/lnsigma	-0.501***	-0.500***	-0.470***	-0.459***	-0.447***	-0.458***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.021)	(0.021)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Province effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Selection equation	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,175	11,310	8,176	11,311	4,324	6,281
k	62	62	62	62	62	62
F	127.9	175.0	122.6	162.6	149.4	209.6
rho	-0.356	-0.447	-0.411	-0.525	-0.382	-0.412
sigma	0.606	0.606	0.625	0.632	0.639	0.632
lambda	-0.216	-0.271	-0.257	-0.332	-0.245	-0.261
selambda	0.0271	0.0204	0.0245	0.0174	0.0421	0.0339
converged	1	1	1	1	1	1

Regression on working in agricultural sector or not using sub-sample of employed observation. Hence much smaller number in the observations

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Standard errors are clustered in household level and all samples are weighted.

Variables definition refer to table 6

Table 11: Heterogenous Effect: Quantile and Migrated as Child

Dep. var: Children's ln Household per capita expenditure	(1) Quantile o f expenditure Father	(2) Mother	(3) Children migrated as Child Father	(4) Mother
Parents' ln household per capita expenditure (excap)	0.429***	0.502***	0.609***	0.618***
	(0.04)	(0.03)	(0.02)	(0.02)
Parents' migration (migration)	1.620**	0.693	0.426	1.134***
	(0.72)	(0.78)	(0.50)	(0.41)
Interaction: parents migration and excap	-0.141**	-0.059	0.014	-0.041
	(0.07)	(0.08)	(0.04)	(0.04)
Interaction: being in quantile 2 and excap	-0.362***	-0.421***		
	(0.04)	(0.04)		
Interaction: being in quantile 3 and excap	-0.376***	-0.448***		
	(0.04)	(0.03)		
Interaction: being in quantile 4 and excap	-0.396***	-0.466***		
	(0.04)	(0.03)		
Interaction: being in quantile 5 and excap	-0.393***	-0.464***		
	(0.04)	(0.04)		
Interaction: being in quantile 2 and migration	-1.523*	-0.525		
	(0.78)	(0.83)		
Interaction: being in quantile 3 and migration	-1.782**	-0.644		
	(0.75)	(0.80)		
Interaction: being in quantile 4 and migration	-1.638**	-0.679		
	(0.74)	(0.79)		
Interaction: being in quantile 5 and migration	-1.853**	-1.107		
	(0.85)	(0.85)		
Interaction: being in quantile 2, excap and migration	0.140*	0.051		
	(0.07)	(0.08)		
Interaction: being in quantile 3, excap and migration	0.163**	0.064		
	(0.07)	(0.08)		
Interaction: being in quantile 4, excap and migration	0.149**	0.067		
	(0.07)	(0.08)		
Interaction: being in quantile 5, excap and migration	0.170**	0.104		
	(0.08)	(0.08)		
Interaction: migaschild and excap			-0.085**	-0.044
			(0.04)	(0.04)
Interaction: migaschild and parents' migration			1.063	-1.431
			(1.13)	(0.93)
Interaction: migaschild, parents' migration and expcap			-0.09	0.124
			(0.098)	(0.082)
Constant	7.371***	6.846***	6.026***	6.271***
	-0.375	-0.334	-0.572	-0.352
/athrho	-0.125***	-0.180***	-0.432***	-0.518***
	-0.043	-0.053	-0.093	-0.087
/lnsigma	-1.263***	-1.280***	-0.477***	-0.478***
	-0.025	-0.022	-0.017	-0.017
Year effects	yes	yes	yes	yes
Province effects	yes	yes	yes	yes
Control variables	yes	yes	yes	yes
Selection equation	yes	yes	yes	yes
Observations	8,211	11,377	6,991	9,847
F	976	1330	127	138.3
lambda	-0.0351	-0.0495	-0.252	-0.295
Converged	1	1	1	1

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

The quantile is taken from the whole respondents in the survey for each wave, not only our matched children.

