Parents Divorce and the Gender Gap in Long Term Labor Market Outcomes

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Abstract

This paper explores the importance of divorce in explaining the gender gap in children's long term educational outcomes. I find large differences in gender gap between divorced and non-divorced families. Boys perform much worse in divorced families. I use a sibling fixed effects model to find that relative to their sisters, boys in divorced families have lower likelihood of graduating high school and attending college. My results show that boys likelihood of graduating high school declines by 6.4 percentage points if their parents are divorced before they turn 13, and their chances of attending college decline by 12.2 percentage points if they are a teenager at the time of divorce. I find that divorce of parents is unrelated to the gender gap in achievement scores. My event study models show a drop in boys achievement scores relative to girls around the time of divorce.

1 Introduction

The gender gap in educational attainment has reversed substantially over the past four decades. This reversal in the gender gap has happened in many rich countries including the United States. On average, 84 percent of young (25-34) women have attained at least an upper secondary level of education compared to 81 percent of young men (OECD 2013). Family disruption leads to lower educational attainment of children. Family disadvantage has been shown to have a causal effect on the gender gap in test scores and behavioral outcomes (Autor et al. 2019). These emerging gender gaps suggest reason for concern. Education has become an increasingly important determinant of lifetime income. The employment prospects of low educated youths have declined sharply in recent years. Currently, little

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is known about how divorce affects the gender gap in long term educational outcomes. In this paper, I focus on divorce as a potential explanation for the gender gap in long term labor market outcomes. My analysis looks at how long term outcomes of children are impacted by divorce before the age of 13. Children in single parent families are more likely to be living with their mothers. The lack of a male role model in single parent families can have an adverse effect on boys relative to girls (Cobb-Clarke and Tekin 2011). I hypothesize that divorce differentially affects the long term outcome of boys relative to girls, either because these outcomes are more elastic to family circumstances among boys than girls (Bertrand and Pan 2013), or because differential parental investment in girls relative to boys varies positively with age in single parent families (Bibler 2019).

As a motivating example for my analysis, consider Figure 1, which plots the median math (Peabody Individual Achievement Mathematics test) and reading (Peabody Individual Achievement Reading and Recognition test) test scores for children from divorced families at different time periods before and after divorce. Boys start of with a higher median mathematics test score than girls. However, as they approach the event of divorce, the gap gets narrower and eventually reverses in favor of girls. The eventual outcome in the case of the gap in reading scores is similar, but, the patterns from the figure reveal a different path. While boys do start off with a higher median reading score compared to girls, that advantage quickly disappears as they move closer to the event of divorce. This is due to a sharp fall in the average reading score for boys accompanied by a consistent rise in girls reading score. It is a known fact that on average girls do better than boys in terms of reading as they age and it is the opposite for math scores. The figure shows that boys reading scores fall while their math scores do not rise sufficiently at the median as they age. These trends motivate the hypothesis that divorce is more consequential for educational outcomes of boys. The effects of a divorce may start affecting children's outcomes years before the actual event. This may be a reason why boy's reading scores start dropping around the time of their parents divorce. Other factors like behavioral and non-cognitive outcomes may also have a role to play in a child's long term outcomes.

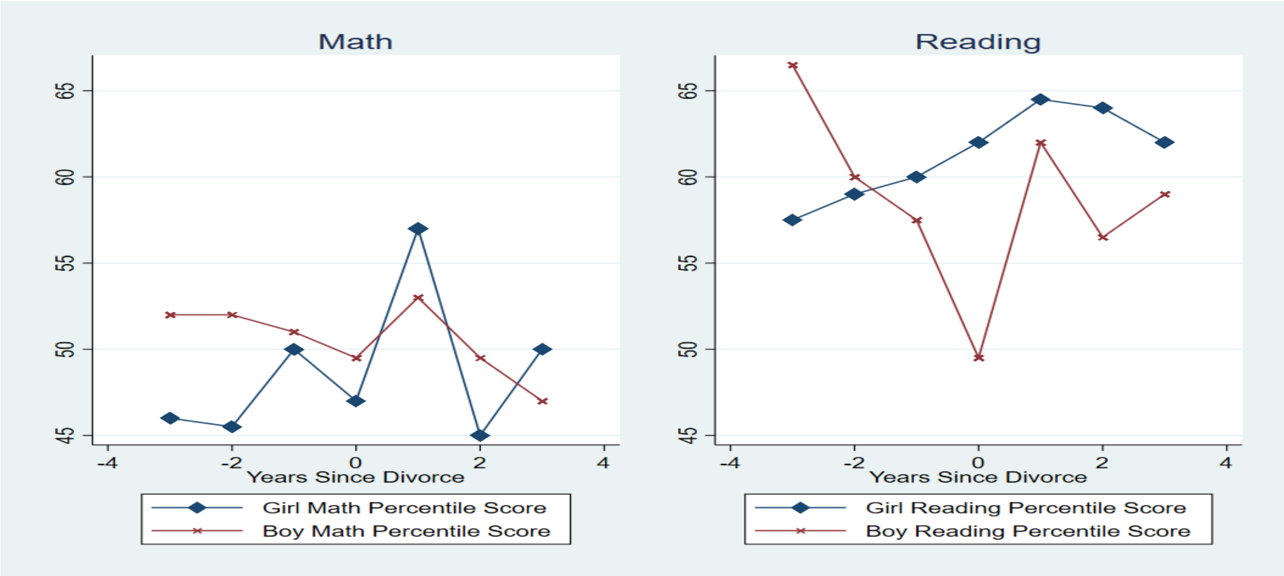

Fig. 1 Test Score trends with time from Divorce
Note: The figure plots the median math and reading test scores for children of divorced families against the years since their parents have been divorced. The data used in this graph is from the CNLSY. The test scores are the Peabody Achievement scores given by the CNLSY. This figure considers divorce occurring before age 13.

This paper seeks to quantify the contribution of divorce to the gender gap in long term educational outcomes. To carry out this analysis, I tackle two important obstacles, lack of suitable data and credible identification. To address the data challenge, I exploit the child supplement of the national longitudinal survey of youth (CNLSY). The CNLSY tracks all children born to the women of the NLSY-1979 from 1984. The children born post 1984 are tracked from birth to adulthood. The NLSY is a nationally representative sample of youth who were 16-22 in 1979. These longitudinal data sets offer remarkable detail on family characteristics, early educational outcomes including achievement tests for math and english, high school graduation, college graduation, college attendance, criminal convictions, self reported health and labor market outcomes.

The second obstacle to my study is that divorce is intrinsically confounded with inherent outcomes independent of their impact on family environment. For example, highly educated parents are disproportionately likely to have stable marriages, enroll their children in higher quality schools, and may have children with above average latent ability. My challenge is to separate the direct impact of divorce from the hereditary confounds that would lead to biased outcomes among children without any causal effect of divorce on children's outcomes. My empirical approach removes these confounds by contrasting the outcomes of opposite-sex siblings linked to the same mother. This provides valid identification of the differential effect of divorce on boys relative to girls, based on the assumption that, any difference in educational outcomes that girls may have before divorce relative to their male siblings is not systematically larger or smaller relative to non-divorced families. I offer confirmations of the plausibility of this assumption through placebo tests and event study analyses. The event study analysis is useful for two reasons. First, they offer an impact effect of a divorce achievement scores.

Second, it allows me to check if there are any existing pre-trends. I make use of scores in various subjects as well as a measure of home environment. In all these cases the outcomes differ systematically by gender and marital status. Yet, in no case is the brother-sister gap in these outcomes predicted by whether or not parents eventually get divorced. Brothers and sisters appear equally advantaged or disadvantaged by families future marital status.

My analysis shows that the timing and intensity of the impact of divorce differs across children. Looking at divorce through a cutoff point of age 13 may simply identify the effect of being divorced at a young age versus an older age. To address this challenge, I run two kinds of exposure time models. The first uses exposure time as a linear model. This captures the impact of being exposed to divorce for a year before turning 18. The second uses age categorizations to look at the impact of being divorced at different age groups. A minor hurdle to my study is that some respondents do not show up in all waves of the data, either due to incarceration or for other reasons of non-interview. Including them in my sample may bias my estimates. To overcome this I am running two different sets of regressions. The first drops all individuals who have ever been incarcerated. The second considers individuals who only show up in at least eighty percent of the waves. The NLSY has also changed young adult interview rules over different waves. This has caused some unintended attrition in certain waves. In both cases I find no significant difference in outcomes caused by attrition.

The rest of the paper is organized as follows: Section 2 reviews the literature. Section 3 describes the Data. Section 4 discusses the empirical strategy for the main cutoff model. Section 4 discusses the results for the main cutoff model. Section 5 discusses the placebo tests. Section 6 presents the exposure time models. Section 7 presents the event study models. Section 8 concludes.

