Childhood Family Residential Mobility and Long-run Education & Labor Outcomes

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Abstract

This study analyses the impact of residential mobility in childhood on an individual's long-run education and labor outcomes. We use micro-level data from the Panel Study of Income Dynamics (PSID, 1968-2021) to locate children who have moved between ages 6 to 18 years, their household characteristics, and their educational and income outcomes later in life. We deploy an instrumental variable approach controlling for sources of selection into moving to ascertain the impact of mobility and age at the time of the move on long-run outcomes. We find that the negative effect of childhood moving on educational outcomes is most prominent for younger children, with children between the ages of 6 and 8 being particularly vulnerable. The coefficient on the treatment dummy for income outcomes gives a negative yet non-significant result. The findings contribute to the literature in disentangling the effects of childhood mobility experience and shed light on the importance of childhood for human capital accumulation.

1 Introduction

The impacts of rising inequality and efforts to decompose them in conjunction with social phenomena and welfare policies have been studied in varied contexts. Human capital formation is being widely studied to understand the dynamism of inequalities pertaining to labor income. Within the ambit of human capital, childhood is a phase in an individual's life that is particularly relevant to understand closely. This is the time when many skills and traits are developed by an individual, which then capitalizes during later stages in life and informs key outcomes such as educational attainment and performance, social and interpersonal relationships, and labor outcomes throughout life. This is supported by the theoretical idea, which underscores the importance of developing learning skills early on in childhood and their impact on augmenting earning skills later in life, as well as increasing returns to later skill investments. Further, evidence (Heidrich, 2015) shows that neighborhood quality is an important determinant for ensuring positive outcomes for children's outcomes in health and education. This brings us to the question of mobility in childhood and whether moving to different neighborhoods, regions, states, or locations can have an impact on children's long-run outcomes.

In this paper, we aim to investigate how the childhood experience of family moving influences education attainment and labor outcomes in early career and mid-career age. From a theoretical perspective, both positive and negative associations between childhood re-locations and various outcomes may be expected (Chetty and Hendren, 2015; Chetty et al., 2015, 2014; Black and Devereux, 2011). The effect of moving partially comes from the motivation behind relocation itself. In some cases, households make mobility decisions to optimize future outcomes, which may include better labor outcomes for the head of the household or his spouse, improving the living conditions for the whole family, and providing better educational resources to their child(ren). These factors should contribute to the human capital formation and income level of the next generation. In other cases, households may be subject to outside forces to make relocation decisions, such as divorce, job displacement, and serious health concerns. These shocks to households naturally translate into a negative influence on the next generation's education and labor outcomes.

*This paper is an updated version of a course project completed with my group mates Bhavya Pandey and Yicheng Zhang. Below is an excerpt of the paper that reflects my work. Certain sections are omitted due to page limits. I have asked for my co-authors' permission to use the following sections as my writing sample for PhD application.

The other part of the effects comes from the disruption of living caused by the action of residential relocation itself. The moving experience is found to be related to the disruption of human capital accumulation and income growth, most prominently through:

> Network Destruction (Keene et al., 2010): When families move, important relationships, information sources, and networks could be disrupted. Families tend to be less resourceful and are more vulnerable to external shocks. All members of the family need to build new connections and familiarize themselves with the environment. The process could be effortful and time-consuming, posing challenges to the financial stability of the family.
>
> Destruction of "intra-family" social capital (Démurger, 2015): Parent–child relationships may be distorted and re-established and could negatively impact the child's personal development.

However, in the real world, it is very challenging to disentangle the disruption effects from the effects led by the initial motivation to move. Most existing studies take a step back by investigating the aggregate effects and drawing conclusions on which side of the effects dominates the impact on children's long-run outcomes. If, despite the good intention of moving, a negative effect is still observed, then we could conclude that disruption due to moving has indeed posed long-run costs for the next generation's development.

Our paper complements the strand of literature estimating the potential long-run costs of childhood moving incurred by individuals in the long run. Heidrich (2016) defined these costs as the "effect of childhood moving on long run adult income" and has put forth that not only do such costs exist, but that they increase in the number of times a child moves while growing up and also that the timing of the move matters. Considering the dynamic nature of human capital development, disruption during childhood or adolescence could potentially accumulate long-term effects. The canonical three-period model of human capital accumulation stresses that agents invest in learning how to learn during their childhood (before 18 years old) to improve their learning efficiency during the following skill acquisition period, such as college and postgraduate study. Such investment in learning efficiency translates into human capital, which contributes to the agent's earnings when entering the workplace. We may expect that disruptions coming from mobility act as negative shocks in learning efficiency while children are growing up and thus have a potentially negative effect on the skill formation process. The final skill level (measured by education attainment) then influences these children's future incomes. In this sense, the observation of a negative effect of childhood moving on education attainment would be an indicator of the long-run costs of childhood moving.

With regards to educational attainment, instances in literature have shown that frequent moves can lead to poor academic performance, difficulty in making social connections, and lower levels of educational attainment (Schmidt et al., 2017). Children who move frequently may experience disruptions in their education, such as having to adjust to new schools and curricula, and may struggle to keep up with their peers academically (Friedman et al., 2017). Further, Tonnessen et al. (2016) studied childhood residential mobility and long-term outcomes and found that children with more residential moves are more likely to drop out of high school, have a lower adult income, and experience early parenthood. Most of these associations are weaker in the sibling fixed effects models explored by the group. Also, the age of moving matters. There is evidence of heterogeneity among age groups in education and health outcomes. Children who moved during their teens have more adverse outcomes than those who did not move at that age.

For the long-run costs on labor outcome, an example of these estimates has been showcased by leveraging granular Swedish Register Data. Using OLS regression models, Heidrich (2016) finds that children's long-run incomes are significantly negatively affected by moving during childhood, and the effect is larger for those who move more often. Controlling for important sources of selection such as parent separation, parents' unemployment, education, long-term income, and immigration background, it is also evidenced that the negative effect of childhood moving on adult income is increasing in age at the move. This study concludes that: "children benefit economically from the quality of the region they move to only if they move before age 12 (sons) and age 16 (daughters)".

Methodologically, there is limited existing literature using an empirical strategy that explores the causal relationship between residential mobility and long-run education or labor outcomes. Previous studies mainly attempt to understand the research question by estimating OLS regression models. Although tryouts had been made in drawing causal identification, such as the sibling fixed effect model in Tonnessen et al. (2016)'s work, their research paradigm lacks an effective approach in addressing the omitted variable bias.

To address our research question, we use an instrumental variable (IV) approach to estimate the average effects of experiencing family mobility between ages 6 and 18 on the educational attainment and early to mid-career income of the child, controlling for the family resources and demographics. We consider the age of the parents at the time of moving and the frequency of moving for the head of the household as potential IVs.

The rest of the paper is organized as follows. Section 2 of the paper details our methods and empirical strategy, followed by a description of the data in Section 3. Estimated results for education and labor outcomes are presented in Section 4. Section 5 discusses the findings and limitations of the study. The final section concludes.

2 Empirical Strategy

2.1 Hypotheses

Based on existing literature on the possible effect of moving, we form the following hypotheses:

- The disruption due to moving induces negative effects on long-run education and labor outcomes.
- The effect of disruption would be stronger for teenagers than younger children.

