Jurnal Ekonomi dan Pembangunan Vol. 31 No. 1 Tahun 2023
Journal homepage: https://ejournal.brin.go.id/JEP
ISSN 0854-526x (print) | e-ISSN 2503-0272 (online) DOI: 10.55981/jep.2023.1014

ESTIMATING INTERGENERATIONAL INCOME MOBILITY IN INDONESIA

Muhammad Imam Adli[1], Gumilang Aryo Sahadewo[2]

[1,2]Department of Economics, Faculty of Economics and Business, Universitas Gadjah Mada
Email: gasahadewo@ugm.ac.id

Abstract

This study estimates the intergenerational income mobility in Indonesia using data from the 1st, 2nd, 3rd, and 5th of the Indonesian Family Life Survey (IFLS). Intergenerational income mobility is proxied by intergenerational elasticity, which measures the correlation between parents and their children's incomes. Intergenerational elasticity is also regarded as a measure of equality of opportunity. The estimates in this study suggest that intergenerational elasticity for father-son pairs in Indonesia is between 0.44 and 0.50. Compared to other ASEAN countries, Indonesia is less mobile than Singapore but more mobile than Malaysia. Further analyses of the income mobility matrix indicate relatively low mobility for individuals in the upper-income quartile and medium mobility for individuals in the lower-income quartile.

Keywords: Intergenerational income mobility; intergenerational elasticity; equality of opportunity.

INTRODUCTION

Inequality of economic opportunities suggests that children of poor and rich households have different opportunities to succeed (Black and Devereux 2011). A measure of inequality of economic opportunities that has been widely used in the literature is the degree of intergenerational mobility (Ueda, 2013). Intergenerational mobility itself is the association between parent's and children's socioeconomic status, usually measured by income. Understanding intergenerational mobility is important because it provides broader policy implications about how a government should invest in human capital. Despite its importance, such an estimate for Indonesia is missing.

Existing studies on the dynamics of income inequality in Indonesia are limited to the intergenerational persistence of poverty among poor households or the relationship between parental investment and child poverty in East Java (Pakpahan, Suryadarma, & Suryahadi, 2009; Surachman & Hartoyo, 2015). While these studies provide an important insight into how poverty is transmitted across generations, these studies do not provide an economy-wide estimate of intergenerational mobility. This study fills this gap in the literature by estimating intergenerational mobility in Indonesia using the intergenerational income elasticity.

Estimating intergenerational income elasticity, particularly in developing countries, is quite challenging. Household surveys in these countries provide individuals' annual income data but with limited frequencies. Thus, it is difficult to construct a measure of permanent income using available data. There are also potential biases in estimating intergenerational income elasticity (Black & Devereux, 2011). First, a single-income observation cannot represent permanent income owing to income shocks. A study shows that an estimate of intergenerational income elasticity changes with the length of income observations (Mazumder, 2005). Second, a measure of a father's and his son's permanent income are constructed using their income at different ages. Due to data availability, a parent's income is usually observed at an older age than when a son's income is.

Previous studies proposed different methodologies to deal with these issues. An earlier study recommends using either long income observations or an instrumental variable (IV) technique to estimate a parent's income to overcome the issue of attenuation bias (Solon, 1992). Another study proposes a

Submitted : 04-01-2022
Revised : 11-12-2022
Accepted : 19-06-2023

two-sample two-stage least square (TS2SLS) method to overcome the issue of limited income observations (Björklund & Jäntti 1997). This method uses available data for parents, such as their socioeconomic characteristics, to predict their income.

This study uses the Indonesian Family Life Survey (IFLS) to estimate the intergenerational income elasticity for Indonesia. The Indonesian Family Life Survey is a comprehensive panel data that tracks households across periods and records individuals' characteristics and outcomes, including income. To our knowledge, the IFLS is the only dataset in Indonesia to estimate intergenerational income mobility. This study uses the 1st, 2nd, 3rd, and 5th waves of the IFLS for the years 1993, 1997, 2000, and 2014, respectively, to construct parents' and sons' permanent income (Strauss, Witoelar, & Sikoki, 2016). Specifically, this study uses the 1st to the 3rd wave of the IFLS to construct parents' permanent income and the 5th wage of the IFLS to construct sons' permanent income.

There are several advantages of using the IFLS to estimate intergenerational income mobility. First, the data provides us with multiple income observations for parents, and the gaps between income observations are quite short. Thus, this study takes an average of these income observations to measure permanent income. Second, the data provides socioeconomic variables that allow us to implement the IV method that addresses the attenuation bias issue. Lastly, the attrition rate of the sample in IFLS is relatively low (Strauss, Witoelar, & Sikoki, 2016). These factors provide a large parent-son sample to estimate the intergenerational income elasticity.

It is important to note several shortcomings of using the IFLS, particularly in estimating the sons' permanent income. This study can only use a single income observation to estimate sons' permanent income. Furthermore, the study can only use income observations when the sons were relatively young. The observed income may not reflect the sons' permanent income. Despite the shortcomings, the IFLS still offers the best data to estimate the intergenerational income elasticity in Indonesia.

This study estimates the intergenerational income elasticity, β, for Indonesia, which ranges from 0.44 to 0.50. If parameter β is intergenerational elasticity, then $(1–\beta)$ measures intergenerational mobility (Black and Devereux 2011). A value of 0 means no intergenerational mobility and 1 means perfect intergenerational mobility. The estimated elasticities for Indonesia are relatively similar to the estimated elasticities for Japan (0.41 – 0.46), but these estimates are smaller than those for developing countries such as Brazil (0.66), Chile (0.57), Malaysia (0.54), China (0.63), and South Africa (0.62-0.67) (Grawe 2004; Piraino 2015; Gong, Leigh, & Meng 2012; Nunez & Miranda, 2010; Ferreira & Veloso, 2006; Ueda 2009; Dunn 2007). A higher intergenerational elasticity value means more dependencies between the father's and son's income and thus less intergenerational mobilities.