2 Literature Review

My paper makes a contribution to various strands of the literature. There is an active literature studying the gender gap in educational outcomes. Buchmann and DiPrete (2006), Autor et al. (2019) and Autor and Wasserman (2013) look at how gender gaps in educational outcomes are affected by different family structures. Autor et al. (2019) assess whether family disadvantage exerts a differential effect on the educational outcomes of boys relative to girls. The study finds that boys in disadvantaged families have more disciplinary problems, lower achievement scores and are less likely to graduate high school. They provide evidence that a sizeable portion of the documented minority-white difference in educational and behavioral gender gaps is attributable to higher degrees of family disadvantage among minority families. The authors support their claim of causal inference by showing that the gender gap in neonatal health is unrelated to family disadvantage. I contribute to this literature by specifically looking at the impact of divorce on long term educational outcomes.

Prior research draws a contrast between boys and girls born to different mothers to assess the relationship between family disadvantage and the gender gaps in child outcomes. This approach leaves open the possibility that unmeasured differences among families with children of different sexes or unobserved changes in family structure occurring in childhood may in part explain the contrast in developmental outcomes. Fan et al. (2015) provide evidence from Norwegian registry data that educational gender gap is correlated to mothers labor force participation. They find evidence that boys are more susceptible at early ages if their mothers are employed. Kristoffersen et al. (2014) check whether gender differences in behavioral outcomes can explain the gender gap in school outcomes. The authors find relationships between school outcomes and behavioral outcomes to be more sensitive to family and school environment for boys than girls. Buchmann and DiPrete (2006) explore how family background and academic achievement can affect the gender gap in educational outcomes. The authors provide evidence that boys are especially susceptible to the presence of a low educated or an absent father. Ferguson et al. (1994) document that family disruptions negatively affect test scores of children. They find no significant effect of parental separation on educational outcomes if separation occurs before school entry.

Allison and Frustenburger (1989) look at how children are affected by marital dissolution. The authors do not find evidence to show that boys are made more worse off than girls after marital dissolution. Owens (2016) documents that gender gap in longer term educational outcomes can be explained by behavioral problems in early life. Cherlin et al. (1991) use a descriptive study to show that much of the detrimental effect of divorce existed prior to that of separation. Interestingly these pre-divorce effects seem to be higher for boys than for girls. Kalil et al. (2015) use administrative data from Norway to show how father presence affects inter-generational transmission of educational attainment. They find that longer paternal exposure increases father child association in education. Liu (2007) has used data from the panel study of income dynamics (PSID) to model educational attainment in a duration framework. The author has found evidence that educational attainment is affected through family disruption differently for girls and boys. My study is the first to use a sibling fixed effects model to study the gender gap in long term educational outcomes.

Another strand of literature to which I contribute, analyses how changes in family structure impact behavioral outcomes. Cobb-Clark and Tekin (2011) show that adolescent boys engage in more delinquent behavior if there is no father present. They find that the girl child's tendency to show delinquent behavior is not affected by the presence of the father. Prevoo and Ter Weel (2003) find statistically significant correlations between family disruptions before age 16 and personality development. The study finds that divorce has the largest negative effect of all the disruptions. They report that the effect gets smaller as the the children get older, and the impact is stronger on girls. Bertrand and Pan (2013) offer a thorough exploration of how family background affects gender differences in early childhood outcomes. The authors document that boys raised in single-parent families have twice the rate of behavioral and disciplinary issues as boys raised in two-parent families, and are more than twice as likely to be suspended from school by the eighth grade.

Finally my paper also adds to the literature looking at the impact of family disruption on long term educational outcomes. Keith and Finlay (1988) use National Survey data to find that parental divorce leads to lower educational attainment and marriage age for both sexes. Interestingly they find that daughters of divorced parents have higher probability of getting divorced. Krein and Beller (1988) document that the effect of living in a one parent family increases with no. of years spent in that specific kind of family. This effect is greatest in preschool years and higher for sons than daughters. The authors have used matched Mother-Son and Mother-daughter samples from the National Longitudinal Surveys. Chetty et al. (2016) also look at effects of childhood disadvantage on gender gaps in adult life. They find evidence that poor childhood living conditions lead to boys having lower rates of formal employment. The definition of poor childhood living conditions is along metrics such as income, neighborhood minority concentration and crime rate. This analysis has been performed with the help of population tax records for children born in the 1980s. These results support my hypothesis that boys will be more negatively affected if their parents get divorced when they are at a young age. I look at longer term outcomes such as high school graduation, college attendance[1], college graduation, crime[2], poor health[3] and idleness[4]. My results show that, when parents are divorced, the male child's educational outcomes are more likely to be negatively impacted.

3 Data

The primary data set I use in this analysis is the CNLSY. In 1986, the National Longitudinal Survey (NLS) began a separate survey of the children of the 6,283 women in the NLSY. The CNLSY tracks every child born to an NLSY respondent, enabling a comparison of siblings within the same family. Furthermore, mothers are surveyed extensively prior to the birth of their children, which allows for a rich set of controls for early life circumstances. I have used the NLSY 1979 to get this information. The NLSY contains information on youths aged 14-22 in 1979. These youth are then surveyed using a detailed questionnaire every two years. This provides the date of marriage and the date of end of the marriage. I am only considering children who are full biological siblings in my analysis. One drawback of the CNLSY is that it is not very straightforward to distinguish between full, half, or even

[1] All educational outcomes are based off the response to the highest level of educational attained in the last survey the respondent shows up in

[2] This variable is set equal to one if the respondent has ever been in jail,been convicted,been sentenced or been on probation

[3] Since the 1994 wave the NLSY has been asking respondents to describe their present health. They offer them 5 options- Excellent(5), Very Good(4), Good(3), Fair(2) and Poor(1). If the responses have been less than good on average, I code them as having poor health

[4] If the respondent is not earning a positive salary annually and is not enrolled in school in the last wave he/she is interviewed then I define them as idle

adopted siblings. This makes it difficult for the analysis to look at the impact of divorce in a within sibling analysis. From the 2006 data release the CNLSY has asked respondents whether or not they share the same biological father. However, the large number of missing values and tediousness of the task make it difficult to identify full biological siblings. To do this I have used the data set provided by Rodgers et. (2016). The authors have provided a reliable kinship link to assist researchers using the CNLSY for within family analysis. This helps me avoid blended families, where it is a stepfamily for one child and a two biological parent family for the other.

In the sample for the main regression I am only considering families with at least two children and both genders. In order to check the impact of early divorce on the gender gap in long term outcomes, children who are labeled as early divorced need to be less than 13 at the time their parents get divorced. In the final regression sample I am also removing all respondents whose age at last interview is less than 19. I remove anyone below 26 for the regression on the variable of college graduation and 22 for college attendance. In my analysis I am only considering children from married families. All children from mothers who remain unmarried while raising their children are removed from my sample. The sample size for the main regression is 2842 with 656 children belonging to families where parents get divorced before age 13. In the comparison group 633 children experience a parental divorce after they turn 13 and 1564 never experience. So, there are 656 children belonging to families with at least two or more children of different genders whose parents are divorced before they turn 13. I use these 656 children to identify the effect of early divorce on gender gap in outcomes, for my main cutoff model. Figure 2 plots the distribution of children's age at the time of parents divorce by gender. For this figure, I am considering children whose parents are divorced on or before they turn 18. There are 962 children whose parents have divorced before they become adults. Of the 962 there are 478 girls and 484 boys, these are the children I use to identify the effect of divorce from my exposure time and age group models. There is a slight spike in the no. of girls whose parents get divorced while they are in their early infancy. The pattern reported by the figure is similar to the results of Dahl and Moretti (2008), in which they show that families with first born daughters are much more likely to get divorced.