The first hypothesis suggests that when children experience a significant disruption in their lives due to moving, it will have a detrimental impact on their long-term educational and labor outcomes. The disruption caused by moving may lead to various challenges, such as changing schools, adjusting to a new environment, and building new social connections. These challenges can potentially disrupt academic progress and hinder the development of skills and knowledge necessary for successful educational and occupational trajectories. Hence, we expect to observe negative effects on education and labor outcomes as a result of moving.

The second hypothesis proposes that the negative impact of moving-induced disruption on education and labor outcomes will be more pronounced among teenagers compared to younger children. This is based on Tonnessen et al. (2016)'s work, which shows that "...those who moved before elementary school do not have severe long-term outcomes compared with children who did not move at that age, whereas children who moved during teens did have more adverse outcomes than those who did not move at that age". It is hypothesized that older children tend to typically have more established social and educational networks, and their educational trajectories and career aspirations may already be forming. Moving during this critical developmental stage may disrupt their connections, educational continuity, and the stability required for pursuing long-term goals. Consequently, we expect the effect of disruption to be stronger for teenagers than for younger children.

2.2 Baseline model and challenges for identification

The baseline model can be represented by the following OLS estimation equation:

$$Y_i = \beta D_i + \alpha X_i + \gamma_i + \epsilon_i \tag{1}$$

Here Y_i represents the child's long-run outcome we are interested in, namely, highest education attainment and average annual income between 25 and 35 years old. D_i is the treatment Dummy indicating whether the child has moved during age 6-18 years old. We add individual and household-level controls in X_i, including parents' education, family income level at five years old, and basic demographic information such as the age when the child moves, gender, and race. Finally, as we may anticipate some regional and birth cohort variation in long-run outcome, we add γ_i, which are the year fixed effect and region/state fixed effect when the child was five years old.

2.2.1 Multicollinearity

The multicollinearity between the control and target variables would give inaccurately estimated coefficients and their statistical power. To address this potential issue, we tested the Variance Inflation Factors (VIF) between our target variable D_i and controls X_i. The VIF of D_i (*has moved*) within the sample investigating the labor outcome is 2.50, indicating that there is a moderate correlation between the target variable and other controls. To see the magnitude of the collinearity problem, we plot the correlation matrix across all the right-hand side variables, and all the correlations between the treatment dummy and controls remain small. In interpreting the results, we would assume such collinearity does not severely bias the results.

2.2.2 Omitted variable bias (OVB)

There could be variables influencing the long-run outcome of children that we are unable to control their effects fully. Only when such omitted variables are uncorrelated with our target and outcome variable we could safely ignore the bias caused. However, it is possible that moving is led by certain endogenous motivations or reasons that would decide the future development of the children. The direction of OVB is challenging to predict as we are identifying the effect in a fairly long time frame, and these unaccounted motives could lead to mixed effects on moving decisions and children's long-run outcomes. For instance, people may move to better accommodate household production or consumption needs, which could also imply their effort to build a better future for the next generation. On the other hand, external forces such as displacement, divorce, or health issues could force households to move, and the future development of children could be disrupted mainly by these events accompanying the relocation.

2.2.3 Measurement error

We worry that the existence of (classic) measurement error would lead to attenuation bias to our estimated coefficients. A measurement error could be manifested in many ways in this study and even arise due to external biases such as social desirability or recall. If the measurement error is random, it can attenuate the estimated coefficients towards zero, making the outcome relationships appear weaker, leading to a problem of underestimation. The direction and magnitude of the bias introduced by non-random measurement error depend on the specific nature of the measurement error and its relationship to the true values. If there is a systematic underreporting or misclassification of moving, it may lead to an underestimation of the true effect of moving on education and labor outcomes. Conversely, if there is a systematic overreporting or misclassification, it may lead to an overestimation of the effect.

2.3 Instrumental Variable Approach

Given the limitations of the OLS model in identifying causal relationships, we seek the use of an Instrumental Variables (IV) strategy to eliminate the influence of measurement error and omitted variable bias. The following two-stage system of equations represents the empirical model we choose to estimate:

$$D_i = \delta Z_i + \theta X_i + \gamma_i + u_i \tag{2}$$
$$Y_i = \beta D_i + \alpha X_i + \gamma_i + v_i \tag{3}$$

With constraints of the available data, we tried to identify some potential Instrumental Variables (IVs) represented by Z_i in the equation system:

- Parent's age when giving birth to the child
- Number of states or regions the head/reference person has lived in

Those factors are possible predictors of people making mobility decisions (when their children were at age 6-18) but are not directly related to the educational outcomes or labor market outcomes of the children when they grow up.

For parent's age, we expect that younger parents may be more likely to relocate for production or consumption needs, but parents' age may not have a direct impact on children's future outcomes. Younger parents may be less established in careers but may have more energy devoted to children's development. On the other hand, relatively older parents may make more mature parenting decisions and have better financial conditions.

For the second instrument, we conjecture that the experience of household heads moving across states may lead to the household being more flexible in residential relocation. Although the high frequency of moving may be related to the profession of the household head, there seems to be no prominent concern of this variation of profession casting a decisive influence on their children's future outcome.

Admittedly, each of these variables has flaws. In the main part of the analysis, we used the mother's age when the child was five years old as the instrument. We display the results using the instrument "Number of states or regions the head/reference person has lived in" in the Appendix.

2.4 Assumptions for identification strategies

Here, we recapitulate the assumptions for identifying the target variable regression estimates in baseline OLS and 2SLS models.

- **Ordinary Least Squares (OLS)**
  A multivariate linear regression model is given by:

  $$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + ... + \beta_k X_{ki} + u_i$$

  where $i = 1, 2, ..., n$.

  The Ordinary Least Squares (OLS) assumptions for linear regression are as follows:

  - A1: Regressors $(X_{1i}, X_{2i}, ..., X_{ki})$ are drawn such that the assumption of independent and identical distribution $(i.i.d)$ holds.
  - A2: u_i represents the error term with conditional mean zero, given the regressors: $E(u_i|X_{1i}, X_{2i}, ..., X_{ki}) = 0$.
  - A3: There is unlikeliness in the occurrence of larger outliers ensuring that Y_i and $X_{1i}, ..., X_{ki}$ have finite fourth moments.
  - A4: There is no incidence of perfect multicollinearity.

  As mentioned above, an emerging challenge is that of the Omitted Variable Bias (OVB) that arises when the regressor, X, is correlated with an omitted variable. This issue violates the second OLS assumption. For omitted variable bias to occur, two conditions are generally fulfilled:

  - X is correlated with the omitted variable.
  - The omitted variable is a determinant of the dependent variable Y.

  Thus, we seek to use instrumental variables to correct the OVB problem, assuming the following assumptions hold.

- **Instrumental Variables (IV)**
  Regression models may suffer from problems like omitted variables, measurement errors, and simultaneous causality. We focus on the Two-Stage Least Squares (2SLS) tool to deploy an Instrumental Variables (IV) technique in this paper. Consider a simple linear regression model as follows:

  $$Y_i = \beta_0 + \beta_1 X_i + u_i, i = 1, ..., n$$

where the error term is correlated with the regressor X_i (X is endogenous) such that OLS is inconsistent for the true β_1. In its simplest form, an IV regression makes use of a single instrumental variable Z to obtain the value of a consistent estimator for β_1. In this case, Z must satisfy the following two conditions to be a valid instrument

- A5: Relevance: X and its instrument Z must be correlated.
- A6: Exogeneity: Instrument Z only influence Y through X; that is, it must not be correlated with the error term u_i.

