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ORIGINAL RESEARCH

Does Economic Inequality Constrain Intergenerational Economic Mobility? The Association Between Income Inequality During Childhood and Intergenerational Income Persistence in the United States

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Abstract
Using the National Longitudinal Study of Youth 1979, I examine the association between income inequality and intergenerational income mobility in the United States. This study finds that rising income inequality is associated with strengthening the importance of parental family income to child's income. Particularly, the evidence that greater income inequality decreases intergenerational income mobility is clearer when interstate migration problems are addressed. This evidence indicates that income inequality matters since it hinders the equal opportunity to succeed, especially for children from low-income families. If equality of opportunity is a value for policymakers, it provides justification for policy interventions and government efforts to reduce income inequality. A number of sensitivity tests confirm that the main results are robust and reliable.

Keywords Intergenerational income mobility · Intergenerational elasticity · Income inequality · Geographical differences · Interstate migration · The united states

1 Introduction

The link between economic inequality and intergenerational economic persistence has been of endless concern to social scientists since economic inequality constrains opportunities for children to succeed and shapes to what extent economic advantages are passed on between generations. The connection has been given much attention recently, as income inequality in the United States has sharply risen in recent decades. Piketty and Saez (2003)

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provide robust evidence that income inequality remained stable until the early 1980 s when it started jumping and continued rising throughout the 1990 s and the 2000 s to the present.[1] Such rising income inequality conceptually strengthens intergenerational income persistence which, in other words, induces a decline in intergenerational income mobility (Bloome and Western 2011; Jencks and Tach 2006; Reardon 2011).

However, intergenerational income mobility trends remain uncertain. Within the United States as income inequality rose, intergenerational income mobility appears to have remained stable (Chetty et al. 2014b; Hertz 2007; Lee and Solon 2009), though some uncertainty remains because studies using different data, measures, or birth cohorts find that mobility decreased (Aaronson and Mazumder 2008; Chetty et al., 2017; Mazumder and Levine 2003), increased (Fertig 2001), or decreased and then increased (Mayer and Lopoo 2005). The emerging body of empirical studies that examine the association between income inequality and intergenerational income mobility has also revealed mixed results. For example, several mobility researchers confirmed that there is a strong correlation between income inequality measured by the Gini coefficient and intergenerational income persistence measured by the intergenerational elasticity (IGE) (Berman, 2018, 2019; Chetty et al., 2014a). In addition, Chetty et al. (2017) revealed that greater inequality in the distribution of economic growth has affected the trends in the rates of upward income mobility that has fallen over the past half century. Bloome (2015), however, reported different results that the IGE is unresponsive to rising income inequality. These mixed results to date indicate that additional investigations with different model specifications and reliable national data are needed to empirically identify the link between income inequality and intergenerational income mobility.

Building upon prior studies, this study adds more evidence of the association between income inequality and intergenerational income mobility, with an emphasis on addressing measurement errors caused by interstate migration during childhood. The prior studies aforementioned extensively examined the U.S. inequality-mobility relationship using reliable national data, but neither took into account measurement errors caused by interstate migration. More than 25% of children moved from state to state before 14 years old, and at least 10% of American families changed residence from state to state in the past 5 years.[2] Without addressing the measurement errors caused by interstate migration during childhood, the actual relationship between income inequality and intergenerational income mobility would be obscured. Additional analysis could settle the question. Substantial interstate migration during childhood exposes some children to different inequality levels, thereby introducing errors in point-in-time measurements of childhood inequality.

The paper is structured as follows. In the following section, I start with discussing the link between income inequality and intergenerational income mobility. The method section explains estimation and data. The results section reports the degree of intergenerational elasticity of income and the association between income inequality and intergenerational income mobility. Robustness checks are conducted to test how reliable the main results are in various specifications. I then conclude by describing the main findings, limitations of this study, and implications for social policy and policy analysis.

[1] They used income share of the top decile (P90-100) to measure income inequality, and updated it to 2014, which is posted in the following link: http://eml.berkeley.edu/~saez/#income.

[2] The percentages are author's calculation using the NLSY79 Geocode data and the 1980 Annual Social and Economic Supplement to the Current Population Survey (CPS ASEC).

2 Background

There is a well-known finding, called the Great Gatsby Curve (GGC) that explains the relationship between income inequality and intergenerational income mobility: Countries with greater income inequality also experience less mobility across the generations (Corak 2013; Krueger 2012). However, whether the evidence of the cross-national relationship provided from the GGC holds within a country is questionable because the differences among countries are many; they differ in terms of family roles, institution, population, culture and social norm, labor market and economy, and in many other aspects. Recent studies unevenly support the hypothesis of the correlation between income inequality and international income mobility. On the one hand there is evidence that intergenerational income mobility in the US has been unchanged, even slightly increased in recent decades (Chetty et al. 2014b; Hertz 2007; Lee and Solon 2009; Mayer and Lopoo 2005); on the other hand, some studies have found that the trend in mobility corresponds to the trend in income inequality, showing mobility declined as inequality rose (Aaronson and Mazumder 2008; Bloome and Western 2011; Chetty et al., 2017; Mazumder and Levine 2003). But then again, Berman (2018) found that the trends nearly correspond to the business cycle.

