Instrumental Variable Approach to Intergenerational Mobility: Evidence from Indonesia[1]

Rafia Zafar[2]

Abstract

By 2030, more than 85 percent of the world's population will be living in the developing world. Yet there is very little evidence on intergenerational mobility (IGM) for these countries. In this paper, we use multiple waves of the Indonesian Family Life Survey (IFLS) to estimate both absolute and relative IGM in income and consumption expenditure for Indonesia. Our estimates of IGM range from 0.08 to 0.62 as we use a more permanent measure of income and correct for measurement error bias. OLS estimate of relative income mobility is 0.08 suggesting high mobility, however, the preferred IV estimates that account for measurement error bias in income increases the elasticity coefficient to 0.456, indicating substantially lower mobility. We find low mobility using per capita consumption expenditure indicating lower mobility than what OLS estimates of income show. We also examine absolute mobility that specifically captures the extent of upward and downward mobility in income and consumption expenditure. At 20th and 40th percentiles of parental income distribution the elasticity estimate is 0.27 and 0.77 respectively. These estimates suggests lower upward mobility for their children. This paper shows that even in the absence of tax records, household survey data on income and consumption available from developing countries can facilitate mobility estimates. Our results are robust to sample attrition, choice of controls, functional form specification, and household composition.

[1] I am grateful to Subha Mani for her guidance. I would also like to thank Sophie Mitra and Andrew Simons for their feedback and inputs. This paper has also benefited from feedback from seminar participants at Fordham University and conference participants at NYSEA (2018), SEA (2018), and EEA (2019). All errors are our own.

[2] Fordham University, rzafar1@fordham.edu.

1 Introduction

There is a global decline in intergenerational mobility (IGM) both in developed as well as in developing economies with most of the evidence on intergenerational mobility in income coming from developed countries such as Denmark, Sweden, Canada, and US (Chetty et al. 2017b; Corak, Lindquist, and Mazumder 2014; Asadullah 2012; Azam 2016). Existing research on IGM is focused exclusively on developed countries primarily due to access to high quality tax records and or rich panel data sets that follow both children and their parents.

This trend is accompanied by rising inequality and is partly driven by the concentration of income at the top. Public policies such as cash transfers have led to significant declines in poverty around the world, yet around 80 percent of the world's population lives in countries where income inequality is widening. However even today, 80 percent of the world's population resides in the developing world for which mobility estimates remain sparse. The problem of rising inequality and declining intergenerational mobility is more severe in the developing world[3]. Furthermore, approximately 61 percent of the world's population is employed in the informal sector (ILO report, 2018) with no tax records, therefore, leaving them out of current mobility estimates.

This paper not only provides evidence on intergenerational mobility for a developing country (Indonesia) but also shows that we can estimate IGM even in the absence of rich tax records. We show that it is possible to combine multiple waves of rich household survey data on income and consumption expenditure to estimate relative and absolute mobility in income addressing both measurement error bias and life-cycle bias in income. The life-cycle bias is addressed by including age controls and using per capita consumption expenditure as a more permanent measure of income. Instrumental variable approach corrects for the random measurement error bias.

To estimate intergenerational mobility, we construct parent-child pairs using five rounds of the Indonesian Family Life Survey (IFLS) collected over 25+ years. We estimate absolute and relative mobility using both income and per capita consumption expenditure. Since inequalities varies

[3] 2007 Human Development Report (HDR), United Nations Development Program, November 27, 2007, p.25.

across generations, to address this we estimate rank-rank slope and rho[4] estimates by controlling for varying standard deviations of income in both generations. More importantly, we generate IV estimates for relative mobility in income correcting for measurement error bias and life-cycle bias in mobility. Finally, we also allow mobility to differ by gender, ethnicity, and urban location.

Recent trends of rising inequality and income concentration in developing countries are worrisome because of its potential impact on future economic growth and inequality [5]. World Bank's report on IGM finds that IGM in income is lower in developing countries than in high income countries. Of particular concern here is the impact of income inequality on (in)equality of opportunities i.e. the extent to which childhood conditions determine adult economic outcomes. Existing evidence shows that inequality of income and inequality of opportunities are correlated (Corak 2013) as inequality in one generation is passed on to the future generations through inequality of opportunities. Realized opportunity in any country is measured by estimating intergenerational transmission of income between generations. Since (equal) access to opportunities is determined by intergenerational mobility, it has consequences on long-run levels of inequality and social welfare. Therefore, IGM is a matter of interest for both researchers and policy makers.

Most of the evidence on IGM exists for developed countries (Chetty et al. 2014a; Björklund, Roine, and Waldenström 2012; Chetty et al. 2014b; Corak and Heisz 1999). This rise in inequality, especially in developed countries, is explained by the rise in divergence of income between the top 1 percent and the rest. Another factor that contributes to income inequality is stagnant income in the middle of the distribution and increased income of the highly skilled workforce (Corak, Lindquist, and Mazumder 2014; Chetty et al. 2017a).

United States is among the least mobile developed nations and most estimates of intergenerational elasticity fall between 0.3 and 0.5 (Chetty et al. 2014a). For cohorts born between 1940-1980, there was an increase in mobility in United States, however it started to decline for children born

[4]See discussion in methodology section

[5]Narayan, Ambar, Roy Van der Weide, Alexandru Cojocaru, Christoph Lakner, Silvia Redaelli, Daniel Gerszon Mahler, Rakesh Gupta N. Ramasubbaiah, and Stefan Thewissen. 2018. Fair Progress? Economic Mobility across Generations around the World. Washington, DC: World Bank.

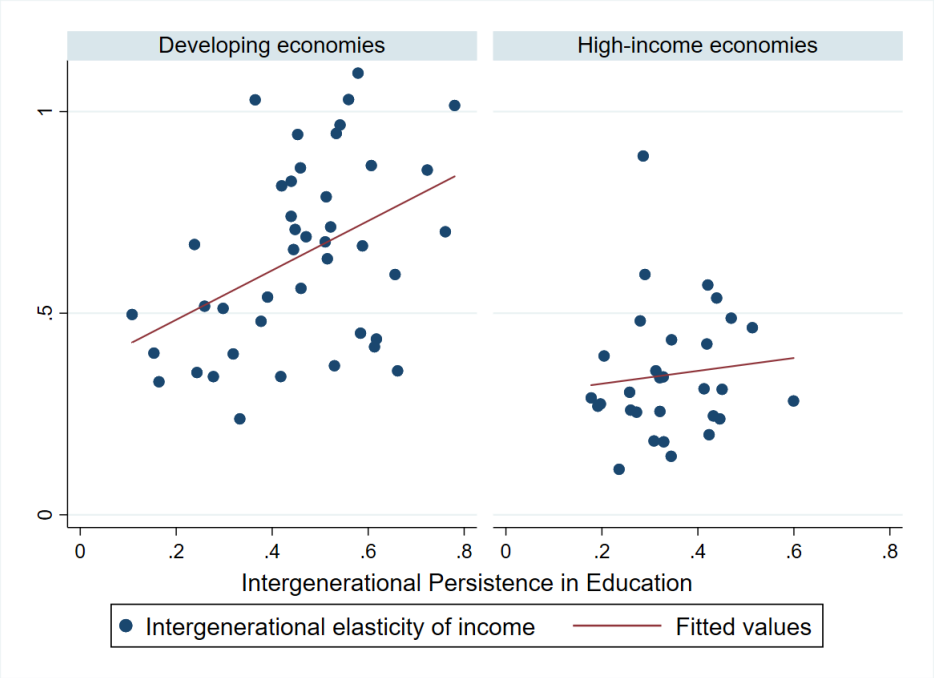
after 1980 (Hilger 2015; Chetty et al. 2014a; Lee and Solon 2009). Aaronson and Mazumder (2008) find that intergenerational elasticity for men fell (high mobility) in United States between 1960-1980 before it started going up (low mobility) after the 1980s. They also find that family income is the most important factor that determines children's social mobility and income. In comparison, Canada has a lower intergenerational elasticity (higher mobility) than US. Corak (2013) shows that more inequality is associated with lower intergenerational mobility. For example, among developed countries, United States and United Kingdom both have high inequality and lower mobility whereas Finland, Norway, and Denmark have lower inequality and higher intergenerational mobility in income.

While developing countries like India, Indonesia, China and others are also characterized by high rates of economic growth and inequality, the evidence on economic and social mobility is limited. Some exceptions include, Asher, Novosad, and Rafkin (2017) who find some gains in rank mobility in education for low caste groups, but mobility losses for Muslims in India. Bevis and Villa (2017) find strong correlation between daughters and parent's income and education in the Philippines. Asadullah (2012) estimates intergenerational persistence in wealth between father-son pairs in Bangladesh to be between 0.35 and 0.53, which suggests lower intergenerational mobility in rural Bangladesh. A comprehensive study by Grawe (2004) studied the father-son earnings data from the US, UK, Pakistan, Peru, Nepal, Malaysia, and Ecuador. He finds significantly lower intergenerational mobility in developing countries. The author notes that mobility in developing countries is no better than mobility in developed countries.

A larger portion of the population in developing countries is subject to multi-dimensional inequalities such as unequal access to education, health services, and employment opportunities. However, unavailability of quality data makes the study of intergenerational mobility in developing countries difficult. By 2030, 85 percent of the world's population will be living in developing countries (World Bank Development Indicators, 2008). Therefore, understanding the dynamics of IGM in developing countries is essential. Figure 1 shows the distribution and correlation between intergenerational mobility in income and intergenerational persistence in education for both developing and high-income economies. Higher value represents lower mobility (for both income and education measures of mobility). The graph shows, on average, both income and education mobility

in developing countries is higher as compared to high-income countries.

Figure 1: Intergenerational Mobility by Income Group



Data for this figure is taken from GDIM. 2018. *Global Database on Intergenerational Mobility.* Development Research Group, World Bank. Washington, D.C.: World Bank Group.