Further, an extension of the OLS assumptions also holds for the IV setup, for the method to delineate causality. Additionally, regarding A1, specific to our context, we assume the incidence of randomized treatment across age groups in our sample, but we allow for the slackness of such randomization across regions. We apply clustered standard error to address the within-group correlation of error at the regional level.

3 Data

The Panel Study of Income Dynamics (PSID) has a data structure that enables us to test our hypotheses. The study surveyed 4802 households in 1968 and ran follow-up surveys to these households and their derived households from 1969 to 2021. As of 2021, there are 42 rounds of surveys and a total of 84121 individuals recorded. In this project, we directly requested all rounds of available surveys on both the individual level and household levels from the PSID website. We then identify the children who were between six and eighteen years old when their family relocated. In total, we located 17936 children who moved in 6-18 from a sample of 29116 children. For all the children in our sample, we identify their parents with the help of household identifiers. Based on data availability, we further restricted our sample to children in households with valid education attainment and income records that span from their childhood to mid-career age. The final sample size is 6605 for the education outcome and 1272 for the labor outcome.

For the treatment, we identify children who were in a household that has moved since the previous round of survey when they are between ages 6 and 18. We adopt a binary treatment indicating whether the children have experienced moving and a linear treatment indicating the total number of family relocations when the child was between the ages of 6 and 18.

The instrument we use in the main analysis is the mother's age when giving birth to the child. This data is acquired by matching each child to its mother using the household identifier and then calculating the age of the mother when the child is at the age of five.

The outcome variables we extracted from the survey are as follows:

- Educational Attainment: The children's educational attainment taken at the age of 27 (measured by years of schooling).
- Income: All available income of the child from young adulthood (25 yrs) to mid-career age (35 yrs). The extracted list of incomes is then converted to $Income25-30$, $Income25-35$, and $Income30-35$, measuring the partial average of the child's income during the corresponding ages.

The covariates that may influence children's education attainment and future income include:

- Child's race and gender, recorder with the dummy *white* and *male*.
- Child's birth cohort
- Child's age when moving
- Both parents' available incomes when the child was between ages 0 and 5. [1]
- Parents' education attainment
- Living state and region of the household head for all covered years. [2]

4 Results

4.1 Education outcome

Table 1: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
has moved	6,605	13.572	2.252	1	17
education	6,605	13.572	2.252	1	17
education (father)	6,605	13.034	2.608	1	17
education (mother)	6,605	13.181	2.281	3	17
male	6,605	0.519	0.500	0	1
white	6,605	0.643	0.479	0	1
age	6,605	8.295	3.182	6	18
family income	6,605	19,261.380	16,020.020	2,007.000	99,000.000
year at 5yrs old	6,605	1,981.768	8.247	1,968	2,009

Table 2 presents our estimated average treatment effects of a child's moving experience on his / her educational attainment. We specify the outcome variable as the educational attainment of the child when he/she is 27 years old or above. *age* captures the age of the child when the family moved. We measure family income using the partial average of the sum of parents' income during the child's age 0 to 5.

As reported in column (1), when coarsely regressing on the treatment dummy *has moved* with the child's birth cohort and the living state at the age of five as fixed effects, the estimated coefficient is negative and significant. As we add demographic controls and controls on households' characteristics, the magnitude of the coefficient continues to shrink and lose a bit of its power but remains negative and significant. The regression results reported in column (3) indicate that a child's experience of family mobility during the years 6 to 18 is associated with a 0.176 decrease in the child's future educational attainment. It is also found that the child being male is associated with 0.57 fewer years of schooling. Moreover, family income and both parents' years of education are positively and significantly associated with the child's educational attainment.

[1] We measure family income for each year as the sum of parental incomes. Then we take the five-year partial average of all sensible family incomes (larger than 200) as the control for pre-treatment family wealth.

[2] These two variables also allow us to identify cross-state- and cross-region-relocation.

To investigate the potential heterogeneous effects of moving experience, we start by interacting the treatment dummy with *male* and *age*, respectively, in columns (4) and (5). The results show that there are no significant heterogeneous effects on the sex of a child but strong heterogeneous effects on children's moving age. Column (5) indicates that children of younger age are more vulnerable to the mobility experience as far as educational attainment is concerned.

Table 2: Effects on Education Attainment

	Dependent variable: Education Attainment				
	(1)	(2)	(3)	(4)	(5)
has moved	-0.475^{***}	-0.382^{***}	-0.176^{**}	-0.194^{*}	-1.134^{***}
	(0.057)	(0.089)	(0.085)	(0.106)	(0.191)
white		0.521^{***}	-0.041	-0.041	-0.028
		(0.086)	(0.087)	(0.087)	(0.086)
male		-0.549^{***}	-0.568^{***}	-0.590^{***}	-0.565^{***}
		(0.051)	(0.052)	(0.079)	(0.053)
log(family income)			0.690^{***}	0.690^{***}	0.656^{***}
			(0.052)	(0.052)	(0.051)
education (father)			0.145^{***}	0.145^{***}	0.145^{***}
			(0.014)	(0.014)	(0.015)
education (mother)			0.178^{***}	0.178^{***}	0.181^{***}
			(0.017)	(0.017)	(0.017)
has moved×male				0.034	
				(0.095)	
age					-0.145^{***}
					(0.020)
has moved×age					0.128^{***}
					(0.023)
Age dummies	No	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	6,605	6,605	6,605	6,605	6,605
R^2	0.105	0.136	0.270	0.270	0.271
Adjusted R^2	0.093	0.124	0.259	0.259	0.261
Note:					*p<0.1; **p<0.05; ***p<0.01

To see detailed breakdowns of the heterogeneous treatment effects, we add a series of age group dummies after dividing the age groups as 6 to 8-year-olds, 9 to 12-year-olds, 13 to 15-year-olds, and 16 to 18-year-olds. Table 3 reports the regression results with and without interacting age group dummies with the treatment dummy. The coefficients of the interactions for age group 6 to 8-year-olds are negative and statistically significant, suggesting that children of age 6 to 8 are particularly vulnerable.

Table 3: Effects on Education Attainment: Heterogeneity on Age Group

	Dependent variable: Education Attainment	
	(1)	(2)
has moved	-0.236^{***}	0.589^{*}
	(0.077)	(0.320)
age 6-8	0.376^{***}	1.136^{***}
	(0.135)	(0.276)
age 9-12	0.332^{**}	-0.299
	(0.131)	(0.363)
age 13-15	-0.097	-0.133
	(0.185)	(0.345)
has moved×age 6-8		-0.995^{***}
		(0.311)
has moved×age 9-12		0.532
		(0.396)
has moved×age 13-15		-0.014
		(0.398)
Baseline Controls	Yes	Yes
Birth Year FE	Yes	Yes
State FE	Yes	Yes
Observations	6,605	6,605
R^2	0.267	0.273
Adjusted R^2	0.257	0.262
Note:		*p<0.1; **p<0.05; ***p<0.01