Children migrated is our adult observations for whom their birth place is different to the place they lived in when they were 12 years old.

Standard errors are clustered at household level and all samples are weighted.

Variables definition refer to table 6

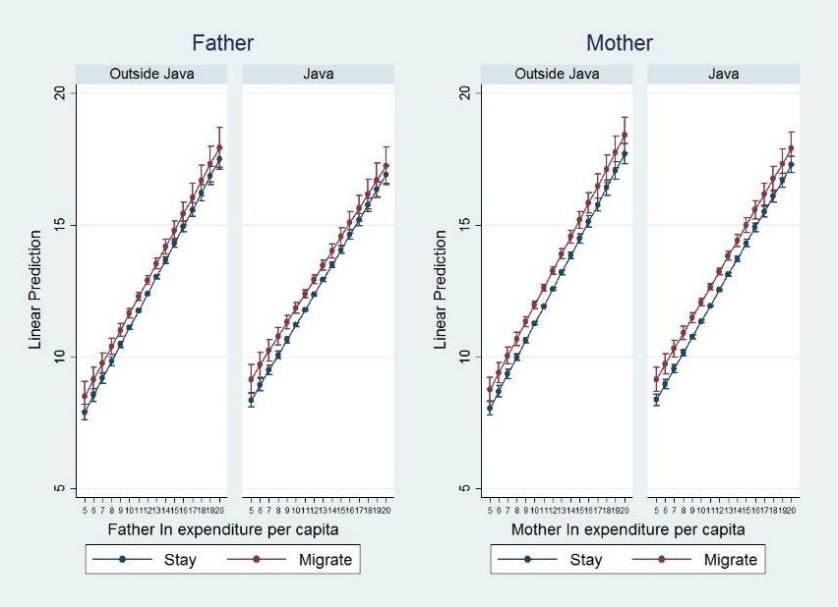

Figure 6: Predictive margins at CI 95% of parents' migration by children being in Java and outside Java on children's log per capita expenditure, averaged over distribution of parents' log per capita expenditure

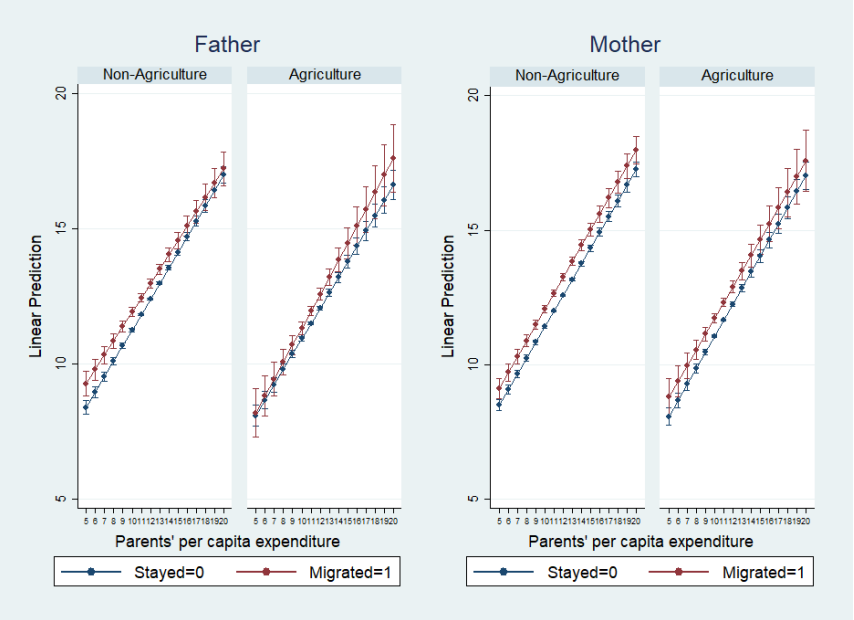

Figure 7: Predictive margins at CI 95% of parents' migration by children working in agriculture and non-agriculture sectors on children's log per capita expenditure, averaged over distribution of parents' log per capita expenditure