Figure 1 again stresses the severity of the problem of lower intergenerational mobility in developing countries, yet the evidence is scarce. This paper aims to fill this gap in the literature by providing evidence on intergenerational mobility in Indonesia. Indonesia is the fourth largest country in the world, and their high economic growth is accompanied by a rising inequality. Approximately, 68 million people in Indonesia are considered vulnerable to economic shocks and 28 million are considered poor (Statistics Indonesia).The current GINI coefficient for Indonesia is 0.4 and it holds the 40th position among the most unequal countries in the world. During 1980-2000, income share held by the top 5 percent increased to around 15 percent in Indonesia (Leigh and Eng 2009). The pace of poverty reduction is also going down and to achieve higher rate of poverty reduction, a significant boost in consumption growth of the poor is required. The agriculture sector is the largest in the economy, which absorbs around 35 percent of the labor force. This also suggests that there is lack of high-productivity jobs and lack of good jobs further creates inequality. Chil-

dren also face multi-dimensional inequality in access to health care, education, and transportation services especially in remote and rural parts of the country. Another important contributor to rise in inequality is the inability of poor households to protect themselves against natural disasters and other negative economic shocks (Statistics Indonesia). Any such shock can push the vulnerable population into poverty.

Existing evidence on mobility uses simple OLS regression techniques to estimate the correlates between parent's income and child's income. However, this estimate suffers from two major econometric concerns. First, parental income is measured later in life (usually around age 40) and hence a more permanent proxy of parent's income, whereas child's income is measured much earlier in life when they are susceptible to more labor market frictions biasing the coefficient estimate on parental income, where the direction of the bias is not clear. Second, labor income, especially from household surveys, is fraught with random measurement error that is likely to cause attenuation bias in the coefficient estimate on parental income. The source of this bias is less of a concern for developed countries where mobility estimates come from tax records. Many studies address life-cycle bias by including controls on both parent's and child's age (Hilger 2015; Chetty et al. 2014a; Lee and Solon 2009; Mitnik et al. 2015), though to our knowledge, none directly addresses the random measurement error bias present in mobility estimates generated for developed and developing countries [6].

Overall, we find that: (a) absolute mobility is lower than relative mobility as suggested by the higher coefficient of 0.097 for absolute income mobility and 0.08 for relative income mobility. Similar trend is observed by using per capita consumption expenditure , (b) OLS estimates of intergenerational elasticity in income is 0.08 which is much smaller than the IV estimate of 0.45, which addresses the measurement error bias, (c) intergenerational elasticity estimates using per capita consumption is 0.255 which is much larger than intergenerational elasticity estimates using income, (d) rank-rank estimate show a 1 pp increase in parent's rank leads to a 0.13 pp increase in child's mean rank in income distribution and a 0.57 pp increase in child's mean rank when estimated using consumption expenditure. Larger estimate of intergenerational mobility suggests lower intergenera-

[6] Tax data is less prone to measurement error especially if it has more years of data on parent's income (Mazumder 2014). Some studies take 5 year average of parental income to remove transitory fluctuations in income (Chetty et al. 2014b)

tional mobility. Finally, I find measurement error (attenuation) bias in relative mobility estimates, suggesting that previous estimates may be severely overestimating intergenerational mobility (that is, finding lower coefficients on IGM elasticity).

This rest of this paper is organized as follows. Section II provides a detailed description of the data used for analysis. The research methodology is discussed in Section III. Main results are presented in Section IV, robustness tests are presented in Section V followed by conclusion in Section VI.

2 Data

The Indonesian Family Life Survey (IFLS) is an ongoing large-scale socioeconomic and health survey. It collects extensive information at the individual, household, and community level. The 1993 (IFLS-1) round represented 83 percent of the Indonesian population, living in 13 of the 26 provinces (Strauss, Witoelar, and Sikoki 2016). It was designed to collect a broad range of information on wealth, consumption, assets, and occupation including farm business. It also provides information at the individual level on health, education attainment, migration, labor market participation and outcomes, and participation in community activities. We use data from the 1993, 1997, and 2014 wave of IFLS.

The IFLS sampling scheme stratified on provinces and then randomly sampled within enumeration areas (EA) within 13 selected provinces. A total of 321 EAs were selected. Within those selected EAs, household's were randomly selected. Urban EAs and EAs in smaller provinces were oversampled for facilitating rural-urban and Javanese-non-Javanese comparisons.

The 1993 survey includes data on 7,224 households. The survey continued to follow the original households and their split-offs thereof during the 1997, 2002, 2007, and 2014 waves. The 2014 survey interviewed 16,204 households and 50,148 individuals. The recontact rate for original households from 1993 (and the split-offs) was 90.5 percent in 2014.

This level of large-scale longitudinal surveys which follow a generation of households for 21 years

are rare in developing countries. Lack of infrastructure and proper documentation in developing countries makes it time consuming and costly to track households over time. Therefore, high attrition is a matter of concern in such surveys. This high re-contact rate in IFLS improves the data quality and reduces attrition bias related concerns. All these features make IFLS a unique and extremely rich data set to study intergenerational mobility.

To estimate intergenerational mobility coefficient in income we combine, track and, merge data on parents' income, consumption, assets, and education from the 1993 wave with similar data available on their children in 2014. We have identified approximately 20,000 parent-child pairs for whom we have rich data on numerous variables. Our sample includes adults who are between ages of 15 and 49 in 2014. Including individuals of age between 30 and 49 gives an approximate estimate of their permanent income as individuals are less likely to change their education and employment type past this age group. This also controls for the early-life fade-out effects which often reappear later in life.

2.1 Variable Definitions

Parent-Child pair: Parents are identified as those listed as father or mother in the IFLS AR module, which lists all the household members in the survey. These are biological parents and in some cases the child may not be co-residing with their parent. IFLS identifies each individual with a unique ID. Using this ID, we track parents from all the waves of IFLS 1993-2007 and match parents with their children in the 2014 wave.

Income: Primary measure of income is monthly income reported by individuals in the survey. This includes wages from both the primary and secondary occupations. It also includes net profit from business income. The income variable also includes cash transfers and non-labor income. Non-labor income includes pension, scholarships, insurance, and lottery winnings. Total individual earnings, therefore, include earned income from both primary and additional employment sources, net profit from business, transfers, and unearned income. For parent's income, we sum father's and mother's total individual earnings. We follow the same procedure to compute child's earnings in 2014. Our sample includes individuals with zero income to avoid selection bias.

Expenditure: Total household expenditure includes household expenditure on food and non-food items. Non-food expenditure includes household expenditure on durables, non-durables (non-frequently purchased items), housing, and education. Transfers in and out of the household are also included in expenditure variable. We next compute per capita consumption expenditure by dividing total household consumption expenditure by the household size.

Data on food consumption includes expenditure on self-produced and purchased products. Households report detailed expenditure on food items which include staples, meat, dried fruits, vegetables etc. The reported expenditure on food items is weekly. We multiply weekly expenditure by 4.33 to arrive at monthly expenditure. Similarly, annual expenditure is computed by multiplying monthly expenditure by 12.

Non-food expenditure includes information on items such as electricity, water, telephone, toiletries, domestic services, recreation, transportation etc. Non-food expenditure is reported monthly, annual expenditure is computed by multiplying monthly expenditure by 12.

Households report education expenditure for the past year for both children living in the household and those living outside the household. It includes expenditure on tuition, uniform, transportation, and boarding for children living outside the household.

Education: Education variable for both parents and children gives the number of years of schooling completed. IFLS provides detailed information on schooling, including primary school, high school, college, and university level education. I coded the education variable as the number of years of schooling completed according to the standard education system of Indonesia. This includes information on individuals who attended the regular school as well those who attended Islamic schools. The highest level of education completed is university graduate which is 16 years of schooling.

Controls: Control variables include age, household size, and location of the household. I also include dummy variables to account for differences in gender, religion, ethnicity, and urban residence.

Real values of household income and consumption are computed using the CPI values for 1993, 1997, and 2014 from Indonesian Statistics (BPS). These values are also converted into U.S dollars using the exchange rate in September 2018.

2.2 Descriptive Statistics

Summary statistics are presented in Tables A1, A2, and A3 in the appendix. The primary estimating sample includes approximately 13,000 parent-child pairs. 50 percent of parent sample is from urban areas and 62 percent of children reside in urban areas. About 90 percent of the sample is Muslim and 42 percent belong to the majority Javanese ethnicity. Our sample has equal representation of male and female children. Average age of children in our sample is 30.

Table A1 presents real annual income statistics. Mean real income for children's generation is higher than mean parent income from both 1993 and 1997 waves. For both children and parent's generation mean income of bottom 25th quantile falls below the poverty line of USD 297 annually. Mean income of the top 75th quantile and above is significantly higher than mean income of the rest of the sample population. This indicates presence of inequality and concentration of income at the top of the income distribution.

A similar pattern can be seen for consumption expenditure as shown in Table A2. Mean real per capita consumption expenditure is highest in children's generation. Also, mean consumption share of people at the top of the distribution is the highest highlighting presence of consumption inequality. In both parent's and children's generation, percentage share of food in total household consumption is the highest. Children's generation spend 58 percent of their total per capita annual consumption expenditure on food and only 7.8 percent on education. Parent's consumption expenditure from 1993 shows that parent's spent 64 percent of their total consumption expenditure on food consumption and 22 percent on education. The share of non-food expenditure has gone up from parent's generation to children's generation.

There was a 6 percent increase in real income from 1993 to 2014. There were substantial im-

provements in completed years of schooling from mean of 5 to 10 years over the two generations. The Indonesian poverty line is USD 297 (BPS, 2016). Mean parental income is USD 178 which is below the BPS-2016 poverty line. The bottom 25 percent of the parent population has income below poverty line as well. For children's generation, mean income is USD 1,584 and mean income for bottom 25 percent is USD 125 which is below the 2016 poverty line. Moreover, mean income for top 75 percent of children's sample is USD 1,384.

Mean household per capita consumption expenditure for parent's sample is USD 224 and USD 653 for the children's population. Bottom 25 percent of the parent's population has mean per capital consumption of USD 79 and USD 283 which is below the 2016 poverty line. Mean consumption expenditure of top 75 percent of children's population is USD 726.

Table A3, shows statistics for children whose parent's belong to bottom 25th, 50th, and 75th percentiles respectively. Mean years of schooling of children is higher for children whose parents belong to the upper end of the income distribution.

Figure A1 in the appendix shows absolute mobility in income. In almost all income percentiles, children experienced absolute upward mobility. 12 percent of the children, with parents in the bottom 25th percentile, remained in the bottom 25th group and 57 percent experienced upward mobility to 75th percentile. 64 percent of children with parents in top 75th percentile remained in the same 75th percentile and 25 percent of children experienced downward mobility.