4.1.1 IV identification

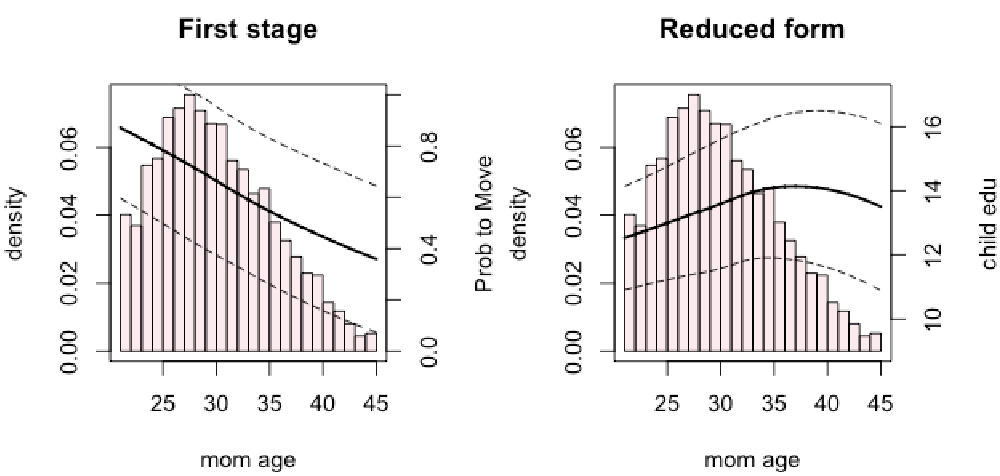

Figure 1: Effect of Mother's Age on Probability to Move (First Stage) and Children's Education Attainment (Reduced Form)

In Figure 1, we present a graphical representation of our IV approach using the mother's age when the child was five years old. In the background of each graph is a histogram of the density of the mother's age. The mean of the mother age variable is 30.73, with a standard deviation of 5.47.

Plot on $First\,stage$ shows the effect of younger mothers on the probability of relocation. The graph is a flexible analog to the first-stage equation, where we plot a local linear regression of actual moving status against the mother's age, with full control of demographic and household financial characteristics, and with birth year, living state fixed effects. The probability of moving is monotonically declining in our mother's age measure and is close to linear.

Plot on $Reduced\,form$ displays the reduced-form effect of a five-year-old child's mother's age against the child's future educational attainment, again using local linear regression with the full set of controls and fixed effects. The child's educational attainment is monotonically increasing in the mother's age for the first 80th percentile of the mother's age while slightly skewed downwards. Dashed lines represent 90% confidence intervals.

Table 4: Effects on Education Attainment: Mother's age as IV

	Dependent variable: Education Attainment		
	OLS	1st stage	2nd stage
has moved	-0.176^{**}		-1.392^{***}
	(0.085)		(0.415)
mother's age		-0.014^{***}	
		(0.001)	
male	-0.568^{***}	-0.008	-0.576^{***}
	(0.052)	(0.010)	(0.048)
white	-0.041	0.027	-0.006
	(0.087)	(0.022)	(0.081)
log(family income)	0.690^{***}	-0.082^{***}	0.542^{***}
	(0.052)	(0.011)	(0.073)
education (father)	0.145^{***}	0.002	0.151^{***}
	(0.014)	(0.004)	(0.016)
education (mother)	0.178^{***}	0.002	0.180^{***}
	(0.017)	(0.003)	(0.019)
Age dummies	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	6,605	6,605	6,605
R^2	0.270	0.364	0.226
Adjusted R^2	0.259	0.354	0.215
F Statistic (df = 99; 6505)	24.289***	37.612***	22.988***
Note:	*p<0.1; **p<0.05; ***p<0.01		

The first column in Table 4 is a recall of our baseline model estimated under OLS regression. The second column reports first-stage estimates, which regress a dummy variable for whether the family moved when the child was 6-18 with a full set of controls and fixed effects included. The coefficient implies that when a child's mother was one year younger, the probability of the child experiencing family mobility during 6-18 years old will increase by 1.4 percentage points. The third column reports the IV estimate, indicating that family mobility during a child's age 6-18 lowers the child's educational attainment by 1.39 years on average. The effect is both statistically and economically significant.

4.2 Labor outcome

Extending on the education outcome, we conducted additional analysis to understand how moving experience may influence the labor outcome. The baseline empirical model of OLS and 2SLS remains the same as Equation (1) - (3), with the only difference in the outcome variable being the average taxable income of the children between 25 and 35 years old.

Table 5 describes the sample we used to investigate the effect of childhood residential mobility on long-run income. Note that due to the data deficiency of income data in the years between 1994 and 2003, we only have 1272 observations. The sampling is thus biased towards individuals in earlier birth cohort, and we have more observations of income before than after 30 years old, which may further bias the average income level.

Table 5: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
income 25-35	1,272	18,570.25	13,964.49	130.00	115,000.00
has moved	1,272	0.62	0.48	0	1
education (child)	1,272	13.94	2.01	8	17
family income	1,272	16,386.55	15,984.33	411.00	131,361.00
education (father)	1,272	12.50	2.76	3	17
education (mother)	1,272	12.81	2.27	3	17
mother's age	1,272	31.72	5.83	21	48
male	1,272	0.54	0.50	0	1
white	1,272	0.61	0.49	0	1
age	1,272	7.94	2.94	6	18
year at 5yrs old	1,272	1,977.79	9.67	1,968	1,997

We conducted similar OLS regression and heterogeneity analysis as in Tables 2 and 3 for labor outcome. As shown in Table 6, compared with education outcomes, we found similar patterns but less significant results in the baseline model for labor outcomes. However, interestingly, we observe an opposite effect across age groups from the results on education attainment. As shown in Table 7, the coefficient of the interactions for age group 6-to-8-year-olds is positive, suggesting that in terms of future income, children of age 6-8 are less negatively impacted by moving.

4.2.1 IV identification

Figure 2 is, again, the graphical representation of our IV approach. In the background of each graph is a histogram for the density of the mother's age at the time that the child was five years old. The mean of the mother age variable is 31.72, with a standard deviation of 5.83.

Plot on $First\,stage$ shows the effect of younger mothers on the probability of relocation. With a full set of baseline controls, the local linear regression of actual moving status against the mother's age can be viewed as representing the first-stage estimation equation (2). Dashed lines still represent 90% confidence intervals. The first stage within this sample is still monotonically declining in our mother's age measure yet with a wider confidence interval.

Plot on $Reduced\,form$ displays the reduced-form effect of a five-year-old child's mother's age against

Table 6: Effects on Long-run Income

	Dependent variable: log(income 25-35)				
	(1)	(2)	(3)	(4)	(5)
has moved	−0.179***	−0.133**	−0.120*	−0.079	0.192
	(0.053)	(0.065)	(0.065)	(0.085)	(0.208)
age					0.041
					(0.029)
log(family income)		0.171***	0.163***	0.162***	0.162***
		(0.041)	(0.041)	(0.041)	(0.042)
education (mother)		0.049***	0.050***	0.050***	0.049***
		(0.013)	(0.014)	(0.014)	(0.014)
education (father)		0.039***	0.037***	0.036***	0.036***
		(0.011)	(0.011)	(0.011)	(0.012)
male		0.301***	0.301***	0.346***	
		(0.049)	(0.049)	(0.079)	
white		0.136**	0.114**	0.116**	0.121**
		(0.053)	(0.057)	(0.058)	(0.058)
has moved:male				−0.074	
				(0.101)	
has moved:age					−0.042
					(0.030)
Age dummies	No	Yes	Yes	Yes	No
Birth Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	Yes	Yes
Observations	1,272	1,272	1,272	1,272	1,272
R^2	0.040	0.159	0.165	0.165	0.136
Adjusted R^2	0.019	0.129	0.132	0.131	0.110
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 7: Effects on Long-run income: Heterogeneity on Age Group