Aaronson and Mazumder (2008) used the Integrated Public Use Microdata Series (IPUMS) of the decennial Censuses from 1940–2000. As trend in the IGEs increased along with rising income inequality, their findings support the widely-accepted view and the GGC finding that income inequality tends to reduce intergenerational income mobility. Nonetheless, there are several studies which are not consistent with the GGC finding. Lee and Solon (2009) measured trends in intergenerational income mobility using the Panel Study of Income Dynamics (PSID) for the 1952–1975 birth cohorts. They found that there is no general increasing or decreasing trend in the IGEs. Evidence from a recent study (Chetty et al. 2014b) also does not correspond to the GGC finding. To explore trends in intergenerational income mobility for the 1971–1993 birth cohorts, Chetty et al. (2014b) constructed a consolidated series of the IGE, and found that the trend is shown to be virtually flat, indicating that the intergenerational income mobility for these birth cohorts has changed little over time. This evidence is striking, in light of the fact that it occurs during periods when income inequality substantially rose.

However, the aforementioned studies did not directly relate the IGEs to income inequality. Only a few empirical studies have recently examined the association between the IGE and income inequality in the U.S. (Bloome 2015; Berman, 2018, 2019; Chetty et al. 2014a). Chetty et al. (2014a) used the GGC framework for a US-specific analogy to cross-national studies by replicating Corak's (2013) work. Using data from the U.S. federal income tax records, they confirmed that there is a strong correlation between the Gini coefficient and the IGE. Berman (2018, 2019)'s results are in line with the empirical evidence that the raising income inequality reduced intergenerational income mobility. Bloome (2015) who used the PSID and National Longitudinal Survey of Youth 1979 (NLSY79) data, however, reported different results that the IGE is unresponsive to rising income inequality. These studies extensively examined the U.S. inequality-mobility relationship using reliable national data, but neither took into account measurement error caused by interstate migration during childhood. Without properly addressing the measurement error caused by interstate migration, the actual relationship would be masked. Thus, this study is to examine the association between income inequality and intergenerational income mobility in the U.S. addressing interstate migration during childhood.

3 Methods

3.1 Statistical Models and Estimation

In practice, the log of child's income with respect to the log of parents' income is commonly used to measure the IGE. To address the effects of the lifetime profile of income for both generations, the common practice is that age and age-squared for both generations are included into the right-hand side of the regression equation (Black & Devereux, 2011; Fox, 2015; Mazumder, 2005). The equation can then be described as follows:

$$\ln y_i^c = \alpha + \beta_1 \ln Y_i^p + \gamma_1 Age_i^c + \gamma_2 (Age_i^c)^2 + \gamma_3 Age_i^p + \gamma_4 (Age_i^p)^2 + \varepsilon_i \tag{1}$$

The reduced-form model for this study can be written as follows:

$$\ln y_i^c = a_0 + \boldsymbol{b} \ln y_i^p + \Lambda X_i' + e_i \tag{2}$$

where $\boldsymbol{b}$ is the IGE; lower-case y_i is the log of income of both generations; and e_i is the error term. X is a set of age and age-squared variables for both generations and Λ is a vector of parameters for the individual variables. The closer $\boldsymbol{b}$ is to 0, the higher the intergenerational mobility, while the closer $\boldsymbol{b}$ is to 1, the less mobility as a large percent of variation in a child's income come from his/her parents' income. In order to estimate how income inequality affects parents' income, the following estimator is used:

$$\ln y_{ist}^c = a_0 + b_0 \ln y_{is\tau}^p + b_1 Gini_{s\tau} + \delta(Gini_{s\tau} * \ln y_{is\tau}^p) + \Omega\left(W_{s\tau}' * \ln y_{is\tau}^p\right) + \Lambda X_{ist}' + \gamma_s + \lambda_\tau + e_{ist} \tag{3}$$

where $Gini_{s\tau}$ is the state income inequality measured by the Gini coefficient in states at time $\tau = 1974$, 1975, 1976, 1977, and 1978. $W_{s\tau}$ is a vector of observable state-level covariates. γ_s and λ_τ are state and time dummies, respectively. In this model, the log of parental income's effect on the log of child income (called the IGE) is estimated as an additive linear function of the Gini coefficient. As a result, the effect of the log of parental family income is conditional on the Gini coefficient. For simplification, Eq. (3) can be described in equivalent form as when taking derivative for the log of parental family income:

$$\theta_{\ln y_{is\tau}^p \rightarrow \ln y_{ist}^c} \cong b_0 + \delta Gini_{s\tau} \tag{4}$$

Expressed in this form, it is apparent that b_0 estimates the conditional effect of the log of parental family income on the log of child's income when the Gini coefficient equals zero. The parameters δ determines how much the effect of the log of parental family income is dependent on the Gini coefficient.

