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Residential Mobility and Estimating its Effects on High School Graduation

Daniel Rowe
University of Cincinnati
Advisor: Dr. Michael Jones, PhD

Kautz-Uible Economics Institute
Carl H. Lindner College of Business
University of Cincinnati
2906 Woodside Drive
Cincinnati, OH 45221-0371

About the Author: Daniel Rowe

Daniel Rowe graduated from the University of Cincinnati Lindner College of business in December 2021, with majors in Business Economics and Business Analytics and a minor in French. He is interested in the use of analytics for equitable education policy and reform.

While at UC, Daniel studied abroad in Egypt, Greece, France, and Montreal; he also completed four co-op rotations to explore his interests in economics, education, and storytelling. He is now a Data Analyst with Possip, an organizational engagement company that primarily works with schools and educational organizations.

Daniel’s research explores the effects of residential mobility on high school graduation through multivariate linear regression using individual and family controls and multiple measures of mobility across a national dataset.

Section 1: Introduction and Literature Review

There are numerous factors that influence children's educational attainment. The investigation of these factors exists since the earliest forms of education, including parents in Shang dynasty China asking divination questions like, "is it auspicious for the children to go to school?" (Lee 2000). This fundamental question has been tweaked and expanded for thousands of years to determine if and how school affects children's outcomes. The advent of American education research was led by Horace Mann and Henry Barnard who pioneered the use of data collection and quantitative experiments to cement education as a science (Frey 2018). The quantitative approach has continued to provide important perspective on practices and situations and is how I approach the impact of residential mobility on educational attainment.

Many of the factors investigated by education researchers are at least somewhat impacted by the location(s) a child is raised. The neighborhood where a child grows up is one of the most important factors in social, psychological, and physical development. These neighborhood factors reflect an interconnected web of effects that results from the interactions people in a neighborhood with the institutions and other people in their community (Jencks 1990). Bronfenbrenner's ecological systems model pairs these neighborhood factors and family characteristics and is the base for much of the child development literature (Bronfenbrenner 1998). The home characteristics that are part of neighborhood factors are becoming a hot topic in urban and housing research across the globe. There is significant research that shows the impact that neighborhood factors and home characteristics in particular have on children's socio-economic development (Haurin 2002, Dietz 2003, Crowder 2011). One of the most popular areas of research is the myriad effects of homeownership., especially on educational achievement. Over the past 40 years, research finds the effects of homeownership positive, but small especially when more factors are considered. A major portion of the homeownership effect is housing tenure, which describes the length of stay in a particular residence and has been shown to reduce educational achievement (Aaronson 2000). Additionally, some of these studies used data from countries outside of the US, including France, Norway, France, and Taiwan. This paper contributes to the literature by examining updated data on the length of stay in a neighborhood on educational achievement in the United States

In this paper I analyze data from over 10,000 individuals over 40 years using regression models to investigate the effects that moving at different stages in childhood have on educational attainment. I conclude by discussing the implications of the findings.

Section 2: Economic Model

To measure adolescents' educational achievement, I examine a discrete variable - whether a person has graduated high school by the age of 19. There are arguments for other options such as academic grades or test scores to measure educational success (Kauppinen 2008). However, significant research has connected obtaining a high school diploma with later educational and economic success and is a necessary step in achieving a college degree which confers a large long-term economic value. Additionally, this dependent variable is used throughout the literature (Aaronson 2000, Chen 2010).

In this study, educational attainment of an individual is associated with childhood residential mobility while controlling for individual and family demographic factors. A typical specification model is described in Figure 1:

$$grad_i = \alpha m_i + \beta X_i + \tau_i + \varepsilon_i \quad (1)$$

Where $grad_i$ is the measure of individual i's educational attainment, m_i is the variable of interest describing a housing characteristic, in this case residential mobility, X_i is the vector of i's observed individual and family characteristics, τ_i represents the individual-specific unobservable characteristics affecting educational performance, such as individual aptitude and neighborhood factors, and ε_i represents the independent error term.