	Dependent variable: log(income 25-35)			
	(1)	(2)	(3)	(4)
has moved	−0.080	−0.608**	−0.108*	−0.513
	(0.052)	(0.296)	(0.056)	(0.406)
age 6-12	0.010	−0.492*		
	(0.082)	(0.289)		
has moved:age 6-12		0.547*		
		(0.302)		
age 6-8			−0.003	−0.377
			(0.129)	(0.385)
age 9-12			0.092	−0.299
			(0.138)	(0.575)
age 13-15			0.021	0.257
			(0.158)	(0.575)
has moved:age 6-8				0.426
				(0.410)
has moved:age 9-12				0.433
				(0.593)
has moved: age 13-15				−0.227
				(0.601)
Controls	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	1,272	1,272	1,272	1,272
R^2	0.161	0.163	0.162	0.164
Adjusted R^2	0.136	0.137	0.136	0.136

Note: *p<0.1; **p<0.05; ***p<0.01

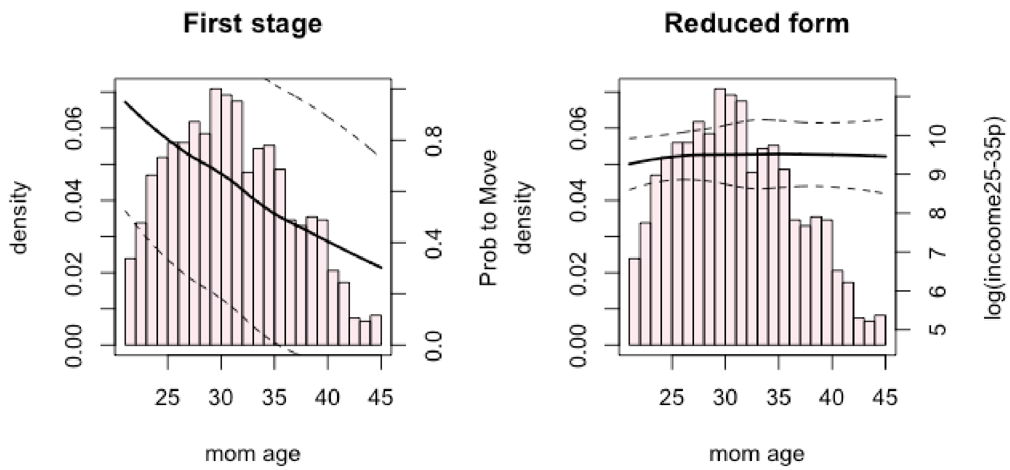

Figure 2: Effect of Mother's Age on Probability to Move (First Stage) and Children's Long-run Income (Reduced Form)

the child's future income between 25 and 35 years old. Using the same plotting strategy, the child's income level remains rather flat, and we do not observe a significant increasing trend as in the sample for analyzing education attainment.

The first column in Table 8 repeats our baseline OLS model with a slight decrease in sample size constrained by data availability of the mother's age. Column (2) reports the first stage of the mother's age as the instrument. It can be shown that a younger mother is associated with a higher probability of moving. The coefficient implies that when a child's mother was one year younger, the probability of the child experiencing family mobility during 6-18 years old will increase by 1.5 percentage points. Column (3) in Table 8 reports the 2SLS estimates using the mother's age as the instrument. The estimated coefficient gives a positive sign with a high standard error.

To account for the potential non-linearity of the treatment of the instrument, we split the mother's age into small subgroups. As shown in Table 18, we found that the treatment effect is only prominent among ages between 23 and 30 (mothers given birth to children between 18 and 25) and ages larger or equal to 35. Among them, the younger age group positively correlated with the probability of moving, and the older age group had a negative correlation with moving, which aligns with our expectations. We then ran another 2SLS estimation using the mother's age between 23-30 as a dummy. As shown in column (5), the estimated coefficient on the treatment dummy gives a negative yet non-significant result. Just by observing the magnitude of the estimates, we also find 2SLS estimates to be larger than the OLS baseline result. This is consistent with our analysis of education outcomes, but the inflating effect of bias correction is less strong.

We also conducted a similar 2SLS analysis using the number of states or regions the household head lived in when the child was five years old, but neither of them give a strong first stage.

Table 8: Effects of Mobility on Long-run Income: Mother's age as IV

	Dependent variable: log(income 25-35)				
	OLS	1st stage	2nd stage	1st stage	2nd stage
	(1)	(2)	(3)	(4)	(5)
has moved	−0.120*		0.091		−0.191
	(0.065)		(0.303)		(0.338)
mother's age		−0.015***			
		(0.002)			
mother's age within 23-30				0.150***	
				(0.022)	
log(family income)	0.163***	−0.084***	0.189***	−0.094***	0.154***
	(0.041)	(0.018)	(0.055)	(0.018)	(0.058)
education (mother)	0.050***	0.002	0.049***	0.001	0.050***
	(0.014)	(0.006)	(0.014)	(0.006)	(0.014)
education (father)	0.037***	−0.007	0.037***	−0.004	0.037***
	(0.011)	(0.005)	(0.011)	(0.005)	(0.011)
male	0.301***	0.014	0.297***	0.013	0.303***
	(0.049)	(0.021)	(0.049)	(0.021)	(0.049)
white	0.114**	0.021	0.110*	0.015	0.115**
	(0.057)	(0.025)	(0.058)	(0.025)	(0.058)
Age dummies	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1,272	1,272	1,272	1,272	1,272
R^2	0.165	0.454	0.157	0.449	0.164
Adjusted R^2	0.132	0.433	0.124	0.427	0.131
F Statistic (df = 48; 1223)	5.017***	21.214***	4.905***	20.759***	4.947***

Note: *p<0.1; **p<0.05; ***p<0.01

4.3 Alternative Specifications and Auxiliary Analysis

4.3.1 Number of times moved

In Table 9, we identify the number of moves the child experienced during the ages 6 to 18 and denote it as *move times*. Column (2) and (3) reports the OLS regression results on *move times* with and without a square term. The estimation of *move times* is negative and significant, indicating that one additional moving experience is associated with a 0.087 decrease in years of schooling. The estimation with the square of the number-of-move is positive but not significant. In column (4), we add four dummies to explore the treatment effects of different numbers of moves. The variable $move1$ indicates the child has one moving experience in total, and the variable $move4+$ indicates the child has more than three moving experiences. The regression results suggest that children living in families with frequent moving have an average of fewer years of schooling. For example, children who experience three times moving attain 0.386 fewer years of schooling than those who never move. Moreover, moving only once seems to be associated with slightly more years of schooling, but the estimation is not significant.

We then conduct parallel analysis for labor outcomes. In Table 10, we report the regression results using *move times* as the target variable. Baseline OLS results are in Columns (1) to (3). The estimation of *move times* is negative and significant, indicating that one additional moving experience is associated with a 2.9% decrease in income. Column (4) aims to investigate the second-order relationship between moving times and long-run income. The estimation with the square of the number-of-move is positive but with a very small magnitude and not significant. In column (5), we decompose the number of moving times and explore the treatment effects of different numbers of moves. The regression results suggest that children living in families with frequent moving have an average of lower future income. For example, children who experience moving twice have 19.4% less income than those who have never moved. However, such an effect is more noisy for children who have moved three times.

Table 11 repeats the 2SLS analysis on labor outcome as in using the dummy treatment variable *hasmoved*. The negative relationship persists but the magnitude of the 2SLS estimates becomes slightly below the OLS estimate. We also note that, the F-statistics of the first stage decreases significantly, making the results less reliable.