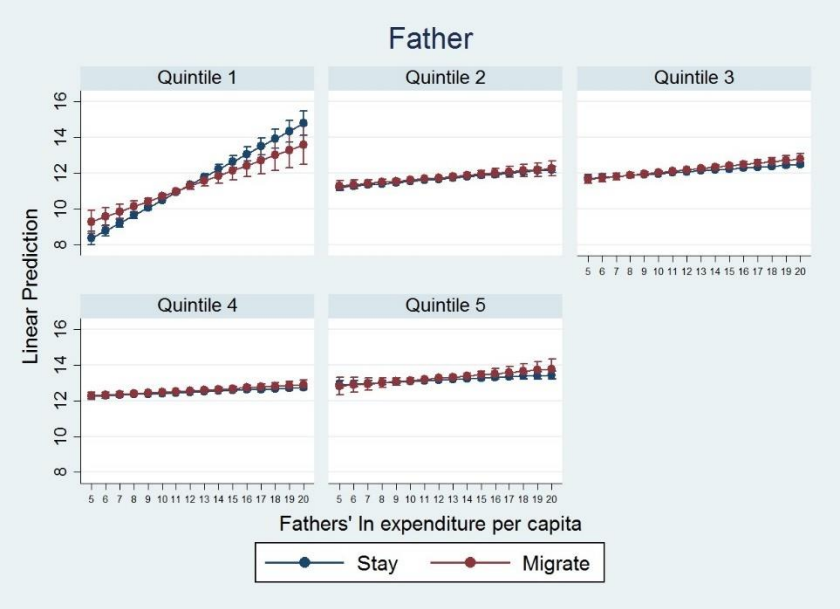

Figure 8: Predictive margins at CI 95% of fathers' migration by children's expenditure distribution on children's log per capita expenditure, averaged over distribution of fathers' log per capita expenditure.

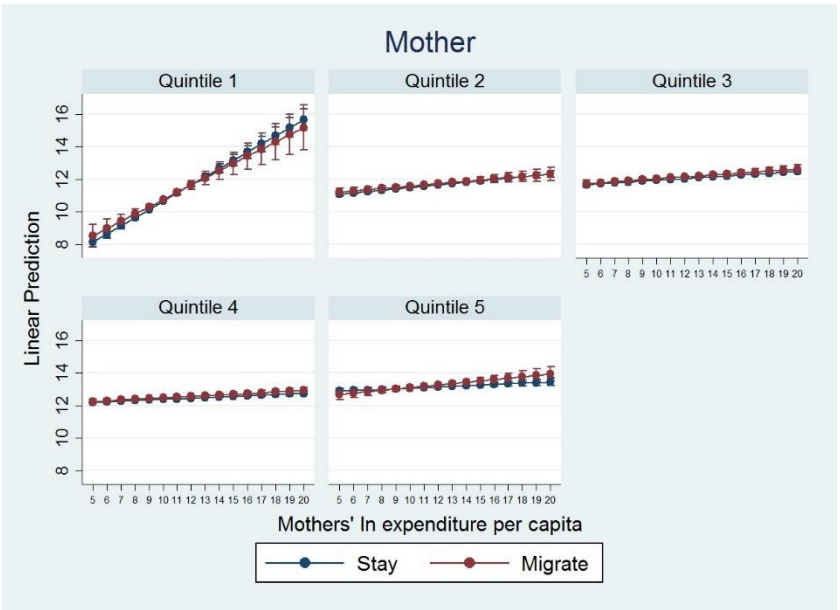

Figure 9: Predictive margins at CI 95% of mothers' migration by children's expenditure distribution on children's log per capita expenditure, averaged over distribution of mothers' log per capita expenditure.