A major challenge to measuring the effect of the housing environment is the correlation between the variable and the error term. Eq. 2 shows how, if the model is not free from endogeneity, the regression results will likely be violated.

$$\alpha_i OLS = \alpha_i + \frac{cov(\tau, \beta\Sigma X_i)}{var(\tau_i)} + \frac{cov(\tau_i, \varepsilon_i)}{var(\tau_i)} \quad (2)$$

Unfortunately, in this case, the strength of the relationship between housing variables and education results would not be distinguishable due to omitted, unobservable variables. I attempt to address this by considering a vector of housing variables instead of just one variable:

$$grad_i = \alpha M_i + \beta X_i + \tau_i + \varepsilon_i \quad (3)$$

One strategy to address endogeneity is the use of instruments like Goux and Maurin (2005), however with a variety of variables this is hard due to the difficulty in selecting quality instruments with strong correlations to the endogenous explanatory variables; finding several high-quality instruments is a challenge and using low-quality instruments may lead to biased estimates (Baker 1995). By including a literature-based set of control variables, the likelihood of endogenous determination is lessened. In the analysis, controls cover the major sources of endogeneity identified in earlier studies: parental education, family wealth, family structure, race, and sex (Davidson 1993).

In this paper I use a linear probability model to estimate the effects of residential mobility because the results are generally similar to logit/probit models. However future research should also include these more accurate approaches (Perraillon 2019).

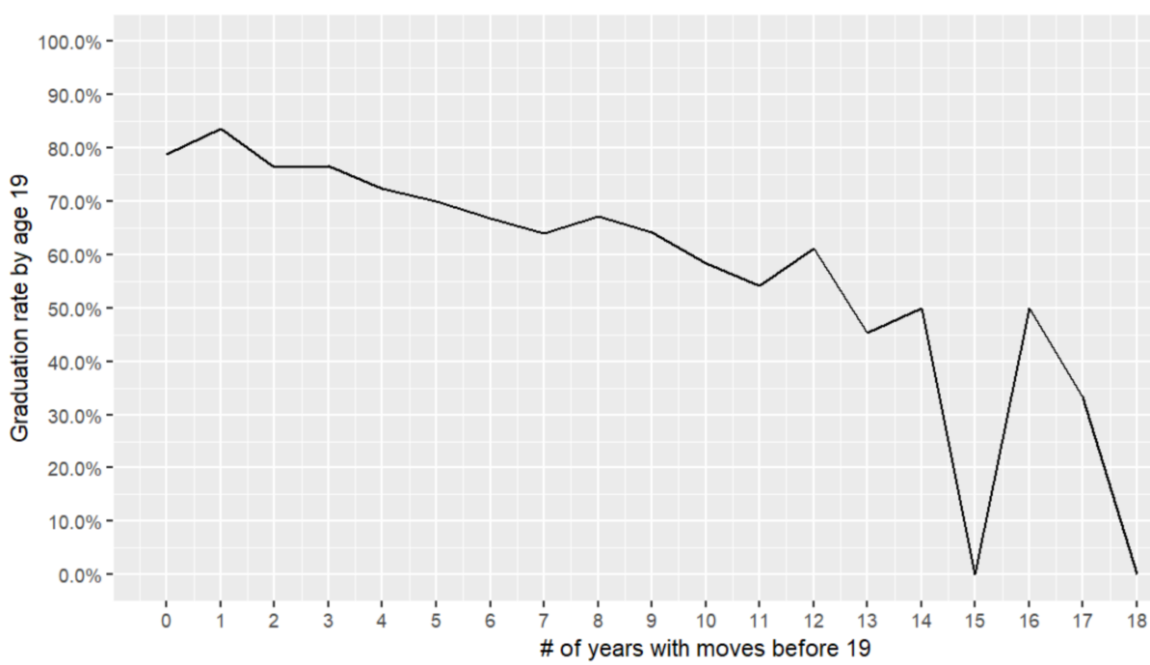
Section 3: Data

The data for the analysis comes from the Panel Study of Income Dynamics (PSID) from 1968 – 2019. The PSID is a longitudinal survey of American households that offers rich demographic controls for robust analysis with tens of thousands of individuals. The dependent variable is whether or not a person graduated from high school by the age of 19, not including GED. Those receiving GED's were not included because of the marked differences in economic and social outcomes between GED and high school diploma earners (Ou 2008). The PSID data is annually from 1969 – 1997 and from then on is conducted biannually for 1997 – 2019. After restrictions for clarity and robustness, the final sample used for analysis contains 10,382 individuals. This data set is reliably robust and is used in a similar analysis by Aaronson (Aaronson 2000). Considering this, it is important to define the primary variable of interest as the number of years with a move during childhood since the question from which the analysis is based asks if a person has moved since the last survey. Later in the methods section I will discuss how this is used to create the variables used in the analysis.