These estimates imply that Indonesia experiences higher intergenerational mobility, thus, more equal opportunities than these developing countries. Nevertheless, Indonesia is still less mobile relative to other developed countries such as South Korea (0.35), Australia (0.20-0.30), Taiwan (0.18), and Sweden (0.28) (Ueda, 2013; Kan, Li, & Wang, 2015; Björklund & Jäntti 1997; Leigh 2007).

This study also constructs an intergenerational income mobility matrix for Indonesia. This study finds that sons of fathers in the lowest income quartile have a 32.7% probability of staying in the lowest income quartile, 28.2% of moving to the second income quartile, 22.9% of moving to the third income quartile, and 16.3% of moving to the top income quartile. On the other hand, this study finds that sons of fathers in the top-income quartile have lower intergenerational mobility. For example, the Son of a father in the highest income quartile has a 41.2% chance of staying in the top income quartile. This result suggests more persistent intergenerational income mobility among high-income than low-income individuals.

This study provides accompanying empirical evidence for theoretical works on intergenerational mobility (Cholli & Durlauf, 2022; Becker, Kominers, Murphy & Spenkuch, 2018). This study also contributes to the broader literature on poverty dynamics and intergenerational economic mobility in Indonesia (Fatimah & Kofol 2023; Dartanto & Otsubo 2016; Dartanto & Nurkholis, 2013; Dartanto, Moeis, & Otsubo, 2019; Bah 2014; McCulloch, Timmer, & Weisbrod, 2016). The latest study in the literature by Dartanto, Moeis, and Otsubo (2019) shows that economic mobility in Indonesia between 1993 and 2014 was quite significant. Using 5 waves of IFLS, they find that human and physical capital investments are significant drivers of economic mobility.

The remainder of the paper is organized as follows. Section 2 discusses the empirical framework and methodology of intergenerational elasticity estimation. Section 3 discusses the data and sample selection for the estimation of intergenerational income elasticity. Section 4 presents the main results of the estimation of intergenerational income elasticity. Section 5 concludes the discussion.

METHODOLOGY

Basic framework for estimating intergenerational mobility

Estimates for intergenerational mobility relate parents' earnings with those of their children (Cholli & Durlauf, 2022; Black & Devereux, 2011). In particular, the calculation should estimate the elasticity of parents' and children's lifetime income (Gong, Leigh, & Meng, 2012). This study follows the recent estimation strategy in the intergenerational mobility literature by taking into account differences in age and differences in the living standard across provinces in Indonesia (Ueda 2013; Gong, Leigh, & Meng, 2012; Kan, Li, & Wang, 2015). Specifically, the main specification in this study is:

$$y_{ci} = \alpha + \beta y_{pi} + \phi_1 A_{ci} + \phi_2 A_{ci}^{\ 2} + \gamma_1 A_{pi} + \gamma_2 A_{pi}^{\ 2} + \delta R_{cpi} + e_i, \quad (1)$$

where i indicates the father and son pair. The notation y_c denotes the natural logarithm of the son's income, y_p denotes the natural logarithm of the father's income. This study aims to capture real lifetime income; therefore, this study uses inflation-adjusted income using 2014, the latest year of IFLS, consumer price index as the base. The notation A_c denotes son's age, measured at IFLS 2014, minus 40. Similarly, the notation A_p denotes the father's age minus 40, recorded during IFLS 1997. The age is measured by 40 – age to correct for lifecycle bias as income varies with age. The discussion in Section 2.2 explains this technique in detail. For control covariates, the specification incorporates a vector R which includes the father's province of residence dummies in 1993, 1997, and 2000 and the son's province of residence dummies in 2014. Lastly, e denotes unobservable characteristics.

The parameter of interest is β, which measures the intergenerational elasticity. The parameter takes a value between 0 and 1. A value of 0 implies no relationship between parents' income and those of their children, and the value represents perfect intergenerational mobility. Conversely, a value of 1 implies perfect intergenerational mobility. The opposite of intergenerational income elasticity, intergenerational mobility, measures how mobile the income is across a generation. The estimated intergenerational mobility is $(1 - \beta)$.

This study estimates the coefficient β in Equation 1 using both the ordinary least square (OLS) and the instrumental variable (IV) method. Using OLS, the logarithm of the father's income from IFLS 1993 is regressed to the son's income from IFLS 2014. The estimate of β using OLS is the lower bound for the intergenerational elasticity owing to attenuation bias which will be explained in section 2.2.

This study uses an IV method to mediate the issue of attenuation bias. Ideally, the chosen instrument is correlated with the fathers' permanent income but not with the measurement errors. In other words, the instrument must fulfill the relevance and exclusion restriction criteria. The specification in this study uses three instrument variables to predict parents' income: educational attainment, employment sector dummies, and employment status dummies.

Educational attainment is measured by self-reported years of fathers' schooling. The employment sector dummies are binary variables that classify ten different economic sectors. The employment status dummies are also binary variables with seven classifications. Both the employment sector and status dummies are instrumental variables based on the information available in the IFLS 2. For robustness check, the estimation specification uses several combinations of instruments to predict parents' permanent income. In each combination, the estimation specification always uses years of schooling as one of the instruments. Using the IV method, the estimation first predicts the fathers' income using the instrumental variables, socioeconomic characteristics, and demographics. The first-stage regression is shown in Equation (2):

$$Y_{ni} = \alpha + \rho\rho Z_{ni} + \theta\theta_1 A_{ci} + \theta\,\theta_2 A_{ci}^{\,2} + \varphi\varphi_1 A_{pi} + \varphi\varphi_2 A_{pi}^{\,2} + \eta\eta R_{pci} + e_i, \qquad (2)$$

where Z is a vector of instrumental variables, as discussed above. The IV estimation then uses the predicted fathers' income, $\hat{y}_{pi}$, in the second-stage regression using Equation (1).

Indeed, studies have shown that years of schooling are correlated with income (Card 1999). Thus, the relevance criteria for the instrument are fulfilled. The exclusion criterion states no correlation between years of schooling and income shocks. Parents with higher years of schooling are less likely to experience higher or lower income shocks. This assumption is quite difficult to fulfil because studies have shown that income shocks affect human capital investment (Jacoby & Skoufias, 1997; Jensen, 2000).