Figure A2 presents graph for absolute mobility in household consumption. For parents in 25-50 percentile, 23 percent of the children remained in the same group and 31 percent moved to the top 75th percentile. Children with parents in the top 75th percentile experienced the most absolute downward mobility. 37 percent of the children remained in top 75th percentile and 18 percent moved to the bottom 25th percentile.

Trends in income show more upward than downward absolute intergenerational mobility in children's generation whereas consumption expenditure show both upward and downward absolute mobility.

3 Research Methodology

We seek to measure the extent to which parent's income determines their child's economic opportunities. These economic opportunities and outcomes are difficult to measure therefore, We use income as a proxy for economic opportunities.

Log-log approximation: We begin with the mainstay model specified in equation (1) where log of child's income is regressed on log of parent's income. The coefficient estimate on parent's income in this specification, β_1, is called the intergenerational elasticity (IGE). This elasticity represents the degree to which parent's socio-economic status influence's child's economic outcomes (income or education). A coefficient of one on IGE indicates no mobility, a coefficient of zero indicates perfect mobility. The higher the coefficient (closer to one), the lower the mobility, that is, the child is more likely to inherit the economic status of their parents. A lower estimate of IGE suggests high intergenerational mobility. This can be considered advantageous for children especially those belonging to the lower end of the parental income distribution.

$$lnY_c = \beta_0 + \beta_1 lnY_p + \epsilon_c \tag{1}$$

In an OLS regression model, the value of β_1 is influenced by the change in standard deviation in income in both the child's and the parents' generation. Therefore, change in value of β_1 may not truly reflect the change in income persistence over time. To ensure that the value of β_1 is not completely driven by change in standard deviations, We normalize the income in both generations by their respective standard deviations. Therefore, We estimate the following equation;

$$\frac{lnY_c}{\sigma_c} = \beta_0 + \rho \frac{lnY_p}{\sigma_p} + \epsilon_c \tag{2}$$

In equation (2), the value of ρ estimates the absolute measure of intergenerational mobility of income whereas the β_1 from equation (1) estimates a relative measure of intergenerational mobility of income as it takes into account the change in income inequality in both the parent and child's

generation. Change in the value of ρ will provide a change in income persistence. Both measures, β_1 and ρ, behave differently overtime. Therefore, we include both measures of intergenerational mobility.

Rank-Rank estimation: Relative mobility can also be measured using simple correlations between parent-child ranks. In this approach, we first compute the percentile rank of the parent and child in their respective income distributions. The regression of child's rank on their parent's rank yields the correlation coefficient which measures the association between a child's relative position in the income distribution and his/her parent's relative position in the distribution (Chetty et al. 2014b).

$$P_c^y = \beta_0 + \beta_1 P_p^x + \epsilon_c \tag{3}$$

where, P_c^y is child's percentile rank his/her own generation's earnings distribution and P_p^y is parent's percentile rank in their own generation's earnings distribution (Dahl and DeLeire 2008).The coefficient estimate on parent's rank, β_1, captures relative rank mobility between parents and their children.

Spline regressions: We also estimate the following specification where parental rank is specified in splines to capture mobility at different points on the parental income distribution. This specification is of great interest as it captures absolute mobility in income and allows to see if the IGE is smaller for households with lower parental income (Chetty et al. 2014b; Björklund, Roine, and Waldenström 2012).

$$lnY_c = \beta_0 + \sum_{j=20,30,40,50,60} \beta_{ji} lnY_{pj} + \epsilon_c \tag{4}$$

We estimate equation (4) to capture absolute mobility where the slope of the IGE is allowed to vary along the jth (10th, 20th, 50th, 80th, and 90th) percentile of the parental income distribution. The interpretation of the IGE coefficient for each of these regressions is the percentage differential in child's expected income with respect to a marginal percentage differential in parent's income,

given the parent's income is in the respective percentile.

Instrumental Variable Estimation: In the absence of rich tax records, especially in developing countries where majority of the households engage in informal work, household surveys provide important information on income and assets. However, self-reported sources of income are also likely to suffer from measurement error bias. Income is subject to transitory fluctuations and measurement error. Random measurement error is the difference between the observed value and actual value of a variable, this can be caused by an unrelated (or random) factors as shown in equation below.

$$Y_c = \beta_0 + \beta_1 Y_p^* + \epsilon_c \tag{5}$$

$$e_p = Y_p - Y_p^* \tag{6}$$

The variable of interest is actual parent income (Y_p^*). Since we cannot observe actual income, we use self reported income (Y_p).

If β_1 is positive $\hat{\beta}_1$ will underestimate β_1. This creates a downward bias is the elasticity estimates causing attenuation bias. Similar measurement error is also present in child's income, that is, the dependent variable. Presence of measurement error in the dependent variable though only increases the variance of the error term and hence the probability of a Type II error, rejecting the null when it is true.

To address the measurement error bias in parental income, we use instrumental variable approach. IFLS provides rich sources of income over time and across modules. To address the measurement error problem in parental income, we replace parental income from 1993 with 1997 and instead use the income from 1993 as an instrument for income from 1997, assuming measurement error in 1993 is uncorrelated with measurement error in 1997. The first and second stage are set up in equations below.

$$Y_{p97} = \beta_0 + \beta_1 Y_{p93} + \mu_1 \tag{7}$$

$$Y_c = \beta_0 + \beta_1 \hat{Y_{p97}} + \mu_2 \tag{8}$$

This is the first paper to address the problem of random measurement error in income (and consumption) by using instrumental variable approach.

4 Results and Discussion

In this section, we provide estimates of intergenerational mobility based on the econometric specifications outlined in the previous section. In all specifications, we cluster the standard errors at the community level. [7]

4.1 Relative mobility estimates

4.1.1 Intergenerational elasticity

We first present intergenerational mobility estimates on relative mobility obtained using the popular specification, that is, the log-log income specification outlined in equation (1). This estimate of β considers the ratio or variances and takes the change in inequality into account. Estimates on intergenerational mobility are reported in Table 1, where we regress log of child's income on log of parent's income. All specification control for age, gender, location (urban), religion, and ethnicity. These results do not vary across gender. Column 1 shows intergenerational elasticity (IGE) estimates using income. IGE estimate is 0.08 and significant at 1 percent level which indicates higher intergenerational mobility.

[7] The results are also robust to double clustering at the community and year of birth level.

Table 1: Intergenerational Elasticity- Beta estimates

	(1) Income	(2) Consumption Expenditure	(3) Non-food Expenditure
Parent's income	0.0806***		
	(0.0144)		
Parent's total expenditure		0.255***	
		(0.0200)	
Parent's non-food expenditure			0.263***
			(0.0204)
Observations	8,676	12,640	12,637
R-squared	0.072	0.102	0.121

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses. All specifications control for age, gender, urban location, religion, and ethnicity.

The intergenerational elasticity estimates can vary over the life of an individual. Typically, incomes are lower for new entrants in the labor market and it increases with the age of the individual. Therefore, it is important to account for age at which an individual's income is measured. Another important concern is that children's and parent's income are measured at different ages. Parent's lifetime income can be approximated using an average of their past income, but this may not be possible when measuring child's income because the child may be a new entrant in the labor market. In case of parent's income, it is measured at a later age that reflects the maximum income level they can achieve but this cannot be observed for children if their income is measure at an earlier age. This introduces life-cycle bias in the IGE estimates. Since income increases with age, if child's income is measured earlier in life the intergenerational mobility estimate might be biased downward.

There are several ways to account for life-cycle bias. One way is to include age and age squared terms in the regression for both the child and the parent at the time when their incomes are measured (Corak and Heisz 1999). To address this concern, we also control for linearities and/or non-linearities in age for both generations, though IGE remains similar across different specifications. Reported results include age polynomials up to degree 2. The preferred specification on relative mobility included in column 1 of Table 1 shows that a 1 percent increase in parental income is associated with an approximately 8 percent increase in child's income, suggesting relatively high

income mobility in Indonesia.[8]

To capture gender difference in IGM, we include an interaction term between the male dummy and the parental income variable. Results show there are no significant gender differences in intergenerational mobility in Indonesia. The interaction term is not even significant at 10 percent significance level suggesting that boys have no significant advantage over girls. This finding is not surprising, as most of the literature on early childhood development in Indonesia has shown that there are no significant gender differences in investments in human capital such as health and education, which are important contributors to income later in life.[9]

4.1.2 Intergenerational rank association

To estimate the rank correlation measure, we regress child's percentile rank in their generation's earnings distribution on their parent's percentile rank in earnings (Dahl and DeLeire 2008). OLS estimates of equation (3) give the estimate of intergenerational rank association (IRA). The results are presented in Table 2. The baseline estimate gives an IRA of 0.13. Similar to IGE estimation, we include age controls (to account for life-cycle bias) and gender control (to estimate gender difference in mobility).

[8] United States is among the least mobile developed nations and most estimates of intergenerational elasticity fall between 0.3 and 0.5 (Chetty et al. 2014a)

[9] Duflo (2001), Asadullah (2012), and Behrman et al. (2013)

Table 2: Intergenerational Rank Association

	(1)	(2)	(3)
	Income	Consumption Expenditure	Non-food Expenditure
Percentiles			
Parent's income	0.132***		
	(0.0135)		
Parent's consumption expenditure		0.574***	
		(0.0320)	
Parent's non-food expenditure			0.592***
			(0.0338)
Observations	8,676	12,640	12,637
R-squared	0.166	0.131	0.145

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses. All specifications control for age, gender, urban location, religion, and ethnicity.

All estimates are positive and significant at 1 percent significance level. The estimate shows that a one percentage point increase in parent's rank is associated with a 0.13 percentage point increase in child's mean rank. IRA estimates for U.S., Canada and Denmark are 0.34, 0.18 and 0.17 respectively (Chetty et al. 2014a). The smaller rank slope, as compared to the U.S, suggest a lower gain in childâĂŹs mean income rank as compared to these three countries. This suggests lower income mobility in Indonesia. Once again there is no gender difference in rank mobility.