The data set was restricted on a number of variables to support complete and robust analysis. Since the earliest year with all control variables was 1968, only individuals born in that year or more recently were included to allow for full analysis of moves throughout childhood. Also, any individuals who did not either graduated high school or were 19 years or older in 2019 were excluded from the sample. Additionally, any person whose graduation year changed was removed since there was no way to determine the correct year.

Since the source of the data is a survey, not every person is reached every interview and therefore some data is missing, which impacts the formation of certain variables. The studied effect of number of years with a move during childhood experiences a downward bias because years where there was no survey are coded the same as if the survey was answered with the respondent having not moved. Figure 1 displays number of years with a move compared against likelihood of graduating by the age of 19 and shows that more moves have a negative correlation. At ten moves, there are less than 100 people in each bucket and the small sample sizes for these outlier move counts explain the significant variation. This means that the missing values push down the size of the estimated effect, so that the results can be interpreted as having an effect at least as large as estimated. Demographic variables are measured at birth to provide a consistent reference point.

Figure 1: Graduation Rate by # of years with moves before 19



These variables are 2 guardian household, family income, and presence of guardian high school dropout. For individuals who did not respond to the survey in their birth year, the nearest value after birth was used, so if someone born in 1985 had no survey response, their family income was computed from the 1986 response. Presence of high school dropout was used instead of other measures of parental education level because it captured the important indicator of high school success; many studies show that parental college education is predictive of children's college achievement, however in related literature there is mixed results on the impact of additional education beyond high school on high school achievement (Chen 2010, Lien 2008).

Two controls, race and family income at birth, were bucketed to ensure valid sample size and meaningful comparisons. Race is broken down into White, Black, and Other, where other is comprised of Hispanic, Asian, Native Hawaiian, Latino, American Indian, and others depending on the year of the survey. While it is important to consider these groups separately as there are certainly important factors for each, the structure of the survey questions size of the sample prohibits this analysis as only 3% of the individuals in the sample identify outside of White or Black. Family income at birth is bucketed into three groups: bottom, middle, and top. For each year, the family's income was ranked relative to other family incomes for that year into one of the three categories simply by thirds. This is to account for the disparity in nominal income across the 50 years. This approach is simpler to understand and implement than adjusting every income as this could be done by inflation, cost of living, etc.

Unlike some analyses, notably Aaronson's in 2000, I did not include dummy variables for time because of the sample size after I cleaned the data. Table 2 provides variable definitions and Figure 3 provides descriptive statistics for all of the variables used in the models.

Table 2: Variable Definitions

Variable Name	Source	Definition
Sex	PSID	The sex of the individual, male or female
Race	PSID	The race of the individual at birth, White, Black, or Other
MaritalStatus_AtBirth	PSID	Dummy variable for if the head of the household is married or cohabitating, if so, it is a 2-guardian household (HH)
FamIncome_AtBirth	PSID	The family income at birth, rank bucketed into thirds for each year
NoHS_Presence	Calculated	Dummy variable for if there is a guardian present in the household that did not finish high school
Graduatedby19	Calculated	Dummy variable for if the individual graduated by the age of 19
FirstMoveAge	Calculated	The age at which the individual first moved
LastMoveAge	Calculated	The age at which the individual last moved
MOVEDBEFORE_5	Calculated	Dummy variable for if the individual moved before the age of 5
MOVED_5_13	Calculated	Dummy variable for if the individual moved between the ages of 5 and 13
MOVED_13_19	Calculated	Dummy variable for if the individual moved between the ages of 13 and 19
MOVES0	Calculated	Dummy variable for if the individual never moved before the age of 19
MOVES1	Calculated	Dummy variable for if the individual moved once before the age of 19
MOVES2	Calculated	Dummy variable for if the individual moved twice times before the age of 19
MOVES3	Calculated	Dummy variable for if the individual moved three times before the age of 19