Despite this drawback, using the instrumental variable method serves two purposes. First, the instrumental variable estimates would provide an upper bound for the estimates of the intergenerational income elasticity. Second, this study uses the instrumental variable method for comparability with existing studies in the literature.

This study also discusses the estimation of intergenerational mobility, focusing on the mobility of a father's income quartile to a son's income quartile. This is done by first estimating the lifetime income of both son and father, given their age and province of residence. The predicted incomes for father and son are then categorized into their respective quartile and constructed as a matrix and converted into percentiles.

Problem in Estimating Intergenerational Mobility

The main challenge in estimating intergenerational income elasticity is obtaining an accurate measure of lifetime earnings. Existing panel data surveys in developing countries measure observations for a limited number of periods. Denote the measured income in each survey as:

$$y_1 = y_0 + v_a, \qquad (3)$$

Where y_1 is an individual's income recorded in the survey year, y_0 is the average lifetime income, and v_a is the yearly shock to income. Black & Devereux (2011) show that the estimate of the intergenerational elasticity will converge to:

$$plim\,\hat{\beta} = \left(\frac{var\,(y_0)}{var\,(y_0) + var\frac{(v_a)}{T}}\right)\beta \qquad (4)$$

where $\hat{\beta}$ is the estimate of intergenerational elasticity obtained after averaging over T years.

In Equation 4, an estimate of β will be downward biased since variance is always positive. This is referred to as an attenuation bias. Such bias can be reduced by averaging income over a longer time horizon, which increases T and reduces the variance of the shock in the denominator of equation 3. Mazumder (2005) finds that the estimated coefficient β for the United States varies from 0.25 when $T = 2$ and 0.61 when $T = 16$. These results indicate a significant attenuation bias when the lifetime income is constructed using relatively short income observations.

Solon (1992) recommends using long-horizon income observations or an IV method to address the issue of attenuation bias. Given the limited income horizon in surveys administered in developing countries, the IV method proves to be quite useful. Björklund & Jäntti (1997) argue that the IV method gives an upper bound on the estimated intergenerational elasticity. On the other hand, estimates using a single-year income observation gives a lower bound for the estimated intergenerational elasticity due to the downward attenuation bias.

The second problem in estimating intergenerational elasticity is the lifecycle bias. Income varies with age, and given that income is only recorded at one or several periods, the measured income may deviate from lifetime income. A study finds that this issue results in lower estimates of intergenerational elasticity (Grawe 2006). Previous studies also find that income approaches its peak at age 30, and it is relatively stable until age 50. Therefore, it is quite important to control for age in the regression framework to accommodate the issue of lifecycle bias (Haider and Solon 2006). For example, this study includes age minus 40 and the square of age minus 40 in the model specification. These variables are included because both lifecycle bias is at the minimum and the expected income is at the maximum at age 40.

Data

This study uses the Indonesia Family Life Survey (IFLS), a panel data of households and individuals. The survey was conducted in 1993, 1997, 2000, 2007, and 2014. The survey covers 13 provinces in the most populous regions in Indonesia, and the sample represents about 83% of the population. The main advantage of using IFLS is that it tracks split-off members from the original households. Thus, the IFLS household sample expanded from 7,224 households in 1993 to 16,204 households in 2014 (Strauss, Witoelar, & Sikoki, 2016; Frakenberg & Karoly, 1995). The survey includes detailed household information such as income, employment status, educational attainment, expenditure, childhood, and health.

More importantly, the survey provides information about parents' and their offsprings' income. The data span 21 years, which means that the offsprings of parents observed in the first wave of IFLS were already in the labor market in that latest wave of IFLS. The fact that IFLS tracks split members of households and have a low attrition rate ensures a decent sample size. This study also considered using other data sources, such as the National Socioeconomic Survey (Susenas), in conjunction with IFLS. However, the limited information on the nationwide survey makes an accurate estimation of intergenerational elasticity difficult.

This study estimates intergenerational mobility using father and son pairing. This pairing was chosen because of the high rate of labor participation among males between 1993 and 2000. There is also a culture that considers fathers as the breadwinner in households. Previous studies in the literature also estimate intergenerational income elasticity using father-son pairings (Black & Devereux, 2011). This study uses the father-son pairing for comparability with estimates from the existing studies.

This study obtains income information from the labor section in IFLS book 3A. This study calculates an individual income by adding wage and profit from his primary and secondary job. Both wages and profits are measured annually, and they are self-reported. This study constructs a father's lifetime income by averaging his inflation-adjusted income in 1993, 1997, and 2000. On the other hand, this study constructs a son's lifetime income using the 2014 IFLS. Note that this study does not use the 2007 IFLS to construct a father's or a son's income. Using the 2007 IFLS would imply that the data include a father's income when he was too old and his son's income when he was too young.

Sample selection

First, this study restricts the sample to fathers aged between 25 and 45 in the IFLS1. This selection criterion yields a respectable sample size while ensuring the estimated income can reflect a father's lifetime income. This selection means that the sample in this study includes fathers aged 28-49 years in the IFLS2 and 32-52 years in the IFLS 2000. The sample also includes sons with an age range of 25-45 years in the IFLS2. As a result, the average age of fathers across 3 waves of IFLS is 41. On the other hand, the average age of sons is just 31 years. This discrepancy may result in a lifecycle bias, but the specification mediates such bias by controlling for age in the regression.

The study then restricts the sample to include individuals who worked full-time or near full-time in periods where income was measured. This study selects individuals who reported income above 0, worked more than 7 hours a week, and worked more than 5 weeks a year. The summary statistics for age and inflation-adjusted annual income are presented in Table 1.

ESTIMATION RESULT

Intergenerational elasticity regression result

The intergenerational elasticity is estimated using the Ordinary Least Square (OLS) and IV models. The model encompassing all control variables includes province dummies, age, education, employment industry, and employment sector as instrumental variables. The combination of different instruments allows us to check the robustness of the estimates. Table 2 shows the results of different models, and the main variable of interest is the log of the father's income. The first-stage regression results of the IV estimations, including test batteries for the instrumental variable regressions, are reported in Table A1 in the Appendix.