4.2 Absolute Mobility

4.2.1 Intergenerational elasticity

To ensure that the value of β_1 is not driven by the change in standard deviations of parent and child's income, I use equation (2) to estimate intergenerational mobility. The value of ρ is not affected by the changes in standard deviations or the possible evolution of the distribution. The estimates of ρ are shown in Table 3. Intergenerational elasticity of income slightly increases to 0.097 from 0.080 and intergenerational elasticity of consumption expenditure increases to 0.412. IGE estimates using non-food consumption however declines slightly to 0.146. These estimates are also presented in Figure 4 with 95 percent confidence interval bands.

Table 3: Intergenerational Elasticity- Rho estimates

	(1) Income	(2) Consumption Expenditure	(3) Non-food Expenditure
Parent's income	0.097***		
	(0.0161)		
Parent's total expenditure		0.412***	
		(0.0306)	
Parent's non-food expenditure			0.146***
			(0.0112)
Observations	8,676	12,640	12,637
R-squared	0.138	0.099	0.124

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses. All specifications control for age, gender, urban location, religion, and ethnicity.

If we compare estimates of β and ρ, a lower β suggests high variance in income and consumption expenditure in parents' distribution as compared to child's income and consumption distribution. Therefore, controlling for changes in variances and the differences in income/consumption distribution in both generations, the results show lower absolute income/consumption mobility in Indonesia.

4.2.2 Spline estimates

We use the spline specification of equation (4) to estimate absolute intergenerational mobility. This specification allows the intergenerational estimates to vary along different points of the parental income distribution. Table 4 presents the estimates of spline regressions using income as a measure of economic mobility. I define knots at 20th, 30th, 50th, and 60th percentile. I use the percentiles of parent's income, at the specified knots, and regress them on the child's income, the estimation includes standard controls as discussed earlier.

Table 4: Absolute Mobility

	(1)	(2)	(3)
	Income	Total Expenditure	Non-food Expenditure
Parent's income/expenditure			
20th	0.275**	0.393***	0.228**
	(0.133)	(0.127)	(0.115)
30th	-0.315	0.291*	0.406***
	(0.264)	(0.157)	(0.125)
40th	0.777*	0.763***	0.479***
	(0.430)	(0.146)	(0.127)
50th	0.538	0.284***	0.430***
	(0.369)	(0.0851)	(0.0840)
60th	0.325	-0.231***	-0.310***
	(0.322)	(0.0488)	(0.0758)
Observations	8,676	13,298	12,637
R-squared	0.079	0.136	0.151

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses. All specifications control for age, gender, urban location, religion, and ethnicity.

At the 20th percentile I find an elasticity of 0.27. This estimate is positive and significant at 10 percent significance level. This elasticity estimate is higher than the relative income mobility of 0.08 I find using the linear specification. This indicates there is lower mobility at the bottom of the distribution compared to the average in the sample reported by the OLS specification in column 1 of Table 1. We find absolute downward mobility at the 30th percentile, however the results are not significant.

These results are in line with the intergenerational mobility estimates found for other countries such as USA, Canada, and Sweden. [10]

[10] Corak, Lindquist, and Mazumder (2014) report largest downward mobility from the top of the income distribution in Canada, followed by Sweden and least downward mobility in the United States. They find no difference in the upward mobility estimates for the bottom of the income distribution in these three countries. In Sweden, top 10 percent of the distribution has intergenerational elasticity of 0.9 (Hilger 2015), (Chetty et al. 2014a), and (Björklund, Roine, and Waldenström 2012).

4.3 Instrumental variable estimates

Following the methodology from section 3, the instrumental variable estimates are presented in Tables 5-8. For annual household income, the first stage results are shown in Table 5. The instrument, 1993 parental income, is significant at 1 percent level. The F-statistic for joint significance is also significant at 1 percent level and is greater than 10. This shows that 1993 parental income is a strong instrument. To make the IV estimates comparable to OLS estimates, I first estimate relative mobility using parental income from 1997 in the RHS. The relative mobility estimate, using the OLS specification, gives an IGE of 0.14, which is higher than the IGE estimates using the 1993 parental income. The IGE estimate increases to 0.456 in IV estimation (see Table 6). This result is not surprising as the OLS estimate of IGE is biased downwards due to the attenuation bias. This result indicates substantially lower intergenerational mobility in Indonesia. This IV estimate is comparable to the intergenerational elasticity estimate for Bangladesh reported between 0.5 and 0.77 (Asadullah 2012). Figure A5 in the appendix shows the graphical comparison of OLS and IV estimates of IGE, shown with 95 percent confidence interval bands. Again it shows that OLS estimates suffered from attenuation bias and therefore, IV estimates correct for measurement error in income.

Table 5: Instrumental Variable- First Stage for Income

	(1) 1997 Income	(2) 1997 Income Percentile
1993 Income	0.1489***	
	(0.0093)	
1993 Income Percentile		0.2099***
		(0.0166)
Observations	12,093	12,093
R-squared	0.1489	0.2099
F-statistic	298.952	522.843

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses.

Table 6: Instrumental Variable Estimates of Mobility- Income

	OLS Estimates		IV Estimates	
	(1) IGE	(2) Rank	(3) IGE	(4) Rank
Parent's income	0.081***		0.456***	
	(0.0144)		(0.0955)	
Parent's income percentile		0.132***		0.295***
		(0.0135)		(0.0393)
Observations	7,160	7,160	7,160	7,160
R-squared	0.013	0.166	0.128	0.109

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses. All specifications control for age, gender, urban location, religion, and ethnicity.

We also estimate intergenerational rank association using the instrumental variable method. The relative mobility estimate (IRA) increases to 0.29 from 0.13 after correcting for measurement error. Both sets of results for IGE and rank estimation using instrumental variable are presented in Table 6 and their first stage results are shown in Table 5. Both sets of results indicate (1) presence of random measurement error and attenuation bias and (2) lower intergenerational mobility in income in Indonesia.

To check the consistency of these IV estimates, we use the Hausman test. If μ_1 and μ_2 from equations 7 and 8 have zero covariance then the OLS estimation is consistent, if the covariance is non-zero the OLS estimator is inconsistent and IV estimator is consistent (Hausman 1978). Therefore, if we reject the null of zero covariance the IV estimator is preferred. We are able to reject the null hypothesis for both income and consumption IGE estimates [11]. This concludes that the IV estimates are in fact consistent and efficient as compared to the OLS estimates of intergenerational elasticity. Therefore, the preferred set of results are the IV estimates.

These results, when compared with mobility estimates from other countries, suggest lower intergenerational mobility in income and consumption in Indonesia. For example, intergenerational elasticity in U.S in between 0.3 and 0.5 (Chetty et al. 2014b). Wealth mobility in Bangladesh ranges

[11] Prob>chi2 = 0.0022 for income estimates and Prob>chi2 = 0.0000 for consumption estimates.

from 0.53 to 0.77 (Asadullah 2012). These numbers indicate presence of lower intergenerational mobility in Indonesia.

4.4 Intergenerational Mobility- Consumption Expenditure

To our knowledge, the literature only uses sources of current income to estimate intergenerational mobility that is normally observed at a certain point in life and as a result susceptible to life-cycle bias. Intergenerational mobility can be estimated more accurately if we were able to measure income at around age 40 for both the parent and the child, which is the closest proxy to permanent income, or if we have some other measure of permanent or lifetime income. To address this problem, we estimate absolute and relative mobility coefficients using both child and parent's household per capita consumption expenditure instead of income.

Consumption is a theoretically better measure of (economic) well-being especially in developing countries where primary source of income is from agriculture or informal sector. Moreover, in the absence of tax records, household consumption expenditure can be used to estimate intergenerational mobility. In Indonesia, 72 percent of the population is employed in the non-agriculture informal sector (ILO, 2009). For these people the best measure of household income is to use consumption expenditure. Source of income is not always clear or correctly reported for example, self-employment and farm income is primary income of many household's especially in rural areas (Deaton and Zaidi 2002). Income is often not properly reported and collected by household surveys as they rely on self-reported income. If the primary source of income is not clearly defined or is dependent on the agricultural outcomes then income is also not a stable measure of the household's economic wellbeing. Consumption on the other hand is less variable and more stable than income particularly in agriculture economies such as Indonesia where rice production (farm income) is a main source of household income and consumption.

Consumption is a better proxy for lifetime income and is less susceptible to measurement error as it is more easily recalled and measured (Aguiar and Hurst 2005; Stephens Jr 2001; Hall 1978). In most of the mobility literature, income comes from tax data or other federal income sources. In IFLS, household's report their income and this income is not verified using any tax data or em-

ployment record [12]. In this case, the income can be misreported by the household's. In household surveys consumption is reported with less noise as compared to income.

Indonesia is a largely agrarian economy and the primary source of household income is from family owned farms. This income is difficult to measure and sometimes not reported by households under annual or monthly income. However, it is reflected in household's total consumption expenditure (this expenditure also includes consumption of goods from family owned businesses). Household expenditure can also be considered a good measure of permanent household income. Typically, households tend to smooth their total consumption against their lifetime income. They may choose to borrow money against future income to smooth their current consumption. This borrowing is not reflected in the reported household income.

To get a better estimate of intergenerational elasticity using consumption expenditure, we separate household expenditure into food and non-food components. Non-food components include household expenditure on utilities, entertainment, education, and housing. Since non-food consumption is most effected by changes in income than the food consumption, this can give a more accurate measure of IGE as compared to total consumption expenditure.

Relative mobility estimates (both IGE and IRA) are higher when estimated using expenditure. Tables 1 and 3 show the results on intergenerational elasticity estimates and Table 2 shows results of intergenerational rank association. The IGE is 0.25 using consumption expenditure. The signs and significance of the estimates is the same as those estimated using income. However, the elasticity coefficient is much higher, suggesting a lower intergenerational mobility. Similar to previous results, we find no significant gender difference in intergenerational mobility. For comparison, IGE estimates using income and consumption are presented in Figure A3 in the appendix with 95 percent confidence intervals. Estimates suing total consumption and non-food consumption are very similar whereas IGE estimates using income are much lower.

[12] Tax compliance is low in Indonesia, with only 27 million out of an adult population of 185 million were registered as taxpayers in 2015. Ministry of Economic Affairs Indonesia also estimates that between 55 and 65 percent of employment is in informal sector, which is concentrated in rural areas.

Intergenerational rank association (IRA) measure also increases to 0.57 when estimated using expenditure. This result also indicates a lower intergenerational mobility and the increase in IRA estimates further proves the presence of life-cycle bias and measurement error bias in previous estimates of income.