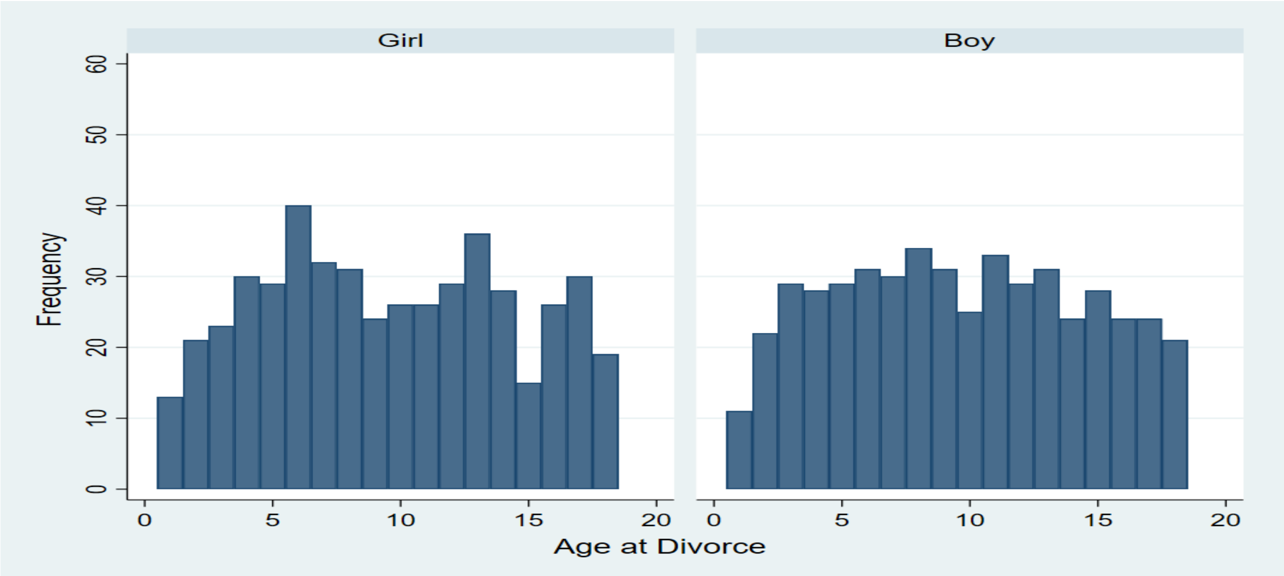

Fig. 2 Distribution of ages of children at the time of Parents Divorce by gender
Note: This figure is only considering the fixed effects sample where each family has at least two children of both genders. There are 478 girls and 484 boys whose families are divorced before they turn 18.

Table 1 presents the summary statistics of all the outcome variables by gender and family structure. Children are classified as late divorced if their parents are divorced after they turn 13, and never divorced if their parents have never been divorced. The gender gap in high school graduation, college attendance, and idleness deteriorates when moving from late divorced to early divorced families. The gender gap for all outcomes is considerably worse for boys when comparing between divorced and never divorced families. The table reveals that girls belonging to early divorced families are less likely to be idle than girls from late divorced families. It is possible that girls from early divorced families are more likely themselves to get divorced after marriage. This may put extra pressure on single mothers to find employment.

Table 1

Summary Stats By Gender & Family Structure

	EarlyDivorced			LateDivorced			NeverDivorced		
	Girl	Boy		Girl	Boy		Girl	Boy	
VARIABLES	mean	mean	Raw-Diff	mean	mean	Raw-Diff	mean	mean	Raw-Diff
HSGrad	0.868	0.734	0.134	0.856	0.771	0.085	0.910	0.842	0.068
CollegeAtt	0.563	0.373	0.190	0.626	0.439	0.187	0.661	0.583	0.078
CollegeGrad	0.286	0.171	0.115	0.325	0.201	0.124	0.400	0.300	0.100
Idle	0.145	0.122	0.023	0.170	0.110	0.060	0.163	0.120	0.043
Crime	0.245	0.443	-0.198	0.187	0.412	-0.225	0.130	0.299	-0.169
PoorHealth	0.157	0.107	0.050	0.161	0.131	0.030	0.0917	0.0604	0.0313

Note: Crime is defined as 1 if the respondent has ever been convicted , been on probation,been sentenced or been in jail. A respondent is classified as Idle if they are not enrolled in an educational institution or earning positive wages in the last wave they show up in. A person is classified as having poor health if on average he/she reports his/her health to be less than good.

Figures 3 and 4 plot cross-race and income differences in gender gap in educational outcomes between early divorced and late divorced children. I am defining the children from families in the top quintile of permanent income[5] from my sample as high income, and children from the bottom quintile as low income. The vertical axis lists the graduation/attendance rates and the horizontal axis the educational outcomes separately by gender and family structure. The sample considered is the fixed effects sample used for the main regression. The figure provides graphical evidence of the difference in gender gap between early divorced and late divorced families. The gender gap in high school graduation increases for low income families, while the gender gaps in college attendance and graduation go up for high income families. When splitting the sample by race, there is a slight divergence in educational outcomes for children of both races, with big increases in college attendance for non-white and high school graduation for white children.

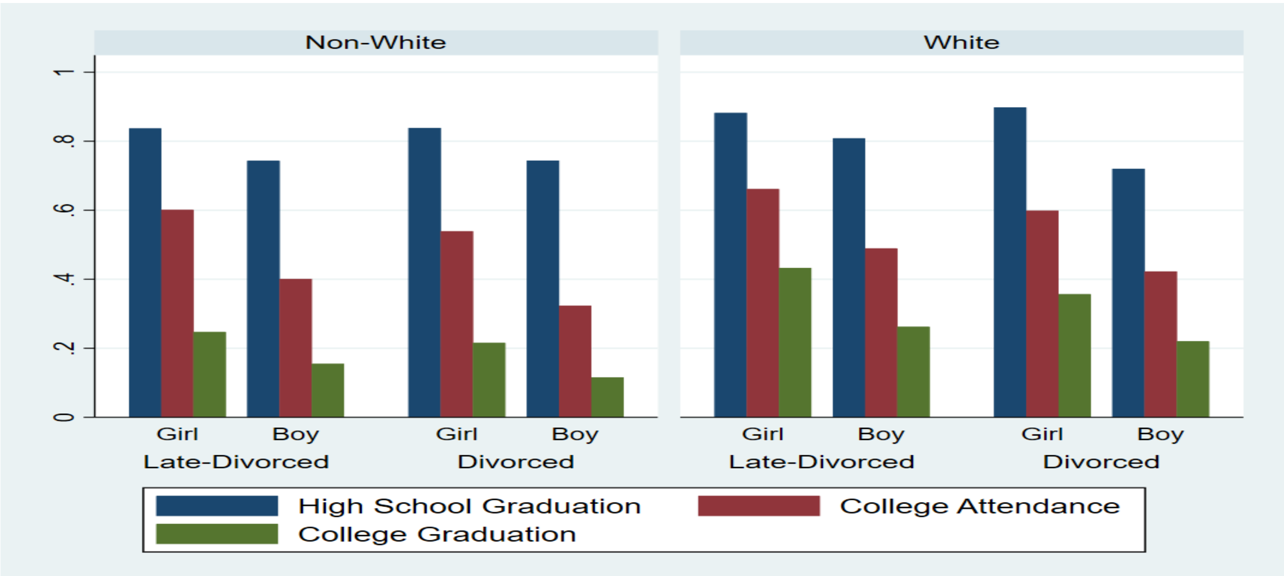

Fig. 3 Educational Outcomes for each gender by Race and Family Structure
Note: Each bar gives the average educational attainment for each category of gender, family structure and race. The data comes from the CNLSY and only for children atleast 19 years of age at the time of their final interview. For college attendance and college graduation the cutoffs are 22 and 26 respectively.

[5] Average family income before 18

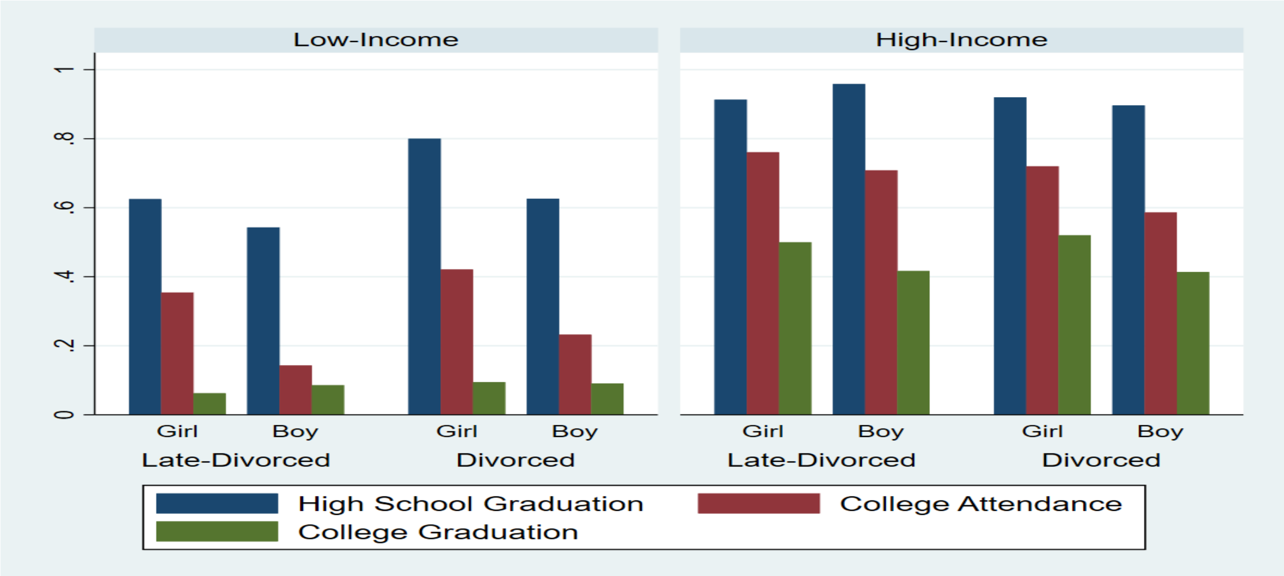

Fig. 4 Educational Outcomes for each gender by Income level and Family Structure Note: Each bar gives the average educational attainment for each category of gender, family structure and family income. High income families are those with Permanent Income in the top quintile of the distribution and low income families in the bottom quintile of the distribution. The data comes from the CNLSY and only for children atleast 19 years of age at the time of their final interview. For college attendance and college graduation the cutoffs are 22 and 26 respectively.