Robust standard errors are clustered on the state, which is conventional and reliable, to account for individual correlation across households. All covariates but parental family income are standardized to a mean of 0 and standard deviation of 1. Standardizing the variables offers several advantages. Standardization makes it easier to interpret results of regressions, which contain different scales of magnitudes. Also, standardization is an easy, useful technique to address multicollinearity which occurs when regression models contain interaction terms, while inference that matters in terms of estimation and interpretation of the results is little affected (Hayes 2013). Furthermore, the parameterizations do not affect the results obtained with the interaction, though some of the regression coefficients differ from what they would be without standardizing (Hayes 2013). It should be noted that I do not intend to identify a causal relationship in this study and as such, estimates should not be interpreted as the causal influence of parental income.

3.2 Data

3.2.1 Challenges and Limitations of Data for Intergenerational Income Mobility

The majority of empirical studies on intergenerational income mobility in the US have relied heavily on survey data such as the PSID and NLSY. These survey data have greatly contributed to improving empirical work of the US mobility studies, by allowing researchers to examine a variety of topics on intergenerational mobility. However, one of the biggest challenges in using survey data is related to measurement issues plagued by errors of response. For example, the misreports and top codes of earnings and income are common limitations of survey data that hinder mobility researchers from precisely estimating the IGE. Moore and Welniak (2000) reported that there are a wide range of error properties across income sources and amounts. Particularly, underreporting problems of transfer incomes are pronounced in survey data (Meyer, Mok and Sullivan 2009).

A few researchers have recently begun to use administrative data, such as the tax records maintained by the IRS's Statistics of Income (SOI). These types of data allow mobility researchers to improve estimations of the IGE by providing more precise information on earnings and income. Work by Chetty et al. (2014a) has currently been hailed as the pathbreaking mobility study because, using administrative data, they were able to provide very reliable estimates of the U.S. IGE. However, this study is not free from measurement errors as well, and has several limitations and challenges caused by the nature of administrative data (Mazumder 2016; Mitnik et al. 2015). For instance, it is important to use a comprehensive measure of household income for intergenerational income mobility, given that children's well-being and development depend heavily on their family's total income (Bloome 2015). Family's total income includes earned, unearned, and transfer incomes, all of which are available to survey data, but not to administrative data. Income from other family member is also not available to administrative data (Mazumder 2016). Ignoring these types of income sources produces omitted-variable biases. Thus, survey data have the advantage over administrative data in that they allow researchers to use a more comprehensive income measure.

Furthermore, zero income and non-filers are problematic in both survey data and administrative data. The majority of mobility studies drop zero income in analyses, but there is no clear rationale for this conventional practice. A way to address to this problem is to employ non-parametric estimation (Mitnik et al. 2015). To address non-filers problems, we can use imputation technique to replace missing values based on information available in data. Given that survey data have much more rich information for imputation than administrative data, estimates from survey data can be more reliable and accurate.

None of the data is perfect in practice. Survey data have advantages and disadvantages over the administrative data. Thus, it is ideal to use a combination of survey data and administrative data. However, given that the access to administrative data such as the IRS's SOI data is very restricted and not available to general researchers, it is reasonable to use publicly available best data such as the PSID or NLSY data. The NLSY79 is selected for this study because (a) the NLSY79 is one of the longest panel data in the US, which is long enough to provide sufficient information on earnings and income of both generations; (b) it provides much larger sample size compared to the PSID; (c) it provides rich information on income resources; and (d) more importantly, the NLSY79 Geocode data provide information on location (county and state) at birth, age 14, and in 1979 in which children grew up. This information is used to address the measurement error caused by interstate migration that would otherwise confound state variations in income inequality and government spending.

3.2.2 Base Sample

This study relies primarily on data drawn from the National Longitudinal Survey of Youth 1979 (NLSY79), which surveyed a national sample of 12,868 youths who were born between 1957 and 1964. For the analysis, a total of 4,824 parents-children pairs are selected. Sample restriction rules for this study are as follows. First, the military sample (N = 1280) was excluded. Second I restrict the sample to children aged 14–18 who lived with their parents in 1979. Following prior studies (Fox 2013; Mayer and Lopoo 2005; Mazumder 2012), I further exclude parents and children who do not have positive income.[3]

In addition to the individual microdata, I use state-level data on income inequality, government expenditures, and other covariates which come from different data sources such as the U.S. Census of Governments, the Bureau of Labor Statistics (BLS), and Frank (2016) who provides measures of income inequality based on the IRS records. State-level covariates are unemployment rates, population, percent Black, median family income, and percent female-headed families. Since the size of government spending can be a function of state economy or income inequality, it is necessary to control state economy factors such as unemployment rates and median family income. For instance, states with higher income inequality can have greater government spending while richer states may have less spending.