Furthermore, we estimate mobility using non-food household expenditure as well. An increase in household income is mostly reflected in an increase in non-food consumption such as education, utilities etc.[13] Table 1 column 3 and Table 2 column 3 show the results using non-food per capita consumption expenditure. The results are similar to IGE and IRA estimates using total expenditure. IGE estimate is 0.26 and IRA estimate is 0.59. These results again point to the presence of life-cycle and measurement error bias. They also indicate lower intergenerational mobility. These elasticity estimates indicate lower relative mobility in Indonesia when compared to US, Sweden, and Canada (Corak, Lindquist, and Mazumder 2014).

Moreover, in order to account for random measurement error in household consumption reported for parent's generation we use the same instrumental variable approach as applied to income. The estimates, shown in Tables 7 and 8, use 1993 household consumption for parent's generation as an instrument for 1997 household consumption for parent's generation. The first stage results, shown in Table 7 show that the instrument is significant at 1 percent significance level. The F-test for joint significance is also significant at 1 percent significance level and the F-statistic is also greater than 10. This shows that 1993 household consumption expenditure is a valid and strong instrument. The results from Table 8 indicate presence of random measurement error bias as both IGE and rank estimates increase to 0.622 and 0.621 from 0.255 and 0.574 respectively. These results also highlight the presence of lower intergenerational mobility in Indonesia. Figure A6 shows this OLS and IV comparison using 95 percent confidence intervals, this further confirms the presence of measurement error bias in OLS estimates of IGE using consumption expenditure.

[13] Aguiar and Hurst (2005), and Stephens Jr (2001)

Table 7: Instrumental Variable- First Stage for Consumption

	(1) 1997 Consumption	(2) 1997 Consumption Percentile
1993 Consumption	0.378***	
	(0.0228)	
1993 Consumption Percentile		0.401***
		(0.0139)
Observations	15,511	15,511
R-squared	0.2425	0.2905
F-statistic	276.473	1068.01

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses.

Table 8: Instrumental Variable Estimates of Mobility- Consumption

	OLS Estimates		IV Estimates	
	(1) IGE	(2) Rank	(3) IGE	(4) Rank
Parent's consumption	0.255***		0.622***	
	(0.0200)		(0.0319)	
Parent's consumption percentile		0.574***		0.621***
		(0.0320)		(0.0315)
Observations	12,640	12,640	12,927	12,927
R-squared	0.102	0.131	0.0895	0.100

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses. All specifications control for age, gender, urban location, religion, and ethnicity.

5 Robustness

In this section, we repeat the analysis by incorporating different methodologies to check the validity of our results. Here we will also attempt to show the internal and external validity of our estimates of intergenerational mobility.

5.1 Attrition

Attrition and tracking in survey data is a major problem. If attrition in the survey is not random then it could present some bias in the estimates. We check for attrition in our sample for parent's whose children were present in the 1993 survey but they dropped out of the 2014 survey. Our primary goal is to check whether we have selective attrition by parental income. If attrition is selective by parental income then the mobility estimates will be biased. To check for attrition, we follow Hanaoka, Shigeoka, and Watanabe (2018) and McKenzie (2015).

First we test the null hypothesis that the mean income and mean years of schooling of parent's whose children dropped out of the sample (N=1,508) and those who did not is the same. We could not reject the null hypothesis for mean income (p-value= 0.982) and for mean years of schooling (p-value= 0.437). This implies that mean income and years of schooling of parents whose children dropped out of the survey is not statistically different from parents whose children did not drop out.

Furthermore, we regress the dummy variable for attrition on parental income, years of schooling, and per capital household consumption expenditure to check if attrition is correlated with any of these variables. The results are shown in Table A4. The results from Table A4 show that attrition is not correlated with parental income and parent's years of schooling. These two sets of results show that attrition is not selective by parental income and parents' years of schooling. Therefore, the estimates of intergenerational mobility in income are unbiased.

We repeat the same procedure to check if attrition is correlated with per capital household consumption expenditure. The t-test shows that we reject the null hypothesis (p-value= 0.000) of zero mean difference in per capita household consumption expenditure. The t-test shows that the mean income of parents whose children dropped out is 14.0 where as the mean income of parents whose children did not drop out is 14.5. Similarly, the regression results from Table A4 show that attrition is correlated with per capita household consumption expenditure. Hence attrition is selective in this case.

To correct this, we use inverse probability weights (IPW). Attrition adjusted estimates of inter-

generational elasticity for consumption expenditure are shown in Table A5. The IGE estimates are slightly larger than the estimates from the entire sample (0.255 for the entire sample and 0.305 after adjusting for attrition). This indicates slightly lower intergenerational mobility (in consumption) in Indonesia once adjusted for attrition.

5.2 Co-residence

In this section, we estimate mobility for sample of children who live in multi-generation households. This includes children's sample from 2014 whose parent's are still living with them in the same household. Our sample has approximately 3000 children who live in co-resident household's and out of them we have non-missing household information on 1,222 individuals. Family linkages are important especially in developing countries where families rely on informal forms of borrowing to smooth consumption and to invest in human capital (Raut and Tran 2005; Cameron and Cobb-Clark 2008). Therefore, pooled household income and family networks play an important role in determining social mobility. Literature (LaFave and Thomas 2017) suggests that family linkages are important in Indonesia where families not only support each other in times of a negative shock but also to invest in next generation.

The estimates are presented in Table A6. The elasticity coefficients for income and consumption are all lower than the estimates for the entire sample in Table 1. These lower estimates suggest relatively higher mobility for children who live in co-resident household's. For example, IGE estimate using consumption expenditure is 0.25 for the entire sample and is 0.18 for the co-resident household sample. These estimates suggest that household's do pool resources, as discussed in earlier literature, and this helps them achieve higher intergenerational mobility.

Table A7 shows the measurement error corrected estimates (using the IV method) for the co-resident household's. These estimates also show that, once corrected for measurement error, the IGE estimates are lower for the co-resident household's suggesting relatively higher mobility for co-resident households. IGE using consumption declines from 0.62 for the full sample to 0.49 for the co-resident sample again suggesting that children living in co-resident household's experience

high mobility.

5.3 Nonparametric Analysis

Instead of assuming a linear relationship between parent's income and child's income, we use non-parametric estimation for intergenerational elasticity. Non-parametric regression yields consistent estimates of the mean function which are robust to functional form misspecification.[14]

The results from non-parametric estimation are reported in Table A8. Overall these results are closer to the linear estimation, suggesting the estimates of intergenerational mobility are not sensitive to the functional form. The marginal effect of parental income on child's income is 0.08 and significant, this estimate is closer to the linear regression estimate. Similarly, the marginal effect of parental consumption expenditure on child's consumption expenditure is 0.32 and significant. This is slightly larger than the OLS estimate. Lastly, the marginal impact of parental non-food consumption expenditure on child's non-food consumption expenditure is 0.28.

The kernel density plots from Figures A7 and A8 show the mean function of child's income and consumption expenditure. Both graphs show that the functional form is closer to a linear function. Therefore, suggesting that results are not sensitive to functional form misspecification.

5.4 Sample Representation

The original sample of IFLS in 1993 surveyed 13 out of 26 provinces in Indonesia. Although more household's were added to the sample in following waves it still does not fully represent the entire Indonesian population. To show how much representative our sample is of the Indonesian population we use data from the census survey, SUPAS. The intercensal survey is conducted every ten years by the Central Bureau of Statistics of Indonesia. We use the 2010 survey. Since income variable is not well reported in SUPAS, we use years of schooling to check for external validity of our sample. Education itself is a good indicator of earnings and economic outcomes.

[14] We use Kernel regressions as a non-parametric technique to estimate the marginal effect.

The kernel density graph of years of schooling from both the IFLS and SUPAS is shown in Figure A9. Both distributions are bimodal which show that most people in Indonesia complete 6 and 12 years of schooling. The mean and the standard deviation of both distributions are similar which suggests that IFLS does in fact represent the Indonesian population.

5.5 Sensitivity to Controls

Intergenerational mobility is estimated by regressing log of parental income and log of child's income. The estimated β gives the elasticity of intergenerational mobility. In order to control for the life-cycle bias, age controls (polynomial terms) are included for both child's and parent's age. In our reported estimates we include polynomial age controls as well restrict the child's sample to age 25 and above. The average age of our sample is 30 so we use the child's income later in their life to control for life-cycle bias.

The sample has equal gender representation and majority of the sample is Muslim and Javanese (these being the majority religion and ethnicity in Indonesia). Moreover, we control for the household size in the consumption expenditure estimates by using per capita household consumption. We also control for total assets owned by the parents.

Table A9 shows results with baseline estimates, age controls, and all sets of control variables. The consumption estimates show that child's education is significant and positively effect their income. The results are slightly sensitive to the inclusion of controls however, conventional practice does not include controls other than age in the mobility estimation due to the correlation between parental income and child's characteristics such as total assets, years of schooling etc. Therefore, we report estimates that include age controls only to control for the life-cycle bias.

6 Conclusion

We use data from multiple waves of the Indonesian Family Life Survey to estimate intergenerational mobility in income and consumption in Indonesia. Once we control for individual characteristics,

random measurement error, and life-cycle bias we find low intergenerational mobility in Indonesia as suggested by the IGE coefficient of 0.62. Indonesia is the fourth most populous country, which is facing the problem of rising inequality.[15] Findings of this paper also suggest lower intergenerational mobility. This certainly emphasizes the importance of studying intergenerational mobility for Indonesia and the need for policy reforms.

Using annual income, the intergenerational elasticity estimate is 0.08. Whereas the intergenerational elasticity estimate increases to 0.25 after using consumption expenditure, which is a better and a long-term measure of lifetime income. Similarly, using the instrumental variable approach to control for random measurement error, the income elasticity estimate increased to 0.46. These results, along with IRA of 0.13 and spline estimates of absolute mobility, indicate low intergenerational income mobility in Indonesia. This is comparable to the intergenerational elasticity estimate for Bangladesh reported between 0.5 and 0.77 (Asadullah 2012). The elasticity estimates are even higher when estimated using per capita consumption expenditure, which is a more long term measure of household income.

