The Ripple Effect of Teenage Pregnancy

investigating how teenage mothers impact successive generations' educational and employment outcome

Introduction

The Centers for Disease Control and Prevention (CDC) identifies teen pregnancy as a significant public health issue (CDC, 2022). It is especially worth concerning in the United States since it has the highest adolescent parenthood rate among developed countries, despite the fact that the rate has declined 78% over the past three decades (Congress Research Service, 2022). There already exist programs that aim at stopping teenage parenthood, such as the Teen Pregnancy Prevention (TPP) program. However, most existing programs focus on simple education (Congress Research Service, 2024), so that research is needed for better understanding the consequences of teenage parents and implementing policy with clear targets.

This research aims to explore whether teenage parenthood negatively impacts the educational attainment and employment outcomes of subsequent generations. While this relationship has been extensively studied in the past, this research takes a novel approach by employing a unique generalized ordered logit modeling framework that addresses issues overlooked by prior studies. It also innovatively incorporates a three-generation, two-cohort analysis, utilizing data from the National Longitudinal Survey of Youth 1979 (NLSY79) and its subsequent Child and Young Adult (NLSY YA) surveys.

In addition, the research tests for several sub-hypotheses aimed at uncovering the specific mechanisms of how teenage mothers and grandmothers impact education and employment outcomes. By doing so, this research not only aims to confirm the well-documented negative effects of teenage pregnancy, but also seeks to identify the nuanced conditions under which these effects are intensified. Through this analysis, the study hopes to provide valuable insights that can guide more effective policy-making to break cycles of intergenerational disadvantage.

This research is structured as follows: We begin with a review of the existing literature, and point out the contribution and significance of this research. Then, in the methodology section, we will provide information on how we obtained and preprocessed our dataset, followed by the presentation of our main and sub-hypotheses. Then, this paper will explain the rationale behind our model selection and present the results of relevant tests. In the result section, we will analyze and discuss the regression results for both educational and employment outcomes across the two cohorts. Moreover, we will check the model's robustness and conduct a sensitivity analysis to address potential endogeneity issues. Finally, this paper will provide policy recommendations and suggest some future research directions, before drawing a conclusion.

Literature Review

In this section, this research will summarize previous literature that seeks to investigate the relationship between teenage mothers and their children's education and employment outcome. This literature review will also present the significance and innovation of our work.

A negative association between being a teenage mother and their own educational attainment and early employment outcome has been widely found in early studies using different datasets. Moore and Waite (1977) found teenage mothers completed up to 4 years less education compared to females of the same age. Klepinger, Lundberg, and Plotnick (1999) utilized the same National Longitudinal Survey dataset as the one used in our study, found that teenage pregnancy reduces female youth's years of schooling and teenage wages through reduction in human capital investment. Similarly, in studies that used the National Longitudinal Study of Adolescent Health (Add Health) dataset, research found that teenage mothers are 5 to 10 percent less likely to complete high school compared to their peers (Fletcher and Wolfe, 2009; Pirog et al., 2018). Similar negative link has been established in early adulthood income, such that teenage pregnancy relates with $1000-2400 loss in annual income (ibid). Those research successfully create great significance and draw policy attention into assisting teenage mothers in their attempt to seek better education and employment opportunities.

Then, many studies became interested in exploring whether the negative impact of teenage childbearing persists into having an intergenerational effect. Again, previous research has reached similar conclusions, though magnitude of effect varies, using a wide range of datasets and methodologies. Early research done on the project TALENT dataset discovered compared to their peers at the same age, children of teenage mothers significantly demonstrated worse educational performance (Card, 1981). Hardy et al. (1997) discovered children born by teenage mothers are less likely to complete high school and face more financial hardship before turning 30 years old, through conducting multivariate logistics regression using data from the Pathways to Adulthood Study. Children are also found to be 35% less likely to be school-ready when both their mother and grandmother were once teenage mothers (Wall-Wieler et al, 2014).

Many past studies choose to utilize the same NLSY dataset as we do, since it contains abundant information both on the parental side and on children's side.
Among these studies, findings on whether children of teenage mothers face greater challenges in achieving higher educational attainment did not reach consensus. Some found a huge negative impact, for example, Children born in their mother's early teenage years are found to be 3.23 times less likely to complete high school with heterogeneity in children's gender (Addo et al, 2015). Others disagree by showing the significant negative impact on obtaining high school and college diplomas disappear after accounting for endogeneity (Gorry, 2022).

Other studies conducted an OLS regression on various cognition scores, PIAT reading, and PIAT mathematics score found mixed result between adolescence parenthood and their children's outcome using the NLSY79 dataset (Negative: Geronimus et al. ,1994, Levine et al., 2001, Hofferth and Reid, 2002; insignificant:

Cooksey, 1997, Gorry, 2022). Ducan et al. (2008) discovered that one year delay in motherhood is associated with around 0.03 standard deviation in children's math, reading and delinquency score. Our study will also use the PIAT reading and mathematics scores, however, we controlled for multiple generations' family background and included grandparental, to better control for the genetic differences within individuals. Most studies using other datasets also report lower cognition scores for children of teenage mothers. Using the Millennium Cohort Study, it is found that children of teenage mothers have a cognition score 3.8 to 8.9 points lower than their peers at 5 years old, which is equivalent to a delay in development for around 4 to 11 months (Morinis et al., 2013).

More recent studies began to note that a big issue faced by both direct effect and intergenerational research is that the determinants of education and employment outcome can be very complicated, thus it is nearly impossible to avoid omitted variable and endogeneity issues. There are few attempts on using miscarriages as the instrument variable for teenage pregnancy (Hotz et al. 2005; Miller, 2009) . However, many later studies began to cast doubt on the choice of instrument variable. Some studies noted that misscarriage is not an ideal instrument as many termination of birth would still happen through abortion even if the individual has not miscarriage the child (Ashcraft and Lang, 2006) . Subsequent studies built on the idea and incorporating information on timing of the birth termination and usage of birth control, found a much smaller but still negative association between teenage birth and the following educational attainment (Fletcher and Wolfe, 2009) .

Another group of research uses the siblings fixed effects model to eliminate all time-invariant family background effects to account for potential endogeneity

(Ducan et al., 2008; Myrskylä et al., 2013; Gorry, 2022). Many find the results are still negative and significant although size of effect is generally smaller after controlling for the fixed effect (Aizrer et al., 2020). The fixed effect methods, however, faced criticism by Altonji et al. (2017), pointing to the neglect of family spillover effect between siblings that led to biased estimates. Family size may also be a factor that contributed to inaccurate estimates for the average effect of teenage mothers, where there are likely more comparison pairs within a larger family (Miller et al., 2019). Later studies were able to address the family size issue using weighting based on the number of sisters in a household and female education levels, however, the spillover effect remains largely overlooked. Aizrer et al. (2020) uses the weighted Norwegian register data, find that children of teenage parents are 16% less likely to finish high school and obtain a degree when not controlling for fixed effect, and the gap reduced to 6% less likely to finish high school when controlled for endogeneity (Aizer et al., 2020). Similarly, teenage parents' children's income at 30 falls from having a 11% gap to a 4% one when controlled for family fixed effect, serving to the thinner literature on impact on children's early income outcome (ibid). Our study follows neither of the strategies to treat endogeneity, but instead choose to adopt a sensitivity analysis, where we consider the edge case when all variables are endogenous, and investigate if the previously found effect still holds significance for the main explanatory variables (Diegert et al., 2022). This way, this study hopes to contribute to the literature by evaluating the robustness of previously significant findings using different methods.

Our study made improvements on previous research utilizing similar datasets, and thus contributed to the literature in two ways. First, most studies adopted multivariate logit regression on educational attainment results. A multivariate logit regression disregards the ordinal information contained in educational attainment and thus loses estnation efficiency, while ordered logit regression requires parallel trend assumption that is proved to fail in our dataset. This study therefore constructed a generalized ordered logit regression with partial odds assumption in the estimation of educational attainment, allowing for more accurate and efficient estimation. Moreover, most educational investigations only estimate the likelihood of high school graduation, while this research expands the focus from investigating a wider range of educational milestones, from middle school completion to obtaining postgraduate degree. Similarly with income, this research analyzes earnings across various early career ages, instead of having a singular outcome variable. Both settings allow us to study the prolonged influence of teenage parenthood. Additionally, we uniquely constructed two cohorts based on the two surveys, incorporating the assessment of teenage fatherhood and grandparental influence where possible.

Methodology

Data source and preprocessing

This essay uses data from the National Longitudinal Survey of Youth 1979 (NLSY79) and the following survey, the National Longitudinal Survey of Youth 1979 Children and Young Adult (NLSY79 Children), which target the identified children of original NLSY79's female respondents.

Both surveys track individuals over many years, making them an excellent resource for intergenerational studies. This essay seeks to fully utilize both waves to extract as much intergenerational information as possible. Unlike most studies that only link the children of NLSY79 respondents to their own offspring, this essay constructs two intergenerational panels.

First, we extract parental and household background information from the original NLSY79 sample and combine it with NLSY79's outcome variables to create the first panel, referred to as 'ORG79.' Second, using data from the NLSY79 Children and Young Adult survey, the essay merges outcome variables from the children respondent into the original NLSY79 dataset based on 'MOMID'. This allows for the connection between the NLSY79 mothers' responses and their children's responses, creating the 'CHILD79' panel. The 'CHILD79' panel now includes not only one layer of intergenerational information but also information from the grandparents' level derived from the 'ORG79' panel.

By applying our model to both panels, this essay aims to uncover the impact of teenage pregnancy and female career engagement on their children and grandchildren. Additionally, it seeks to investigate whether this impact varies across different eras.

As shown in Fig 1, birth years for the 'ORG79' category are concentrated in a narrow range, allowing us to focus on female-related intergenerational impact for households with children born between 1957 and 1965. The corresponding box plot illustrates the median birth year and the interquartile range (IQR), with most data points tightly clustered within this period, reflecting a relatively uniform distribution. In contrast, the birth years for the 'CHILD79' are much more dispersed, spanning from the early 1980s to the early 2000s. The box plot for CHILD79 reveals a larger IQR, indicating greater variation in the birth years within this group. Notably, several outliers are present, especially in the later years. The 'CHILD79' panel thus allows us to investigate households with children born from 1970 to 2014.