To build data for analysis, I match individual-level variables to state characteristics in the state where children lived when they were 13 years old. For example, state characteristics in 1978 were assigned to the 1964 birth cohort, and those in 1977 were assigned to the 1963 birth cohort, and so on.[4] This matching method maximizes the state-year variation in the NLSY79 sample. However, the matching years do not correspond exactly to the years when parental incomes of older birth cohort were observed. For example, parental income was observed only in 1978 for all the birth cohort while state factors for the 1960′s birth cohort (the earliest birth cohort of the sample) come from the 1974′s information, those for the 1961′s birth cohort come from the 1975′s information, and so on.

For comparison, I re-estimate the models by assigning children state characteristics from 1978. This matching method minimizes state-year variations because all values come from a single year of 1978. Table 1 provides the results estimated with the Gini coefficient and state covariates measured in 1978. The overall results are similar to the main estimates presented in the first column. This robustness check in part addresses a limitation of my analytical approach that government spending at age 13 does not capture the full stream of government benefits that a child might have benefited from during their childhood (from birth to age 17), though it is one of limitations. Across all analyses, I use income adjusted for family size to address unobserved factors within families. I additionally report the main

[3] But, I test the estimates including zero incomes in the robustness check section.

[4] Income was measured in past calendar year. For example, income in 1979 was for the previous calendar year of 1978.

Table 1 Comparison for the association between intergenerational income mobility and income inequality by replacing with the 1978′s information on the Gini coefficients and state characteristics

	Main results (1)	Using the 1978′s information (2)
Parental income	0.529***	0.539***
	(0.027)	(0.024)
Gini	−0.460*	−0.121
	(0.270)	(0.468)
Parental income*gini	0.062**	0.040
	(0.029)	(0.027)
N	3613	3591
Individual covariates	×	×
State covariates	×	×
State-year dummies	×	×
Same state from birth to age 13	×	×

Robust standard errors clustered on the state are presented in parentheses. Family size-adjusted income is the family income divided by the square root of family size

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

results using earnings and unadjusted family income measures in Appendix because these types of income measures are also interesting.

3.2.3 Selection of Geographical Areas

There are different geographical areas in the U.S. such as county, commuting zone, and state. Selecting appropriate geographical areas is important for this study because these different geographical areas affect intergenerational income mobility differently. Since there are no clear theoretical grounds for one optimal geographic grouping (Bloome 2015), it is ideal to explore all of the geographical areas, in order to fully characterize the geography of intergenerational income mobility. However, it is difficult to exploit all of the geographical areas in practice. For example, estimating the IGE at the county-levels using the NLSY79 is not appropriate due to small observations within counties. Also, there is little variation in government spending at narrow geographical areas such as the county-levels, instead there is greater variation at the state-levels.

Commuting zones (CZs) might also be appropriate geographic units for examining the effects of income inequality (Chetty et al. 2014a). However, the effects of government spending across CZs are confounded because jurisdictional regions for government spending are based on state or congressional district, instead of CZs where several states can be a CZ. For this reason, I do not use CZs as the geographic area for this study. The state-level of geographical areas has advantages over the other geographical areas in that demographics, economy, welfare programs, population, and many other dimensions greatly differ from state to state, making it possible to fully exploit the heterogeneous effects of income inequality. Furthermore, political jurisdictions for tax rates and redistributive government spending on education, welfare, and health care, which are greatly likely to affect children's future socio-economic status, are based mainly on the state-level of geographical areas (Bloome 2015). By focusing on the state-level of geographical areas, this study

Table 2 Estimates of the intergenerational elasticity of income and its association with income inequality

	Model (0)	Model (1)	Model (2)	Model (3)
Parental income	0.537***	0.530***	0.544***	0.575***
	(0.022)	(0.024)	(0.025)	(0.022)
Gini		−0.312	−0.501**	−0.498*
		(0.250)	(0.239)	(0.210)
Parental income*gini		0.034	0.055**	0.067**
		(0.027)	(0.026)	(0.022)
N	4824	4824	3613	3613
Individual covariates	×	×	×	×
State covariates				×
State-year dummies				×
Same state from birth to age 13			×	×

Robust standard errors clustered on the state are presented in parentheses. Family size-adjusted income is the family income divided by the square root of family size

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

is able to optimally exploit the heterogeneities of income inequality in intergenerational income mobility. As such, I focus on state-level variations for the analysis.

4 Results

4.1 Main Results

The first column of Table 2 presents the estimates of the intergenerational elasticity (IGE). The IGE is about 0.54, which implies that if parental income differs by 10%, child's income, on average, differs by 5.4%. The degree of the IGE aligns with the previous evidence that the best estimate of the American IGE is 0.4 or higher (Mazumder 2005; Solon 1992). When switching the income measure to earnings and unadjusted family income, the degree of the IGEs does not greatly change, though they become a little smaller, shown in "Appendix" Table 2.