The different effects of parental migration by children's household expenditure quantile status only mattered when the father migrated. The differences in the first quantile mainly determine this difference. Graphs 8 and 9 show that if the father migrated, the children from the poorest quantile have more intergenerational mobility compared with the children of non-migrant fathers from the same group. In the higher quantile groups, the lower slope shows more intergenerational mobility than the poorest quantile. However, overlay lines

show that parents' migration does not have any effect on intergenerational mobility and that there is even the same level of children's per capita expenditure regardless of parents' past migration for people from the second to the fourth quantile, the middle class. Children in the first quantile benefited from parental migration if their parents were also poor. The children from the wealthiest quantile slightly benefit from their parents' migration if their parents are also rich.

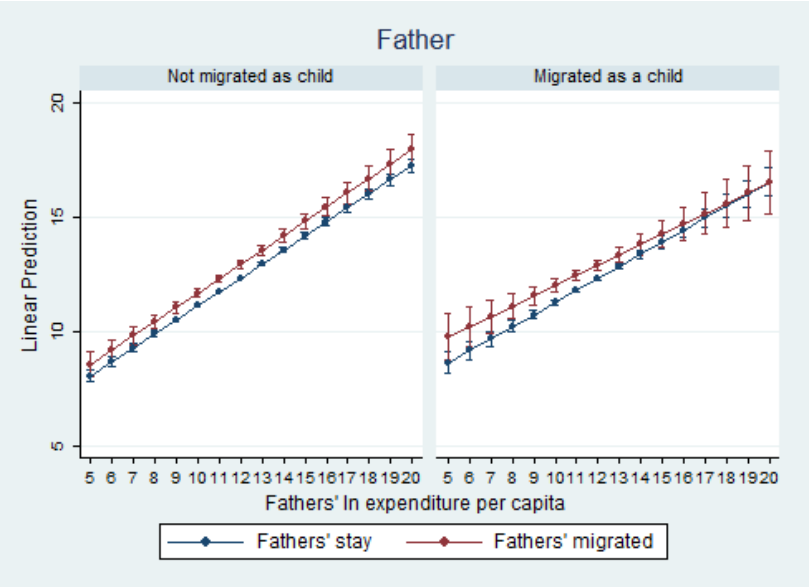

Figure 10: Predictive margins at CI 95% of fathers' migration across children's migration status at age 0-12 y.o on children's log per capita expenditure, averaged over distribution of fathers' log per capita expenditure.

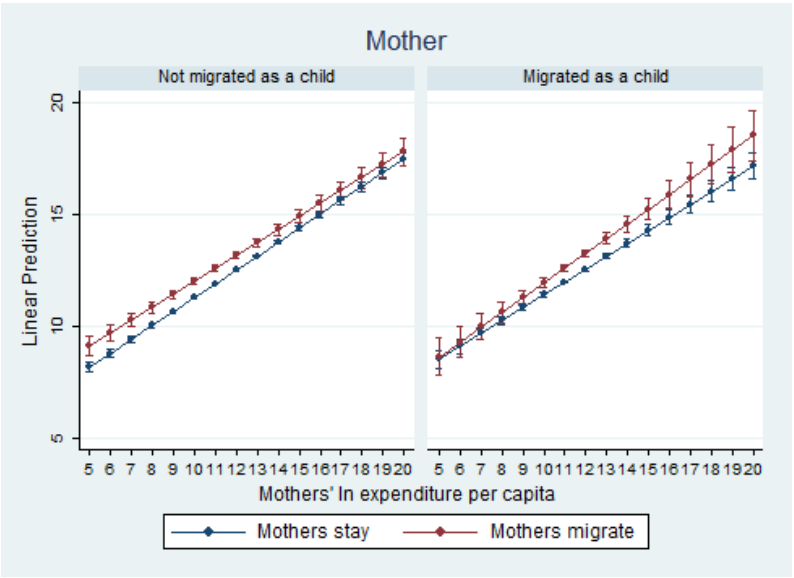

Figure 11: Predictive margins at CI 95% of mothers' migration by children's migration at age 0-12 y.o on children's log per capita expenditure, averaged over distribution of mothers' log per capita expenditure.