MOVES4	Calculated	Dummy variable for if the individual moved four times before the age of 19
MOVES5	Calculated	Dummy variable for if the individual moved five times before the age of 19
MOVES6	Calculated	Dummy variable for if the individual moved six times before the age of 19
MOVES7p	Calculated	Dummy variable for if the individual moved seven or more times before the age of 19

Figure 3: Data Set Summary
Dimensions: 8809 x 22

Variable	Stats / Values	Freqs (% of Valid)	Graph
Male [numeric]	Min: 0 Mean: 0.5 Max: 1	0 : 4570 (51.9%) 1 : 4239 (48.1%)	
Race [character]	1. Black 2. Other 3. White	3589 (40.7%) 702 (8.0%) 4518 (51.3%)	
TwoGuardianHH_NoHS [numeric]	Min: 0 Mean: 0.1 Max: 1	0 : 7690 (87.3%) 1 : 1119 (12.7%)	
TwoGuardianHH_OneHS [numeric]	Min: 0 Mean: 0.1 Max: 1	0 : 7710 (87.5%) 1 : 1099 (12.5%)	
TwoGuardianHH_TwoHS [numeric]	Min: 0 Mean: 0.3 Max: 1	0 : 6424 (72.9%) 1 : 2385 (27.1%)	
OneGuardianHH_NoHS [numeric]	Min: 0 Mean: 0.3 Max: 1	0 : 6145 (69.8%) 1 : 2664 (30.2%)	
OneGuardianHH_OneHS [numeric]	Min: 0 Mean: 0.2 Max: 1	0 : 7267 (82.5%) 1 : 1542 (17.5%)	
OneGuardianHH_TwoHS [numeric]	1 distinct value	0 : 8809 (100.0%)	
FamIncomeBucketed [character]	1. Bottom 2. Middle 3. Top	2913 (33.1%) 2933 (33.3%) 2963 (33.6%)	

Graduatedby19 [numeric]	Min: 0 Mean: 0.7 Max: 1	0 : 2222 (25.2%) 1 : 6587 (74.8%)	
MOVEDBEFORE_19 [numeric]	Min: 0 Mean: 0.8 Max: 1	0 : 1740 (19.8%) 1 : 7069 (80.2%)	
MOVEDBEFORE_5 [numeric]	Min: 0 Mean: 0.5 Max: 1	0 : 4368 (49.6%) 1 : 4441 (50.4%)	
MOVED_5_13 [numeric]	Min: 0 Mean: 0.6 Max: 1	0 : 3697 (42.0%) 1 : 5112 (58.0%)	
MOVED_13_19 [numeric]	Min: 0 Mean: 0.5 Max: 1	0 : 4005 (45.5%) 1 : 4804 (54.5%)	
MOVES0 [logical]	1. FALSE 2. TRUE	7069 (80.2%) 1740 (19.8%)	
MOVES1 [logical]	1. FALSE 2. TRUE	7450 (84.6%) 1359 (15.4%)	
MOVES2 [logical]	1. FALSE 2. TRUE	7499 (85.1%) 1310 (14.9%)	
MOVES3 [logical]	1. FALSE 2. TRUE	7695 (87.4%) 1114 (12.6%)	
MOVES4 [logical]	1. FALSE 2. TRUE	7948 (90.2%) 861 (9.8%)	
MOVES5 [logical]	1. FALSE 2. TRUE	8037 (91.2%) 772 (8.8%)	
MOVES6 [logical]	1. FALSE 2. TRUE	8273 (93.9%) 536 (6.1%)	
MOVES7p [logical]	1. FALSE 2. TRUE	7692 (87.3%) 1117 (12.7%)	

This data set oversamples the following populations: Black people, middle- and upper-income families, and women. It under samples the following populations: individuals who have graduated high school by age 19, White people, and people who do not identify as Black or

White. The most notable difference is that 40.7% and 51.3% of the sample is Black and White respectively compared to 13.4% and 76.3% respectively in the overall US population. The national average high school graduation rate in four years was 84% in 2016, a similar metric to graduated by 19, which is 74.8% in the PSID sample. This is a large difference however graduation rates have risen significantly since 1970 so this is not unexpected (National Center for Education Statistics 2019). I did not use the sample weights for the analysis because it is not necessarily valid for linear probability models (Solon 2013).