4 Empirical Strategy

I use a difference-in-differences with fixed effects regression framework to see how divorce before age 13 affects the gender gap in long term labor market outcomes. Y_{ij} is the outcome of child i in family j. The first equation represents the regression with sibling fixed effects and the second one without. The coefficient β_2 captures how parents divorce before age 13 affects boys outcomes differently than girls, γ_j here is the sibling fixed effects while X_i contains controls that may differ across siblings like birth-order, birth-month, age of mother at birth[6] ,etc.

$$Y_{ij} = \alpha + \beta_1 boy_i + \beta_2 boy_i * earlydivorce_i + \beta_3 earlydivorce_i + \beta_4 boy_i * white_j + \beta_5 X_i + \gamma_j + e_{ij} \quad (1)$$

$$Y_i = \alpha + \beta_1 boy_i + \beta_2 boy_i * earlydivorce_i + \beta_3 earlydivorce_i + \beta_4 boy_i * neverdivorce_i + \beta_5 neverdivorce_i + \beta_6 boy_i * white_i + \beta_7 white_i + \beta_8 X_i + e_i \quad (2)$$

The main assumption which helps interpret the coefficient β_2 as the causal effect of early divorce on gender gap is that the latent gender gap in sibling outcomes is independent of divorce before age 13. I test the plausibility of this assumption by running multiple placebo tests on achievement tests administered by the CNLSY. I also provide event study analysis that show clear visual breaks from trend in achievement scores right around the time of the divorce. This also helps to show that there are

[6]Age difference and birth order are both important within sibling variations. The age of the mother at birth is perfectly correlated with the relative age gap between siblings

no pretrends in my analysis. My definition of early divorce helps me identify whether a boy is going to be more harmfully impacted than his sister if he is less than 13 at the time of divorce. The 13-year cutoff is probably conservative, but, it minimizes the probability that some of the children have left home. I am also presenting results for running the same regression as mentioned above without the sibling fixed effects i.e simple OLS. I am using the same sample for both the OLS and sibling fixed effects models.

5 Results

The educational outcomes I look at are high school graduation, college attendance and college graduation. The non-educational outcomes I look at are crime[7], poor health[8] and idleness[9].

5.1 Educational Outcomes

The second column of table 2 reports the estimates of the regression for the high school graduation outcome with sibling fixed effects. The coefficient β_2 tells us that boys likelihood of graduating high school relative to their sisters goes down by 6.4 percentage points as a result of early divorce and are 15.6 percentage points less likely to graduate high school than their sisters if their parents had been divorced before they turn 13. Relative to baseline estimates (The average high school graduation rate in my entire sample is 84.4 percent) this translates to a 18.4 (15.6/84.4*100) percent decrease in high school graduation. This result carries significant economic consequences. Males under age 40 with high school or lower education have seen their real earnings drop by 25 percent between 1979-2010 (Autor and Wasserman 2013). Column 4 looks at the effect of early divorce on the gender gap in college attendance. Early divorce reduces the likelihood of boys attending college relative to their sisters by 8 percentage points. Boys from early divorced families thus have a 23.9 percentage point lower chance of attending college than their sisters. Relative to baseline estimates[10] this translates to a 40.8 (23.9/58.5*100) percent decrease in college attendance.

[7]Set equal to 1 if the respondent has ever been in jail,been convicted,been sentenced or been on probation.

[8]Since the 1994 wave the NLSY has been asking respondents to describe their present health. They offer them 5 options- Excellent(5), Very Good(4), Good(3) , Fair(2) and Poor(1). If the responses have been less than good(3) on average then I am coding them as having poor health

[9]If the respondent is not earning a positive salary annually and is not enrolled in school in the last wave he/she is interviewed then I define them as idle

[10]The average college attendance rate in my entire sample is 59 percent

Table 2

Educational Outcome regression values

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HSGrad	HSGrad	CollegeAtt	CollegeAtt	CollegeGrad	CollegeGrad
EarlyDivorce	-0.004	-0.014	-0.086**	-0.091	-0.015	-0.005
	[0.027]	[0.039]	[0.040]	[0.059]	[0.046]	[0.062]
Boy	-0.095***	-0.092***	-0.212***	-0.159***	-0.128***	-0.110***
	[0.032]	[0.020]	[0.043]	[0.027]	[0.044]	[0.028]
Boy x EarlyDivorce	-0.046	-0.064**	-0.015	-0.080*	0.011	-0.011
	[0.042]	[0.032]	[0.057]	[0.043]	[0.061]	[0.047]
Premature	0.005	-0.019	-0.003	-0.009	0.015	-0.003
	[0.016]	[0.022]	[0.025]	[0.031]	[0.029]	[0.037]
Birth Order	-0.069***	-0.017	-0.097***	-0.044**	-0.088***	-0.051**
	[0.007]	[0.017]	[0.009]	[0.021]	[0.012]	[0.025]
Boy x White	0.006	0.021	0.051	0.068**	-0.054	-0.024
	[0.026]	[0.023]	[0.039]	[0.034]	[0.047]	[0.041]
Age of Mother at Birth	0.019***	0.007	0.028***	0.011	0.025***	0.009
	[0.002]	[0.006]	[0.003]	[0.007]	[0.004]	[0.010]
NeverDivorce	0.009		-0.031		0.089**	
	[0.022]		[0.034]		[0.040]	
Boy x NeverDivorce	0.019		0.098**		0.053	
	[0.034]		[0.048]		[0.054]	
Observations	2,842	2,842	2,351	2,351	1,466	1,466
R-squared	0.100	0.566	0.114	0.616	0.121	0.620
Sibling FE	NO	YES	NO	YES	NO	YES

Robust standard errors in brackets

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

Note: Robust Standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ The regression with college graduation as outcome only considers respondents who were 26 and over at the time of their last interview.Similarly the cutoff is 22 for college attendance. All races are that of the child. In every interview the CNLSY asks its respondents their highest educational qualification. There are correspondents who mention that they are still in college and their highest qualification till date is college attendance.A respondent is classified as premature if he/she was born early or late.

The estimates for the effect of early divorce on the gender gap in college graduation are neither economically nor statistically significant. The odd numbered columns in table 2 provide regression results with the fixed effects sample but by running just OLS. I notice that the coefficient on β_2 becomes more negative as we move from OLS to the fixed effects models. It is possible that this is due to the fixed effects model taking care of family specific variation. I have provided standardized values for the educational outcome results in the appendix in table 9.

5.2 Non Educational Outcomes

Table 3 presents estimates for the regression specification in equation 1, for non educational long term outcomes. Early divorce does not have a statistically significant effect on the gender gap for the reported outcomes. These estimates by themselves are economically significant, however, my results are statistically insignificant due to a lack of power. Divorce before the age of 13 increases the likelihood that boys will be idle compared to their sisters by 2.4 percentage points. Relative to baseline estimates this translates to a 18 percent higher chance of being idle. Boys from early divorced families are more likely to commit a crime by 1.3 percentage points relative to their sisters. Interestingly, girl's health outcomes relative to their brothers go down by 3 percentage points as a result of early divorce. Relative to baseline estimates this translates to an almost 12 percent increase in likelihood of self reported poor health.