We also look at the migration of the children at the age of 0-12 years old. The children are coded as migrated during that age if the birth district is different from the district where they live at 12 years old. However, the children who did not migrate during the age of 0-12 years old and had parents migrated can be different with our children left-behind. As we define children left-behind if their father or mother migrated at least once without any of the children when the children aged 0-14 years old.

We find that children who migrated at the age of 0-12 years old and had a father who also migrated are more intergenerationally mobile than those whose fathers did not migrate, although the benefit of fathers' migration is similar for children whose fathers have higher per capita expenditure (Figure 10). The mother-child pairs showed a similar story when children did not migrate when they were 0-12 years old. However, children who migrated and whose mother also migrated appear to be less mobile than if mothers stayed (Figure 11). The contrary is true when looking at father-child pairs.

8 Mechanisms

We test three mechanisms that can explain the impact of migration on children's per capita expenditure and their intergenerational mobility. The three mechanisms are parents' investment in education, the children's migration when adults, and the children's working in agriculture when adults. We found that children whose fathers migrated have on average four years more education than those whose fathers stayed. Similarly, children whose mothers migrated have four additional years of education compared to the children whose mothers stayed (see table 12). The education attainment of children left behind is similar to the one with the whole sample with rounding to four years more schooling than the children of stayers.

The finding on education is consistent with the results from previous studies. The magnitude of this finding is similar to the Resosudarmo and Suryadarma (2014) study that uses data from Rural-Urban Migration in China and Indonesia (RuMiCI). They found that permanently migrating as a child adds 4.5 years of schooling. Antman (2012) also found a positive relationship between parental migration and children's educational attainment. She discovered that father's migration to the US from Mexico added a year of educational attainment of the left-behind girls.

Looking at the effect of parental migration on the propensity of children to mi- grate, children of a migrant father migrate twice as often in their adulthood than those whose father stayed. Mother's migration does not affect children's migration movements when adults. These findings can be explained within the context of the patriarchal Indonesian society. Even in adulthood, approval from the parents, especially their father, is important. This approval is even institutionalised for aspiring international migrant workers, as they need to provide a parent's letter of approval to officials (Hugo, 1995)[1]. Fathers who experienced migration tend to allow their children to migrate as well as to facilitate their children migration network.

Our semi- structured interviews confirm that migrant parents are more lenient regarding their adult children's migration than those who never migrated. Prejudice about destinations and migration risks were the reasons behind parent's negative responses. Hence, children migrated more if their father migrated as well. Parental migration has also contributed to decreasing the probability that their children work in the agricultural sector compared to the children of the stayers. In this respect, mother migration shows less impact than father migration. These results are in-line with our result on the children completed years of education. Migrated parents invest more in their children education, and they are more likely to encourage their children to migrate and, as a result, their children are less likely to work in the agricultural sector.

[1] In 2013 the government formalised this parent's approval letter in the Government Regulation no. 4 of 2013 states that one of the required documents needed for international migrant worker from Indonesia is letter of approval from their partners if they are married, and from their parents or guardian if they are not married

Table 12: Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Education				Migration as Adult				Working in Agriculture			
Variables	Father	Father LBC	Mother	Mother LBC	Father	Father LBC	Mother	Mother LBC	Father	Father LBC	Mother	Mother LBC
Parents' migration	4.296***	3.914***	4.547***	4.335***	1.705***	1.858***	0.037	0.090	-1.268***	-1.058*	-1.174***	-0.992***
	(0.431)	(0.664)	(0.378)	(0.613)	(0.056)	(0.061)	(0.074)	(0.345)	(0.286)	(0.547)	(0.162)	(0.345)
/lnatrho	-0.624***	-0.547***	-0.662***	-0.589***	-1.081***	-1.199***	0.031	-0.009	0.947**	0.569	0.804***	0.570**
	(0.074)	(0.108)	(0.069)	(0.106)	(0.074)	(0.075)	(0.036)	(0.173)	(0.421)	(0.417)	(0.186)	(0.257)
/lnsigma	1.275***	1.234***	1.277***	1.239***	0.125***	0.067***	0.005	0.001				
	(0.016)	(0.016)	(0.018)	(0.017)	(0.020)	(0.019)	(0.018)	(0.019)				
Province effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls on outcome equation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selection equation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,039	7,255	11,035	9,855	8,241	7,441	11,410	10,194	8,241	7,441	11,410	10,194
F	50.33	137.9	77.26	165.7	72.48	141.4	35.03	134.9	223.3	115.0	244.1	163.5
lambda	-1.984	-1.710	-2.079	-1.826	-0.900	-0.891	0.0307	-0.00884				
converged	1	1	1	1	1	1	1	1	1	1	1	1