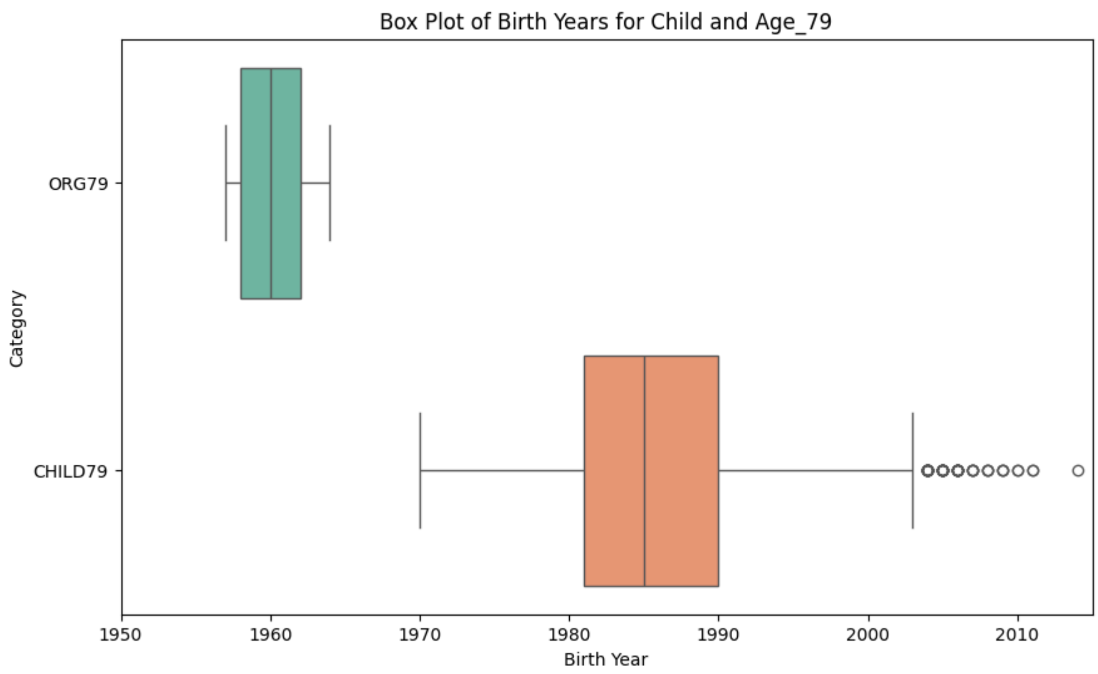


Fig 1. Birth year plot for 'ORG79' and 'CHILD79'

Hypothesis

This research aims to test one major hypothesis: that teenage parenthood has a detrimental impact on the educational attainment and income outcomes of the next generation. This negative relationship and its mechanism of influence has been well-established in the existing literature, as detailed in the literature review section. However, this study distinguishes itself by employing a unique modeling approach and by including an analysis that spans multiple generations, thereby providing a more comprehensive understanding of the intergenerational effects of these factors.

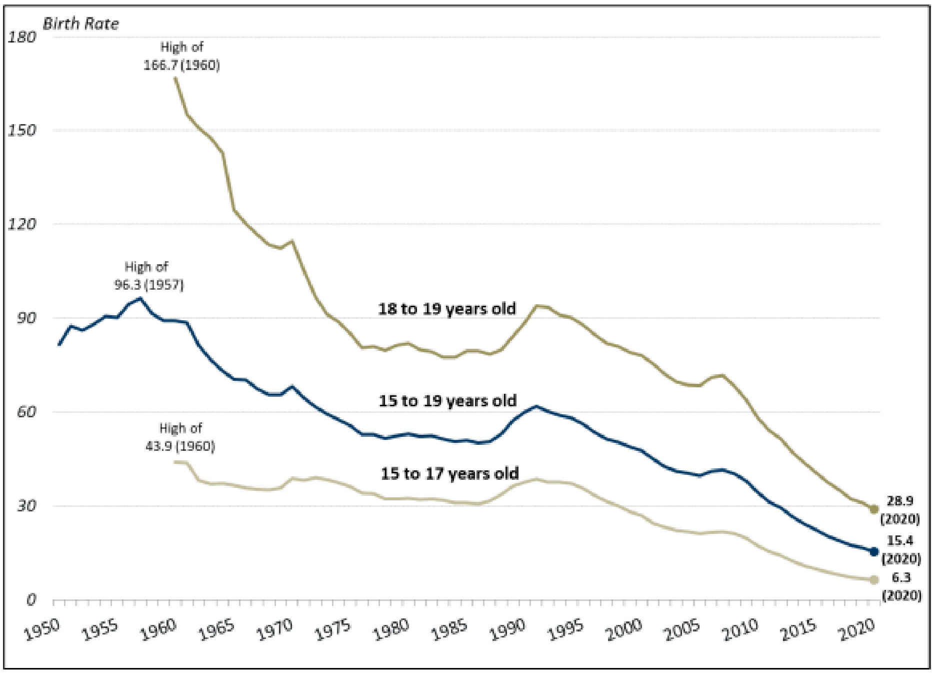
In addition to the primary hypothesis, this research also seeks to explore several sub-hypotheses that explore deeper into the underlying mechanisms of intergenerational impact. The goal is to identify the core reasons behind these effects and to guide the development of more targeted policies aimed at mitigating their impact.

Sub-hypothesis 1: *The influence of teenage parenthood is magnified in later 'CHILD79' cohorts.*

This hypothesis is based on the fact that societal norms and cultural expectations have evolved over time. What was once considered acceptable or normative behavior may now be viewed as outdated or harmful. Teenage pregnancy in the United States has been steeply declining for decades, with a peak of birth per thousand females of 96.3 in the 1950s, to only 15.3 in the 2020s as shown on Fig 2 (Congress Research Service, 2022).

For the 'ORG79' cohort, those born within the interquartile range of the sample experienced an average US teen birth rate of 74.1[1]. In contrast, the 'CHILD79' cohort saw a significant decline of 51%, with the average teen birth rate dropping to 36.1. This shift indicates a broader evolution in social norms and perceptions, suggesting that our cohort division effectively captures such changes over time, thus the comparison between cohorts provides valuable insights.

Birth rate is per 1,000 females aged 15 to 19 (15 to 17 and 18 to 19 subgroup data became available in 1960)



Source: Congressional Research Service (CRS), based on data from the U.S. Department of Health and Human Services (HHS), Centers for Disease Control and Prevention (CDC), National Center for Health Statistics (NCHS), December 2016; and the following: 1950-1959 data is from Stephanie J. Ventura et al., "Births to Teenagers in the United States, 1940–2000," *National Vital Statistics Report*, vol. 49, no. 10, September 2001, https://www.cdc.gov/nchs/data/nvsr/nvsr49/nvsr49_10.pdf; 1960-2009 data is from Stephanie J. Ventura et al., "National and State Patterns of Teen Births in the United States, 1940–2013," *National Vital Statistics Report*, vol. 63, no. 4, August 2014, https://www.cdc.gov/nchs/data/nvsr/nvsr63/nvsr63_04.pdf; 2010-2020 data is from Michelle J.K. Osterman et al., "Births: Final Data for 2020," HHS, CDC, NCHS, *National Vital Statistics Report*, vol. 70, no. 17, February 2022, https://www.cdc.gov/nchs/data/nvsr/nvsr70/nvsr70-17.pdf.

Fig 2. Teen birth rate 1950 - 2020 (Congress Research Service, 2022)

[1] Average teen birth rate calculated using Appendix Table A from 2022 congress report on teen birth. Source: Centers for Disease Control and Prevention, National Center for Health Statistics https://crsreports.congress.gov/product/pdf/R/R45184#:~:text=The%20rate%20ticked%20up%20in,two%20years%2C%202006%20and%202007.

As a result, children still born by teenage mothers in later periods are expected to be experiencing more severe negative outcomes compared to previous generations.

Sub-hypothesis 2: *The adverse effects of teenage pregnancy are expected to be exacerbated when the father is significantly older, with the negative impact intensifying as the age gap increases.*

Teenage mothers are often being portrayed as the culprit of worse children's outcomes, while the father's side is often overlooked both by research and by policy-makers. In our datasets, 70% children of teenage mothers have an adult dad. This hypothesis suggests that the age disparity between teenage mothers and adult fathers may contribute to greater instability, which in turn magnifies the negative consequences for the child's educational and income outcomes. By proving this hypothesis, we hope to clarify the stigma attached to teenage mothers, and provide clearer direction for policy making.

Sub-hypothesis 3: *The impact of teenage parenthood is the most detrimental during the early years of a child's education.*

The research posits that once an individual has passed a certain threshold in their educational journey, the negative effects of having a teenage mother diminish. This, if proven true, suggests that early educational interventions may be particularly crucial in mitigating the long-term impacts.

Sub-hypothesis 4: There is heterogeneous effect on gender such that *the negative consequences of adolescent parenthood are more severe for daughters than for sons; and The role model effect of grandmother is still strong for their grandchildren's development.*

This sub-hypothesis is based on the idea that daughters may be more susceptible to the influence of female role models within the household, and thus more negatively affected by the absence of positive female participation in the workforce.

Finally, this research hypothesizes that the role model effect of a grandmother is more influential than that of a grandfather. This could be due to the traditionally stronger caregiving role that grandmothers often play in many cultures, which may have a more profound impact on the social and educational development of their grandchildren.

In summary, this study not only seeks to confirm the widely recognized negative impacts of teenage pregnancy and female exclusion from the workforce on subsequent generations but also aims to uncover the nuances and specific conditions under which these effects are intensified. By doing so, the research hopes to contribute to more informed and effective policy-making that addresses the root causes of intergenerational disadvantage.

Variables

Education Outcome - HGC, PIAT, AFQT

This research uses two key measurements for educational outcomes: educational attainment and standardized test scores.

In both the NLSY79 and NLSY79 Child datasets, the primary measure of educational attainment is the Highest Grade Completed (HGC), which is collected repeatedly in each wave of interviews (NLSinfo, 2024). We collected the highest grade ever reported to create an HGC variable for both cohorts.

It is important to note that the definition of educational attainment has changed over time due to shifts in societal norms and increased levels of education. For the 'ORG79' cohort, HGC is recorded as the number of years of schooling, ranging from 1 to 20. In contrast, for the 'CHILD79' cohort, all education below the 8th grade is coded as 1, and the subsequent codes represent a certain range of schooling. Additionally, the 'CHILD79' dataset provides more detailed information on vocational training, both at the high school and postgraduate levels. To maintain consistency in measuring educational attainment, vocational training is grouped with corresponding traditional education levels, based on evidence indicating that the benefits of vocational training are similar to those of a standard academic curriculum.

Table 1 shows the relative reference coding of both cohort's HGC.

HGC_ORG79	HGC_CHILD79	Reference HGC level
1	1	some primary school
2		some middle school
3		completed middle school
4	2	some high school or equivalent
5	3	completed high school or equivalent
6	4	some college regardless of degree
7	5	completed college regardless of degree
8	6	some master or equivalent
9	7	complete master or equivalent
10	8	some doctoral
	9	complete doctoral and above

Table 1. HGC categories explained

We also employ standardized test results as a supplementary measure for educational outcomes. There is no single test score available for both cohorts. For the 'ORG79' cohort, the AFQT (Armed Forces Qualification Test) score is used as a proxy for educational achievement. This score is derived from the Armed Services Vocational Aptitude Battery (ASVAB), which includes questions on various topics such as mathematics, reading comprehension, mechanical knowledge, and general scientific and factual information (NLSinfo, 2024). For the 'CHILD79' cohort, we use the PIAT (Peabody Individual Achievement Test) math and reading scores. The PIAT is a standardized assessment that evaluates academic performance in children aged 5 years and older (ibid). In both cases, we use the percentile score as the outcome variable. This approach allows for normalization and offers a more accurate representation of a child's relative ability compared to their peers.

Employment Outcome - income_at_age

In both surveys, respondents were repeatedly asked for their exact or estimated income from the year prior to the interview. We constructed multiple variables that capture Income at a specific age as the employment outcome for two main reasons. First, respondents were born in different years, meaning that income reported in a given interview year reflects their earnings at various life stages, making direct comparisons between individuals at different ages (such as someone at 40 versus someone fresh out of college) impractical. Second, by constructing an income trajectory over time, the research aims to evaluate the enduringness of having a teenage mothers on the subsequent generation's wages.