Now I turn the attention to the association between income inequality and intergenerational income mobility. To test the relationship between income inequality and intergenerational income mobility in the U.S., I exploit state-year variations in income inequality measured by the Gini coefficient.[5] Although the Gini coefficients stayed relatively at lower levels during the period from 1974 to 1978 when the children of the sample were 13 years old, there is substantial variation across states over the sample period. For example, South Dakota, North Dakota, Nevada are the top three states with the highest Gini coefficients at

[5] I choose the Gini coefficient as a measure of income inequality because it is (1) the most commonly used measure of income inequality, (2) easily interpreted, (3) useful to compare income distributions across different population groups, and (4) less sensitive to changes at the top and bottom income distribution (Wolff 2009). With a range of 0 to 1 (or 0% to 100%), a low value of the Gini coefficient indicates less inequality, while a high value indicates more inequality. For instance, 0 and 1 are the extremes indicating that a society with a Gini coefficient of 0 is perfectly equal whereas a society with 1 is perfectly unequal.

0.577, 0.536, and 0.517, respectively; by contrast West Virginia, Ohio, and New Hampshire are the top three states with the lowest Gini coefficients at 0.428, 0.440, and 0.444, respectively. By using variation across state and year, this study more fully exploits the heterogeneity available for learning about how income inequality during childhood is associated with intergenerational income mobility. To examine the relationship, I test the interaction of the log of parental income and the Gini coefficient.

The second column in Table 2 reports the association between income inequality and intergenerational income mobility. Intergenerational income mobility is measured by the intergenerational elasticity (IGE) and income inequality is measured by the Gini coefficient at state levels. The main effect of parental family income on child's family income in Model (1) is about 0.530 when the Gini coefficient equals zero, and is statistically significant. The simple effect of the Gini coefficient on child's family income is about − 0.312 when parental family income equals zero. The estimate of the interaction between parental family income and the Gini coefficient is about 0.034, and is statistically indistinguishable from zero. The results in Model (1) are consistent with Bloome's study (2015) reporting that intergenerational income mobility is irresponsive to rising income inequality in the United States.

However, these results do not take into account interstate migration nor do they control for movers, which may mask the actual association between intergenerational income mobility and income inequality. For example, more than 25% of children in the NLSY79 data moved from state to state before turning 13 years old. To handle the migration problem, I restrict the sample of analyses to children who have stayed in the same states from birth to the age of 13. Model (2) presents the estimates with the restricted sample and provides more favorable results that the higher Gini coefficients play a role in strengthening the importance of parental family income to child's income. For example, the IGE in Model (2) is about 0.54 in states and years with average inequality, while it becomes about 0.60 in moderately unequal states and years (the Gini coefficient of one standard deviation above the mean) and increases to about 0.72 in extremely unequal states and years (the Gini coefficient of three standard deviations above the mean).

To control for state-level factors that can affect income inequality and parental family income, I include state covariates such as state unemployment rates, population, percent Blacks, median family income, percent female-headed families, and state spending on education, welfare, health into the model and interact them with parental family income in Model (3). Furthermore, I include the state and year dummies to purge unobservable regional and year factors as described in the method section. Inclusion of state and year factors does not greatly alter the overall estimates in Model (2), for which the results are robust with the inclusion of these state-level factors. This exercise shows that the IGE is greater with increases in the Gini coefficient. So the findings support the supposition that income inequality undermines intergenerational income mobility in the United States.

The NLSY79 data have the advantage over other types of panel data in that nearly lifetime income of children's generation with a large sample is available. One of the biggest practical challenges of estimating the IGE is that we are unable to observe lifetime income in data. In the absence of data on lifetime income in practice, estimates of the IGE may be affected by measurement error on both sides (left hand side income measure for sons and right hand income measure for fathers). Fortunately, the NLSY79 data measures the income of children's generation from 1979 to 2012, which allows researchers to generate likely-lifetime income. I produce the likely-lifetime income by averaging children's income from 1990 to 2012 in which the youngest cohorts of the children were at least 25 years old by 1990, which is a typical age at which individuals

Table 3 The association between intergenerational income mobility and income inequality using the children's averaged income from 1990 to 2012 income

	Model (1)	Model (2)	Model (3)
Parental income	0.595***	0.607***	0.634***
	(0.025)	(0.028)	(0.029)
Gini	−0.314	−0.433**	−0.475**
	(0.216)	(0.209)	(0.219)
Parental income*gini	0.035	0.048**	0.053**
	(0.023)	(0.026)	(0.024)
N	5713	4245	4245
Individual covariates	×	×	×
State covariates			×
State-year dummies			×
Same state from birth to age 13		×	×

Robust standard errors clustered on the state are presented in parentheses. Family size-adjusted income is the family income divided by the square root of family size

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

would have participate in labor market. Although this study cannot completely address the life-cycle bias due to absence of data on lifetime income of parental generation, the life-cycle bias is minimized with the use of the likely-lifetime income of children generation. Using the likely-lifetime income, I replicate the models from (1) to (3) in Table 2 which are estimated with the five-year averaged income. The replicated results are presented in Table 3. The overall results are not much different from the estimates from the five-year averaged income.