LBC is left-behind children

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Column (9)-(12) results using seemingly unrelated bivariate probit regression rather than endogenous treatment regression due to its bivariate outcome variable

Dependent Variable for (1)-(4) is children's complete years of schooling, column (5)-(8) is children's number of between district migration as adults, column (9)-(12) is children's working in agriculture as adults

Control variables are born in urban, age, being male, being in urban variables on selection equation is the same as the one in the main equation variables definition refer to table 6

Standard errors is clustered in household level, samples are weighted

9 Robustness Checks

One concern we had was that being in the Indonesian capital of Jakarta and it most populous island Java could drive our results. To check for this, we run our estimates excluding people who live in Jakarta and Java and we found that the results are consistent with our main results, with higher magnitude in the intergenerational elasticity coefficients (see table 13, columns (1) to (4)). Another concern was that setting the predicted permanent per capita expenditure at age 40 years old may not reflect living conditions in Indonesia. We, therefore, estimate the same model specification with the log permanent per capita expenditure at 30 years old and found a consistent result compared with our main result (see table 13, columns (5) and (6)).

We also use individual income instead of household per capita expenditure. The number of observations is much smaller than using expenditure data because there is an issue of missing data as well as sample selection. The result is still consistent, although the intergenerational elasticity coefficients are much smaller than those with expenditure data, and the parental migration coefficients are not statistically significant (see table 13, columns (7) and (8)).

We find similar consistent result in the interest variables of intergenerational elasticity coefficient and parental migration when adding parental education in the selection variables (see table 13, columns (9) and (10)). We define parental education as father's or mother's years of schooling. The addition of parental education in the robustness check to show that excluding some parental variables in selection to migrate will not affecting our result. In our defense, as parental education data that we have is the highest years education at surveys but no information on the parental education before migration, especially if the parental migration happened before the survey years, then it may not precisely explain the self-selection to migrate.

We also use, as a robustness check, different definitions of migration. Instead of migration across districts, we check on migration across regions. We also redefine the across-districts migration by the type of origin and destination. We have a combination of across-districts migration from rural to urban, rural to rural, urban to rural and urban to urban. We use the information on urban and rural status at the place where the parents lived at age 12 years old as origin, and the information of the place they migrated to as the destination.

The intergenerational elasticity coefficients in all estimations are still consistent with the main estimation (see table 14). However, we find that if we redefine the migration dummy as between-regions migration, the migration coefficient switches to negative, and the interaction of fathers' migration and fathers' per capita expenditure is positive and significant. This suggests that fathers' migration out of their island leads to lower per capita expenditure for their children compared with the children from fathers who migrate in-island or stay. This also suggests that long-distance parental migration may not benefit the children. The interaction variable is positive and statistically significant, suggesting that migration out of an island leads to more intergenerational persistence (see table 13, column (1)). According to other definitions of migration, the sign of other migration coefficients is consistent except for migration from urban to rural areas, which is negative. How- ever, all of the migration coefficients are not statistically significantly different from our main estimation. The interaction variables are consistently non-significant as in our main estimations, although the signs are mixed.