4.3.2 Move across states or regions

Table 12 and 13 reports the results when regressing education and income respectively on *has moved* from five different samples with the same control group (households that never move) but different treatment groups as in the full sample, the sample of households that move across states, the sample of households that move within states, the sample of households that move across regions and a sample of households that move within regions.

Table 12 shows a distinctive difference in the treatment effects between the across-states vs. within-states and the across-regions vs. within-regions, demonstrating that long-distance relocation is linked to higher educational attainment. For instance, Columns (4) and (5) indicate that children whose families relocated across regions likely have 0.47 more years of education than their peers

Table 9: Effects of Number of times moved on Education Attainment

	Dependent variable: Education Attainment			
	(1)	(2)	(3)	(4)
has moved	-0.176^{**}			
	(0.085)			
move times		-0.087^{***}	-0.098^{**}	
		(0.018)	(0.042)	
move times squared			0.002	
			(0.005)	
move1				0.150
				(0.098)
move2				-0.264^{**}
				(0.108)
move3				-0.386^{***}
				(0.110)
move4+				-0.351^{***}
				(0.108)
male	-0.568^{***}	-0.569^{***}	-0.568^{***}	-0.565^{***}
	(0.052)	(0.050)	(0.050)	(0.051)
white	-0.041	-0.027	-0.027	-0.031
	(0.087)	(0.085)	(0.085)	(0.086)
log(family income)	0.690^{***}	0.645^{***}	0.644^{***}	0.643^{***}
	(0.052)	(0.051)	(0.051)	(0.053)
education (father)	0.145^{***}	0.145^{***}	0.145^{***}	0.146^{***}
	(0.014)	(0.014)	(0.014)	(0.014)
education (mother)	0.178^{***}	0.180^{***}	0.180^{***}	0.180^{***}
	(0.017)	(0.017)	(0.017)	(0.017)
Age dummies	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	6,605	6,605	6,605	6,605
R^2	0.270	0.274	0.274	0.276
Adjusted R^2	0.259	0.262	0.262	0.264

Note: *p<0.1; **p<0.05; ***p<0.01

Table 10: Effects of Number of times moved on Long-run Income

	Dependent variable: log(income 25-35)				
	(1)	(2)	(3)	(4)	(5)
move times	−0.048***	−0.029**	−0.027**	−0.052	
	(0.013)	(0.013)	(0.014)	(0.036)	
move times squared				0.004	
				(0.005)	
move1					−0.033
					(0.085)
move2					−0.194**
					(0.088)
move3					−0.101
					(0.094)
move4+					−0.147*
					(0.082)
log(family income)		0.163***	0.155***	0.153***	0.153***
		(0.042)	(0.042)	(0.042)	(0.042)
education (mother)		0.050***	0.050***	0.050***	0.050***
		(0.013)	(0.014)	(0.014)	(0.014)
education (father)		0.039***	0.037***	0.037***	0.037***
		(0.011)	(0.011)	(0.011)	(0.011)
male		0.302***	0.302***	0.302***	0.301***
		(0.049)	(0.049)	(0.049)	(0.049)
white		0.139***	0.117**	0.116**	0.114**
		(0.053)	(0.058)	(0.058)	(0.058)
Age dummies	No	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	Yes	Yes
Observations	1,272	1,272	1,272	1,272	1,272
R^2	0.042	0.160	0.165	0.165	0.167
Adjusted R^2	0.020	0.129	0.132	0.132	0.132
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 11: Effects of Mobility on Long-run Income: Mother's age as IV

	Dependent variable: log(income 25-35)				
	OLS	1st stage	2nd stage	1st stage	2nd stage
	(1)	(2)	(3)	(4)	(5)
move times	−0.027**				
	(0.014)				
mother's age		−0.077***	0.017		
		(0.009)	(0.058)		
mother's age_23-30				0.839***	−0.034
				(0.104)	(0.060)
log(family income)	0.155***	−0.631***	0.192***	−0.676***	0.149**
	(0.042)	(0.087)	(0.063)	(0.086)	(0.065)
education (mother)	0.050***	0.035	0.049***	0.029	0.050***
	(0.014)	(0.028)	(0.014)	(0.028)	(0.014)
education (father)	0.037***	−0.020	0.036***	−0.007	0.037***
	(0.011)	(0.024)	(0.012)	(0.024)	(0.011)
male	0.302***	0.084	0.297***	0.078	0.303***
	(0.049)	(0.100)	(0.049)	(0.100)	(0.049)
white	0.117**	0.200*	0.108*	0.166	0.118**
	(0.058)	(0.118)	(0.059)	(0.118)	(0.059)
Age dummies	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1,272	1,272	1,272	1,272	1,272
R^2	0.165	0.234	0.158	0.229	0.165
Adjusted R^2	0.132	0.204	0.124	0.199	0.132
F Statistic (df = 48; 1223)	5.031***	7.774***	4.906***	7.577***	4.953***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: Effects on Education outcome: Subgroup of whether moved across states/regions

	Dependent variable: Education Attainment				
	(1)	(2)	(3)	(4)	(5)
has moved	−0.176**	0.177*	−0.198**	0.285***	−0.189**
	(0.085)	(0.095)	(0.095)	(0.103)	(0.094)
male	−0.568***	−0.548***	−0.593***	−0.574***	−0.579***
	(0.052)	(0.064)	(0.063)	(0.064)	(0.060)
white	−0.041	0.159	−0.083	0.169	−0.076
	(0.087)	(0.100)	(0.091)	(0.112)	(0.090)
log(fam_income)	0.690***	0.624***	0.694***	0.627***	0.696***
	(0.052)	(0.075)	(0.051)	(0.071)	(0.054)
dad_edu	0.145***	0.146***	0.133***	0.145***	0.135***
	(0.014)	(0.024)	(0.015)	(0.023)	(0.016)
mom_edu	0.178***	0.178***	0.183***	0.170***	0.187***
	(0.017)	(0.022)	(0.019)	(0.024)	(0.018)
Type of move	Full sample	Across state	Within state	Across region	Within region
Age dummies	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	6,605	3,243	5,682	3,034	5,891
R^2	0.270	0.291	0.271	0.299	0.269
Adjusted R^2	0.259	0.269	0.258	0.276	0.257
Note:				*p<0.1; **p<0.05; ***p<0.01	

whose families relocated within areas. This finding is particularly intriguing as it may suggest different associated mechanisms of family mobility on children's educational attainment. Moreover, these results seem to be countering the theoretical arguments pointing to the negative effects of network destruction caused by relocation. Further research into the relationship between relocating distance and family wealth would be worth exploring.

However, as seen in Table 13, this distinction is less pronounced when considering labor outcomes. As we noted in the discussion, the estimation's precision is compromised by the omitted variable bias as well as our noisy measurement of labor outcomes.

4.3.3 Reasons to move

Table 14 and 15 shows the baseline OLS regression results using different subgroups moved for different reasons. Column (1) in both tables shows a positive but non-significant association between moving and children's outcomes. As for moving for consumption reasons, we find that there is a negative yet insignificant relationship between moving and education attainment or income. As expected, moving due to outside force seems to be especially detrimental for long-run income and education outcomes. Although we lack enough statistical power to make firm conclusions on such relationships, it is a starting point and motivates further study on different mechanisms of moving and their long-term effects.