4.2 Robustness Checks

Several robustness checks were carried out to test the sensitivity of the results in this section. First of all, one concern may be that the Gini coefficient is not the only index of measuring income inequality. Alternative measures of income inequality are used to test the sensitivity of the Gini coefficient. The alternative indices for income inequality are the top 10% income share, relative mean deviation, and Theil index. Table 4 presents changes in estimates with different indices for income inequality. The overall estimates with the alternative indices are nearly identical to those of the Gini coefficient, and significance levels also little sensitive to different indices for income inequality.

Concerned that Ginis at the state-level are quite volatile from year to year, I further investigate sensitivities in which the state Ginis are averaged across 5 years (centered on the year in which a child was 13) to better capture the variation in exposure to inequality. Column (1) of Panel B reports the estimates with the averaged Ginis, and the results indicate that the estimates are robust. Additionally, I test the alternative indices for income inequality averaged over 5 years and the results are almost identical, indicating that the main results are robust.

Next, I investigate sensitivities with imputed values for children's income averaged over 5 years and 22 years, respectively. The estimates with the imputed values—shown in the second and forth columns of Table 5—are consistent with the estimates using non-imputed

Table 4 Robustness checks for different indices for income inequality

		Gini (1)	Top 10% (2)	Mean dev (3)	Theil (4)
A. Income inequality for each year	Parental income	0.575***	0.585***	0.576***	0.579***
		(0.022)	(0.022)	(0.021)	(0.026)
	Income inequality	−0.498*	−0.444**	−0.520**	−0.522***
		(0.210)	(0.215)	(0.212)	(0.160)
	Parental income* Income inequality	0.067**	0.053**	0.068***	0.068***
		(0.022)	(0.022)	(0.022)	(0.018)
B. Income inequality averaged over 5 years	Parental income	0.580***	0.581***	0.580***	0.581***
		(0.021)	(0.022)	(0.021)	(0.023)
	Income inequality	−0.150	−0.446*	−0.148	−0.327
		(0.245)	(0.229)	(0.254)	(0.198)
	Parental income* Income inequality	0.054**	0.060***	0.054*	0.060***
		(0.020)	(0.021)	(0.021)	(0.018)
N	3613	3613	3613	3613	
Individual covariates	×	×	×	×	
State covariates	×	×	×	×	
State-year dummies	×	×	×	×	
Same state from birth to age 13	×	×	×	×	

Robust standard errors clustered on the state are presented in parentheses. Family size-adjusted income is the family income divided by the square root of family size. Gini refers to the Gini coefficients; Top 10% refers to the top 10% of income share; Mean Dev. refers to the relative mean deviation; and Theil refers to the Theil index. The income inequality metrics are averaged across 5 years centered on the year in which a child was 13

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

Table 5 Robustness checks for the association between income inequality and intergenerational income mobility with imputed values

	Averaged children's income from 1994 to 1998		Average children's income from 1990 to 2012	
	Non-imputed	Imputed	Non-imputed	Imputed
Parental income	0.575***	0.539***	0.634***	0.547***
	(0.022)	(0.024)	(0.029)	(0.027)
Income inequality	−0.498*	−0.375*	−0.475**	−0.426**
	(0.210)	(0.219)	(0.219)	(0.173)
Parental income* Income inequality	0.067**	0.053**	0.053**	0.048**
	(0.022)	(0.023)	(0.024)	(0.019)
N	3,613	3,659	4,245	4,326
Individual covariates	×	×	×	×
State covariates	×	×	×	×
State-year dummies	×	×	×	×
Same state from birth to age 13	×	×	×	×

Robust standard errors clustered on the state are presented in parentheses. Family size-adjusted income is the family income divided by the square root of family size. ***$p<0.01$, **$p<0.05$, *$p<0.1$

values, though the sizes of the overall estimates with imputed values are slightly reduced compared with the estimates with non-imputed values.

Additionally, I test sensitivities for measurement errors caused by (a) lifecycle biases that are likely to attenuate the IGE (Haider and Solon 2006; Mazumder 2016); (b) non-linearity in estimating the IGE (Chetty et al. 2014a; Corak and Heisz 1999; Mitnik et al. 2015); (c) including zero incomes in the analytical sample (Chetty et al. 2014a; Mitnik et al. 2015); and (d) the restriction to non-movers during childhood that may causes selection biases if certain populations are restricted or excluded. Overall, the sensitivity tests confirm that the main results are quite robust and reliable. These results are available from the author upon request.

5 Conclusion

This paper examines the association between income inequality and intergenerational income mobility in the U.S. Main findings are summarized as follows. The intergenerational elasticity (IGE) of earnings is about 0.54.[6] The estimate is consistent with the previous evidence that the best estimate of the American IGE is 0.4 or higher (Mazumder 2005; Solon 1992, 1999). Rising income inequality is associated with strengthening the importance of parental family income to child's income. Particularly, the evidence that higher

[6] The IGEs of family income and earnings are about 0.50 and 0.43, accordingly.

income inequality decreases intergenerational income mobility is obvious when measurement error caused by interstate migration are addressed.