Table 13: Robustness Check

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	excluding Jakarta		Excluding Java		Excap at 30 y.o		Income		Parental Education	
	Father	Mother	Father	Mother	Father	Mother	Father	Mother	Father	Mother
Ln Expenditure per capita (excap)	0.610***	0.626***	0.642***	0.651***	0.589***	0.722**			0.599***	0.630***
	(0.016)	(0.014)	(0.024)	(0.021)	(0.016)	(0.338)			(0.017)	(0.015)
parents' migration (migration)	0.852**	0.886***	0.924	1.087**	0.754*	0.608***	0.093	0.452	1.310***	0.964***
	(0.403)	(0.333)	(0.566)	(0.473)	(0.394)	(0.014)	(0.624)	(0.686)	(0.436)	(0.369)
Interaction: migration and excap	-0.022	-0.012	-0.018	-0.015	-0.016	-0.001			-0.060	-0.025
	(0.036)	(0.030)	(0.049)	(0.043)	(0.035)	(0.029)			(0.037)	(0.032)
ln Income							0.112***	0.130***		
							(0.020)	(0.020)		
Interaction: migration and income							0.024	0.014		
							(0.041)	(0.049)		
Constant	5.874***	6.075***	5.335***	5.639***	5.781***	5.750***	13.721***	14.004***	5.969***	6.002***
	(0.211)	(0.171)	(0.317)	(0.265)	(0.209)	(0.175)	(0.467)	(0.440)	(0.222)	(0.189)
/athrho	-0.461***	-0.624***	-0.597***	-0.816***	-0.429***	-0.580***	-0.162*	-0.199***	-0.503***	-0.598***
	(0.084)	(0.060)	(0.156)	(0.071)	(0.088)	(0.077)	(0.098)	(0.066)	(0.071)	(0.079)
/lnsigma	-0.474***	-0.458***	-0.372***	-0.330***	-0.470***	-0.460***	-0.089***	-0.010	-0.479***	-0.484***
	(0.018)	(0.017)	(0.030)	(0.026)	(0.016)	(0.016)	(0.020)	(0.022)	(0.017)	(0.018)
Province effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls on outcome equation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selection equation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,582	10,520	3,308	4,599	8,211	11,377	2,902	2,600	7,202	8,935
F	127.7	180.8	69.89	101.3	123.9	173.9	75.49	402.5	114.3	159.3
lambda	-0.268	-0.350	-0.369	-0.484	-0.253	-0.330	-0.147	-0.194	-0.288	-0.330
converged	1	1	1	1	1	1	1	1	1	1

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent variable for estimation (1) to(4) is children's household per capita expenditure predicted at age 40 y.o, and 30 y.o for (5) and (6) Dependent variable for (7) and (8) is log income predicted at age 40 y.o and we add control variables of being in employment and have additional job(s) Dependent variable for (9) and (10) is children's household per capita expenditure predicted at age 40 y.o but we add parental education in selection variables Variables definition refer to table 6

All estimation standard errors are clustered in household level and all samples are weighted

Table 14: Robustness Check: Different Definition of Migration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Across regions migration		Across districts: rural-urban		Across districts: urban-rural		Across districts: urban-urban	
	Father	Mother	Father	Mother	Father	Mother	Father	Mother
Parents' ln per capita expenditure (excap)	0.587***	0.604***	0.588***	0.611***	0.588***	0.620***	0.586***	0.612***
	(0.015)	(0.013)	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)
Parents' migration (migration)	-1.536**	-0.878	0.874	0.424	-0.297	0.913	1.127	0.503
	(0.698)	(0.578)	(0.746)	(0.629)	(0.992)	(1.136)	(0.798)	(0.566)
Interaction: migration and excap	0.166***	0.056	-0.043	0.033	0.062	-0.036	-0.056	0.007
	(0.057)	(0.045)	(0.065)	(0.057)	(0.085)	(0.100)	(0.068)	(0.049)
Constant	6.245***	6.402***	6.212***	6.277***	6.222***	6.296***	6.232***	6.393***
	(0.198)	(0.164)	(0.199)	(0.166)	(0.198)	(0.181)	(0.200)	(0.185)
/athrho	-0.222**	0.249**	-0.164**	-0.523***	-0.306***	-0.349***	-0.293***	-0.399***
	(0.098)	(0.112)	(0.071)	(0.066)	(0.064)	(0.077)	(0.085)	(0.072)
/lnsigma	-0.500***	-0.509***	-0.501***	-0.497***	-0.499***	-0.537***	-0.499***	-0.535***
	(0.015)	(0.017)	(0.016)	(0.014)	(0.016)	(0.016)	(0.016)	(0.016)
Province effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls on outcome equation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selection equation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,211	11,377	8,211	10,045	8,211	8,344	8,211	8,344
N	8211	11377	8211	10045	8211	8344	8211	8344
F	126.5	169.1	122.0	164.3	122.6	1063	122.3	762.2
lambda	-0.132	0.147	-0.0987	-0.292	-0.180	-0.196	-0.173	-0.222
Converged	1	1	1	1	1	1	1	1