Table 3

Non-Educational Outcome regression values

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Crime	Crime	Idle	Idle	PoorHealth	PoorHealth
EarlyDivorce	0.078**	0.032	-0.017	-0.029	0.001	0.044
	[0.032]	[0.047]	[0.029]	[0.041]	[0.029]	[0.040]
Boy	0.256***	0.227***	-0.048	-0.023	-0.045	-0.036*
	[0.038]	[0.024]	[0.030]	[0.021]	[0.030]	[0.018]
Boy x EarlyDivorce	-0.034	0.013	0.030	0.024	-0.015	-0.030
	[0.050]	[0.039]	[0.038]	[0.031]	[0.039]	[0.031]
Premature	0.014	-0.059**	0.038**	0.029	0.011	0.014
	[0.020]	[0.030]	[0.017]	[0.022]	[0.015]	[0.021]
BirthOrder	0.036***	-0.012	0.039***	0.026	0.021***	0.010
	[0.008]	[0.019]	[0.007]	[0.018]	[0.006]	[0.015]
Boy x White	-0.051	-0.084***	-0.020	-0.032	0.024	0.022
	[0.032]	[0.031]	[0.026]	[0.026]	[0.023]	[0.023]
Age of Mother at Birth	-0.018***	-0.005	-0.007***	-0.005	-0.004***	-0.001
	[0.002]	[0.006]	[0.002]	[0.006]	[0.001]	[0.005]
Never Divorce	-0.016		0.009		-0.062***	
	[0.026]		[0.025]		[0.024]	
Boy x NeverDivorce	-0.056		0.019		0.004	
	[0.040]		[0.032]		[0.031]	
Observations	2,841	2,841	2,841	2,841	2,841	2,841
R-squared	0.095	0.513	0.032	0.443	0.025	0.422
Sibling FE	NO	YES	NO	YES	NO	YES

Note: Robust Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. A respondent is classified as premature if he/she was born early or late. The race is that of the child.

5.3 Educational Outcomes By Demographics

In tables 4 & 5, I report the main regression outcomes by race and income level. For table 4 I split my sample along race (white and non-white). For table 5 I consider only the top (which I define as high-income) quintile (Top 20 percentile) and bottom (low-income) quintile of permanent income in my sample. Column 1 of table 4 shows that early divorce has a strong impact on the gender gap in high school graduation for white children. The estimates show that early divorce reduces the likelihood that a white boy will graduate high school by 10.6 percentage points relative to his sister. White boys from early divorced families have a 16.8 percentage point lower chance of graduating high school than their sisters.

Table 4

Educational Outcome regression values by Race

VARIABLES	White HSGrad	Non-White HSGrad	White CollegeAtt	NonWhite CollegeAtt	White CollegeGrad	NonWhite CollegeGrad
EarlyDivorce	-0.047	-0.013	-0.028	-0.166**	-0.033	0.034
	[0.055]	[0.055]	[0.080]	[0.084]	[0.108]	[0.074]
Boy	-0.062***	-0.102***	-0.095***	-0.158***	-0.144***	-0.097***
	[0.014]	[0.021]	[0.027]	[0.028]	[0.039]	[0.029]
Boy x EarlyDivorce	-0.106**	-0.022	-0.073	-0.087	0.039	-0.066
	[0.042]	[0.049]	[0.059]	[0.062]	[0.077]	[0.059]
Birth Order	-0.021	-0.011	-0.068**	-0.027	-0.062	-0.038
	[0.023]	[0.023]	[0.033]	[0.028]	[0.047]	[0.029]
Premature	0.007	-0.049	-0.034	0.006	0.030	-0.019
	[0.024]	[0.036]	[0.045]	[0.043]	[0.065]	[0.044]
Age of Mother at Birth	0.003	0.009	0.013	0.010	0.014	0.003
	[0.008]	[0.007]	[0.011]	[0.010]	[0.019]	[0.012]
Observations	1,397	1,445	1,130	1,221	648	818
R-squared	0.615	0.535	0.650	0.579	0.624	0.596
Sibling FE	YES	YES	YES	YES	YES	YES

Note: Robust Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. A respondent is classified as premature if he/she was born early or late. The race is that of the child. The regression with college graduation as outcome only considers respondents who were 26 and over at the time of their last interview. Similarly the cutoff is 22 for college attendance.

Table 5 reports the impact of early divorce on educational outcomes after splitting the sample by permanent income. Early divorce does not have a statistically significant effect on the gender gap in educational outcomes after splitting the sample by income. It is possibly that my results from the whole sample are driven by children from families not at the ends of the distribution. However early divorce does seem to have a strong negative effect on the gender gap of childrens outcomes within the same family for college graduation in high income families and college attendance in low income families. These results are imprecise due to a lack of sufficient power.

Table 5

Educational Outcome regression values by Income Level

	Hi-Income	Lo-Income	Hi-Income	Lo-Income	Hi-Income	Lo-Income
VARIABLES	HSGrad	HSGrad	CollegeAtt	CollegeAtt	CollegeGrad	CollegeGrad
EarlyDivorce	-0.004	0.136	0.054	0.047	-0.301	0.070
	[0.039]	[0.121]	[0.064]	[0.133]	[0.221]	[0.118]
Boy	0.005	-0.128**	0.014	-0.203***	-0.004	-0.103*
	[0.028]	[0.052]	[0.075]	[0.060]	[0.142]	[0.058]
Boy x EarlyDivorce	0.001	-0.097	-0.027	-0.107	0.407	0.014
	[0.067]	[0.093]	[0.123]	[0.103]	[0.257]	[0.076]
Birth Order	-0.023	-0.067	-0.013	-0.044	-0.123	0.028
	[0.030]	[0.045]	[0.052]	[0.042]	[0.089]	[0.053]
Boy x White	-0.006	0.023	-0.023	-0.054	-0.124	0.096
	[0.032]	[0.095]	[0.083]	[0.109]	[0.151]	[0.112]
Premature	-0.006	-0.015	-0.021	-0.049	0.010	-0.126*
	[0.022]	[0.078]	[0.054]	[0.077]	[0.119]	[0.069]
Age of Mother at Birth	0.012	0.050***	-0.002	0.028	0.043	-0.017
	[0.012]	[0.017]	[0.020]	[0.018]	[0.034]	[0.032]
Observations	552	591	412	486	223	282
R-squared	0.642	0.633	0.749	0.632	0.688	0.676
Sibling FE	YES	YES	YES	YES	YES	YES

Note: Robust Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. A respondent is classified as premature if he/she was born early or late. The race is that of the child. The regression with college graduation as outcome only considers respondents who were 26 and over at the time of their last interview. Similarly the cutoff is 22 for college attendance.

6 Placebo Tests

Interpretation of the above estimates as the causal effect of early divorce on the gender gap in child outcomes relies on the assumption that the latent gender gap in sibling outcomes is independent of future marital status. I provide a falsification test by analyzing the relationship between early divorce and gender gap in achievement scores for children whose parents are yet to be divorced. I use outcomes of the , Peabody Individual Assessment Math (PIATMT) subtest, Reading (PIATRR) subtest, Behavioral Problems Index (BPI) score, Home inventory score (HOME) for ages 5 and 6. Children whose parents have already divorced by the time they take the tests are removed from the sample.

Children who are divorced before age 7 are removed from my sample. The outcome variable for each regression is the percentile score for that particular test.

The results in table 6 support the claim that there is no inherent difference in the gender gap in educational outcomes that occurs prior to divorce. My estimates are to an extent imprecisely estimated due to a lack of sample size. I have provided standardized values for the placebo test results in the appendix in table 10.

Table 6

Assessment Score Regression values restricted to pre-divorce

	(1)	(2)	(3)	(4)
VARIABLES	BPI-5	HOME-5	PIATMT-5	PIATRR-5
Boy	3.647**	-2.594*	-1.025	-5.777***
	[1.636]	[1.354]	[1.802]	[1.663]
Boy x EarlyDivorce	0.936	1.643	-2.692	2.589
	[3.729]	[3.087]	[3.992]	[3.562]
EarlyDivorce	0.783	-3.053	1.804	-7.068*
	[3.646]	[3.457]	[4.319]	[4.082]
Boy x white	-0.952	0.313	0.547	1.389
	[2.029]	[1.771]	[2.242]	[2.082]
BirthOrder	-1.119	-0.583	-1.701	-2.744**
	[1.128]	[0.915]	[1.173]	[1.193]
Premature	0.020	-1.091	-1.026	-2.878
	[1.721]	[1.561]	[1.889]	[1.800]
Age of Mother at Birth	-0.853**	-0.775***	0.295	0.703**
	[0.335]	[0.279]	[0.349]	[0.335]
Observations	2,648	2,663	2,585	2,542
R-squared	0.706	0.791	0.667	0.675
Sibling FE	YES	YES	YES	YES

Note: Robust Standard errors in brackets.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. I am taking two year gaps because the surveys are conducted every two years. PIATMT-5 is the Peabody Math achievement score for a child at ages 5 or 6. It is a percentile score. A child is classified as premature if he/she has been born early or late. The race is that of the child

6.1 Attrition Effects

The CNLSY takes interviews of its respondents every two years from the 1986 wave. For those born in 1986 and after, they are interviewed since birth. There are a number of respondents who may not show up in every wave of the survey due to a number of reasons including incarceration, military assignment, major illness, leaving the parents household or changes in survey cut offs for young adults (between waves). The interviews for these respondents are inconsistent, for example in a number of waves some respondents are interviewed even while in jail. The young adult cut off age was also changed for two waves and adult respondents over the age of 30 are interviewed every other wave. These attrition effects may sometimes bias the estimates for the long term outcomes. I have run regressions on two different specifications to check whether this causes a bias in the estimates. First, I run the main regression model for the sibling fixed effects and OLS regressions, removing respondents who have been incarcerated. Second, I run these regressions on respondents who show up in at least 80 percent of the waves. I do not find significant changes in the main outcomes for any of these regressions. This robustness check further clarifies that there are no significant attrition effects which are biasing the estimates. The results for the non-incarcerated and consistent response samples are provided in the appendix in table 11 and 12.