These findings not only show incidence of low intergenerational mobility in Indonesia, but various econometric techniques used in estimating mobility draw attention to the problem of attenuation bias caused by measurement error. If this bias is not addressed the elasticity estimates are biased downward and suggest higher IGM which could be misleading. Another unique contribution of this paper is to use consumption expenditure to estimate IGM. This shows that IGM can be estimated for developing countries even in the absence of reliable income data such as tax records. Even in the presence of tax records or income data, consumption expenditure is still a better measure of household economy in developing countries due to lower tax base and heavy reliance on informal employment and agricultural output.

This paper contributes to the existing literature on intergenerational mobility, more specifically to the scant literature on developing countries. Little research has been done on intergenerational

[15] Gini coefficient of 0.4 and 40th rank in countries with largest inequality according to the recent World Bank report.

mobility, especially income and consumption mobility, in developing countries.[16] and, to our knowledge, none has been done on Indonesia.

This evidence from Indonesia, combined with intergenerational mobility estimates from the U.S ((Chetty et al. 2017b)), Bangladesh ((Asadullah 2012)), India ((Azam 2016)), Philippines ((Bevis and Barrett 2015)), and Sweden ((Corak, Lindquist, and Mazumder 2014)) highlight a global pattern of decline in both absolute and relative intergenerational mobility. This makes it both a national as well as a global concern for policy makers, economists, and social scientists. Therefore, this paper serves as a policy reminder for developing countries in general and Indonesia in specific for introducing reforms to improve intergenerational mobility.

[16]Bevis and Villa (2017), Bevis and Barrett (2015), Asadullah (2012), and Asher, Novosad, and Rafkin (2017)

References

Aaronson, Daniel and Mazumder, Bhashkar (2008). "Intergenerational economic mobility in the United States, 1940 to 2000". *Journal of Human Resources* 43.1, pp. 139–172.

Aguiar, Mark and Hurst, Erik (2005). "Consumption versus expenditure". *Journal of Political Economy* 113.5, pp. 919–948.

Asadullah, M Niaz (2012). "Intergenerational wealth mobility in rural Bangladesh". *Journal of Development Studies* 48.9, pp. 1193–1208.

Asher, Sam, Novosad, Paul, and Rafkin, Charlie (2017). "Estimating Intergenerational Mobility with Coarse Data: A Nonparametric Approach".

Azam, Mehtabul (2016). "Household Income Mobility in India, 1993-2011". *Dept. of Economics, Oklahoma State University.*

Behrman, Jere R, Schott, Whitney, Mani, Subha, Crookston, Benjamin T, Dearden, Kirk, Duc, Le Thuc, Fernald, Lia CH, and Stein, Aryed H (2013). "Intergenerational transmission of poverty and inequality: Young Lives".

Bevis, Leah EM and Barrett, Christopher B (2015). "Decomposing intergenerational income elasticity: The gender-differentiated contribution of capital transmission in rural Philippines". *World Development* 74, pp. 233–252.

Bevis, Leah EM and Villa, Kira (2017). "Intergenerational Transmission of Mother-to-Child Health: Evidence from Cebu, the Philippines".

Björklund, Anders, Roine, Jesper, and Waldenström, Daniel (2012). "Intergenerational top income mobility in Sweden: Capitalist dynasties in the land of equal opportunity?" *Journal of Public Economics* 96.5, pp. 474–484.

Cameron, Lisa A and Cobb-Clark, Deborah (2008). "Do coresidency and financial transfers from the children reduce the need for elderly parents to works in developing countries?" *Journal of Population Economics* 21.4, pp. 1007–1033.

Chetty, Raj, Hendren, Nathaniel, Kline, Patrick, Saez, Emmanuel, and Turner, Nicholas (2014a). "Is the United States still a land of opportunity? Recent trends in intergenerational mobility". *The American Economic Review* 104.5, pp. 141–147.

Chetty, Raj, Hendren, Nathaniel, Kline, Patrick, and Saez, Emmanuel (2014b). "Where is the land of opportunity? The geography of intergenerational mobility in the United States". *The Quarterly Journal of Economics* 129.4, pp. 1553–1623.

Chetty, Raj, Friedman, John N, Saez, Emmanuel, Turner, Nicholas, and Yagan, Danny (2017a). *Mobility report cards: The role of colleges in intergenerational mobility.* Tech. rep. National Bureau of Economic Research.

Chetty, Raj, Grusky, David, Hell, Maximilian, Hendren, Nathaniel, Manduca, Robert, and Narang, Jimmy (2017b). "The fading American dream: Trends in absolute income mobility since 1940". *Science* 356.6336, pp. 398–406.

Corak, Miles (2013). "Income inequality, equality of opportunity, and intergenerational mobility". *Journal of Economic Perspectives* 27.3, pp. 70–102.

Corak, Miles and Heisz, Andrew (1999). "The intergenerational earnings and income mobility of Canadian men: Evidence from longitudinal income tax data". *Journal of Human Resources*, pp. 504–533.

Corak, Miles, Lindquist, Matthew J, and Mazumder, Bhashkar (2014). "A comparison of upward and downward intergenerational mobility in Canada, Sweden and the United States". *Labour Economics* 30, pp. 185–200.

Dahl, Molly W and DeLeire, Thomas (2008). *The association between children's earnings and fathers' lifetime earnings: estimates using administrative data.* University of Wisconsin-Madison, Institute for Research on Poverty.

Deaton, Angus and Zaidi, Salman (2002). *Guidelines for constructing consumption aggregates for welfare analysis.* Vol. 135. World Bank Publications.

Duflo, Esther (2001). "Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment". *American economic review* 91.4, pp. 795–813.

Grawe, Nathan D (2004). "Intergenerational mobility for whom? The experience of high-and low-earning sons in international perspective". *Generational income mobility in North America and Europe*, pp. 58–89.

Hall, Robert E (1978). "Stochastic implications of the life cycle-permanent income hypothesis: theory and evidence". *Journal of Political economy* 86.6, pp. 971–987.

Hanaoka, Chie, Shigeoka, Hitoshi, and Watanabe, Yasutora (2018). "Do risk preferences change? evidence from the great east japan earthquake". *American Economic Journal: Applied Economics* 10.2, pp. 298–330.

Hausman, Jerry A (1978). "Specification tests in econometrics". *Econometrica: Journal of the econometric society*, pp. 1251–1271.

Hilger, Nathaniel G (2015). *The Great Escape: Intergenerational Mobility in the United States Since 1940*. Tech. rep. National Bureau of Economic Research.

LaFave, Daniel and Thomas, Duncan (2017). "Extended families and child well-being". *Journal of Development Economics* 126, pp. 52–65.

Lee, Chul-In and Solon, Gary (2009). "Trends in intergenerational income mobility". *The Review of Economics and Statistics* 91.4, pp. 766–772.

Leigh, Andrew and Eng, Pierre Van der (2009). "Inequality in Indonesia: What can we learn from top incomes?" *Journal of Public Economics* 93.1-2, pp. 209–212.

Mazumder, Bhashkar (2014). "Black–white differences in intergenerational economic mobility in the United States". *Economic Perspectives* 38.1.

McKenzie, David (2015). *Identifying and spurring high-growth entrepreneurship: Experimental evidence from a business plan competition*. The World Bank.

Mitnik, Pablo, Bryant, Victoria, Weber, Michael, and Grusky, David B (2015). "New estimates of intergenerational mobility using administrative data". *Statistics of Income Division working paper, Internal Revenue Service (ht tps://www. irs. gov/pub/irssoi/15rpintergenmobility. pdf)*.

Raut, Lakshmi K and Tran, Lien H (2005). "Parental human capital investment and old-age transfers from children: Is it a loan contract or reciprocity for Indonesian families?" *Journal of Development Economics* 77.2, pp. 389–414.

Stephens Jr, Melvin (2001). "The long-run consumption effects of earnings shocks". *Review of Economics and Statistics* 83.1, pp. 28–36.

Strauss, John, Witoelar, Firman, and Sikoki, Bondan (2016). "The fifth wave of the Indonesia family life survey: overview and field report". *RAND: Santa Monica, CA, USA*.

Appendix

Table A1: Real Annual Household Income

	Income		
	Children	Parent 1993	Parent 1997
Mean	1584.00	178.20	924.00
(s.d)	10560.00	2442.00	1584.00
Quantiles			
< 25	34.99	0.12	82.48
25-50	383.84	0.48	335.23
50-75	976.80	1.29	772.20
> 75	5101.80	706.20	2514.60
N	11,791	14,064	23,111

Notes: All values are in USD. Poverty line in Indonesia is USD 24.8 a month (USD 297.6 annual) (Source: BPS, 2016).

Table A2: Real Annual Per Capita Household Expenditure

	Consumption Expenditure		
	Children	Parent 1993	Parent 1997
Mean	653.40	224.40	257.40
(s.d)	792.00	468.60	409.20
Quantiles			
< 25	201.74	74.93	75.39
25-50	364.71	81.30	143.68
50-75	571.15	134.56	231.93
> 75	1465.20	606.98	578.97
Percentage Share			
Education	7.88	22.94	9.49
Food	58.59	64.71	66.67
Non-food	40.40	35.29	33.33
N	13,328	22,377	16,657

Notes: All values are in USD. Poverty line in Indonesia is USD 24.8 a month (USD 297.6 annual) (Source: BPS, 2016). Non-food expenditure includes education expenditure as well.

Table A3: Summary Statistics

a) Income					
		Children with parents in following income quantiles			
Child's variables		P0-25	P25-50	P50-75	>P75
Income (USD)	Mean	1117	1314	2037	1642
	(s.d)	3285	5232	1577	9856
Age	Mean	31.16	30.01	30.26	28.20
	(s.d)	8.35	8.18	7.82	8.94
Years of Schooling	Mean	8.59	9.53	11.27	11.18
	(s.d)	4.13	3.84	3.50	3.52
N		1321	2222	2349	5899
b) Expenditure					
Expenditure (USD)	Mean	460	723	920	854
	(s.d)	525	788	1183	850
Age	Mean	27.42	31.77	33.16	32.14
	(s.d)	8.99	7.06	7.23	8.10
Years of Schooling	Mean	9.84	11.25	12.85	11.98
	(s.d)	3.72	3.70	3.12	3.52
Urban	Percentage		62.00		
Male	Percentage		51.00		
Muslim	Percentage		89.00		
Javanese	Percentage		42.00		
Household Size	Mean		4.00		
N		5449	5375	2472	68

Notes: Poverty line in Indonesia is USD 24.8 a month (USD 297.6 annual) (Source: BPS, 2016).