The present study does have a number of limitations worth discussing. This study relied on analyses for short-term time periods from 1974–1978 due to data limitations. There was relatively little over time variation in income inequality during the periods, though there are larger variations by state. Given the evidence that income inequality has considerably increased in recent decades, historical analyses will provide more evidence of trends in intergenerational income mobility with respect to changes in income inequality. In addition, measurement problems in income challenge mobility researchers who rely heavily on earnings and income measures. It is well known that the underreporting of income is a problem in survey data including the NLSY. Correcting for the underreporting may provide a different picture of intergenerational income mobility and its association with income inequality and government spending. An alternative way to address underreporting problems is using administrative data such as the tax records maintained by the IRS's SOI. Although access to the administrative data is restricted to just a few researchers, these types of data allow mobility researchers to improve estimations of the IGE by providing more precise information on earnings and income. Furthermore, although the robustness checks provide the evidence that the main results are overall robust and reliable, the indices are imperfect measures of income inequality. I also exclusively use parental incomes as a proxy for parental investment. So, further robustness checks are needed with different indices and measures. Moreover, although this study tried to address interstate migration problems during childhood by restricting to non-movers, this restriction can rule out people who exited and returned to a state during early childhood, and it also excludes people who were born in a different state but moved soon after birth to a permanent home. Lastly, it should be noted the context of omitting a variety of family characteristics in the estimator may influence children income. This study, however, followed the common practice that mobility researchers in general include only parents' and children's ages in the estimator to adjust for life-time income, which allows many pathways and vehicles through which parents' income in whole or in part influences children's future income. Despite the limitations, the findings of this study have policy implications. One clear finding is that rising income inequality acts to strengthen the transmission of economic advantages and disadvantages across generations through parental resources available for children's development that are attributable to diverging children's human capital and skills. As such rising income inequality is likely to make individuals depend more on family background to succeed, while independent of their efforts. The findings indicate that income inequality matters since it hinders the equal opportunity to succeed, especially for children from low-income families. If equality of opportunity is a value for policymakers, it provides justification for policy interventions and government efforts to reduce income inequality.

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Appendix

See Tables 6, 7, 8, 9, 10.

Table 6 Robustness checks for the association between intergenerational income mobility and income inequality by replacing with the 1978′s information on the Gini coefficients and state characteristics

	Main results (1)	Using the 1978′s information (2)
Panel A: Earnings measure		
Parental income	0.416***	0.435***
	(0.030)	(0.032)
Gini	−0.506*	−0.704
	(0.251)	(0.677)
Parental income*gini	0.056**	0.077**
	(0.026)	(0.029)
N	3,356	3,339
Panel B: Family income measure		
Parental income	0.487***	0.490***
	(0.026)	(0.025)
Gini	−0.397	−0.047
	(0.349)	(0.481)
Parental income*gini	0.050	0.027
	(0.035)	(0.031)
N	3613	3591
Individual covariates	×	×
State covariates	×	×
State-year dummies	×	×
Same state from birth to age 13	×	×

Robust standard errors clustered on the state are presented in parentheses. Earnings measure refers to the child's earnings and parental family income pair. Family income measure refers to the child's family income and parental family income pair

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

Table 7 Estimates of the intergenerational elasticity of income

	Model (0)	Model (1)	Model (2)	Model (3)
Panel A: Earnings measure				
Parental income	0.431***	0.422***	0.420***	0.483***
	(0.030)	(0.028)	(0.035)	(0.041)
Gini		−0.435**	−0.550**	−0.584*
		(0.189)	(0.249)	(0.294)
Parental income*gini		0.045**	0.056**	0.064**
		(0.019)	(0.026)	(0.031)
N	4,460	4,460	3,356	3,356
Panel B: Family income measure				
Parental income	0.495***	0.489***	0.502***	0.540***
	(0.023)	(0.025)	(0.025)	(0.023)
Gini		−0.347	−0.546*	−0.452
		(0.364)	(0.324)	(0.257)
Parental income*gini		0.035	0.056*	0.056**
		(0.037)	(0.033)	(0.025)
N	4824	4824	3613	3613
Individual covariates	×	×	×	×
State covariates				×
State-Year dummies				×
Same state from birth to age 13			×	×

Robust standard errors clustered on the state are presented in parentheses. Earnings measure refers to the child's earnings and parental family income pair. Family income measure refers to the child's family income and parental family income pair

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

Table 8 The association between intergenerational income mobility and income inequality using the children's permanent income from 1990 to 2012 income