To handle income data, several steps are followed. Initially, respondents who are reluctant to disclose their exact income are asked to provide an estimated range or answer questions such as "Is your salary greater than $5,000 / less than $15,000?" The averages of these reported ranges and responses are used to estimate their income. Second, all income data is adjusted for inflation to the price level of 2010 using the Consumer Price Index (CPI) to ensure comparability. As shown on Fig 3, the CPI has generally increased over time, so income from years prior to 2010 is adjusted upward, while income from years after 2010 is down-weighted.

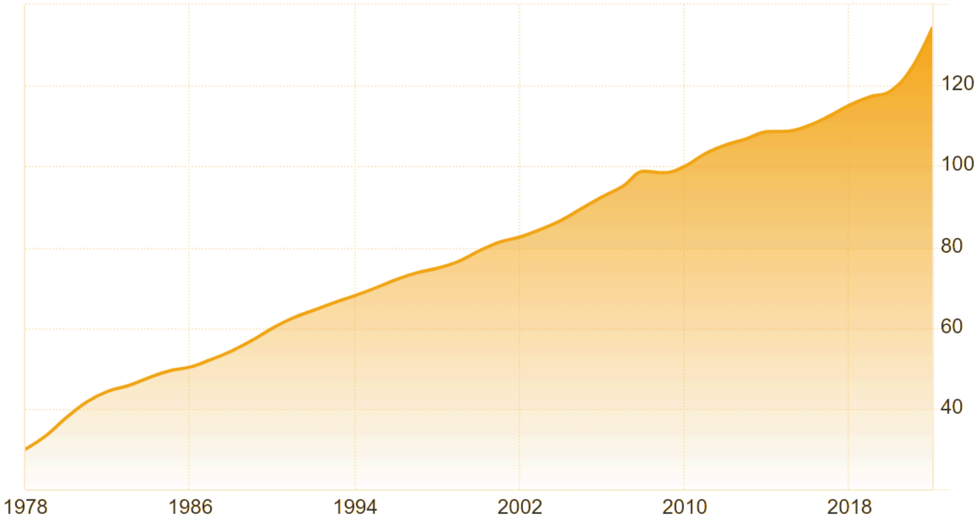


Fig 3. United States CPI index with base year 2010 (World Bank, 2024)

Finally, the dataset is pivoted to calculate income by age, based on each year's reported income and the respondent's birth year. To simplify calculations, we ignore the birth month as interviews occur over several months each year. Fig 4 shows the income_by_age variables's availability in both cohorts.

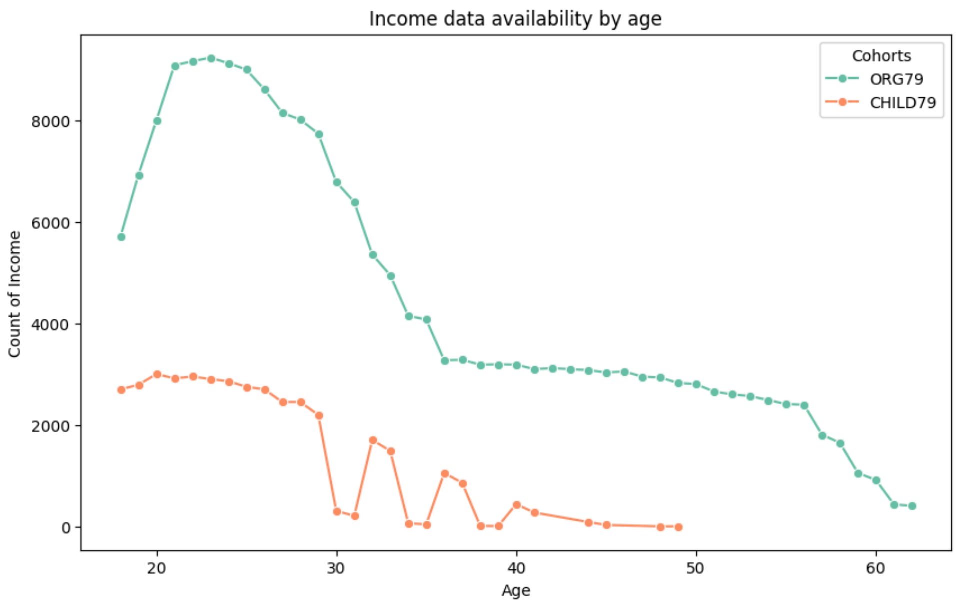


Fig 4. Income availability by age for 'ORG79' and "CHILD79'

In the 'ORG79' survey, income data is available for respondents aged 14 to 62. For the 'CHILD79' survey, income data spans from ages 13 to 49. Both surveys provide the most detailed income information for respondents in their 20s. Therefore, the research will focus on analyzing income in respondents' 18 to 30, as this range offers the most comprehensive and informative data.

Fig 5 below illustrates the income trajectory of the average person's income from ages 18 to 30 in both cohorts. It can be observed that both trajectories are similar, except for an initial dip in the CHILD79 cohort. This dip aligns with the drop in household income in the early 2000s, which coincides with the period when most income data for 18 to 21-year-olds in the CHILD79 cohort was collected (FRED, 2022).

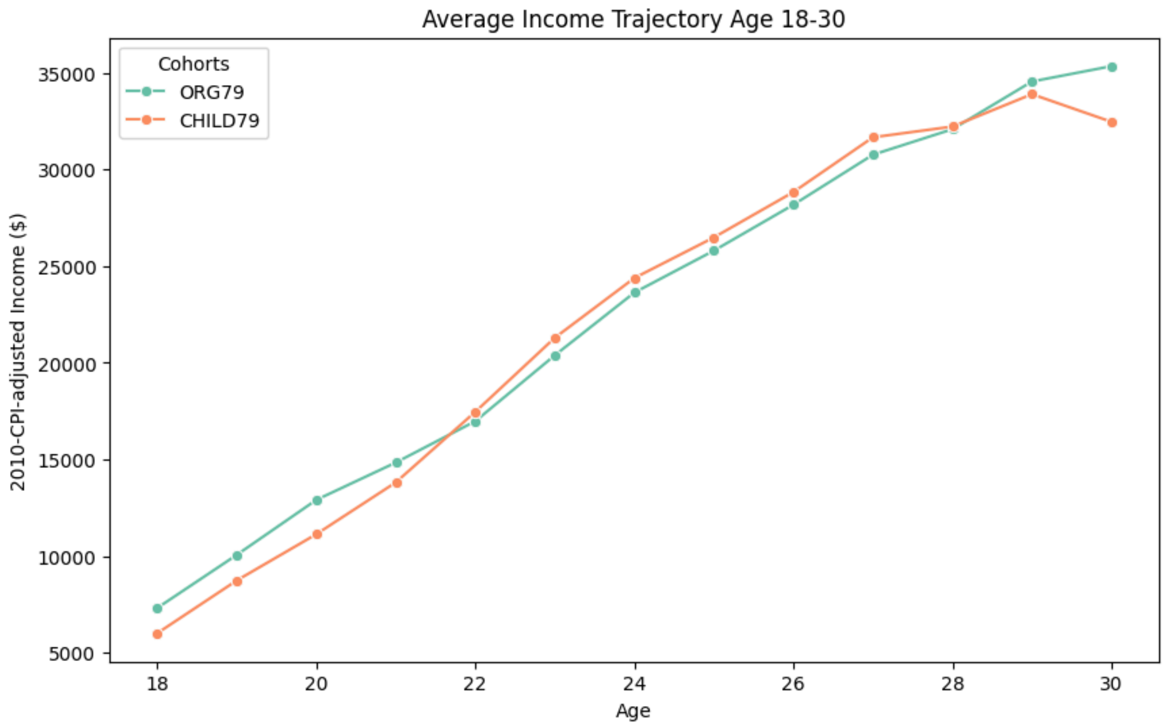


Fig 5. Typical early income trajectory for 'ORG79' and "CHILD79'

Main explanatory variable

Since our study examines the impact of having a teenage mother on education and early income outcomes, the primary explanatory variable is 'teen_mom.' This is a binary indicator where a value of 1 denotes that the individual has a teenage mother, and a value of 0 indicates the individual was born to an adult mother.

For the 'ORG79' cohort, the parents' age at the birth of a child is not directly available. This study follows the guidelines provided in the NLSY79 family background section and estimates parental age at birth using various models as in Table 2 (NLSY, 2024). Specifically, we first identify the codes for the children's mother and father from the reported relatives, then extract the relevant information from those individuals. To calculate the mother's age at birth, we subtract the respondent's age in 1979 (or 1980) from the mother's age in 1979 (or 1980). We were able to determine the father's age for 77.6% of cases and the mother's age for 86.6%, which aligns with expectations from the NLSY guidelines[2]. In 'CHILD79', there is a 'MAGEBIR' variable capturing the mother's age when giving birth to the child.

We define 'teen_mom' as individuals who were 20 years old or younger when they gave birth, excluding extreme cases of those younger than 10 years old. The cutoff is set at 20 years old because most individuals who gave birth at this age likely became pregnant at 19, which aligns with the technical end of adolescence. While this cutoff may include a few cases where individuals became pregnant just after turning 20, we believe that the life-stage boundary is flexible. This age period typically involves key

[2] Quoting from NLSY79 guideline: ' This program, and the similar one for mothers, results in an age for almost 77 percent of fathers and almost 87 percent of mothers.'. Specific methodology available at: https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/family-background

transitions, such as finishing high school, starting college, or entering the workforce (Addo et al., 2016). Additionally, this definition ensures consistency with much of the literature we are comparing our results to. Based on this definition, the percentage of teenage mothers is 19.73% in the 'ORG79' cohort and 18.57% in the 'CHILD79' cohort. The 'ORG79' cohort also includes 7.18% of teenage fathers.

A	if (R2303200 > 0) then dad_age = R2303200 - 8	1) If age in 1987 exists, set age to - 8. The subtraction results in the father's age in 1979 NOT 1987. End algorithm.
	if (R2505400 > 0) then dad_age = R2505400 - 9	2) If age in 1988 exists, set age to age - 9. End algorithm.
B	if (R2303100 ^= 66) and (R2303100 > 0) then dad_age = 79 - R2303100	1) Try birth year from the 1987 survey. Note 66 means the respondent never knew the parent.
	if (R2505300 ^= 66) and (R2505300 > 0) then dad_age = 79 - R2505300	2) Try birth year from the 1988 questionnaire.

C	if ((R0175800 = 4) and (R0175900 > 0)) then Dad_age = R0175900;
	if ((R0176700 = 4) and (R0176800 > 0)) then Dad_age = R0176800;
	if ((R0177600 = 4) and (R0177700 > 0)) then Dad_age = R0177700;
	if ((R0178500 = 4) and (R0178600 > 0)) then Dad_age = R0178600;
	if ((R0179400 = 4) and (R0179500 > 0)) then Dad_age = R0179500;
	if ((R0180300 = 4) and (R0180400 > 0)) then Dad_age = R0180400;
	if ((R0181200 = 4) and (R0181300 > 0)) then Dad_age = R0181300;
	if ((R0182100 = 4) and (R0182200 > 0)) then Dad_age = R0182200;
	if ((R0183000 = 4) and (R0183100 > 0)) then Dad_age = R0183100;
	if ((R0183900 = 4) and (R0184000 > 0)) then Dad_age = R0184000;
	if ((R0184800 = 4) and (R0184900 > 0)) then Dad_age = R0184900;
		Look at the household record to see if the father lived in the household in 1979. If the father lived in the household, his age should be listed. Fathers are coded as "4" on the household record.