Section 4: Results

As mentioned previously, the dependent variable is whether an individual has graduated from high school by the age of 19. Results from Figure 4 show the effects of having moved at various ages and Figure 5 shows the effects of having moved different amounts of times. Differing from other studies, I do not average the residential mobility as to examine its impact at different stages which would not be possible if using that method. The base individual is a Black woman living in a one guardian household with a high school degree whose family income is in the bottom third and who has never moved as a child. Expectedly, being White, living in a two-guardian household, and higher economic statuses are positively correlated with graduating by 19. Also, having a guardian who is a high school dropout is significantly negatively associated with timely high school graduation, about 50% decrease in all models.

Figure 4 investigates the age at which an individual moves, which has been shown to impact children differently (Chetty 2016). Investigating column 1 first, only considering a person's residential mobility before the age of 19 explains an incredibly small amount of the variation (R^2

= .012). Column 2 includes individual level characteristics, which is more explanatory, and column 3 includes family characteristics, which is the most robust.

We see from column 3 that moving between the ages of 5 and 19 has a negative effect on likelihood of graduation by 4-5 percentage points. The magnitude of many of the control effects are similar, between 4 – 7 percentage points, with having a one-guardian household where they do not have a high school degree having an estimated 8.9 percentage point negative effect. One of two controls that are statistically insignificant is identifying as a race besides White or Black, which may be due to that makes up so little of the sample. The other is having a two-guardian household with only one high school degree. The reasoning for this could be that there is no additional education input to the child and the effect of any additional income is already controlled for so there is no positive effect. The estimated effect of moving before the age of 5 is almost 0 and statistically insignificant, which corroborates the existing literature that moving at a very young age is better than moving at a later age. It is possible that the reasons for moving at the age of 5 or later are more homogenously negative, whereas the reasons for moving before 5 are heterogeneously positive and negative.

Figure 4: Moved before Age 19 Regressions	*Dependent variable:*		
Independent variables:	Graduatedby19		
	(1)	(2)	(3)
MOVEDBEFORE_5	0.007	0.008	-0.006
	(0.010)	(0.010)	(0.010)
	p = 0.450	p = 0.428	p = 0.566
MOVED_5_13	-0.052	-0.042	-0.043
	(0.010)	(0.010)	(0.010)
	p = 0.00000	p = 0.00004	p = 0.00002

MOVED_13_19	-0.069	-0.069	-0.050
	(0.010)	(0.010)	(0.010)
	p = 0.000	p = 0.000	p = 0.00000
RaceWhite		0.098	0.036
		(0.013)	(0.014)
		p = 0.000	p = 0.010
RaceOther		-0.022	0.019
		(0.027)	(0.027)
		p = 0.410	p = 0.485
Male		-0.105	-0.110
		(0.014)	(0.014)
		p = 0.000	p = 0.000
OneGuardianHH_NoHS			-0.089
			(0.015)
			p = 0.000
TwoGuardianHH_OneHS			0.017
			(0.017)
			p = 0.318
TwoGuardianHH_TwoHS			0.071
			(0.015)
			p = 0.00001
TwoGuardianHH_NoHS			-0.071
			(0.018)
			p = 0.0001
FamIncomeBucketedMiddle			-0.015
			(0.013)
			p = 0.233
FamIncomeBucketedTop			0.061
			(0.015)

			p = 0.0001
RaceWhite:Male		0.061	0.067
		(0.019)	(0.019)
		p = 0.002	p = 0.0004
RaceOther:Male		0.060	0.067
		(0.037)	(0.036)
		p = 0.108	p = 0.067
Constant	0.812	0.790	0.816
	(0.008)	(0.013)	(0.018)
	p = 0.000	p = 0.000	p = 0.000
Observations	8809	8809	8809
R^2	0.012	0.040	0.072
F Statistic	36.140*** (df = 3; 8805)	45.902*** (df = 8; 8800)	49.011*** (df = 14; 8794)
Note:	*p**p***p<0.01		
	Standard errors in parentheses		