6.2 Alternate cutoffs

I have tested the sensitivity of this result to multiple age cutoffs. While using adjacent ages like 12 and 14 yield very similar results (as expected), I have also checked the sensitivity of these results at ages which are much more farther apart. I have provided results for using cutoff ages as low as 5 and as high as 15 in the appendix in tables 13 and 14.

7 Exposure Time Models

The regression specification in equation 1 uses a particular cutoff age to try and measure the effect of divorce on the gender gap in children's outcomes. The early divorce variable in the sibling fixed effects model looks at whether a child was less than 13 versus greater than 12 at the time of divorce. This approach is measuring the effect of the timing of the divorce on the child. It may be the case that boys are worse off if parents get divorced at an earlier age than girls. It may also be the case that girls are less susceptible if the parents get divorced when they are teenagers. Thus, the timing and intensity of divorce varies across children in the same family. To overcome this hurdle, I run exposure time models. I have run two models, with and without fixed effects, on the same sample used for the previous regressions. There are 962 children in the main regression sample whose parents are divorced before they turn 18. This consists of 484 boys and 478 girls. I use these 962 children to identify the effect of parents divorce during childhood on gender gap in outcomes, for the exposure time models.

$$Y_{ij} = \alpha + \beta_1 boy_i + \beta_2 boy_i * exposure_i + \beta_3 exposure_i + \beta_4 boy_i * white_j + \beta_5 X_i + \gamma_j + e_{ij} \quad (3)$$

$$Y_{ij} = \alpha + \beta_1 boy_i + \beta_2 boy_i * young_i + \beta_3 boy_i * midchild_i + \beta_4 boy_i * teenager_i + \beta_5 young_i + \beta_6 midchild_i + \beta_7 teenager_i + \beta_8 boy_i * white_j + \beta_9 X_i + \gamma_j + e_i \quad (4)$$

The first, uses a linear function of (18-age) at divorce in place of the divorce dummy. This variable is labeled as exposure in the equation. The variable of interest β_3 measures the differential impact of being exposed to one year of divorce in boys relative to girls. Suppose there are two children in a family, and their parents get divorced before either of them turn 13. The divorce cutoff variable will be one for both. However, both children may have different length of exposure to the divorce. This specification utilizes this variation in the timing and intensity of divorce. For the second model I am using age groupings. I am using 3 age groupings in the main paper. They are young(ages 0-4), mid-child(ages 5-12) and teenager(ages 13-18). The impact of the length of exposure to divorce may not be linear. Also, family disruptions at different points of time may have varying impacts on different outcomes. For example, divorce during early childhood maybe particularly harmful for high school graduation, but, divorce during teenage years is more harmful for college graduation. I now have three variables of interest β_1, β_2 and β_3. Each captures the differential impact of being divorced in a particular age group on boys relative to girls. The results of the age group regressions are robust to choosing adjacent years in a 3 group setting, or, increasing the no. of groups to 4. These models are run for both the sibling fixed effects and standard OLS.

Table 7 reports the results for the first exposure time model. Column 4 tells us that a one year rise in exposure to divorce reduces the likelihood of attending college by 0.6 percentage points for boys. The average male child who comes from a divorced family in my sample is exposed to it for 8 years before they turn 18. This conveys that boys whose parents are divorced, on average, have a 20.7(0.6*8 + 15.9) percentage point lower chance of attending college than their sisters.

Table 7

Exposure Time linear Regression

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HSGrad	HSGrad	CollegeAtt	CollegeAtt	CollegeGrad	CollegeGrad
Exposure	-0.001	0.003	-0.006*	-0.004	-0.003	0.003
	[0.003]	[0.004]	[0.004]	[0.006]	[0.004]	[0.006]
Boy	-0.116***	-0.095***	-0.208***	-0.159***	-0.142***	-0.113***
	[0.034]	[0.020]	[0.045]	[0.027]	[0.047]	[0.029]
Boy x Exposure	-0.000	-0.004	-0.002	-0.006*	0.003	0.001
	[0.004]	[0.003]	[0.005]	[0.004]	[0.006]	[0.004]
Never Divorce	0.004		-0.026		0.079*	
	[0.023]		[0.036]		[0.042]	
Boy x NeverDivorce	0.041		0.093*		0.068	
	[0.035]		[0.049]		[0.057]	
Premature	0.006	-0.019	-0.003	-0.008	0.015	-0.002
	[0.016]	[0.022]	[0.025]	[0.031]	[0.029]	[0.037]
Birth Order	-0.069***	-0.017	-0.096***	-0.042**	-0.088***	-0.050**
	[0.007]	[0.017]	[0.009]	[0.021]	[0.012]	[0.025]
Boy x White	0.005	0.021	0.052	0.067**	-0.055	-0.026
	[0.026]	[0.023]	[0.039]	[0.034]	[0.047]	[0.041]
Age of Mother at Birth	0.019***	0.007	0.028***	0.010	0.025***	0.008
	[0.002]	[0.005]	[0.003]	[0.007]	[0.004]	[0.010]
Observations	2,842	2,842	2,351	2,351	1,466	1,466
R-squared	0.099	0.565	0.113	0.614	0.121	0.620
Sibling FE	No	YES	No	YES	No	YES

Robust standard errors in brackets

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

Note: Robust Standard errors in brackets.*** p<0.01, ** p<0.05, * p<0.1. Exposure is a linear function of 18-age at divorce.The regression with college graduation as outcome only considers respondents who were 26 and over at the time of their last interview.Similarly the cutoff is 22 for college attendance. A respondent is coded as premature if he/she is born early or late

Table 8 reports estimates for the age group exposure time models. Column 2 looks at the outcome of high school graduation. Parents getting divorced in the middle of a boys childhood increases the within family boy-girl disparity in high school graduation by 7.4 percentage points. Divorce during teenage years negatively impacts boys likelihood of attending college with respect to their sisters. Column 4 reveals that boys impacted by divorce in their teenage years are 12.2 percentage points less likely to attend college than their sisters. The estimates from column 6 do not allow me to precisely measure the impact of divorce on college graduation. The coefficients of interest are almost always made more precise when moving from the OLS to fixed effects model. This is perhaps due to the sibling fixed effects models removing unobserved differences between families.

Table 8

Age group Exposure time Model

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HSGrad	HSGrad	CollegeAtt	CollegeAtt	CollegeGrad	CollegeGrad
Young	-0.030	0.018	-0.091	-0.065	-0.031	0.015
	[0.041]	[0.059]	[0.058]	[0.083]	[0.065]	[0.092]
Mid Child	0.006	-0.023	-0.060	-0.024	-0.011	-0.012
	[0.032]	[0.053]	[0.048]	[0.073]	[0.056]	[0.085]
Teenager	0.004	0.033	0.024	0.138**	-0.042	-0.019
	[0.033]	[0.047]	[0.048]	[0.063]	[0.053]	[0.073]
Boy	-0.073*	-0.085***	-0.174***	-0.141***	-0.104*	-0.100***
	[0.039]	[0.021]	[0.052]	[0.028]	[0.056]	[0.030]
NeverDivorce	0.009		-0.018		0.074	
	[0.027]		[0.041]		[0.048]	
Boy x NeverDivorce	-0.002		0.060		0.030	
	[0.040]		[0.056]		[0.064]	
Boy x Young	0.021	-0.031	-0.060	-0.069	0.077	0.092
	[0.060]	[0.059]	[0.079]	[0.075]	[0.088]	[0.079]
Boy x Midchild	-0.092*	-0.074*	-0.036	-0.075	-0.054	-0.086
	[0.050]	[0.040]	[0.065]	[0.053]	[0.073]	[0.056]
Boy x Teenager	-0.059	-0.055	-0.083	-0.122**	-0.055	-0.040
	[0.051]	[0.040]	[0.067]	[0.053]	[0.069]	[0.053]
Premature	0.005	-0.016	-0.003	-0.004	0.014	-0.002
	[0.017]	[0.022]	[0.025]	[0.031]	[0.029]	[0.037]
BirthOrder	-0.070***	-0.019	-0.097***	-0.042**	-0.090***	-0.055**
	[0.007]	[0.017]	[0.009]	[0.021]	[0.012]	[0.025]
Boy x White	0.005	0.020	0.051	0.066*	-0.056	-0.028
	[0.026]	[0.023]	[0.039]	[0.034]	[0.047]	[0.041]
Age of Mother at Birth	0.019***	0.007	0.028***	0.010	0.025***	0.009
	[0.002]	[0.006]	[0.003]	[0.007]	[0.004]	[0.010]
Observations	2,842	2,842	2,351	2,351	1,466	1,466
R-squared	0.102	0.567	0.115	0.618	0.125	0.623
Sibling FE	No	YES	No	YES	No	YES