Table 2. NLSY79 program for parental age calculation (NLSY, 2024)

Control variable

The NLSY79 and NLSY79 Young Adult surveys contain numerous questions about family background, individual abilities, and other relevant factors. In this study, we incorporate a wide range of control variables on both the parental and children's sides to minimize omitted variable bias.

For individuals' characteristics, we control for basic demographics including race and gender, plus age when discussing income. We also incorporated variables that capture the individual's childhood environment including: Foreign language spoken as a child, Residing in urban or rural or farm at 14 years old, Age stopped living with parents, Relationship with Parents and Cultural influence received as child.

Moreover, we use several scores and indexes to proxy for the children's personal characteristics and performance in school and workplace. Such variables include: Delinquency score, Ever repeated a grade, Outgoingness, and SF12 mental and physical score. We also control for the mother's expected years of schooling on the individual, as it captures the mother's educational aspirations and could serve as a proxy of perceived family resources, socioeconomic background, and children's intelligence.

On the family side, we include Parental ages when the child is born, Parents' and grandparents' HGC, Mother's first marriage age, Parents' working situation, and Family income. We also control for the Number of siblings and the Number of siblings in school to account for the potential influence of sibling dynamics and resource distribution within the family.

It's important to note that some control variables may not be available for both the 'ORG79' and 'CHILD79' cohorts. When this occurs, we seek the closest alternative variables before deciding whether to exclude them. Additionally, to address potential concerns of multicollinearity, since there exist cases where some variables are derived from others, we routinely conduct a Variance Inflation Factor (VIF) test after running a regression to ensure no such issues are present.

Summary Statistics

'ORG79'	**non-teen mom**		**teen mom**		**difference**	
	mean	stddev	mean	stddev		
teen dad	0.02	0.12	0.30	0.46	-0.29	***
hgc	5.67	1.58	5.40	1.46	0.27	***
mother's hgc	4.34	1.80	4.09	1.49	0.25	***
father's hgc	4.41	2.24	4.16	1.84	0.25	***
dad age when born	32.21	7.21	23.65	5.28	8.54	***
mom age when born	29.08	5.63	16.84	2.20	12.21	***
AFQT	44.37	28.94	35.07	26.67	9.30	***
female	0.49	0.50	0.51	0.50	-0.02	
hispanic	0.15	0.36	0.18	0.38	-0.02	***
black	0.23	0.42	0.33	0.47	-0.10	***
other	0.62	0.49	0.49	0.50	0.13	
urban at 14	0.79	0.41	0.78	0.42	0.01	
rural at 14	0.16	0.36	0.17	0.37	-0.01	
farm at 14	0.05	0.22	0.05	0.22	0.00	
move-out age	15.29	4.97	13.73	5.81	1.56	***
female working index	2.01	0.90	1.92	0.87	0.08	***
male working index	1.33	0.66	1.29	0.62	0.04	*
family culture index	0.69	0.33	0.61	0.34	0.08	***
foreign language spoken	0.22	0.42	0.21	0.41	0.01	
# sibling	3.98	2.74	3.36	2.12	0.62	***
# sibling in school	1.79	1.59	2.43	1.60	-0.64	***
ever married	0.80	0.40	0.82	0.39	-0.02	***
first marriage age	24.12	6.37	23.49	6.64	0.62	***
# desired children	2.40	1.34	2.37	1.44	0.03	
# abortion	0.28	0.70	0.29	0.68	-0.01	

Table 3. Summary statistics by 'teen_mom' for 'ORG79'

'ORG79'	**non-teen mom**		**teen mom**		**difference**	
	mean	stddev	mean	stddev		
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AFQT	44.37	28.94	35.07	26.67	9.30	***
female	0.49	0.50	0.51	0.50	-0.02	
hispanic	0.15	0.36	0.18	0.38	-0.02	***
black	0.23	0.42	0.33	0.47	-0.10	***
other	0.62	0.49	0.49	0.50	0.13	
urban at 14	0.79	0.41	0.78	0.42	0.01	
rural at 14	0.16	0.36	0.17	0.37	-0.01	
farm at 14	0.05	0.22	0.05	0.22	0.00	
move-out age	15.29	4.97	13.73	5.81	1.56	***
female working index	2.01	0.90	1.92	0.87	0.08	***
male working index	1.33	0.66	1.29	0.62	0.04	*
family culture index	0.69	0.33	0.61	0.34	0.08	***
foreign language spoken	0.22	0.42	0.21	0.41	0.01	
# sibling	3.98	2.74	3.36	2.12	0.62	***
# sibling in school	1.79	1.59	2.43	1.60	-0.64	***
ever married	0.80	0.40	0.82	0.39	-0.02	***
first marriage age	24.12	6.37	23.49	6.64	0.62	***
# desired children	2.40	1.34	2.37	1.44	0.03	
# abortion	0.28	0.70	0.29	0.68	-0.01	

Table 4. Summary statistics by 'teen_mom' for 'CHILD79'

Model specification

Initial model

The most intuitive and straightforward model is an Ordinary Least Square regression (OLS), which is useful in estimating coefficients of linear relationships. The matrix form of OLS can be represented as follows (Wooldridge, 2019):

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

where $\mathbf{y}$ is a $N \times 1$ vector representing the outcome variable (HGC, PIAT, income_at_age) for our N observations. $\mathbf{X}$ is a $N \times r$ matrix that includes r variables we chose in the former section. β recorded the estimated coefficients and ε captures all residuals, which is assumed to be random for consistent estimates.

OLS is straightforward in its interpretation, however, when dealing with ordered categorical variables such as HGC, using OLS faces several limitations. First, consistent OLS estimation requires a linear relationship with constant intervals, which is not satisfied by our 'naturally-occuring' ordered categories (Williams, 2006). Specifically in this research, the HGC categories are defined based on years of education and specific cutoff points, such as completing high school, college, or postgraduate studies, with higher levels of education falling into higher categories.. However, the distance between categories is not consistent. For example, the gap between the categories 'Some high school' and 'Completed high school' can vary from 1 to 3 years of schooling. Similar inconsistencies go for distance between other categories.

Another critical issue is that OLS assumes ε is normally distributed and identifies homoscedasticity, i.e. constant variance, but these assumptions are often violated with categorical data, leading to inefficient estimates and inaccurate hypothesis testing results (Wooldridge, 2019). Fig 6 is made from an OLS regression for HGC on a set of control variables, and plotting the standard deviation from the fitted residuals against HGC categories . The plot reveals that there exists non-uniform levels of variability of residuals across education categories, suggesting potential efficiency loss.

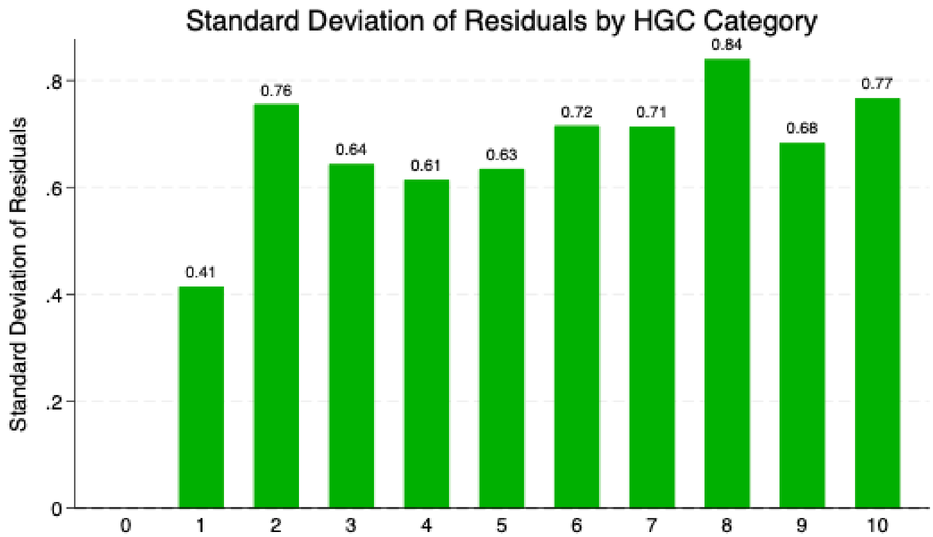

Fig 6. Standard deviation of estimate residual by HGC category

Additionally, OLS regression predicted coefficients can be hard to interpret for categorical outcomes. For example, if we find that having a teenage mom reduces HGC by 0.03, it doesn't provide much insight into quantifying how education attainment is influenced. Instead, it simply indicates a negative relationship.

Therefore, OLS will only be utilized to understand UFRM's impact on the next generation's standardized test scores, serving as supplementary evidence of how it affects children's educational attainment. OLS will also be applied to study the impact on next generation's income, as both variables exhibit linearity and meet the requirements for OLS's Best Linear Unbiased Estimates (BLUE).

Ordered Logit model

The sensible alternative is the Order Logit model where outcome is categorical with natural order. Ordered logit model is widely utilized in studies focusing on one's HGC. In this case, the order occurs from the hierarchy of education level: primary school, middle school, high school, college, and above. The model with M categories can be written as follows (Williams, 2005):

$$P(Y_i > j) = \frac{\exp(\alpha_j + X_i\beta)}{1+[\exp(\alpha_j + X_i\beta)]}, \mathrm{j}=1, 2, \ldots, \mathrm{M}-1$$

The ordered logit model is very similar to a logistic regression. In fact, logistic regression with binary outcome is a special case of ordinal logistic regression with outcome order of 2. The ordered logit regression allows us to compute how likely the outcome can progress into higher categories from lower categories using proportional log odds estimates (Parry, 2016). The coefficient β should be interpreted as the regressor makes one exp(β) times more likely to be in a higher category versus staying in lower ones.

However, an unbiased ordered logit model requires the data to satisfy the proportional odds assumption, also known as the parallel lines assumption. This means that the effect of all predictors must be consistent across different outcome categories (Williams, 2016). Previous studies often overlooked the need for testing parallel line assumption or choose to let go of the ordinal information and do a multinomial logit model (Williams, 2019). In this study, we hope to both preserve the ordinal information in HGC while producing unbiased estimates. We first conducted Wald, likelihood ratio, score, Brant, and Wolfe-Gould tests to assess whether the parallel lines assumption holds for the models, following the guidance of Liu et al. (2023).

The test results for the models 'ORG79' and 'CHILD79', as reported in Tables 5 and 6, respectively, indicate that the null hypothesis is rejected in all cases. This suggests that the regressors have varying effects across different outcome categories, implying that the use of ordered logit regression may lead to biased interpretations.