In Figure 5 we analyze the number of times an individual moves before the age of 19. We again see that only including the moving variables results in a model that explains little of the variation in the sample. The base individual in these models is the same as previous models in that they are a Black woman living in a one guardian household with a high school degree whose family income is in the bottom third and who has never moved as a child. Moving once has almost no effect and is statistically insignificant, which is interesting when considering the general correlation shown in Figure 1. The outcome of the first move, positive or negative, is driven by individual and family characteristics, as well as other factors like the reason for the move that are outside of the model. Because the outcome is so driven by other factors, moving the first time is likely not as disruptive as moving more. Moving more than once is bad, reducing the chance of graduation by at least 4.9 percentage points. Once a child has moved 5 or more times, their likelihood of graduation drops by 10 or more percentage points. There are likely factors that are causing the high number of moves, but it is unknown if they are correlated with graduation as well.

	Dependent variable:		
	Graduatedby19		
	(1)	(2)	(3)
MOVES1	0.048	0.036	-0.001
	(0.016)	(0.015)	(0.016)
	p = 0.002	p = 0.019	p = 0.945
MOVES2	-0.024	-0.029	-0.058
	(0.016)	(0.016)	(0.016)
	p = 0.121	p = 0.069	p = 0.0003
MOVES3	-0.023	-0.027	-0.049
	(0.016)	(0.017)	(0.017)
	p = 0.167	p = 0.102	p = 0.004
MOVES4	-0.064	-0.057	-0.068
	(0.018)	(0.018)	(0.018)
	p = 0.0004	p = 0.002	p = 0.0002
MOVES5	-0.088	-0.086	-0.098
	(0.019)	(0.019)	(0.019)
	p = 0.00001	p = 0.00001	p = 0.00000
MOVES6	-0.121	-0.115	-0.116
	(0.021)	(0.021)	(0.021)
	p = 0.000	p = 0.00000	p = 0.00000
MOVES7p	-0.161	-0.149	-0.143
	(0.016)	(0.017)	(0.017)
	p = 0.000	p = 0.000	p = 0.000

RaceWhite		0.091	0.034
		(0.013)	(0.014)
		p = 0.000	p = 0.013
RaceOther		-0.032	0.013
		(0.026)	(0.026)
		p = 0.233	p = 0.636
Male		-0.102	-0.108
		(0.014)	(0.014)
		p = 0.000	p = 0.000
OneGuardianHH_NoHS			-0.090
			(0.014)
			p = 0.000
TwoGuardianHH_OneHS			0.014
			(0.017)
			p = 0.419
TwoGuardianHH_TwoHS			0.065
			(0.015)
			p = 0.00003
TwoGuardianHH_NoHS			-0.075
			(0.017)
			p = 0.00002
FamIncomeBucketedMiddle			-0.008
			(0.013)
			p = 0.532
FamIncomeBucketedTop			0.060
			(0.015)
			p = 0.0001
RaceWhite:Male		0.058	0.064
		(0.019)	(0.019)

		p = 0.003	p = 0.001
RaceOther:Male		0.056	0.063
		(0.037)	(0.036)
		p = 0.129	p = 0.084
Constant	0.789	0.777	0.818
	(0.010)	(0.014)	(0.019)
	p = 0.000	p = 0.000	p = 0.000
Observations	8809	8809	8809
R^2	0.022	0.047	0.077
F Statistic	27.883^{***} (df = 7; 8801)	35.957^{***} (df = 12; 8796)	40.576^{***} (df = 18; 8790)
Note:	*p**p***p<0.01		
	Standard errors in parentheses		