Table A4: Selective Attrition

	(1) Attrition Dummy
Parent's income	0.0005
	(0.0008)
Parent's total expenditure	-0.0097***
	(0.0017)
Parent's years of schooling	-0.0006
	(0.0004)
Observations	4,863
R-squared	0.046

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses.

Table A5: Attrition Adjusted Elasticity

	(1) Consumption Expenditure
Parent's total expenditure	0.305***
	(0.0318)
Observations	2,639
R-squared	0.140

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses. All specifications control for age, gender, urban location, religion, and ethnicity.

Table A6: Intergenerational Elasticity- Co-resident Sample Estimates

	(1) Income	(2) Consumption Expenditure	(3) Non-food Expenditure
Parent's income	0.063***		
	(0.0225)		
Parent's total expenditure		0.187***	
		(0.0364)	
Parent's non-food expenditure			0.173***
			(0.0326)
Observations	1,222	1,988	1,988
R-squared	0.094	0.067	0.071

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses. All specifications control for age, gender, urban location, religion, and ethnicity.

Table A7: Intergenerational Elasticity- Co-resident Sample IV Estimates

	(1) Income	(2) Consumption Expenditure	(3) Non-food Expenditure
Parent's income	0.457***		
	(0.1667)		
Parent's total expenditure		0.494***	
		(0.0808)	
Parent's non-food expenditure			0.406***
			(0.0608)
Observations	1,051	1,918	1,918
R-squared	0.111	0.104	0.089

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses. All specifications control for age, gender, urban location, religion, and ethnicity.

Table A8: Intergenerational Elasticity- Non-parametric Estimation

	(1) Income	(2) Consumption Expenditure	(3) Non-food Expenditure
Parent's income	0.0806***		
	(0.0144)		
Parent's total expenditure		0.323***	
		(0.0079)	
Parent's non-food expenditure			0.287***
			(0.0067)
Observations	8,676	13,297	13,291
R-squared	0.072	0.131	0.141

Notes:*** p<0.01, ** p<0.05, * p<0.1. Bootstrap standard errors are in parentheses.

Table A9: Intergenerational Elasticity- Controlled Regression

VARIABLES	(1) Income	(2) Consumption Expenditure	(3) Total Non-food Expenditure
Parent's Income	0.0319**		
	(0.0136)		
Child's age	0.484***	-0.0127	-0.0559***
	(0.0235)	(0.0098)	(0.0140)
Child's age squared	-0.0066***	0.0002	0.0009***
	(0.0004)	(0.0001)	(0.0002
Parent's age	-0.0134	-0.0162**	-0.0408***
	(0.0158)	(0.0063)	(0.0085)
Parent's age squared	5.22×10^{-5}	0.0001*	0.0003***
	(0.0002)	(6.74×10^{-5})	(8.59×10^{-5})
Male	0.841***	0.0033	-0.0251
	(0.0517)	(0.0143)	(0.0210)
Muslim	-0.206**	-0.0726	-0.0369
	(0.0854)	(0.0467)	(0.0716)
Javanese	0.0416	-0.140***	-0.151***
	(0.0588)	(0.0290)	(0.0404)
Urban	0.378***	-0.0102	0.0752**
	(0.0692)	(0.0209)	(0.0296)
Years of Schooling	0.0971***	0.0530***	0.0834***
	(0.0079)	(0.0032)	(0.0047)
Parent's Expenditure		0.184***	
		(0.0172)	
Parent's Non-food Expenditure			0.163***
			(0.0189)
Observations	6,292	10,037	10,033
R-squared	0.259	0.193	0.221

Notes:*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the community level are in parentheses.