The IV estimates for the intergenerational elasticity with all covariates range from 0.44 to 0.50. The full model, which includes all covariates and instrumental variables, provides an estimate of 0.44 for the intergenerational elasticity. As shown in Table 2, the results using different instrumental variables are quite consistent. Consistent with findings in previous studies, OLS estimates serve as the lower bound for the estimate of intergenerational elasticity. The OLS estimate suggests that the intergenerational elasticity is 0.24.

Indonesia's intergenerational elasticity is ranked in the middle compared to other countries. It is about the same as the estimated elasticities for Japan (0.41 – 0.46), but it is smaller than the estimated elasticities for developing countries such as Brazil (0.66), Chile (0.57), China (0.63), and South Africa (0.62-0.67) (Grawe, 2004; Piraino, 2015; Gong, Leigh, & Meng, 2012; Nunez & Miranda, 2010; Dunn 2007; Ferreira & Veloso, 2006; Ueda, 2009). The estimated intergenerational elasticity for Indonesia is

Table 1. Summary Statistics For the Variables of Interest

Variables	Average	Median	Minimum	Maximum
Son's Age (IFLS 5)	31.2 (4.27)	31	25	45
Father's Age (IFLS 2)	41.4 (4.86)	42	28	49
Father's annual income (IFLS 1)	214,500 (181,000)	8,315	47	3,950,000
Father's annual income (IFLS 2)	13,800,000 (14,500,000)	9,950,000	16,600	135,000,000
Father's annual income (IFLS 3)	15,300,000 (41,100,000)	10,100,000	69,900	1,170,000,000
Son's annual income (IFLS 5)	27,100,000 (34,700,000)	18,500,000	200,000	396,000,000

Note: Values are inflation-adjust income using CPI with 2014 as the base year and are rounded to 3 significant numbers. The value in parentheses is the standard deviation.

Source: Authors' Calculation

still less than most developed countries such as South Korea (0.35), Australia (0.20-0.30), Taiwan (0.18), France (0.4), Sweden (0.28), and other Scandinavian countries (Ueda 2009, 2013; Kan, Li, & Wang, 2015; Björklund & Jäntti 1997; Leigh 2007; Jäntti et al., 2006; Lefranc & Trannoy, 2005; Narayan et al., 2018).

Overall, the estimate suggests that Indonesia is more mobile than Malaysia, Brazil, Chile, and China but less mobile than France, South Korea, Australia, and Taiwan. The comparison with other countries' intergenerational mobility, as published by the World Bank in Global Database on Intergenerational Mobility (GDIM), can be seen in Table 3.

Estimated intergenerational mobility in Indonesia is quite consistent, as expected based on its Gini Index. A study argues for a relationship between static income inequality measures such as the Gini coefficient and intergenerational mobility measures such as intergenerational elasticity (Corak, 2016). This relationship is usually represented as the Great Gatsby Curve. Figure 1 depicts the Great Gatsby Curve. Indonesia is expected to be about the same mobility as the value estimated in this paper, with its Gini coefficient of 0.389 as of 2018 (BPS, 2018).

The results for the intergenerational mobility matrix are shown in Table 4. The number in each cell represents the percentage distribution son's income quartile given the respective father's income quartile. This suggests that there is a 32.7 percent chance for a father in the first income quartile to have a son in the first income quartile and a 16.3 percent chance for the son to be in the fourth income quartile. In a perfect mobility scenario, in which fathers' income does not affect sons' income, the value in each cell would be 25.

A notable result on the intergenerational mobility matrix is 32.7 percent in quartile 1 of fathers' and sons' income, and 41.2 percent in the fourth income quartile of father and son income. The results in this study are consistent with those in previous studies. Specifically, the driver of within-country intergenerational income

Table 2. Intergenerational Elasticity Estimate Using Different Model

2nd Stage regression – Dependent variable: Natural Logarithm of Son's Income					
	Model 1 OLS	Model 2 IV	Model 3 IV	Model 4 IV	Model 5 IV
Natural Log of Father's Income	0.238***	0.500***	0.465***	0.439***	0.440***
	(0.038)	(0.082)	(0.083)	(0.073)	(0.069)
Son's age – 40					
	0.008	-0.001	0.005	0.005	0.005
(Son's age – 40)^2	(0.026)	(0.027)	(0.026)	(0.026)	(0.026)
	-0.001	-0.000	-0.001	-0.001	-0.001
Father's Age	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	-0.011	-0.016**	-0.011	-0.011	-0.011
(Father's age – 40)^2	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
	-0.002*	-0.002	-0.002	-0.002	-0.002
Constant	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	14.661***	8.854***	10.803***	11.248***	11.233***
Province Dummies	Y	N	Y	Y	Y
IV: Years of schooling	N	Y	Y	Y	Y
IV: Employment status dummies	N	N	N	Y	Y
IV: Employment sector dummies	N	N	N	N	Y
Observations	980	980	980	980	980
R-squared	0.134	0.011	0.102	0.109	0.108

Note: Standard errors are shown in parentheses. The signs ***, **, and * indicate significance at the 1%, 5%, and 10% level. For brevity, the table omits coefficients for province dummies, employment status dummies, and employment sector dummies from the table.

mobility is usually the mobility in the extremes of the income distribution: the lowest and highest quartile (Jäntti et al., 2006). The results in this study imply a moderate difficulty in escaping low-income and exceptionally low mobility in the high-income bracket. This characteristic of lower mobility in the high-income bracket is different in America and Australia where mobility is lower in the low-income quartile. However, it is similar to Japan where lower mobility is evident in the upper tail of income distribution (Leigh, 2007; Ueda, 2009).