Section 5: Conclusion

There have been many efforts to unlock the interactions between the housing environment and educational attainment. In this analysis I focused on the effects of residential mobility, specifically in how the age at which an individual moves affects their likelihood of graduating high school before the age of 19. The literature shows that residential mobility, homeownership, and other housing characteristics along with the neighborhood environment all play a role in determining education outcomes (Chetty 2016, Haurin 2002, Lien 2000). There have been multiple approaches to removing the endogeneity inherent in these relationships, of which instruments are the most common choice. This however is not the only approach and does create uncertainty in the magnitude of estimates. One of the major findings of residential mobility research is that housing tenure, time spent in one residence, accounts for a significant portion of the homeownership effect (Aaronson 2000). This study adds to that understanding by investigating when and how often the change in housing occurs in reference to the child.

The major finding is that moving has a negative effect on graduating high school before the age of 19 relative to not moving. If a must move must be made, it is best to move before the age of four, which may be due to a four-year old making new friends easier than a 13-year-old, or the reasons for moves being different at different ages. When considering the results of Figure 4 and 5, where the effect of moving before the age of 5 is nearly 0 and the effect of moving the first time is also nearly 0, a reasonable scenario is that many of the first moves happen before the age of 5. This group also only moves once, which means they are in control of their mobility. That this effect is not positive and statistically significant is surprising, but its effect is possibly absorbed by the parental income and education variables; family effects seem to be crucial.

With a wide set of controls, my results align with the existing literature asserting the importance of residential stability and its positive relationship with education outcomes. Similar to Chetty, I find that moving later in childhood has a negative effect, although I find that moving at any age has no effect while they find moving while young has a positive effect (2016). However, the findings differ from Aarland who finds that moving once has no statistically significant difference relative to not moving at all (2021). The findings of Swanson are similar in that moving later is associated with lower graduation rates (1999). Their analysis also examines behavioral outcomes, and those children that move later are found to have higher incidences of behavior problems; this is expected and helps to explain a reason why achieving graduation is less likely. We do not find as significant a difference between children who do and do not move as Metzger et al., who find that moving once is associated with a 48% lower likelihood to graduate high school (Metzger 2015). The magnitude of their results is an outlier in the literature.

The differences to some existing research may be due to the use of instruments in the other studies or differing country effects.

The main significance of this paper is to begin addressing the gap in the literature regarding the timing of residential mobility. Following from the findings, a residential move should be made as early as possible to minimize negative effects, so any policies that encourage moving should consider this element. In the case of multiple moves, reducing the number of moves is in the best interest of the child, as it allows for the family to absorb positive neighborhood effects through longer tenure before moving. Future research should consider differentiating between different number of moves through the age lens to provide more depth and translatability of results. Combining the approach of this paper with other elements of the housing environment would also allow for deeper investigation of mobility effects. As this paper only addresses the impacts on moving for the child, considerations of other studies with respect to the benefit to parents should be made to weigh overall benefits and drawbacks. As this paper only addresses the magnitude of the moving effect, analysis of causality such as work that has been done on homeownership through the use of instrumental variables and other means would also be valuable to the field.

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The Kautz-Uible Economics Institute creates opportunities for enhanced learning and growth for students, faculty, and alumni of the University of Cincinnati's nationally ranked Department of Economics in the Carl H. Lindner College of Business. Established in 1982 as the Hewett-Kautz Fund, the institute's mission has steadily expanded and continues its transformational impact.

The institute currently supports the economics department through:

- The Kautz-Uible Fellowship Program, which offers scholarships and the Caroline M. Kautz book prize to outstanding economics students;
- An annual lecture series, presented by prominent economists;
- Annual domestic and international travel by undergraduate and graduate student groups;
- The Kautz-Uible Women in Economics Initiative, which provides scholarships and mentoring to economics students;
- The Kautz-Uible Research Initiative, which provides faculty-supervised research opportunities to undergraduate and graduate students;
- A Pathways to Success Initiative, which offers mentoring, scholarships, and study-related travel opportunities to students who belong to groups that have been historically underrepresented among economics majors at UC;
- The Kautz-Uible International Scholar Program, which financially supports the hosting of a reputed international scholar for up to a year;
- Faculty recruitment and retention through the establishment of chair professorships.