Table 13: Effects on Labor outcome: Subgroup of whether moved across states/regions

	Dependent variable: log(income 25-35)				
	(1)	(2)	(3)	(4)	(5)
has moved	−0.120*	−0.088	−0.118*	−0.118	−0.110
	(0.065)	(0.116)	(0.070)	(0.134)	(0.069)
log(family income)	0.163***	0.194***	0.163***	0.209***	0.156***
	(0.041)	(0.058)	(0.048)	(0.064)	(0.046)
education (mother)	0.050***	0.059***	0.049***	0.059***	0.049***
	(0.014)	(0.020)	(0.015)	(0.021)	(0.014)
education (father)	0.037***	0.019	0.033***	0.013	0.037***
	(0.011)	(0.016)	(0.013)	(0.017)	(0.012)
male	0.301***	0.219***	0.355***	0.251***	0.341***
	(0.049)	(0.067)	(0.053)	(0.070)	(0.051)
white	0.114**	0.037	0.149**	0.078	0.133**
	(0.057)	(0.084)	(0.063)	(0.089)	(0.062)
Type of move	Full sample	Across state	Within state	Across region	Within region
Age dummies	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1,272	629	1,122	594	1,157
R^2	0.165	0.197	0.172	0.198	0.172
Adjusted R^2	0.132	0.132	0.135	0.129	0.136
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 14: Effects on Education outcome: Subgroup based on moving reason

	Dependent variable: educational attainment			
	(1)	(2)	(3)	(4)
has moved	0.167	−0.132	−0.151	0.063
	(0.112)	(0.087)	(0.140)	(0.142)
log(family income)	0.610***	0.726***	0.495***	0.595***
	(0.092)	(0.059)	(0.092)	(0.078)
education (father)	0.154***	0.130***	0.135***	0.136***
	(0.021)	(0.018)	(0.026)	(0.025)
education (mother)	0.187***	0.167***	0.200***	0.189***
	(0.026)	(0.019)	(0.023)	(0.023)
male	−0.572***	−0.600***	−0.616***	−0.586***
	(0.077)	(0.057)	(0.080)	(0.073)
white	0.049	−0.067	0.139	0.142
	(0.121)	(0.101)	(0.100)	(0.123)
Reason for moving	Production	Consumption	Outside force	Other
Age dummies	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	2,987	4,836	2,842	2,760
R^2	0.291	0.268	0.307	0.303
Adjusted R^2	0.266	0.253	0.281	0.277
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 15: Effects on Labor outcome: Subgroup based on moving reasons

	Dependent variable: log(income 25-35)			
	(1)	(2)	(3)	(4)
has moved	0.104	−0.104	−0.370***	−0.082
	(0.107)	(0.078)	(0.141)	(0.144)
log(family income)	0.209***	0.188***	0.174**	0.153**
	(0.066)	(0.049)	(0.074)	(0.072)
education (mother)	0.059***	0.043***	0.065***	0.064***
	(0.020)	(0.016)	(0.022)	(0.021)
education (father)	0.021	0.026*	0.018	0.008
	(0.016)	(0.013)	(0.018)	(0.018)
male	0.334***	0.287***	0.334***	0.297***
	(0.067)	(0.056)	(0.077)	(0.072)
white	0.135	0.100	0.095	0.104
	(0.088)	(0.067)	(0.098)	(0.095)
Reason for moving	Production	Consumption	Outside force	Other
Age dummies	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	624	964	559	557
R^2	0.223	0.166	0.252	0.208
Adjusted R^2	0.160	0.122	0.184	0.135
Note:				*p<0.1; **p<0.05; ***p<0.01

5 Discussion

5.1 Comparison between IV and OLS results

For both sets of analysis on the education and labor outcome, the OLS regression coefficients are smaller than the 2SLS estimates. Such difference is especially pronounced for education attainment, with OLS estimates accounting for around one-eighth of the 2SLS estimates. The implication of the difference can be explained as follows:

- Omitted variable bias (OVB): Using an instrument helps correct the OVB of the empirical model. A more significantly negative result implies that omitted variables cause a large positive bias. This is likely to happen if the motivation for moving is mainly related to improving living and production quality, which further contributes to children's future outcomes.
- Measurement error: As IV corrects the attenuation bias of the measurement error of the treatment variable, it is also likely to have a 2SLS estimate with a larger magnitude.

For labor outcome analysis, our baseline OLS estimate is negative and significant, which is consistent with previous studies such as Heidrich (2016). However, the linear IV results give us positive and insignificant results and the binary IV shows a larger negative yet insignificant result. Although it is possible that the insignificance is caused by the noisy measure for income, we cannot rule out the explanation that there are no long-run costs of residential relocation during childhood that permeate the future income.

5.2 Interpretation of linear IV estimand

In the regression results of education outcome, as we use a linear IV, it is difficult to directly interpret the results as the local average treatment effect (LATE) for compliers. Following Dahl et al. (2014)'s discussion of comparing the LATE and OLS interpretation, the linear IV estimand can be decomposed to evenly stepped subgroups and collectively enter an over-identified model estimated using 2SLS regression. Theoretically, the 2SLS regression should produce the same results as the just-identified model. Table 16 and Table 18 display the first stage of our decomposed IV's. For education outcome analysis, we then use the three subgroups, each as a separate dummy instrument, to re-estimate the model. As shown in Table 17, the coefficients remain negative but lose some statistical power. This reveals that our IV results may still be valid for investigating the effects on education outcomes. For labor outcome, it can be seen that although used as a linear IV, the effect of the mother's age on moving is more like an inversed U-shape for the subsample investigating the effect, possibly leading to the insignificant result in Table 8 column (3). Hence, we conducted further analysis in Table 8, column (4)-(5), as mentioned in previous sections, to estimate the empirical model and gain consistent results.

Table 16: Sample for education attainment - First stage: Discretized Mother's age

	Dependent variable: has moved			
	(1)	(2)	(3)	(4)
mother's age group	0.122***	0.057***	−0.022*	−0.118***
	(0.018)	(0.014)	(0.012)	(0.012)
log(family income)	−0.106***	−0.114***	−0.120***	−0.103***
	(0.011)	(0.011)	(0.011)	(0.010)
education (father)	0.005	0.005	0.005	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
education (mother)	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
male	−0.006	−0.007	−0.007	−0.007
	(0.010)	(0.011)	(0.010)	(0.010)
white	0.030	0.027	0.028	0.026
	(0.021)	(0.022)	(0.022)	(0.022)
Mom's age group	20-24	25-29	30-34	35+
Age dummies	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	6,605	6,605	6,605	6,605
R^2	0.351	0.348	0.345	0.355
Adjusted R^2	0.341	0.338	0.335	0.345
F Statistic	35.511***	34.995***	34.607***	36.089***
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 17: Effects on education attainment: Mother's age (discrete) as IV