Table 4. Intergenerational Mobility Matrices

		Son's Income Quartile			
		1	2	3	4
Father's Income Quartile	1	32.7	28.2	22.9	16.3
	2	25.7	27.8	28.6	18.0
	3	26.1	23.3	26.1	24.5
	4	15.5	20.8	22.4	41.2

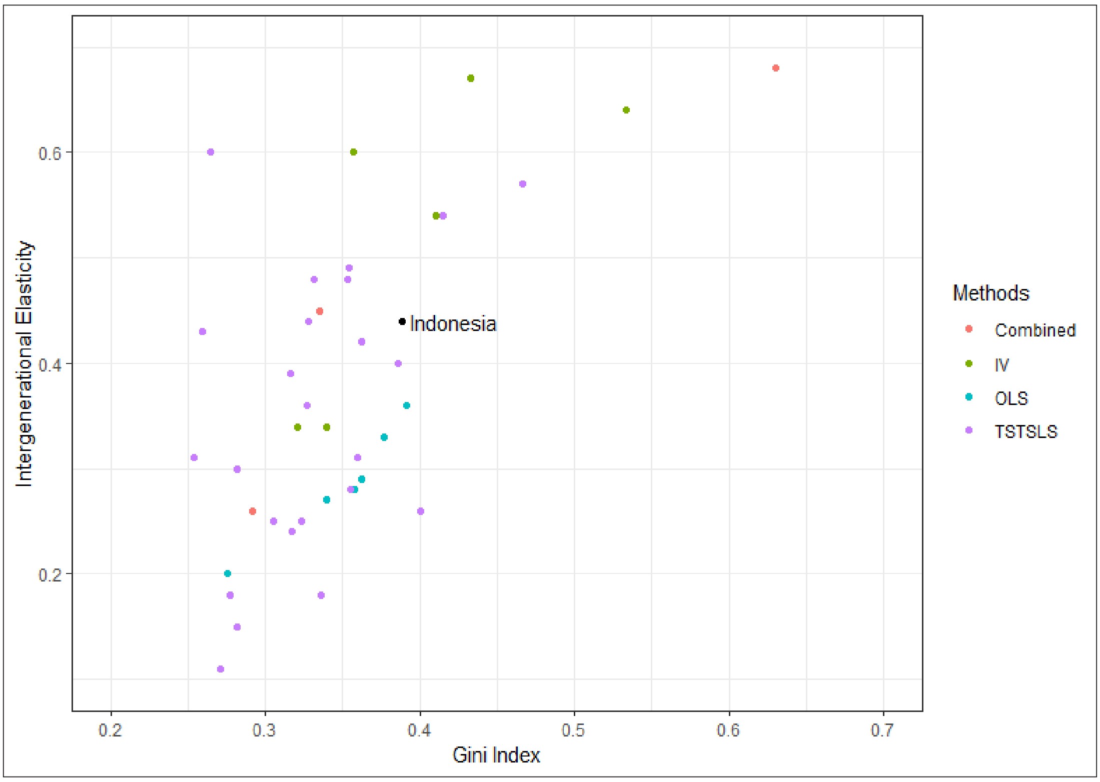
3.2 Sensitivity Analysis

It is important to note that the difference in age between fathers and their sons is a thorny issue in estimating intergenerational income elasticity and mobility. In this study, the issue arises owing to data limitation, particularly observation of sons' income when they were older. Therefore, this study includes a sensitivity analysis to analyze how sensitive the estimates are using a different sample of father-and-son pairs.

The ideal sensitivity analysis uses the same set of father-and-son pairs and estimates the intergenerational elasticity using sons' incomes when they were older. However, given the limitation, this study can only use a subset of father-and-son pairs among fathers aged between 28 and 42 years in IFLS 1. The subset is used for consistency between the father and son's age.

There is an issue when using income when fathers were still quite young. First, individuals might have been working in a temporary occupation or perhaps undergoing on-the-job training when they were young. Their income when they were young may not accurately predict

Figure 1. Great Gatsby Curve linking Gini Index (x-axis) to Intergenerational Elasticity (y-axis)



Source: Author's calculation, Gini Index from World Bank database, Intergenerational Elasticity value edited from GDIM. 2018. Global Database on Intergenerational Mobility. Development Research Group, World Bank. Washington, D.C.: World Bank Group.

Table 3. Intergenerational Mobility Across Countries

Country	Elasticity	Author	Method
Australia	0.28	Leigh (2007), Mendolia and Siminski (2015)	OLS
Austria	0.25	Equalchances (2018)	TSTSLS
Belgium	0.18	Equalchances (2018)	TSTSLS
Brazil	0.64	Ferreira and Velosso (2006), Dunn (2007)	TSIV
Canada	0.27	Chen Ostrovsky Piraino (2017), Corak and Heisz (1999), Corak, Linquist, and Mazumder (2014)	OLS
Chile	0.57	Nunez and Miranda (2010)	TSTSLS
China	0.40	Yuan (2015), Fan (2015)	TSTSLS
Cyprus	0.34	Christofides et.al (2009)	IV
Czech Republic	0.43	Equalchances (2018)	TSTSLS
Denmark	0.15	Equalchances (2018)	TSTSLS
Ethiopia	0.36	Haile (2016)	OLS, predicted
Finland	0.11	Equalchances (2018)	TSTSLS
France	0.36	Equalchances (2018)	TSTSLS
Germany	0.24	Equalchances (2018)	TSTSLS
Greece	0.31	Equalchances (2018)	TSTSLS
India	0.60	Hnatkovska et al (2013)	IV
Indonesia	0.44-0.50	This study	IV
Ireland	0.26	Equalchances (2018)	TSTSLS
Italy	0.49	Equalchances (2018)	TSTSLS
Japan	0.34	Lefranc et al (2014)	TSTSIV
Korea, Rep.	0.39	Ueda (2013)	TSTSLS
Malaysia	0.54	Grawe (2001)	TSIV
Nepal	0.44	Grawe (2001)	TSTSLS
Netherlands	0.30	Equalchances (2018)	TSTSLS
New Zealand	0.29	Gibbons (2010)	OLS
Norway	0.20	Jantti et al (2006), Bratsberg et al (2007), Nilsen et al (2012)	OLS
Pakistan	0.45	Javed and Irfan (2012), Grawe (2001)	Combined
Peru	0.67	Grawe (2001)	TSIV
Portugal	0.28	Equalchances (2018)	TSTSLS
Russian Federation	0.33	Borisov and Pissarides (2016)	OLS with selection correction
Slovak Republic	0.60	Equalchances (2018)	TSTSLS
Slovenia	0.31	Equalchances (2018)	TSTSLS
South Africa	0.68	Piraino (2015), Finn et al (2016)	Combined
Spain	0.42	Equalchances (2018)	TSTSLS