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Variables definition refer to table 6

All estimation standard errors are clustered in household level and all samples are weighted

10 Qualitative findings

Our quantitative analysis results are positive towards migration but show no differences in intergenerational mobility. Our conversation with people from five different districts in Indonesia may be able to explain this phenomenon. According to our conversations, the reason for undergoing internal migration, moving from one district to another within the country, is primarily to get a better income and/or due to a lack of available jobs at origin. However, people will not migrate with neither job security nor any contacts at the destination. Migration is risky, and the contacts and job security at the destination before migration lessen this risk. This is important in our discussion, as the children of migrants will have a well-established social network that leverages their social mobility better than the children of stayers. Borjas (1992) and subsequently, many others have studied and explained that the skills of the parents' social network determine the children's skills in adulthood. Different accumulation of these skills influences more socially mobile migrants' children.

Other than the ethnic capital at the destination, the norm, culture and customs at origin also determine who are the stayers. In all interview sites, both rural and urban, there was an expectation of children to take care of their parents. In some places such as Muara Enim and Selayar, society formalises this into a set of rules regulating property inheritance, that can help explain some of the persistence for stayers. The custom in Perapau, Muara Enim is known as "Tunggu Tubang" where the eldest daughter and her husband are responsible for taking care of the field and inheriting the parents' profession. A similar custom also applies in Selayar with the eldest child as the one who inherits the parents' occupation.

Besides these inheritance norms, in Bekasi and Ciamis, West Java, we found a strong persistence regarding fathers' and sons' profession. People in Ciamis express this sentiment by proverbs such as "fruit falls not far from the tree", which demonstrate the intergenerational social persistence in their society. However, for some children of the migrants to whom we talked, their parents' migration allowed them to escape poverty at their parents' origin. One of the children of migrants who is a migrant himself in Bekasi explained that if his parents had stayed, he would be a farmworker as are his uncles, aunts and cousins who remain at their origin in Cirebon. Even if the origin is an urban area, the children of stayers will likely follow their parents' footsteps.

We do not include the norm and social pressure to inherit profession from parents in the quantitative analysis. However, the quantitative findings of no significant differences in intergenerational mobility between children of migrants and non-migrants may indicate profession persistence between parents and children.

11 Conclusions

In this paper, we try to understand whether parental past migration at the time when the children were aged 0-14 years has a long-term impact on the children's per capita expenditure as adults and therefore the intergenerational mobility. Our findings show that despite parental migration increases the education level of the children and their per capita expenditure, it increases intergenerational mobility compared with non- migrants' children when the grown-up migrant's children live in urban areas, come from the poorest parents, or had migrated as a child. The left-behind children have more intergenerational mobility than the children of non-migrants only when their father migrated, and there is no significant impact when the mother migrated. The results are robust when we exclude the children living in Java, living in Jakarta, use individual income and use a different definition of migration, although migration across regions leads to intergenerational persistence.

Future research may want to look more into the reasons why parental migration failed to break intergenerational persistence and investigate the impact of professional persistence from parents to children. Also, it might want to explore the heterogeneous effects across migration locations. Our robustness checks suggest that changing the parental migration from between districts to between islands, which implies a costlier migration, resulting in negative impacts on the children when adults.

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