Robust standard errors in brackets

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

Note: Robust Standard errors in brackets.*** p<0.01, ** p<0.05, * p<0.1. The three age groups young midchild and teen respectively are for children in age groups (0-4),(5-12) and (13-18) respectively. Standard controls are all included in the model but not provided in the table.The regression with college graduation as outcome only considers respondents who were 26 and over at the time of their last interview.Similarly the cutoff is 22 for college attendance.

8 Event Study Models

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I use the timing of divorce to carry out an event study analysis of achievement scores. This regression model allows me to assess whether divorce leads to an on impact change in trends in achievement scores. I am providing event study analyses for only the fixed effects model. The event studies are generalized difference in difference models similar to Jacobson et al. (1993). Instead of the standard difference in difference, I am using dummy variables for each period before and after divorce for a maximum of 3 periods on either side (leaving out the period before divorce).

The respondents of the CNLSY are surveyed every two years. Each period for my event study is equivalent to two years from the time of divorce. Event studies in the literature normally use a maximum of 4 years before and after the event. 4 periods for my event study will mean 8 years on either side of divorce. This will lead to very wide confidence intervals on top of the already large ones. These achievement scores are only administered to school age children, and there are very few observations at very young ages and mid-late teens. There are challenges to using one year time periods as well. The biennial nature of my data would lead to each respondent showing up in every other period. I am providing event study diagrams for childhood math and reading achievement scores for the sibling fixed effects model. Figure 5 reveals that the gender gap in math assessment scores remain fairly constant till the time of divorce after which there is a sharp fall. There is a similar sharp fall for reading assessment scores in figure 6, where the major drop happens right before the period of divorce. There is no presence of any pre-trends in the math test scores. These figures provide visual evidence supporting my original difference in difference models.

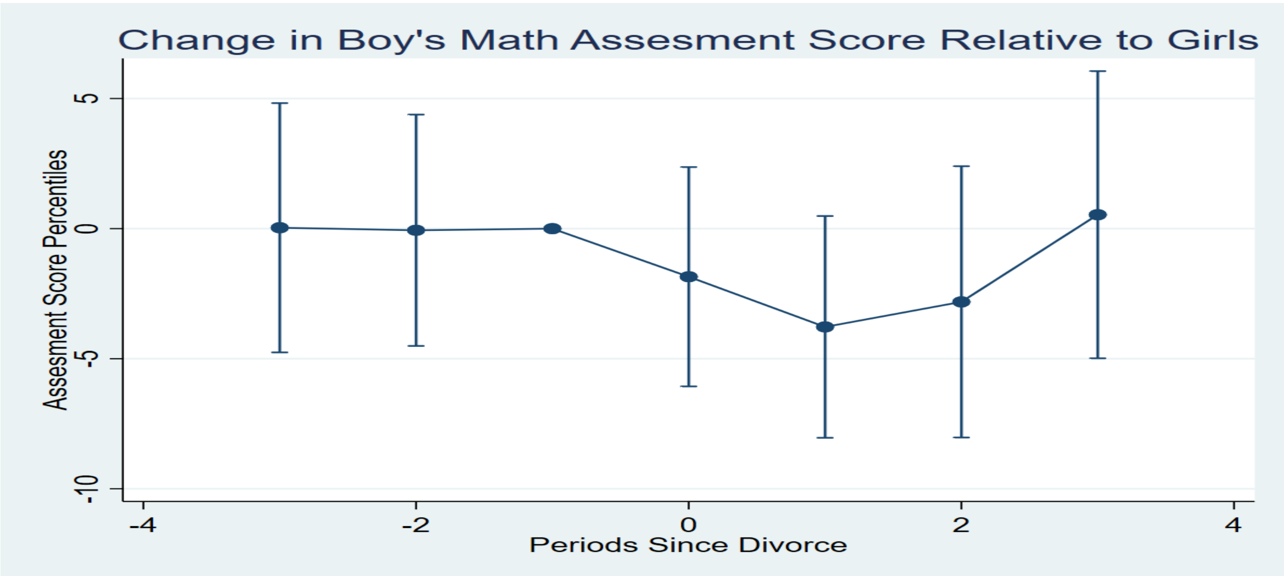

Fig. 5 Sibling Fixed Effect Model Event Study for Math Test Scores Note: This figure reports estimates of event study regressions, which include indicator variables for each two year period before and after year of divorce, with another set of indicators interacted with dummy variable for gender . The event study regression specification includes sibling fixed effects. The blue vertical bars represent confidence intervals

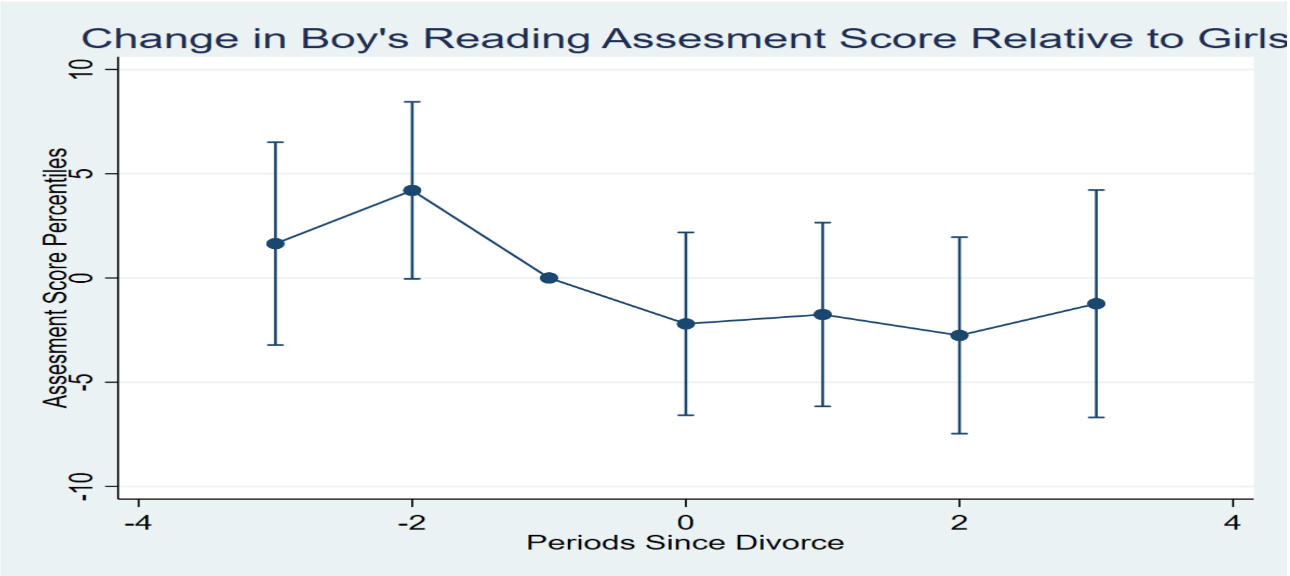

Fig. 6 Sibling Fixed effect Model Event Study for English Test Scores Note: This figure reports estimates of event study regressions, which include indicator variables for each two year period before and after year of divorce, with another set of indicators interacted with dummy variable for gender. The event study regression specification includes sibling fixed effects. The blue vertical bars represent confidence intervals

9 Conclusion

This paper investigates whether divorce exerts a differential effect on the labor market outcomes of boys relative to girls. I use the National Longitudinal Survey of Youth 1979 Child & Young Adult Supplement (CNLSY), and a model that employs within-family brother-sister comparisons. I find that divorce disproportionately negatively affects the long term educational outcomes of boys relative to girls. The event has severe consequences for boys whose parents are divorced while they are teenagers. Divorce during teenage years increases the boy-girl disparity in attending college by 14.4 percentage points. This translates to a 39.7 percent lower likelihood of attending college. Divorce before the age of 13 reduces boy's likelihood of graduating from high school by 15.5 percent. I find no significant effect of divorce differing by gender on non educational long term outcomes. My findings are robust to different specifications including an age cutoff and two different exposure time models. I estimate event study models and placebo tests in reading and math scores, to check for the validity of my assumptions. The event study models and placebo tests provide evidence for the absence of pre-trends and independence of future marital status to gender gap in achievement scores, respectively.