Sweden	0.26	Nybom and Stuhler (2016), Bjorklund and Chadwick (2003), Corak, Linqueist, and Mazumder (2014), Jantti et al(2006), Bjorklund and Jantti (1997)	Combined
Switzerland	0.25	Equalchances (2018)	TSTSLS
Taiwan, China	0.18	Kan et al (2014)	TSTSLS
United Kingdom	0.48	Equalchances (2018)	TSTSLS
United States	0.54	Equalchances (2018)	TSTSLS
Vietnam	0.48	Doan and Nguyen (2016)	TSTSLS

Note: Global Database on Intergenerational Mobility. Development Research Group, World Bank. Washington, D.C.: World Bank Group.
Source: edited from GDIM (2018)

their long-term income. Income, when individuals were young, would underestimate their long-term income. Second, the number of observations for regression analyses would decrease quite significantly. This would decrease the precision of the estimates. Lastly, using a particular subsample would introduce a composition bias. Results across subsamples would be quite different because the estimates use different sets of observations.

For the first sensitivity analysis, this study uses a sample of fathers between 28 and 42 years, with an average of 38 years. This implies that the age range of fathers is between 25 and 38 years, as recorded in the IFLS 1. Using this subsample, the study obtains sons' average age of 30 with an average father-son age difference of 8 years. The father-son age difference in this subsample is two years lower than the 10-year difference in the whole sample. By limiting the sample, the problem of the age difference between fathers and sons persists. The number of observations for estimating intergenerational mobility also decreases quite significantly from 980 to 539. In Table A2 in the Appendix, this study presents the results of estimations using the IFLS2 sample when fathers were 28-42 years old.

This study finds that the estimated intergenerational elasticity is lower in this subsample. The main explanation for this finding is that income of young individuals was relatively lower than their permanent income. This implies that the variance of the income shocks is relatively larger among individuals in this sample. Consequently, the study obtains a lower estimate of intergenerational elasticity coefficients, as suggested by the equation in Black and Devereux (2011). Note that the estimate's precision is lower using this sample because the regression sample has a smaller number of observations.

This study also includes a second sensitivity analysis using a sample of fathers aged between 43 and 49 in IFLS 2. With this approach, the average age of fathers is 46 years, with the average age of sons being 33 years. This implies an average father-son age difference of 13 years. This study presents the results of the estimations in Table A3 in the Appendix. In general, the study finds that the estimated intergenerational elasticity is higher than the estimated intergenerational elasticity using the total sample and that using the sample of fathers between 28 and 42 years. Income shocks are lower when individuals are older, which implies a higher estimated intergenerational elasticity.

The results of these sensitivity analyses suggest a trade-off in the estimation of intergenerational elasticity. The use of the IFLS 2 sample with fathers between 28 and 42 years results in a slightly smaller difference in the father-and-son average age. However, limiting the sample to fathers between 28 and 42 years introduce composition bias as estimated coefficients using different subsample are quite different.

CONCLUSION

There is a challenge in the estimation of intergenerational elasticity in developing countries. Available income data at the individual level do not allow a robust estimation of permanent income, which is key in estimating intergenerational elasticity. In addition to such a challenge, the estimation of intergenerational elasticity is missing for the Indonesian context. This study estimates the intergenerational income elasticity in Indonesia using the 1st to 5th wave of the Indonesian Family Life Survey (IFLS). Using the IV method, this study estimates that the intergenerational elasticity in Indonesia is between 0.44 and 0.50, higher than estimates obtained from OLS. Given the issue of attenuation bias in OLS estimates, this study concludes that the intergenerational elasticity in Indonesia is between 0.44 and 0.50.

The result from Indonesia's intergenerational mobility matrix indicates a lower level of mobility in the income quartile's higher tail than the lower tail. This trend differs from trends in advanced economies such as Australia, Canada, and America where lower mobility is more evident in the lower tail of income distribution. However, the Indonesian trend is quite similar to Japan, where lower mobility is evident in the upper tail of income distribution (Ueda, 2009; Leigh, 2007).

Different intergenerational mobility may be caused by 3 main factors: labor market inequalities, families and investment in human capital, and public policy (Corak 2014). These factors might support the observed low mobility in the high-income quartile. A relatively low tax rate for the high-income and use of familial ties for a career might explain low mobility, especially among individuals in the high-income quartile. This practice has little effect on the Gini index while being an essential part of perceived inequality captured by both intergenerational mobility and intergenerational income mobility matrix. As such, this study captures and confirms Indonesia's moderate inequality and nature from its intergenerational elasticity and intergenerational mobility matrix.

The Indonesian Government has been spending a significant share of the annual national budget on human capital investment in the past decade. The Indonesian government has also been committed to providing social assistance programs targeted at poorer households to improve the education and health outcomes of children in these households. An important inquiry for a future study is to investigate whether Indonesia experiences higher income mobility in the future, particularly among households in the first quantile.

REFERENCES

Bah, A. (2013). Estimating Vulnerability to Poverty using Panel Data: Evidence from Indonesia. *Social Science Research Network*. https://doi.org/10.2139/ssrn.2411921.

Becker, G. S., Kominers, S. D., Murphy, K. M., & Spenkuch, J. L. (2018). A theory of intergenerational mobility. *Journal of Political Economy*, *126*(S1), S7-S25.

Björklund, A., & Jäntti, M. (1997). Intergenerational income mobility in Sweden compared to the United States. *The American Economic Review*, *87*(5), 1009-1018.