	Model (1)	Model (2)	Model (3)
Panel A: Earnings Measure			
Parental income	0.500***	0.504***	0.558***
	(0.034)	(0.037)	(0.039)
Gini	−0.359	−0.431*	−0.382
	(0.284)	(0.247)	(0.319)
Parental income*gini	0.037	0.044*	0.035
	(0.028)	(0.025)	(0.032)
N	5,514	4,099	4,099
Panel B: Family income measure			
Parental income	0.536***	0.547***	0.582***
	(0.025)	(0.029)	(0.030)
Gini	−0.340	−0.475**	−0.445**
	(0.258)	(0.222)	(0.226)
Parental income*gini	0.035	0.049**	0.048**
	(0.036)	(0.022)	(0.022)
N	5713	4245	4245
Individual covariates	×	×	×
State covariates			×
State-year dummies			×
Same state from birth to age 13		×	×

Robust standard errors clustered on the state are presented in parentheses. Earnings measure refers to the child's earnings and parental family income pair. Family income measure refers to the child's family income and parental family income pair

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

Table 9 Robustness checks for different indices for income inequality

		Gini (1)	Top 10% (2)	Mean Dev (3)	Theil (4)
Panel A: Earnings measure					
A. Income inequality for each year	Parental income	0.483***	0.491***	0.485***	0.488***
		(0.041)	(0.041)	(0.041)	(0.044)
	Income inequality	−0.584*	−0.569*	−0.521*	−0.059
		(0.294)	(0.333)	(0.292)	(0.363)
	Parental income* income inequality	0.064**	0.058**	0.057*	0.014
		(0.031)	(0.029)	(0.030)	(0.037)
B. Income inequality averaged over 5 years	Parental income	0.489***	0.492***	0.488***	0.489***
		(0.041)	(0.042)	(0.041)	(0.044)
	Income inequality	−0.232	−0.440	−0.332	−0.093
		(0.375)	(0.406)	(0.350)	(0.380)
	Parental income* Income inequality	0.064*	0.069*	0.064**	0.029
		(0.033)	(0.037)	(0.032)	(0.038)
	N	3,356	3,356	3,356	3,356
Panel B: Family income measure					
A. Income inequality for each year	Parental income	0.540***	0.547***	0.542***	0.544***
		(0.023)	(0.024)	(0.023)	(0.023)
	Income inequality	−0.452	−0.360	−0.452*	−0.497**
		(0.257)	(0.247)	(0.265)	(0.203)
	Parental income* Income inequality	0.056**	0.038	0.055**	0.058***
		(0.025)	(0.025)	(0.026)	(0.029)

Table 9 (continued)

		Gini (1)	Top 10% (2)	Mean Dev (3)	Theil (4)
B. Income inequality averaged over 5 years	Parental income	0.545***	0.546***	0.545***	0.546***
		(0.022)	(0.023)	(0.023)	(0.023)
	Income inequality	−0.142	−0.432*	−0.110	−0.330
		(0.294)	(0.256)	(0.304)	(0.252)
	Parental income* Income inequality	0.045*	0.051**	0.042*	0.054**
		(0.022)	(0.022)	(0.023)	(0.020)
	N	3613	3613	3613	3613
Individual covariates	×	×	×	×	
State covariates	×	×	×	×	
State-year dummies	×	×	×	×	
Same state from birth to age 13	×	×	×	×	

Robust standard errors clustered on the state are presented in parentheses. Gini refers to the Gini coefficients; Top 10% refers to the top 10% of income share; Mean Dev. refers to the relative mean deviation; and Theil refers to the Theil index. Earnings measure refers to the child's earnings and parental family income pair. Family income measure refers to the child's family income and parental family income pair. The income inequality metrics are averaged across 5 years centered on the year in which a child was 13

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

Table 10 Robustness checks for the association between income inequality and intergenerational income mobility with imputed values

	Averaged income from 1994 to 1998		Average income from 1990 to 2012	
	Non-imputed	Imputed	Non-imputed	Imputed
Panel A: Earnings measure				
Parental income	0.483***	0.424***	0.558***	0.445***
	(0.041)	(0.032)	(0.039)	(0.030)
Income inequality	−0.584*	−0.512*	−0.382	−0.155
	(0.294)	(0.255)	(0.319)	(0.232)
Parental income* income inequality	0.064**	0.055*	0.035	0.015
	(0.031)	(0.027)	(0.032)	(0.022)
N	3356	3455	4099	4130
Panel B: Family Income Measure				
Parental income	0.540***	0.501***	0.582***	0.486***
	(0.023)	(0.025)	(0.030)	(0.027)
Income inequality	−0.452	−0.393**	−0.445**	−0.412**
	(0.257)	(0.254)	(0.226)	(0.174)
Parental income* income inequality	0.056**	0.050**	0.048**	0.045**
	(0.025)	(0.024)	(0.022)	(0.017)
N	3613	3659	4245	4326

Robust standard errors clustered on the state are presented in parentheses. Earnings measure refers to the child's earnings and parental family income pair. Family income measure refers to the child's family income and parental family income pair

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

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