Test	Chi2	P>Chi2
Wolfe Gould	524.7	0.000
Brant	456.8	0.000
Score	518.4	0.000
Likelihood Ratio	550.2	0.000
Wald	112.2	0.000

Table 5. 'ORG79' parallel line test result

Test	Chi2	P>Chi2
Wolfe Gould	109.9	0.000
Brant	128.4	0.000
Score	118.1	0.000
Likelihood Ratio	117.9	0.000
Wald	118.3	0.000

Table 6. 'CHILD79' parallel line test result

Partial Proportional Odds Generalized Ordered Logit model

A generalized ordered logit model relax the proportional odds assumption for every variable goes:

$$P(Y_i > j) = \frac{\exp(\alpha_j + X_i\beta_j)}{1 + [\exp(\alpha_j + X_i\beta_j)]}, \mathrm{j} = 1, 2, \ldots, \mathrm{M} - 1$$

It can be observed that the only difference of generalized ordered logit model and ordered logit model is the j subscript on β, showing that all estimates are allowed to be different for each outcome category. This model sacrifices some estimation efficiency for such flexibility.

This research opted for a middle-ground approach by using a **partial proportional odds generalized ordered logit model**, avoiding the extremes of strictly adhering to the proportional odds assumption (ordered logit) or completely relaxing it (generalized ordered logit). This is where we first tested all variables and identified ones that violate proportional odds assumption. This way, this research is able to estimate using the maximum efficiency without violating the basic model assumption and estimate consistency. The operation is made possible using the user-written STATA package gologit2 (Williams, 2006). The model can be specified as (Williams, 2005):

$$P(Y_i > j) = \frac{\exp(\alpha_j + X1_i\beta 1 + X2_i\beta 2 + X3_i\beta 3_j)}{1 + [\exp(\alpha_j + X1_i\beta 1 + X2_i\beta 2 + X3_i\beta 3_j)]}, \mathrm{j} = 1, 2, \ldots, \mathrm{M} - 1$$

Here, β1 and β2 represents estimates for regressor that is the same across different outcome categories, whereas $\beta 3_j$ denotes an estimate specific to the jth category. The coefficient interpretation goes very similar to that of ordered logit regression, besides now each category will be interpreted separately.

Finally, this research conducts one more Wald test on the final specification of the model. Results reported chi2 = 5.47 , Prob > chi2 = 0.7061 for 'ORG79' cohort and chi2 = 11.81 Prob > chi2 = 0.9819 for 'CHILD79' cohort, showing that both constructions do not violate the proportional odds requirement.

Endogeneity sensitivity analysis

The study tried to minimize omitted variable issues and avoid endogeneity by including comprehensive background information for each individual. However, for complex outcomes like educational attainment and employment, it is nearly impossible to completely overcome the issue. As mentioned in the literature review section, when dealing with similar datasets and investigating similar research questions, researchers often adopt either an Instrument Variable approach or make use of siblings' fixed effects. Common instrument variables, miscarriages, have been widely criticized for their nonrandom selection (Ashcraft and Lang, 2006), and siblings' fixed effects also faced criticism for neglecting spillover effects (Altonji et al., 2017). Since there seems to be no good methods of solving the problem of endogeneity, this study decided to adopt a sensitivity analysis, which tests for how endogenous variables need to be in order to completely override significant results found on main explanatory variables. This decision makes sense since we are more interested in informing policy makers whether there is a significant impact worth noticing, while we care less about the accurate size of such a negative effect.

Result

Education: HGC attainment

This section will discuss our findings on the impact of having a teenage mother on children's educational outcomes. We investigated both children's educational attainment measured by highest grade completed (HGC), and general educational result measured by standardized test scores. We will first separately discuss findings in each cohort, and then make comparisons and test some of our time series hypotheses.

This study first runs a generalized ordered logit regression on 'ORG79' and 'CHILD79' cohorts. Note that since the 'CHILD79' cohort includes information from the 'ORG79' cohort, it allows us to account for an additional intergenerational level, incorporating grandparents' data. The 'CHILD79' model also captures the influence of grandparents' highest grade completed (HGC) on their grandchildren's educational outcomes and examines whether having a grandmother who gave birth as a teenager affects the grandchildren's educational attainment.

A generalized ordered logit model coefficient can be interpreted similar to that of a binary outcome logit regression (Williams, 2016). When interpreting the coefficient for outcome category n, it is as if we treat outcome 0 as individuals having an HGC lower than category n, and outcome 1 as individuals progressing into HGC categories equal to or higher than n. In both regression result tables, the column headers indicate the corresponding HGC categories. For example, column (2) for 'ORG79' represents a binary logit model for whether individuals in 'ORG79' attain some middle school education (HGC = 2).

A negative coefficient generally indicates that a particular regressor has a negative impact on the likelihood of children progressing to the next educational outcome category. To quantify the magnitude of this impact, the study also calculates the odds ratio for the key explanatory variables. The odds ratio equal to $e^{coefficient}$ and captures the ratio of $Pr\ (HGC > \ n)$ to $Pr\ (HGC \leq n)$, showing how much more or less likely an individual is to advance to the next educational category compared to remaining in lower ones. Given the property of exponential function e^{x} as shown in Fig 7, we can conclude that if the coefficient is negative, the larger the coefficient's absolute value is, the less likely an individual can progress into the next HGC category; whereas if the impact is positive, then the larger the coefficient is, the individual is more like to progress into the next outcome level.

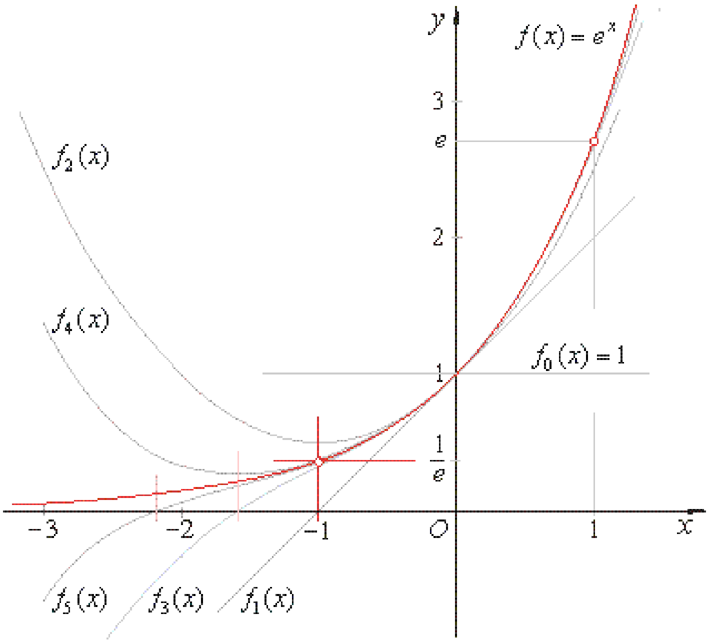

Fig 7. Plot of e^{x} (Nabla, 2020)

ORG79

For the 'ORG79' cohort, after conducting proportional odds test on each individual, we end up with a model where the parallel line restriction is only imposed on variables 'number of siblings', 'number of siblings in school' and 'dad work index', meaning that those variables have a consistent effect on children's educational attainment across outcome categories. The full result is reported in Table 8.

We can observe that having a teenage mother has a negative coefficient across all education categories, although it is only statistically significant for HGC categories 2 to 4, which are the relatively early stages of education. Namely, for individuals who were classified as 'having some middle school education', those who having a teenage mom are $1 / 0.54 = 1.85$ times less likely to complete middle school compared to their peers with all other variables being constant. Similarly, for those who "completed middle school" or have "some high school education," it follows with them being 1.47 and 1.30 times, respectively, less likely to progress to 'some high school education' and 'completed high school' or higher, if they have teenage mothers.

It could be observed that the impact of teenage mothers plays declines as the level of education elevates, and having a teenage mother has no significant effect on after HGC = 5. In other words, after an individual completes high school, having a teenage mother plays no negative role in whether they can get into college education, graduate from college, or enter even higher education categories. The finding is consistent with theories suggesting that parental influence is often found to be strongest during the early stages of a child's human capital development (Coleman, 1988).This finding makes intuitive sense, as students spend more and more time in an external environment, for example peer groups, as they are further into education and entered adolescence. This supported our **Sub-hypothesis 3:** *The impact of UFRM is the most detrimental during the early years of a child's education.*

	teen_mom	**mom HGC**
HGC = 2	0.54**	1.21***
HGC = 3	0.68**	1.14***
HGC = 4	0.77*	1.13***
HGC = 5	0.91	1.11***
HGC = 6	0.89	1.17***
HGC = 7	0.69	1.23***

Table 7. Odds ratio calculation for 'ORG79'

Meanwhile, another pattern regarding the mother's education level could be unveiled. Mother's HGC has a significant positive impact on the likelihood of the child progressing into a higher level of education on all education levels. Specifically, for each additional level of the mother's HGC, the child is 1.11 to 1.21 times more likely to attain a higher level of education. However, similar to the effect of having a teenage mother, the influence of maternal HGC tends to diminish as the child's education level increases, with the exception of the HGC = 7 category, which reflects whether a college graduate decides to pursue postgraduate or doctoral studies.

There are also some interesting side findings. First, a higher paternal HGC is also found to have a significant positive effect on the child's educational attainment. For each additional level of the father's HGC, ceteris paribus, the child becomes 1.11 to

1.31 times more likely to attain higher education. Similar to the maternal side, the influence of paternal HGC declines as the child moves into higher HGC categories.

Additionally, paternal influence shows greater variability across different levels of education. This variability may be further investigated by future research to determine at which educational stages maternal and paternal HGCs have the most significant impacts. Such insights could be valuable for informing family education and welfare policies. For instance, by understanding the heterogeneity in parental influence, policymakers could better target interventions. For example, when trying to maximize high school enrollment rates (HGC 3 to 4) with a highly constrained budget, the government can narrow the focus to children who are most likely to benefit, in this case, those with lower-educated fathers.

Moreover, we incorporated both maternal and paternal ages at the time of birth, and investigated their impact on children's educational attainment. Since the 'teen_mom' variable is derived from 'mom age', we tested for multicollinearity in this model with VIF < 1.14 for all variables (well below the typical threshold of VIF > 5).