Black, S. E., & Devereux, P. J. (2011). Recent developments in intergenerational mobility. In *Handbook of Labor Economics* (pp. 1487–1541). Elsevier BV. https://doi.org/10.1016/s0169-7218(11)02414-2

Badan Pusat Statistik. (2018, July 16). Gini Ratio Maret 2018 Tercatat Sebesar 0.389. https://www.bps.go.id/pressrelease/2018/07/16/1533/gini-ratio-maret-2018-tercatat-sebesar-0-389.html.

Card, D. (1999). The causal effect of education on earnings. In *Elsevier eBooks* (pp. 1801–1863). https://doi.org/10.1016/s1573-4463(99)03011-4.

Cholli, N., & Durlauf, S. N. (2022). *Intergenerational mobility*. https://doi.org/10.3386/w29760.

Corak, M. (2013). Income inequality, equality of opportunity, and intergenerational mobility. *Journal of Economic Perspectives*, *27*(3), 79–102. https://doi.org/10.1257/jep.27.3.79.

Corak, M. (2016). Inequality from Generation to Generation: The United States in Comparison. 9929. [IZA Discussion Paper Series]. Bonn. http://ftp.iza.org/dp9929.pdf.

Dartanto, T., Moeis, F. R., & Otsubo, S. (2020). Intragenerational Economic Mobility in Indonesia: A Transition from Poverty to the Middle Class in 1993–2014. *Bulletin of Indonesian Economic*

Studies, *56*(2), 193–224. https://doi.org/10.1080/00074918.2019.1657795

Dartanto, T., & Nurkholis. (2013). The determinants of poverty dynamics in Indonesia: evidence from panel data. *Bulletin of Indonesian Economic Studies*, *49*(1), 61–84. https://doi.org/10.1080/00074918.2013.772939.

Dartanto, T., & Otsubo, S. (2016). *Intrageneration Poverty Dynamics in Indonesia: Households' Welfare Mobility Before, During, and After the Asian Financial Crisis: Vol. no. 117: 1–42*. JICA-RI Working Paper.

Dunn, C. E. (2007). The intergenerational transmission of lifetime earnings: Evidence from Brazil. *The BE Journal of Economic Analysis & Policy*, *7*(2).

Fatimah, A. M., & Kofol, C. (2023). Migrating for children's better future: Intergenerational mobility of internal migrants' children in Indonesia. *Journal of Asian Economics*, *86*, 101618.

Ferreira, S. G., & Veloso, F. A. (2006). Intergenerational mobility of wages in Brazil. *Brazilian Review of Econometrics*, *26*(2), 181. https://doi.org/10.12660/bre.v26n22006.1576

Frakenberg, E., & Karoly, L. (1995). The 1993 Indonesian Family Life Survey: Overview and Field Report. *RAND, Santa Monica, CA.*

Gong, H., Leigh, A., & Meng, X. (2012). INTERGENERATIONAL INCOME MOBILITY IN URBAN CHINA. *Review of Income and Wealth*, *58*(3), 481–503. https://doi.org/10.1111/j.1475-4991.2012.00495.x

Grawe, N. D. (2004). Intergenerational mobility for whom? The experience of high- and low-earning sons in international perspective. In *Cambridge University Press eBooks* (pp. 58–89). https://doi.org/10.1017/cbo9780511492549.005.

Grawe, N. D. (2006). Lifecycle bias in estimates of intergenerational earnings persistence. *Labour Economics*, *13*(5), 551–570. https://doi.org/10.1016/j.labeco.2005.04.002.

Haider, S. J., & Solon, G. (2006). Life-Cycle Variation in the Association between Current and Lifetime Earnings. *The American Economic Review*, *96*(4), 1308–1320. https://doi.org/10.1257/aer.96.4.1308

Jacoby, H. G., & Skoufias, E. (1997). Risk, financial markets, and human capital in a developing country. *The Review of Economic Studies*, *64*(3), 311. https://doi.org/10.2307/2971716

Jantti, M., Bratsberg, B., Roed, K., Raaum, O., Naylor, R., Osterbacka, E., ... & Eriksson, T. (2006). American exceptionalism in a new light: a comparison of intergenerational earnings mobility in the Nordic countries, the United Kingdom and the United States. *IZA Discussion Paper*, no. 1938 (January): 1–40. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=878675.

Jensen, R. (2000). Agricultural volatility and investments in children. *The American Economic Review*, *90*(2), 399–404. https://doi.org/10.1257/aer.90.2.399Kan,

K., Li, I., & Wang, R. (2015). Intergenerational Income Mobility in Taiwan: Evidence from TS2SLS and Structural Quantile Regression. *B E Journal of Economic Analysis & Policy*, *15*(1), 257–284. https://doi.org/10.1515/bejeap-2013-0008

Lefranc, A., & Trannoy, A. (2005). Intergenerational earnings mobility in France: Is France more mobile than the US?. *Annales d'Economie et de Statistique*, 57-77.

Leigh, A. (2007). Intergenerational mobility in Australia. *The BE Journal of Economic Analysis & Policy*, *7*(2).

Mazumder, B. (2005). Fortunate sons: New estimates of intergenerational mobility in the United States using social security earnings data. *Review of Economics and Statistics*, *87*(2), 235-255.

McCulloch, N., Timmer, C. P., & Weisbrod, J. (2007). Pathways Out of Poverty During an Economic Crisis: An Empirical Assessment of Rural Indonesia. *Center for Global Development Working Paper No. 115*. https://doi.org/10.2139/ssrn.980328

Narayan, A., Van Der Weide, R., Cojocaru, A., Lakner, C., Redaelli, S., Mahler, D., Ramasubbaiah, R. G. N., & Thewissen, S. (2017). Fair Progress?: Economic Mobility across Generations around the World. In *Washington, DC: World Bank eBooks*. https://doi.org/10.1596/978-1-4648-1210-1.

Núñez, J., & Miranda, L. (2010). Intergenerational income mobility in a Less-Developed, High-Inequality context: the case of Chile. *B E Journal of Economic Analysis & Policy*, *10*(1). https://doi.org/10.2202/1935-1682.2339Pakpahan, Y.

M., Suryadarma, D., & Suryahadi, A. (2009). Destined for destitution: intergenerational poverty persistence in Indonesia. *Chronic Poverty Research Centre Working Paper*, (134).