Figure A1: Absolute Mobility in Income

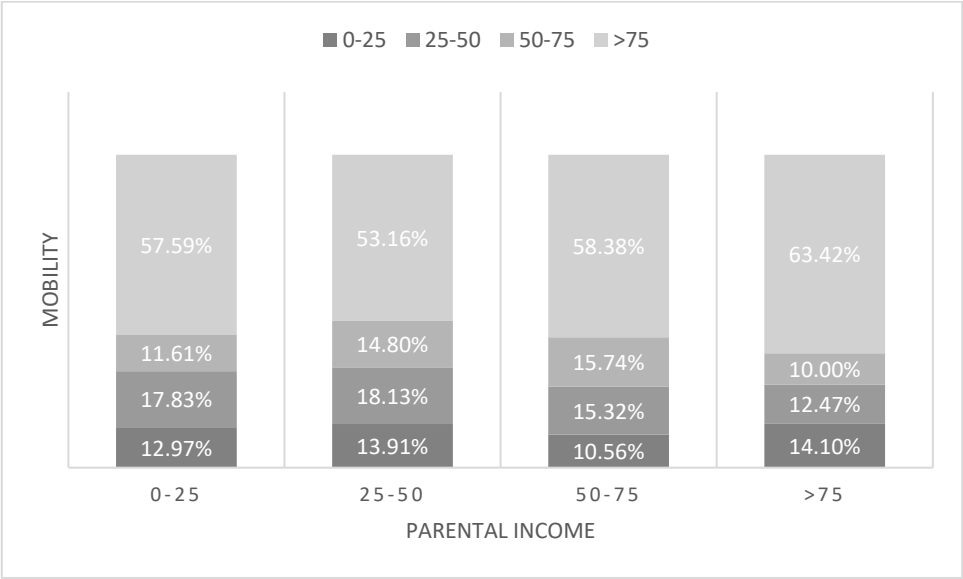


Figure A2: Absolute Mobility in Expenditure

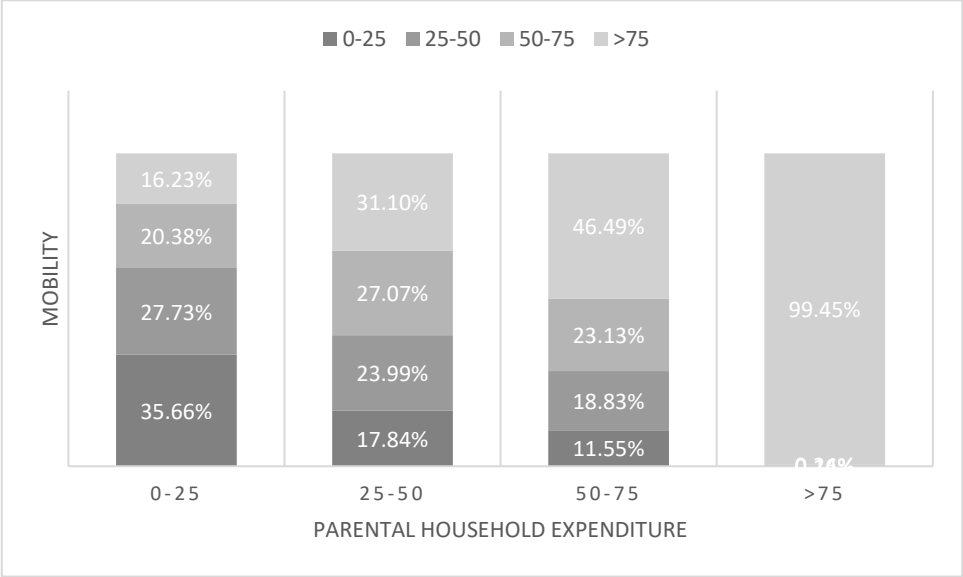


Figure A3: Beta Estimates of Intergenerational Elasticity

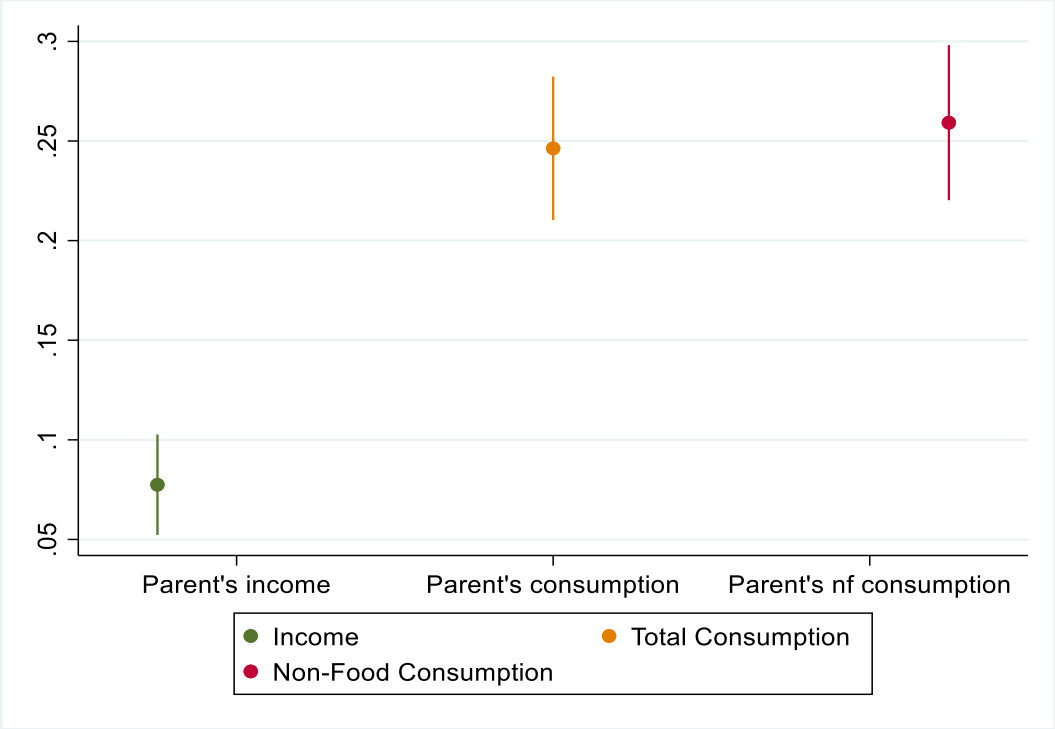


Figure A4: Rho Estimates of Intergenerational Elasticity

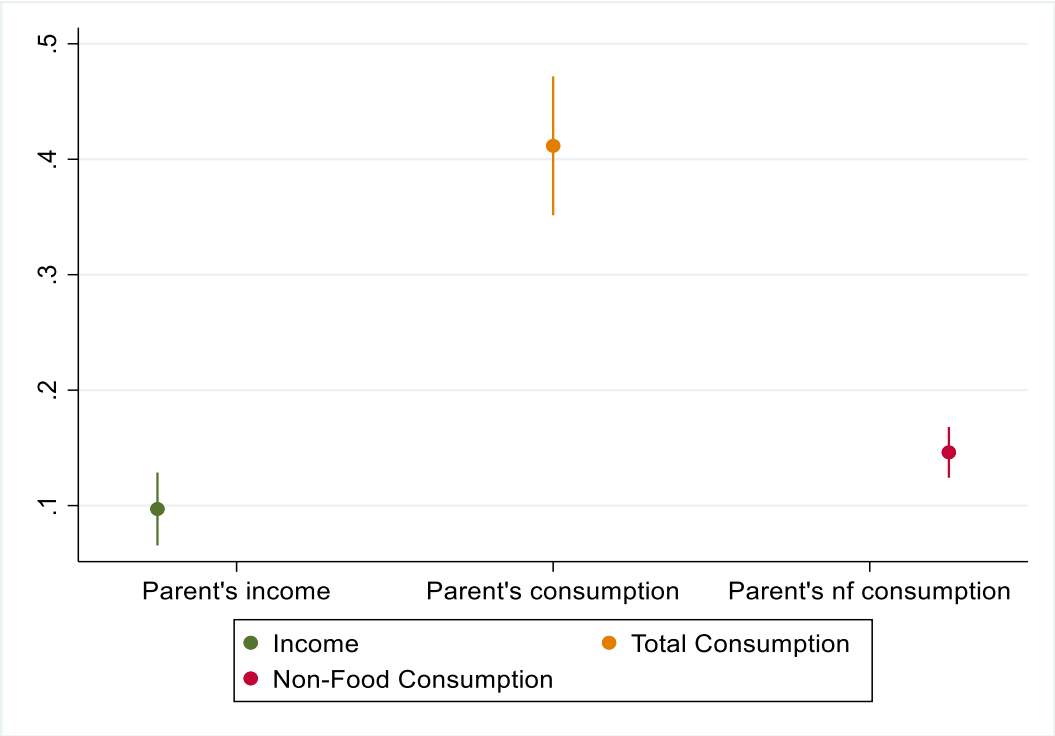


Figure A5: OLS vs. IV Estimates of Intergenerational Elasticity- Income

Figure A6: OLS vs. IV Estimates of Intergenerational Elasticity- Consumption Expenditure

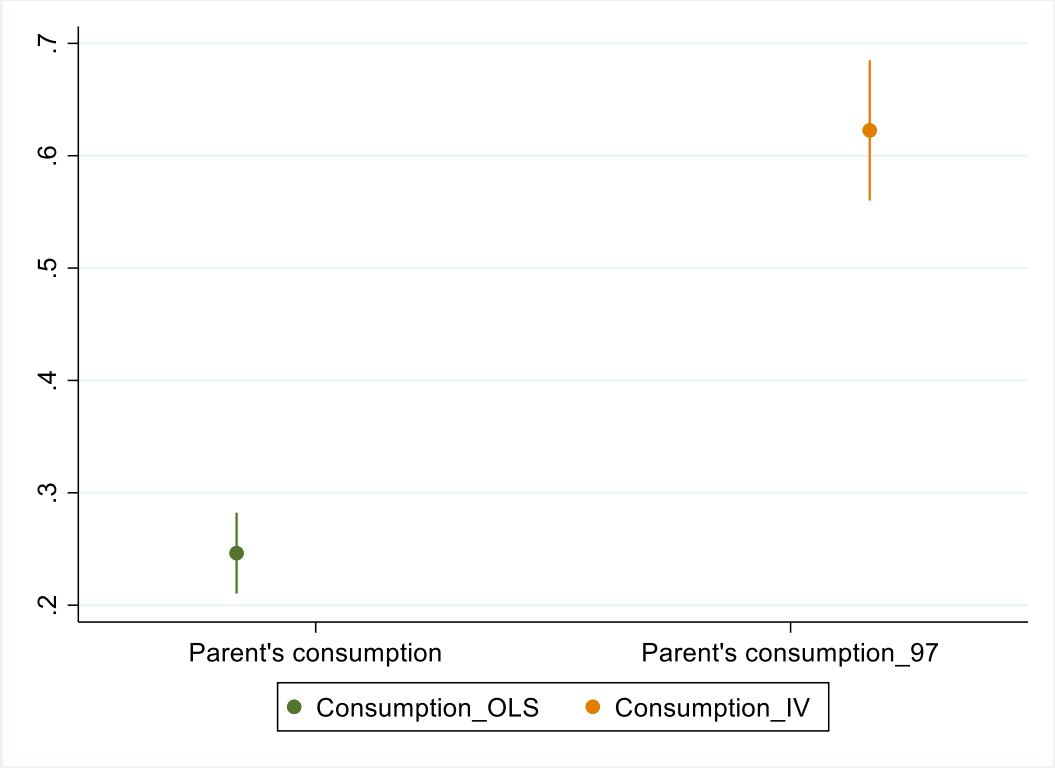


Figure A7: Mean function of log(child's income)

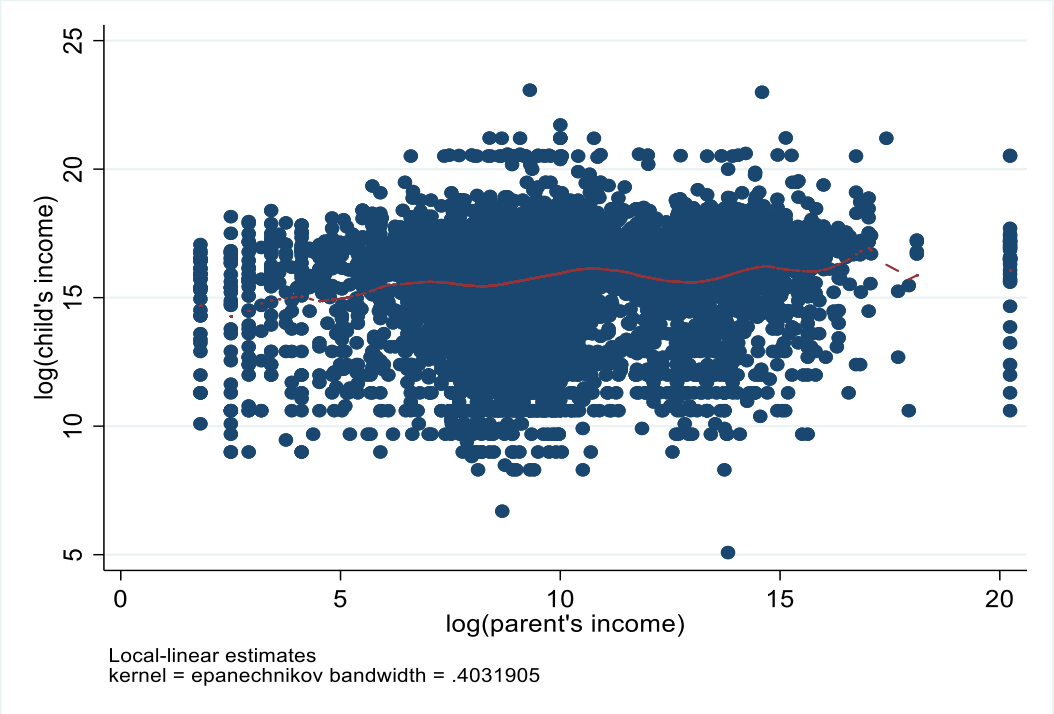


Figure A8: Mean function of log(child's total per capita expenditure)

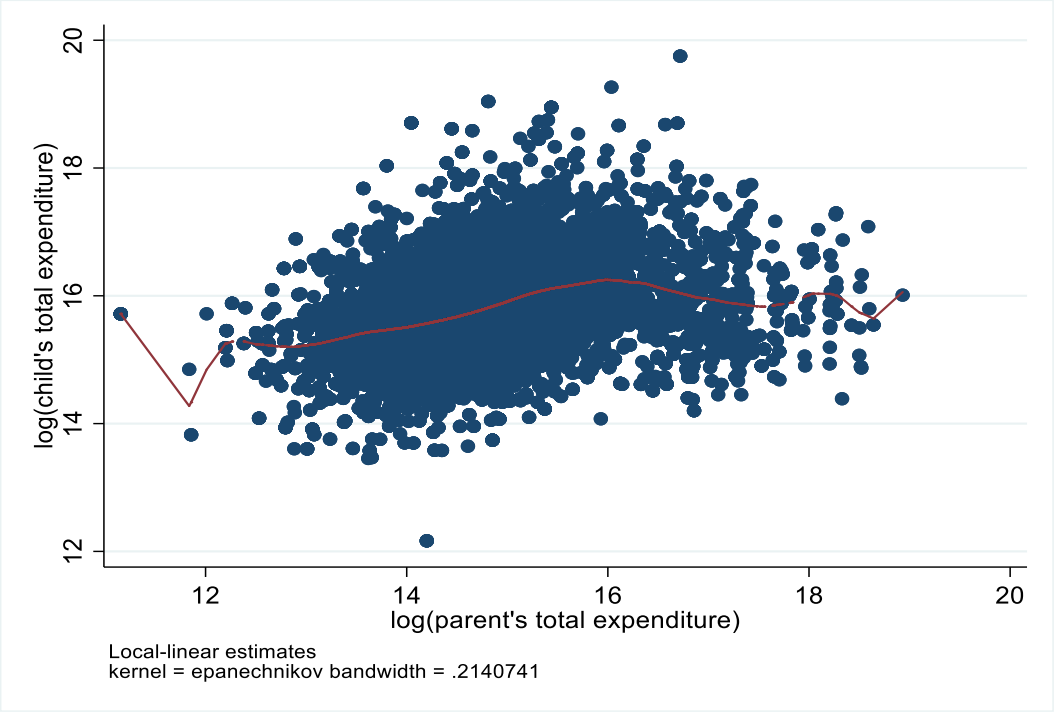


Figure A9: Kernel density plot of years of schooling