Our analysis shows that older maternal age at childbirth significantly increases the likelihood of children completing high school (O.R. = 1.034), entering college (O.R. = 1.033), and completing college (O.R. = 1.034). Paternal age also has a positive effect, though smaller in magnitude, on the likelihood of children entering (O.R. = 1.021) and completing college (O.R. = 1.022). Notice that these relative probability ratios reflect the impact of each additional year of age at the time of birth, such that there exists a multiplier effect which further widens the gap between paternal and maternal birth age influence. In other words, a mother who is five years older beyond her teenage years has a much stronger positive impact on her child's educational outcomes than a father of the same age difference. This issue may be severely underestimated, as the summary statistics show that 70% of children born to teenage mothers have an adult father and might not be considered at risk for poor educational attainment. However, our findings suggest that even when the father is significantly older, the child's educational outcomes can still be dragged down by having a teenage mother. This provided evidence for our ***Sub-hypothesis 2****: The adverse effects of teenage pregnancy are expected to be exacerbated when the father is significantly older, with the negative impact intensifying as the age gap increases.*

	(2) HGC	(3) HGC	(4) HGC	(5) HGC	(6) HGC	(7) HGC
teen_mom	-0.607**	-0.383**	-0.262*	-0.097	-0.113	-0.378
	(0.294)	(0.193)	(0.144)	(0.090)	(0.116)	(0.242)
female	0.220	0.334***	0.340***	0.407***	0.152**	0.272**
	(0.187)	(0.127)	(0.094)	(0.057)	(0.069)	(0.135)
dad HGC	0.214***	0.269***	0.233***	0.213***	0.216***	0.107***
	(0.070)	(0.045)	(0.033)	(0.019)	(0.022)	(0.039)
mom HGC	0.194***	0.127***	0.123***	0.102***	0.154***	0.212***
	(0.073)	(0.049)	(0.036)	(0.023)	(0.029)	(0.055)
dad age	-0.002	0.003	0.005	0.021***	0.022***	0.022
	(0.017)	(0.012)	(0.009)	(0.006)	(0.008)	(0.017)
mom age	0.011	0.022	0.034***	0.032***	0.034***	0.009
	(0.023)	(0.016)	(0.013)	(0.008)	(0.010)	(0.021)
black	0.647**	1.157***	0.750***	0.538***	0.259***	0.206
	(0.271)	(0.205)	(0.131)	(0.075)	(0.095)	(0.194)
#sibling	-0.174***	-0.174***	-0.174***	-0.174***	-0.174***	-0.174***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
#sibling in school	0.205***	0.205***	0.205***	0.205***	0.205***	0.205***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
cultural index	2.158***	1.699***	1.274***	0.805***	0.958***	1.237***
	(0.322)	(0.207)	(0.155)	(0.104)	(0.143)	(0.314)
urban at 14	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
age_indepent	-0.024	0.016	0.037***	0.025***	0.015	-0.008
	(0.029)	(0.016)	(0.010)	(0.007)	(0.009)	(0.017)
mom work index	-0.178	-0.003	-0.039	-0.016	0.054	-0.022
	(0.119)	(0.077)	(0.056)	(0.033)	(0.040)	(0.078)
dad work index	-0.142***	-0.142***	-0.142***	-0.142***	-0.142***	-0.142***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Constant	2.467***	0.088	-1.124***	-3.815***	-5.486***	-6.175***
	(0.887)	(0.510)	(0.391)	(0.263)	(0.322)	(0.604)
Observations	5843					

Standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

Table 8. Generalized ordered logit regression result for 'ORG79'

CHILD79

Regression results are presented in Table 10 for the 'CHILD79' cohort. The parallel line restriction is imposed on the variable 'teen_grandma', which was the 'teen_mom' variable in the previous cohort. This shows that it has a consistent effect on grandchildren's educational attainment across outcome categories. Those whose mother is born by a teenage mom are $1 / 0.84 = 1.19$ times less likely to advance in education across all HGC levels. Such findings provided evidence for part of our **Sub-hypothesis 4:** … *The role model effect of grandmother is still strong for their grandchildren's development.*

Similarly, having a teen mother has a significant negative influence on children's educational attainment from high school throughout college. Specifically, for those born by teenage mothers and are already in high school, the probability of completing high school is reduced 1.37 times compared to their peers. After completing high school, teenage mother's children are only 0.84 times as likely to enter college, and 0.86 times to complete college. After completing college, having a teenage mother does not significantly impact the likelihood of an individual obtaining higher education qualifications.

	teen_mom	**teen_grandma**	**mom HGC**
HGC = 2	0.73***	0.84*	1.26***
HGC = 3	0.84**	0.84*	1.27***
HGC = 4	0.86*	0.84*	1.27***
HGC = 5	0.82	0.84*	1.35***
HGC = 6	0.89	0.84*	1.36***

Table 9. Odds ratio calculation for 'CHILD79'

Higher maternal HGC has a significant and strong impact on children's educational attainment at all stages. For each additional level of a mother's HGC, her children are 1.26 times more likely to graduate from high school, 1.27 times more likely to enroll in and complete college, 1.35 times more likely to advance from undergraduate to graduate studies, and 1.36 times more likely to earn a graduate degree.

Interestingly, grandfather's HGC is not found to be significantly impacting their grandchildren's education progression at any stage of education. While the signs of impact are still positive, the magnitude of impact is minimal even if it is statistically significant. On the other hand, a grandmother's HGC has a consistently larger impact compared to a grandfather's. This effect is particularly significant in HGC categories 6 and 7, which represent the likelihood of progressing from master's coursework to graduation, and from a master's degree to doctoral training. This may demonstrate how a positive female role model in the household has a lasting influence on children's educational choices, extending to multiple generations.

Additionally, maternal expectations regarding their children's educational outcomes prove to be a positive factor in the progression of education. The odds ratios for these expectations range from 1.14 to 1.23, indicating a boost in likelihood for advancing in educational stages. Furthermore, the mother's age of first marriage also turns out to be a significant regressor. Specifically, earlier marriages are associated with a decrease in the likelihood of children achieving higher educational attainment, with the odds of progressing to advanced educational levels reduced to between 0.984 and 0.98.

	(2) HGC	(3) HGC	(4) HGC	(5) HGC	(6) HGC
teen_mom	-0.31***	-0.17**	-0.15*	-0.20	-0.12
	(0.09)	(0.07)	(0.08)	(0.16)	(0.17)
teen_grandma	-0.17*	-0.17*	-0.17*	-0.17*	-0.17*
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
mom HGC	0.23***	0.24***	0.24***	0.30***	0.31***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)
grandpa HGC	0.03	0.02	0.02	0.02	0.00
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
grandma HGC	0.03	0.02	0.04	0.07*	0.09**
	(0.03)	(0.02)	(0.02)	(0.04)	(0.04)
mom expected yos	0.13***	0.21***	0.15***	0.13*	0.04
	(0.04)	(0.03)	(0.04)	(0.07)	(0.08)
female	0.01	0.06	0.09	0.17	0.13
	(0.08)	(0.06)	(0.06)	(0.11)	(0.12)
black	-0.18*	-0.07	-0.19**	-0.09	-0.10
	(0.10)	(0.08)	(0.08)	(0.15)	(0.17)
ln(family income)	0.92***	0.83***	0.82***	0.76***	0.86***
	(0.08)	(0.06)	(0.06)	(0.10)	(0.11)
ln(behavior score)	0.01	-0.01	-0.02	-0.07	-0.07
	(0.11)	(0.08)	(0.07)	(0.12)	(0.12)
ever repeated a grade	-0.16	-0.06	-0.32**	-0.02	-0.05
	(0.15)	(0.12)	(0.14)	(0.07)	(0.07)
desire children #	-0.04	-0.05**	-0.03	0.02	0.02
	(0.03)	(0.02)	(0.03)	(0.04)	(0.05)
mom marriage age	-0.02***	-0.01	-0.02***	-0.04***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Constant	0.18	-2.04***	-2.71***	-4.34***	-3.76***
	(0.33)	(0.26)	(0.27)	(0.50)	(0.56)
Observations	4935				

Standard errors in parentheses
* $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 10. Generalized ordered logit regression result for 'CHILD79'

Comparison

Table 11 consolidates the odds ratio results from the 'ORG79' and 'CHILD79' cohorts, aligning the output to present HGC categories on the same line for easier comparison. This adjustment was made to account for the slight variations in HGC category definitions between the ORG79 and CHILD79 surveys, which stem from differences in the raw data and the questions posed in each survey.

	ORG79			**CHILD79**		
HGC	teen_mom	mom HGC	HGC	teen_mom	teen_grandma	mom HGC
2	0.54**	1.21***				
3	0.68**	1.14***				
4	0.77*	1.13***	2(4)	0.73***	0.84*	1.26***
5	0.91	1.11***	3(5)	0.84**	0.84*	1.27***
6	0.89	1.17***	4(6)	0.86*	0.84*	1.27***
7	0.69	1.23***	5(7)	0.82	0.84*	1.35***

Table 11. Odds ratio comparison

Here, we observe that in all HGC categories available for both cohorts, the 'CHILD79' group experiences a smaller odds ratio on 'teen_mom'. This indicates a more severe downward pressure on education attainment from having a teenage mother. This effect also extends to individuals who completed college and are advancing to postgraduate education (ORG79: insignificant; CHILD79: 0.84**) ; and to individuals with some master's education who are progressing towards completing their master's degree (ORG79: insignificant; CHILD79: 0.86*). This finding supports our ***Sub-hypothesis 1****: The impact of having a teenage mother is more pronounced in the later 'CHILD79' cohorts.*

When looking at the influence of maternal HGC, the 'CHILD79' cohort consistently shows a stronger impact across all available HGC categories compared to the

‘ORG79’ cohort. This suggests the growing importance of having a positive female role model in the family, contributing to higher educational attainment in future generations. Additionally, while having a teenage grandmother exhibit a similar negative impact, the magnitude is smaller across most HGC categories compared to each cohort’s direct maternal effect.

Moreover, in the ‘CHILD79’ cohort, the effect of maternal HGC becomes more pronounced as children progress through higher HGC categories. This rise in odds ratio indicates that a mother’s education plays an increasingly vital role as children advance to higher educational levels. This pattern contrasts with the trend observed in the ‘ORG79’ cohort, where the influence of maternal HGC fades out in higher categories. This finding presents an intriguing area for future research and could inform educational policies aimed at promoting success in higher education.

Education: standardized test score

Table 12 reported the OLS regression result of ‘ORG79’’s AFQT score on ‘teen_mom’, ‘mom HGC’ and other relevant controls. Table 13 reported three OLS regression on (1) PIAT reading recognition score, (2) PIAT reading comprehension score and (3) PIAT math score. It can be observed that when controlling for a family member’s HGC, family income, and one’s behavioral score and school performance, having a teenage mother does not statistically significantly influence any of these standardized test scores. This finding contradicts literature with finding that having a teenage mother negatively impacts students' GPA and PIAT score (Example: Morinis et al., 2013, Aizer et al., 2020). Such inconsistency might be explained by the fact that NLSY79 individuals take the AFQT and PIAT test repeatedly at different ages, and thus we might omit time-variant individual factors, learning to insignificant result. Previous studies on PIAT score also omitted grandparental effect, such that there may be genetic differentials on student's cognitive ability that was not accounted for.

	AFQT
teen_mom	-1.36 (0.91)
female	-0.69 (0.57)
dad HGC	2.56*** (0.18)
mom HGC	2.72*** (0.23)
dad age	0.20*** (0.06)
mom age	0.33*** (0.08)
black	-16.76*** (0.74)
#sibling	-1.75*** (0.17)
#sibling in school	1.30*** (0.24)
cultural index	16.01*** (1.04)
urban at 14	-2.84*** (0.69)
mom work index	-0.23 (0.34)
dad work index	-1.61*** (0.48)
Constant	7.99*** (2.35)
Observations	6199
Standard errors in parentheses * p<0.1 ** p<0.05	*** p<0.01

Table 12. Result on AFQT score for 'ORG79'

	(1) reading recognition	(2) reading comprehension	(3) math
teen_mom	0.52	0.70	-0.08
	(0.51)	(0.43)	(0.43)
teen_grandma	-0.67	-0.48	-0.63
	(0.51)	(0.43)	(0.43)
mom HGC	0.24	0.32**	0.07
	(0.16)	(0.13)	(0.13)
grandpa HGC	0.28**	0.22*	0.25**
	(0.13)	(0.11)	(0.11)
grandma HGC	0.47***	0.57***	0.77***
	(0.16)	(0.14)	(0.14)
female	2.07***	1.09***	-0.64*
	(0.43)	(0.36)	(0.36)
black	-2.99***	-3.16***	-2.99***
	(0.52)	(0.44)	(0.44)
ln(family income)	2.39***	1.73***	1.94***
	(0.38)	(0.32)	(0.32)
ln(behavior score)	-0.51	0.06	-0.43
	(0.51)	(0.43)	(0.42)
ever repeated a grade	-7.39***	-3.85***	-3.96***
	(0.81)	(0.68)	(0.67)
Constant	31.51***	27.76***	32.04***
	(5.21)	(4.39)	(4.35)
Observations	5916	5907	5921

Standard errors in parentheses
* $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 13. Result on PIAT scores for 'CHILD79'

Employment

This section will discuss our findings on the impact of having a teenage mother on children’s early income performance between 18 to 30 years old. We run several regressions for both the income at specific ages, and on average income during this age period. All income data is CPI-adjusted using the 2010 price level.