Piraino, P. (2015). Intergenerational earnings mobility and equality of opportunity in South Africa. *World Development*, *67*, 396–405. https://doi.org/10.1016/j.worlddev.2014.10.027

Solon, G. (1992). Intergenerational income mobility in the United States. *The American Economic Review*, 393-408.

Strauss, J., Witoelar, F., & Sikoki, B. (2016). *The fifth wave of the Indonesia family life survey: overview and field report* (Vol. 1, pp. 1-94).

Santa Monica, CA, USA: Rand.Surachman, A., & Hartoyo, H. (2015). Parental investment and poverty dynamics in West Java, Indonesia. *Journal of Family and Economic Issues*, *36*(3), 340–352. https://doi.org/10.1007/s10834-015-9454-3

Ueda, A. (2009). Intergenerational mobility of earnings and income in Japan. *B E Journal of Economic Analysis & Policy*, *9*(1). https://doi.org/10.2202/1935-1682.2203

Ueda, A. (2013). Intergenerational mobility of earnings in South Korea. *Journal of Asian Economics*, *27*, 33–41. https://doi.org/10.1016/j.asieco.2013.05.002

APPENDIX

Table 5. First-Stage Regression Result

Dependent variable: Natural logarithm of Father's Average Income			
	IV: Educ	IV: Educ, Industry	IV: Educ, Industry, Employment status
Years of Education	0.116***	0.092***	0.080***
	(0.007)	(0.008)	(0.008)
1 if in Mining		-0.627	-0.620
		(0.765)	(0.751)
1 if in Manufacturing		-0.081	0.003
		(0.817)	(0.804)
1 if in Electricity, gas, water		-0.094	-0.055
		(0.768)	(0.755)
1 if in Construction		-0.444	-0.606
		(0.817)	(0.805)
1 if in Wholesale, retail, hotel		-0.193	-0.157
		(0.769)	(0.756)
1 if in Transport, communication		-0.109	-0.095
		(0.767)	(0.754)
1 if in Finance, insurance, real estate		-0.181	-0.138
		(0.768)	(0.756)
1 if in Community, personal service		-0.096	-0.425
		(0.936)	(0.924)
1 if in Other Sectors		-0.073	-0.207
		(0.767)	(0.756)
1 if Self-employed with unpaid worker			0.054
			(0.069)
1 if Self-employed with employees			0.918***
			(0.208)
1 if a Government worker			0.439***
			(0.106)
1 if a Private worker			-0.027
			(0.068)
Constant	14.859***	15.356***	15.377***
	(0.057)	(0.765)	(0.754)
Observations	980	980	980
First-stage *F*-test	231.03	30.25	18.99
Endogeneity test, *p*-value	0.00	0.00	0.00
Overidentifying rest., Sargan *p*-value	.	0.23	0.00
R-squared	0.214	0.283	0.313

Note: the base category for the industry is agriculture, while the base category for employment status is self-employed. Standard errors are shown in parentheses. The signs ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 6. IV Estimates Using the IFLS2 Sample of Fathers between 28 and 42 Years

2nd Stage regression – Dependent variable: Natural Logarithm of Son's Income					
	Model 1 OLS	Model 2 IV	Model 3 IV	Model 4 IV	Model 5 IV
Natural log of father's income	0.177***	0.442***	0.344***	0.319***	0.281***
	(0.055)	(0.130)	(0.124)	(0.100)	(0.096)
Son's age – 40	0.066	0.053	0.070	0.069	0.068
	(0.055)	(0.056)	(0.054)	(0.053)	(0.053)
(Son's age – 40)^2	-0.004	-0.003	-0.005	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Father's Age	0.022	0.001	0.025	0.024	0.024
	(0.031)	(0.031)	(0.030)	(0.030)	(0.030)
(Father's age – 40)^2	-0.006	-0.003	-0.006	-0.006	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	19.687***	9.502***	16.828***	17.322***	17.916***
	(2.081)	(2.035)	(2.672)	(2.403)	(2.359)
Province Dummies	Y	N	Y	Y	Y
IV: Years of schooling	N	Y	Y	Y	Y
IV: Employment status dummies	N	N	N	Y	Y
IV: Employment sector dummies	N	N	N	N	Y
Observations	539	539	539	539	539
R-squared	0.177	0.006	0.162	0.166	0.171

Note: Standard errors are shown in parentheses. The signs ***, **, and * indicate significance at the 1%, 5%, and 10% level. The table omits coefficients for province dummies, employment status dummies, and employment sector dummies.

Table A3: IV estimates using the IFLS2 sample of fathers between 43 and 49 years

2nd Stage regression – Dependent variable: Natural Logarithm of Son's Income					
	Model 1 OLS	Model 2 IV	Model 3 IV	Model 4 IV	Model 5 IV
Natural log of father's income	0.288***	0.537***	0.548***	0.466***	0.517***
	(0.054)	(0.108)	(0.114)	(0.099)	(0.093)
Son's age – 40	-0.015	-0.022	-0.028	-0.023	-0.026
	(0.032)	(0.033)	(0.032)	(0.032)	(0.032)
(Son's age – 40)^2	-0.000	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Father's Age	-0.246	-0.187	-0.161	-0.188	-0.171
	(0.182)	(0.181)	(0.182)	(0.179)	(0.180)
(Father's age – 40)^2	-0.023	-0.017	-0.016	-0.018	-0.017
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Constant	11.538***	7.936***	7.676***	8.900***	8.145***
	(0.973)	(1.633)	(1.779)	(1.560)	(1.478)
Province Dummies	Y	N	Y	Y	Y
IV: Years of schooling	N	Y	Y	Y	Y
IV: Employment status dummies	N	N	N	Y	Y
IV: Employment sector dummies	N	N	N	N	Y
Observations	441	441	441	441	441
R-squared	0.180	0.029	0.133	0.158	0.144

Note: Standard errors are shown in parentheses. The signs ***, **, and * indicate significance at the 1%, 5%, and 10% level. The table omits coefficients for province dummies, employment status dummies, and employment sector dummies.