	Dependent variable: educational attainment					
	1st stage	*2nd stage*	*1st stage*	*2nd stage*	*1st stage*	*2nd stage*
has moved		−0.999		−1.901*		−1.315
		(0.837)		(1.003)		(3.345)
mother's age_20-24	0.122***					
	(0.018)					
mother's age_25-29			0.057***			
			(0.014)			
mother's age_30-34					−0.022*	
					(0.012)	
log(family income)	−0.106***	0.590***	−0.114***	0.480***	−0.120***	0.551
	(0.011)	(0.122)	(0.011)	(0.125)	(0.011)	(0.414)
education (father)	0.149***	0.005	0.154***	0.005	0.151***	
	(0.004)	(0.016)	(0.004)	(0.018)	(0.004)	(0.027)
education (mother)	0.002	0.180***	0.002	0.181***	0.002	0.180***
	(0.003)	(0.018)	(0.003)	(0.019)	(0.003)	(0.018)
male	−0.006	−0.573***	−0.007	−0.579***	−0.007	−0.575***
	(0.010)	(0.049)	(0.011)	(0.048)	(0.010)	(0.054)
white	0.030	−0.017	0.027	0.008	0.028	−0.008
	(0.021)	(0.084)	(0.022)	(0.082)	(0.022)	(0.136)
Age dummies	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,605	6,605	6,605	6,605	6,605	6,605
R^2	0.351	0.250	0.348	0.182	0.345	0.232
Adjusted R^2	0.351	0.250	0.348	0.182	0.345	0.232

Note: *p<0.1; **p<0.05; ***p<0.01

Table 18: Sample for Average Income - First stage: Discretized Mother's age

	Dependent variable: has moved				
	(1)	(2)	(3)	(4)	(5)
mother's age group	−0.009	0.170***	0.053**	-0.009	− 0.162***
	(0.070)	(0.028)	(0.025)	(0.026)	(0.023)
log(family income)	−0.123***	−0.101***	−0.119***	−0.122***	−0.097***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
education (father)	0.0001	−0.003	−0.0004	0.0001	−0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
education (mother)	0.001	0.002	0.0005	0.001	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
male	0.021	0.016	0.020	0.021	0.013
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
white	0.019	0.012	0.019	0.019	0.018
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Mom's age group	20-22	23-26	27-30	31-34	35+
Age dummies	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	1,272	1,272	1,272	1,272	1,272
R^2	0.428	0.445	0.430	0.428	0.450
Adjusted R^2	0.406	0.423	0.408	0.406	0.428
F Statistic (df = 48; 1223)	19.068***	20.431***	19.234***	19.072***	20.812***

Note: *p<0.1; **p<0.05; ***p<0.01

5.3 Limitations of Data

There are several limitations that could potentially hazard our regression estimation and causal inference. Firstly, compared to the data availability of educational data, there are much fewer years of data available for the measurement of income. As we include the income measurement in the regression estimation, the sample size shrinks to below 2000 observations. For the income data that is provided, we remain doubtful about the validity of the measurement, especially when some individuals appear to have large fluctuations in some subsequent years. To try to remedy the issue, we filter out the income record with annual income below 200 dollars. Secondly, we are oversampling younger children in our regression since we are recording the child the first time he/she experienced family mobility. This could be a potential issue when interpreting regression coefficients related to a child's age. Thirdly, we couldn't find a more solid measurement of pre-treatment controls of the family. Relevant measures neighborhood quality measures are not available in the public data. It would be conducive to drawing stronger conclusions if we could gain access to more detailed geographical or private information and match the survey data with other data sources indicating the living neighborhood of the household and the neighborhood's mean income, the number of schools in the living region, or micro-level measurements such as the child's test results before the treatment period.

5.4 Limitations of the Instrument

We choose the instrumental variable approach as there are large sets of omitted variables that could potentially influence the outcome variables. Further, as we focus on the long-term effect, it would be inappropriate to consider exogeneity induced by a discontinuity or construct a difference-in-difference style design. However, there are still drawbacks to the instrument that we choose to use. Although the relevance (A5) assumption is tested valid, one might worry that the mother's age at birth does not fulfill the exclusion restriction (A6). It is possible that the age when the mother gives birth to the child reflects some aspects of the family education the child would have that would, in turn, influence education attainment and future income. For instance, there is a pronounced observational pattern where college-educated females would choose to invest in their education and career first before considering giving birth to their first child. In this sense, if the effect of older motherhood is mainly driven by these more accomplished females, the instrument would have an impact on children's future outcomes through the propensity of having a more well-educated mother. However, as our sample only includes children born before 2004, the potential concern may be partially eliminated.

5.5 Clustered standard error

The change of clustering would change the estimated standard error (SE) of regression coefficients. Across the analysis for education attainment as the outcome variable, we cluster the SE at the state level, which gives 50 clusters, fulfilling the rule of thumb of at least 30 - 50 clusters. On the other hand, for the sample investigating the effects on labor outcome, due to the smaller sample size, we only control for the region-fixed effects along with birth year fixed effects and moving age dummies. Because there are only four clusters, we deem the results to be too conservative. We also try cluster at the birth year (cohort) level, which gives 28 clusters. However, such clustering levels increase the standard errors significantly. We compares the change of estimated standard errors across different clustering levels. The increase in clusters does not bring a linear change in the magnitude of standard errors. The standard error is the largest when cluster at the level of children's age of moving. Having difficulties in understanding the reason behind this, in the above sections, we only reported the regression results with standard errors without clustered adjustment. We suspect that the small sample size leads to fairly noisy estimates. Although the negativity of the effect seems consistent across OLS and 2SLS analysis and under different specifications, we would have reservations in claiming these results to be robust. It would be of our future steps to look into the reasons and, if possible, seek other panel data to repeat the analysis.

6 Conclusion

Our baseline OLS regression results for education outcomes find that a child's experience with family mobility between the ages of 6 and 18 is connected with a 0.17-year decrease in the child's future educational achievement. We also find that children between the ages of 6 and 8 are particularly vulnerable to poor educational outcomes as a result of the ill effects of moving. This effect is corroborated by our IV analysis, where we conclude that when a child's mother was one year younger, the probability of the child experiencing family mobility during 6-18 years old will increase by 1.4 percentage points, furthering that family mobility during a child's age 6-18 lowers the child's educational attainment by 1.39 years on average.

The baseline OLS regression results for labor outcomes indicate that a child's experience of family mobility during the years 6 to 18 is associated with a 12.0% decrease in the child's income during ages 25 to 35 years. However, we find the opposite and quite noisy effect when considering the heterogeneity of age groups in labor outcomes. The coefficient of the interactions for the age group 6 to 8-year-olds and age group 9 to 12-year-olds are positive but not statistically significant. The interaction term becomes negative but also not significant for the age group 13 to 15-year-olds. Upon undertaking a discrete instrument, the first stage coefficient implies that when a child's mother is between 23 and 30 years old, the probability of the child experiencing family mobility between 6 and 18 years old will increase by 1.5 percentage points. The 2SLS coefficient on the treatment dummy for income outcomes shows a 19.1% decrease in the child's income, yet the result is statistically non-significant. Also, as expected, moving due to outside force manifests a larger negative effect on

The findings contribute to the literature in understanding the aggregate effects of childhood mobility experience on long-run education and labor outcomes. Concerning education outcomes, our results echo our first hypothesis that disruption due to moving induces negative effects on long-run outcomes and refute the second one, that the effect of disruption would be stronger for teenagers than younger children. In this sense, the findings shed light on the importance of childhood for human capital accumulation. With regard to long-run labor outcomes, we do not find a significant pattern of causal influence caused by childhood residential mobility. This could mean that existing family resources or investment in production skills during young adulthood may dilute the negative effects of moving on labor outcomes.

As the next steps to further this study, it would be important to understand the mechanism behind mobility-induced long-run effects. Specifically, one might consider investigating the dynamism between the decision to residential relocation and the resources that households possess, such as family wealth and personal networks. Only when the mechanism is well-established one may disentangle the effects of residential relocation and draw more constructive policy implications on how geographical relocation may influence the income distribution.

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