ORG79

In Table 14, column (1), we present the regression results for the logarithm of average income. Youth with a teenage mother appear to earn 4% less than those with an adult mom, keeping everything else constant. This effect is statistically significant and is in line with our expectation. Similar results are frequently cited in previous literature as evidence blaming teenage mothers for their children’s poorer career outcomes (Aizer et al., 2020).

However, when we broke down the regression to examine when the negative effects of having a teenage mother are most pronounced and how long they last, we found that the ‘teen_mom’ variable is only significant for income at age 18 and not significant at any age thereafter when controlling for the children’s educational attainment. Income at age 18 is not an ideal measure of career success, as many individuals at this age are still unemployed, in school, or working part-time jobs such as waitressing, which do not reflect long-term earnings potential. Children of teenage mothers may initially earn less due to various factors, such as limited family resources, fewer educational opportunities, or early responsibilities at home, which could interfere with their early career development. For instance, we already found that having a teenage mother significantly impacts a child's educational attainment, which could confound the income results. We found here that each additional level of HGC is associated with approximately a 2% increase in the respondent's average income, holding other variables constant. This positive relationship is in line with expectations. When we further examined the effect on income at specific ages, the influence of HGC showed an increase in magnitude and became significant over time. At age 30, one higher HGC category is associated with a $624.84 increase in income.

This finding is crucial, as it suggests that the stigma surrounding teenage mothers' impact on their children's income may stem from models that are wrongly specified and highly biased. Such stigma could perpetuate a downward spiral, becoming the real culprit of lower performance in children of teenage mothers instead of the mothers themselves. Policymakers should be mindful of these trends and work toward educating the public to avoid reinforcing these harmful biases.

Additionally, HGC has been shown to become increasingly important as age grows, serving as a key factor contributing to the widening gap in income as individuals progress through their careers. Given the long-term benefits of higher educational attainment, policy efforts should especially focus on improving the educational outcomes of children born to teenage mothers. By helping these children attain higher levels of HGC, their future performance in the labor market will naturally improve, closing the income gap and enhancing their economic prospects.

	(1) lnavginc	(2) income_18	(3) income_20	(4) income_25	(5) income_30
hgc	0.02*	-7.6	13.97	247.40	624.84*
	(0.01)	-123.72	(156.68)	(229.82)	(360.96)
teen_mom	-0.04*	-666.59**	-550.82	-531.91	-591.08
	(0.02)	-318.1	(398.82)	(597.93)	(945.73)
outgoingness	0.02	264.28	227.88	492.02	961.42*
	(0.01)	-185.29	(231.34)	(344.81)	(550.22)
mental score	0.02	5.68	10.88	-17.20	26.59
	(0.00)	-16.34	(19.93)	(29.86)	(47.74)
physical score	0.01	-1.58	-16.81	22.16	14.20
	(0.00)	-16.99	(21.01)	(30.79)	(48.40)

Other controls and constant truncated
Standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

Table 14. regression result on 'ORG79' income

CHILD79

Table 15 Column (1) shows the log of average income regression. We surprisingly found that having a teen mom is associated with a 7% increase in children's average income in early years of career. This effect is statistically significant at the 1% level. The coefficient means that, holding other variables constant, being a teen mom increases average income by about 7%. It is counterintuitive to see such a positive relationship, given the common literature conclusions (negative association) and our finding in the 'ORG79' cohort (insignificant at all ages). However, when we look at specific years of income, teenage mothers do not seem to show a significant effect. This suggests that while teen motherhood might have an overall effect on average income, it doesn’t have a consistent, detectable impact at any specific age. It is possible that when we average across income at different ages, we pooled the income information and reduced the variance of the estimate, such that the overall effect appears wrongly significant.

HGC still has a positive and significant effect on average income, with one level higher HGC being associated with a 14% increase in average income ($p < 0.01$). HGC shows varying significance at different ages. At age 18, the effect is surprisingly negative (-$920.77), similar to the findings on the ‘income_at_18’ variable in the ‘ORG79’ cohort. Again, this might suggest that at very young ages, people who have more education are associated with lower earnings likely because they are still in school and are not yet in full-time employment. At age 22, higher HGC category is associated with an increase in income of $890.42, significant at the 1% level. At age 26, an increase in one educational attainment category has a large and significant positive effect of $2688.83. At age 28, the effect becomes even larger, at $4044.78, significant at 1%. Similar to findings in ‘ORG79’ cohort, the effect of HGC increases with age, and similar policy implications apply here.

In ‘CHILD79’, we have much more detailed maternal income, so we also controlled the mother’s income at the same age for each specific income regression. The income of the respondent's mother generally has no significant impact on the respondent's income. Even though the coefficients are mostly positive, they are not statistically meaningful, suggesting that the respondent’s income isn't strongly tied to their mother's income at this stage. Similar insignificance is concluded with maternal HGC.

	(1) lnavginc	(2) income_18	(3) income_22	(4) income_26	(5) income_28
teen_mom	0.07***	595.38	198.77	193.74	-148.40
	(0.02)	(593.70)	(947.81)	(1026.27)	(1270.74)
HGC	0.14***	-920.77***	890.42***	2688.83***	4044.78***
	(0.01)	(191.32)	(329.57)	(350.69)	(442.63)
mom HGC	-0.01	-136.08	312.14	144.46	464.59
	(0.01)	(161.69)	(300.91)	(331.15)	(416.90)
ln(family income)	0.30***	1061.10**	6849.94***	7677.55***	6951.68***
	(0.02)	(426.96)	(743.86)	(820.79)	(1032.56)
female	-0.09***	-973.81**	-3462.23***	-2601.04***	-2698.23**
	(0.02)	(478.47)	(838.31)	(922.93)	(1158.96)
black	-0.12***	-759.05	-1062.71	-1938.08*	-2209.31
	(0.02)	(618.27)	(993.22)	(1080.53)	(1351.28)
behavior score	-0.01	2.02*	-2.12	-1.40	-3.29
	(0.00)	(1.06)	(1.86)	(2.05)	(2.61)
mom income at 18		-0.01			
		(0.02)			
mom income at 22			0.01		
			(0.02)		
mom income at 26				0.03	
				(0.02)	
mom income at 28					0.03
					(0.03)

Other controls and constant truncated
Standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

Table 15. regression result on 'CHILD79' income

Evaluation and robustness test

Gender heterogeneity

We aim to determine whether having a teenage mother affects daughters and sons differently. In this analysis, we focus specifically on gender differences in children's educational attainment and re-estimated the generalized logit model, as previous models provided the most valuable insights in this area. The interaction term 'teen_mom * female' captures how the effect of having a teenage mother on educational attainment varies by gender. The coefficient can be interpreted as the additional impact that daughters face, compared to sons, when their mother was a teenager at the time of birth.

Table 16 reports the estimated coefficients for the interaction term from a partial odds generalized logit model, with HGC categories adjusted so that each column represents the same HGC category across the 'ORG79' and 'CHILD79' cohorts.

’ORG79’	(2) hgc	(3) hgc	(4) hgc	(5) hgc	(6) hgc	(7) hgc	
teen_mom*female	-0.31 (0.42)	-0.31 (0.29)	-0.21 (0.21)	-0.23* (0.14)	-0.37** (0.19)	-0.54 (0.40)	
’CHILD79’			(2) hgc	(3) hgc	(4) hgc	(5) hgc	(6) hgc
teen_mom*female			0.07 (0.17)	0.06 (0.14)	0.02 (0.15)	0.16 (0.29)	-0.69** (0.35)
Standard errors in parentheses * p<0.1 ** p<0.05 *** p<0.01							

Table 16. Gologit estimation on interaction term for 'ORG79' and 'CHILD79'

The interaction term ‘teen_mom*female’ shows consistently negative coefficients across different HGC categories in the ‘ORG79’ cohort. This suggests that daughters of teenage mothers in the ORG79 cohort are impacted more compared to sons of teenage mothers. Specifically, for HGC category 5, the estimated coefficient is -0.23. This shows that daughters of teenage mothers are approximately $e^{coefficient} = 0.79$ times, or 21%, less likely to advance from high school graduation to having some college training. Similarly, daughters of teenage mothers are 31% less likely to graduate from college compared to sons of teenage mothers.

In the ‘CHILD79’ cohort, teenage mothers do not appear to have significant additional impact on their daughters in most HGC categories, except for category 7. In this category, daughters of teenage mothers are found to be approximately 1.9 times less likely to progress from having some master training to obtaining a master’s degree.

We also discovered that the divergence between teenage mother’s sons and daughters becomes more pronounced in later educational stages, especially after the children enter college. The underlying reason requires further research attention, as it holds policy significance for understanding and better targeting the educational outcomes of children of teenage mothers.

Sensitivity analysis

We followed a sensitivity analysis proposed by Diegert, Masten and Poirier (hereafter DMP, 2022). The DMP method is built on previous work of Oster (2019), which tests for how large the unobservable need to be to overturn previously found results on main explanatory variables. However, Oster's proposition is based on the assumption that all control variables are exogenous, which is often not the case in complex outcome regression involving human achievement and behavior (DMP, 2022).

The DMP method allows us to relax the assumption by manually setting the endogeneity level C on control variables from 0 (completely exogenous) to 1 (completely endogenous). We conducted the sensitivity analysis using OLS on educational attainment outcome where we discovered most insight in previous research, and followed the advice in DMP (2022) to alter control comparison groups for multiple times to calibrate sensitivity parameters.

We plot the extreme situation where all controls are completely exogenous for 'ORG79' in Fig 8. The breakdown point in this case is 33.3%, meaning that the endogeneity on 'teen_mom' needs to be 1.33 times that of the impact of observables on the result (DMP, 2022), in order to erase the negative effect found. Given that our controls have significant explanatory power, breakdown point <1 can also be considered sufficient to conclude a robust relationship (ibid). When we relax the 'completely exogenous' assumption, the breakdown point further expands and reaches 35.3% when considering fully exogenous controls as shown in Fig 9.

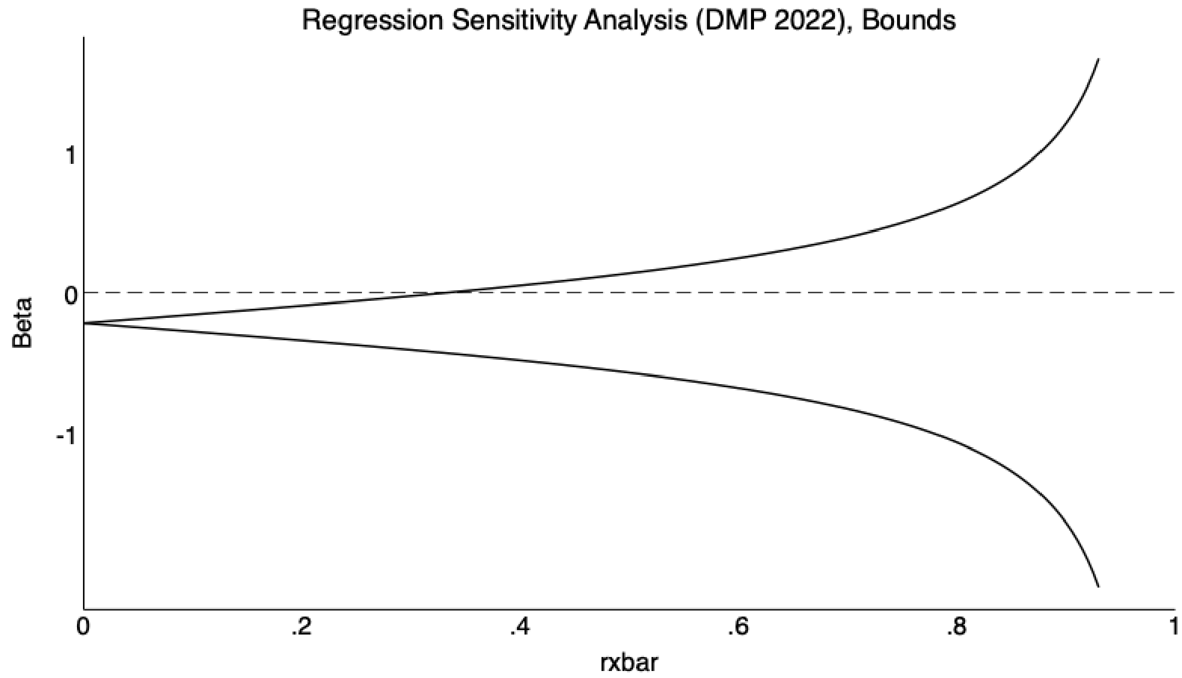

Fig 8. Regression sensitivity plot with C = 1, "ORG79'

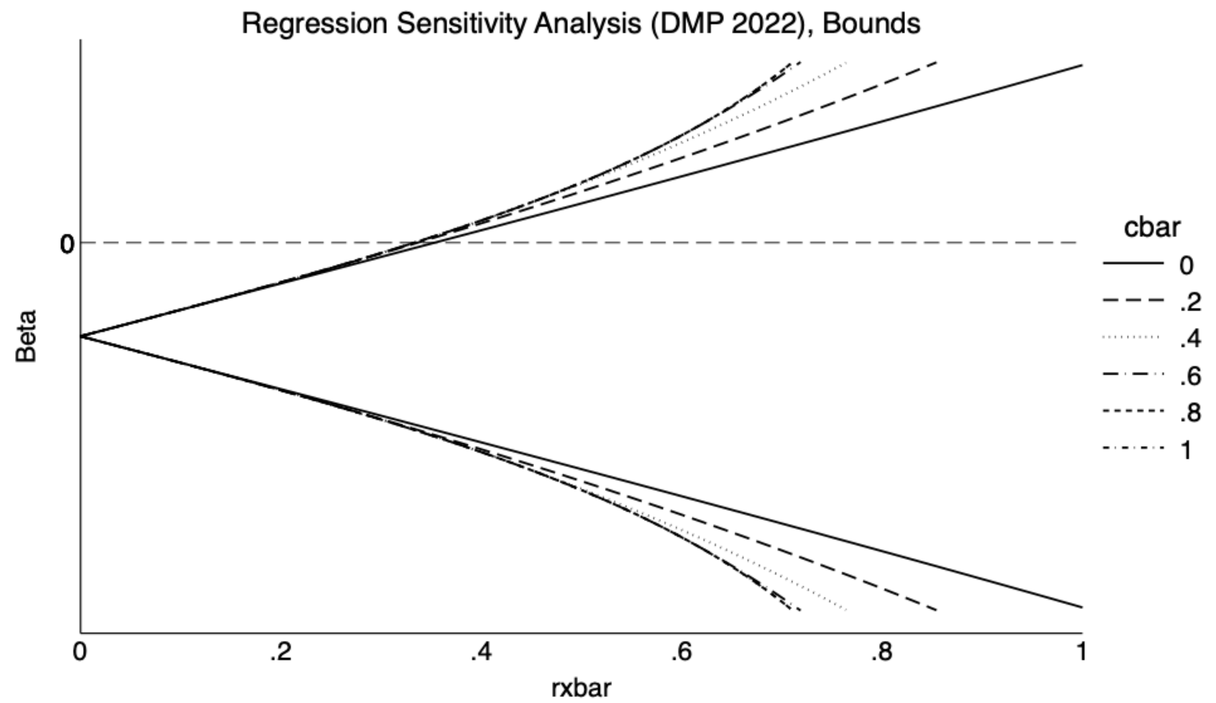

Fig 9. Regression sensitivity plot with C = 1, "ORG79'

Similarly, as shown in Fig 10, when controlling for the most extreme situation where all controls are completely endogenous, 'CHILD79' cohort's breakdown point is at

49.4% . This breakdown point means that the unobservable selection on having a teenage mother needs to be 49.4% larger than the explanatory power of the observables in order to overturn teen_mom's coefficient to insignificant or positive. In Fig 11, we plotted other situations where we gradually relax up to fixing controls to be completely exogenous (C = 0). We can see that as we relax C, the breakdown point increases to 56.8%, meaning that it is even harder to overturn the negative association found between teenage mothers and their children's educational attainment. It can be observed that the breakdown point is now higher than that of 'ORG79', potentially indicating a more robust negative impact of teenage mothers in the later cohort as suggested by our sub hypothesis.

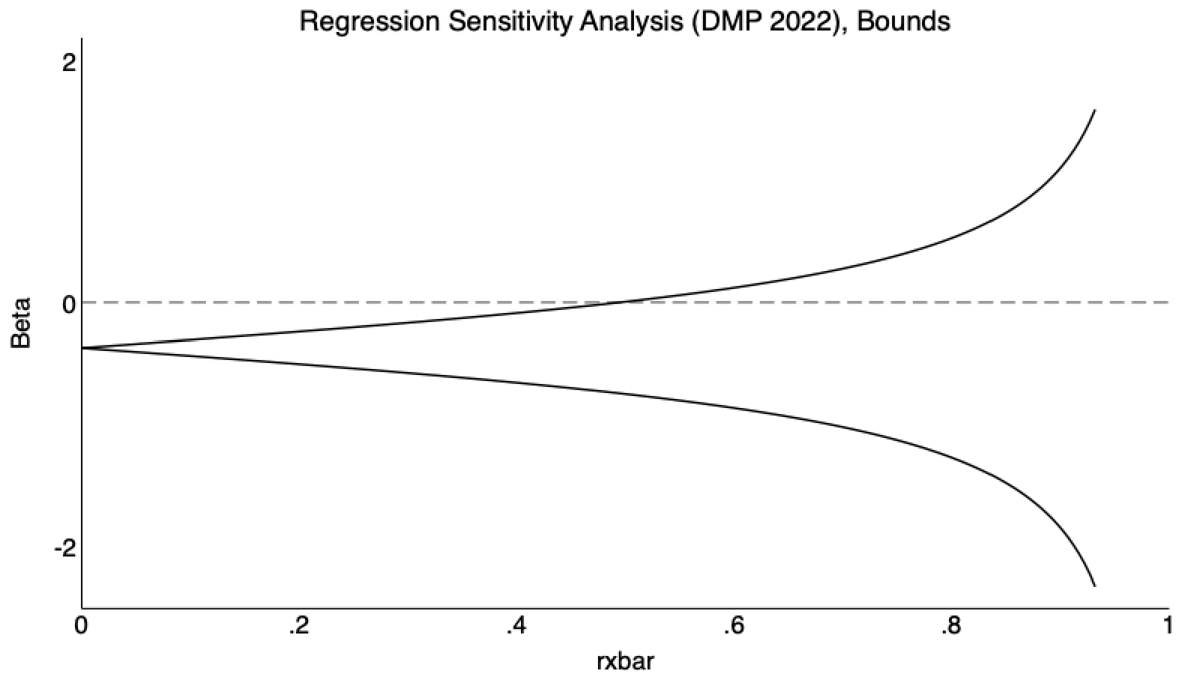

Fig 10. Regression sensitivity plot with C = 1, "CHILD79'

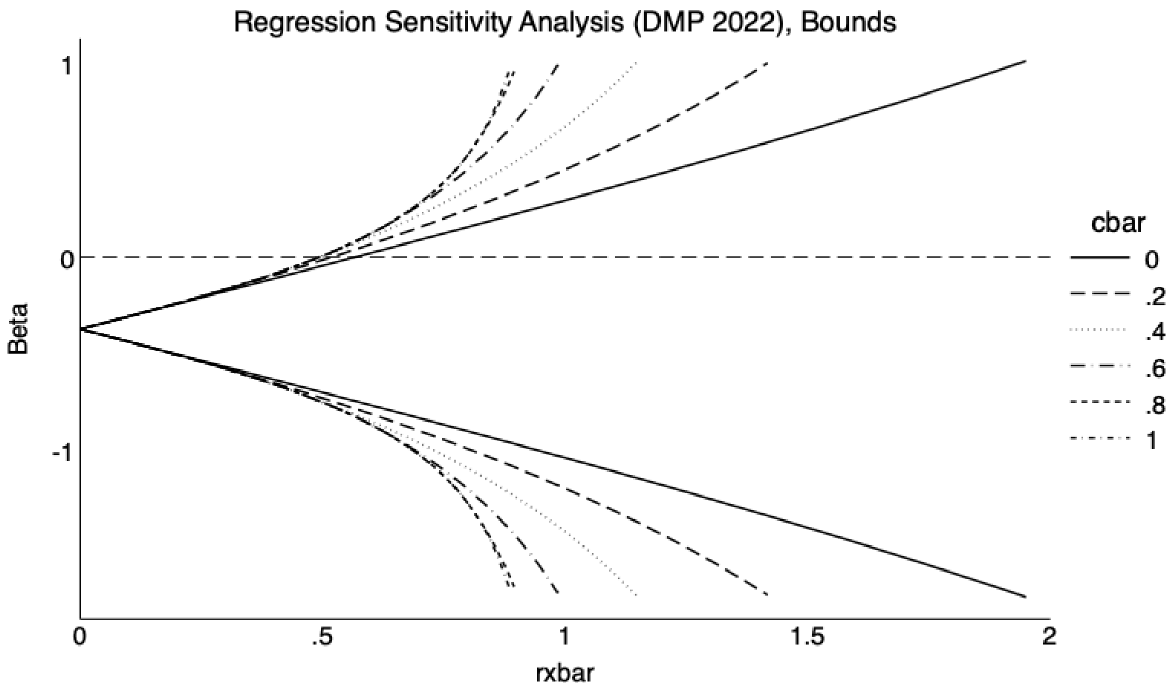

Fig 11. Regression sensitivity plot with various C, ‘‘CHILD79’

<<CONCLUSION TO BE DONE>>