I find that the boy-girl disparity in high school graduation is increased if the divorce happens when the child is less than 13, and especially when the child is between the ages of 5 and 12. While college attendance is affected by divorce in the teenage years and early childhood, it is possible that during the middle childhood years, when children are mainly in primary and early middle school, the impact of divorce affects an outcome like high school graduation which is determined at an earlier age. This may also be an explanation for divorce during teenage years affecting college attendance. There are multiple channels through which divorce may affect boys differently than girls. There is a possibility that the dissolution of a turbulent marriage may have a less negative or even positive impact on the male child. It may also be the case that the absence of a father figure with a negative influence may positively impact a boys life. However, I do not find anything in my results which may support these hypotheses. My analysis provides evidence of different channels through which divorce may be affecting children. First, boys may be more responsive to changes in family structure than girls. Second, with changes in family structure the relative time invested in boys may start to fall with age compared to girls. These hypotheses are supported by Baker and Milligan (2013) , Bertrand and Pan (2013) and Bibler (2019). The data in the CNLSY is not sufficient to test these channels.

Policy makers must be careful in trying to solve this problem. While it is the case that families with male children are less likely to go through divorce (Dahl and Moretti 2008), the consequences of divorce are also more severe for boys. It maybe more fruitful to find out effective ways to target boys from divorced families who are mostly at risk, and to better understand the reasons behind broken marriages of families with children. Policy makers should aim at targeting the children who are suffering from this unfortunate accident and find out a way to reduce such events in the future. Any progress can not only reduce some amount of unfortunate suffering, but also increase the pool of productive adults in society and reduce the already propagating gender disparities.

Appendix

Table 9

Standardized Educational Outcome Regression Values

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HSGrad	HSGrad	CollegeAtt	CollegeAtt	CollegeGrad	CollegeGrad
EarlyDivorce	-0.011	-0.038	-0.174**	-0.184	-0.033	-0.010
	[0.074]	[0.109]	[0.081]	[0.119]	[0.100]	[0.134]
Boy	-0.261***	-0.254***	-0.427***	-0.320***	-0.274***	-0.236***
	[0.088]	[0.054]	[0.087]	[0.054]	[0.095]	[0.061]
Boy x EarlyDivorce	-0.128	-0.178**	-0.031	-0.161*	0.023	-0.024
	[0.117]	[0.089]	[0.115]	[0.087]	[0.132]	[0.101]
Premature	0.014	-0.054	-0.005	-0.017	0.032	-0.007
	[0.045]	[0.060]	[0.050]	[0.063]	[0.063]	[0.079]
Birth Order	-0.190***	-0.048	-0.195***	-0.088**	-0.190***	-0.109**
	[0.020]	[0.047]	[0.019]	[0.042]	[0.025]	[0.054]
Boy x White	0.018	0.059	0.103	0.137**	-0.115	-0.052
	[0.072]	[0.065]	[0.078]	[0.068]	[0.102]	[0.088]
Age of Mother at Birth	0.052***	0.021	0.056***	0.021	0.053***	0.019
	[0.005]	[0.015]	[0.005]	[0.015]	[0.008]	[0.022]
Never Divorce	0.026		-0.062		0.191**	
	[0.061]		[0.069]		[0.087]	
Boy x NeverDivorce	0.053		0.197**		0.114	
	[0.093]		[0.096]		[0.117]	
Observations	2,842	2,842	2,351	2,351	1,466	1,466
R-squared	0.100	0.566	0.114	0.616	0.121	0.620
Sibling FE	NO	YES	NO	YES	NO	YES

Note: Robust Standard errors in brackets.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. The regression with college graduation as outcome only considers respondents who were 26 and over at the time of their last interview.Similarly the cutoff is 22 for college attendance. All races are that of the child. In every interview the CNLSY asks its respondents their highest educational qualification. There are correspondents who mention that they are still in college and their highest qualification till date is college attendance.A respondent is classified as premature if he/she was born early or late.

Table 10

Standardized Assessment Score Regression Values restricted to pre-divorce

	(1)	(2)	(3)	(4)
VARIABLES	BPI-5	HOME-5	PIATMT-5	PIATRR-5
Boy	0.129**	-0.090*	-0.037	-0.221***
	[0.058]	[0.047]	[0.064]	[0.064]
Boy x EarlyDivorce	0.033	0.057	-0.096	0.099
	[0.132]	[0.108]	[0.143]	[0.136]
EarlyDivorce	0.028	-0.106	0.065	-0.270*
	[0.129]	[0.121]	[0.154]	[0.156]
Boy x White	-0.034	0.011	0.020	0.053
	[0.072]	[0.062]	[0.080]	[0.080]
BirthOrder	-0.040	-0.020	-0.061	-0.105**
	[0.040]	[0.032]	[0.042]	[0.046]
Premature	0.001	-0.038	-0.037	-0.110
	[0.061]	[0.054]	[0.068]	[0.069]
Age of Mother at Birth	-0.030**	-0.027***	0.011	0.027**
	[0.012]	[0.010]	[0.012]	[0.013]
Observations	2,648	2,663	2,585	2,542
R-squared	0.706	0.791	0.667	0.675
Sibling FE	YES	YES	YES	YES

Robust standard errors in brackets

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

Note: Robust Standard errors in brackets.*** p<0.01, ** p<0.05, * p<0.1. I am taking two year gaps because the surveys are conducted every two years. So a peabody math test score at age 7 essentially means ages 7 & 8 as a child will only be tested in alternate years. A child is classified as premature if he/she has been born early or late. The race is that of the child

Table 11

Non-Incarcerated Educational Outcome Regression Values

VARIABLES	(1) HSGrad	(2) HSGrad	(3) CollegeAtt	(4) CollegeAtt	(5) CollegeGrad	(6) CollegeGrad
EarlyDivorce	-0.007	-0.014	-0.088**	-0.092	-0.016	-0.005
	[0.027]	[0.039]	[0.041]	[0.059]	[0.047]	[0.062]
Boy	-0.098***	-0.093***	-0.209***	-0.155***	-0.129***	-0.110***
	[0.032]	[0.020]	[0.043]	[0.027]	[0.044]	[0.028]
Boy x EarlyDivorce	-0.043	-0.064**	-0.014	-0.077*	0.011	-0.011
	[0.042]	[0.032]	[0.057]	[0.043]	[0.062]	[0.048]
Premature	0.005	-0.019	-0.003	-0.008	0.013	-0.002
	[0.017]	[0.022]	[0.025]	[0.031]	[0.029]	[0.037]
Birth Order	-0.069***	-0.018	-0.097***	-0.046**	-0.087***	-0.053**
	[0.007]	[0.017]	[0.009]	[0.021]	[0.012]	[0.025]
Boy x White	0.006	0.021	0.048	0.062*	-0.053	-0.027
	[0.026]	[0.023]	[0.039]	[0.034]	[0.047]	[0.041]
Age of Mother at Birth	0.019***	0.008	0.028***	0.011	0.025***	0.009
	[0.002]	[0.006]	[0.003]	[0.007]	[0.004]	[0.010]
NeverDivorce	0.007		-0.032		0.084**	
	[0.022]		[0.034]		[0.041]	
Boy x NeverDivorce	0.023		0.096**		0.053	
	[0.034]		[0.048]		[0.055]	
White	0.036**		0.059**		0.171***	
	[0.017]		[0.028]		[0.036]	
Observations	2,831	2,831	2,341	2,341	1,456	1,456
R-squared	0.100	0.565	0.113	0.617	0.119	0.618
Sibling FE	NO	YES	NO	YES	NO	YES

Note: Robust Standard errors in brackets.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. A child is classified as premature if he/she has been born early or late. The race is that of the child

Table 12

Non-Attrited Educational Outcome Regression Values

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HSGrad	HSGrad	CollegeAtt	CollegeAtt	CollegeGrad	CollegeGrad
EarlyDivorce	-0.004	-0.014	-0.086**	-0.092	-0.015	-0.005
	[0.027]	[0.039]	[0.040]	[0.059]	[0.046]	[0.062]
Boy	-0.094***	-0.092***	-0.212***	-0.159***	-0.128***	-0.110***
	[0.032]	[0.020]	[0.043]	[0.027]	[0.044]	[0.028]
Boy x EarlyDivorce	-0.047	-0.065**	-0.017	-0.080*	0.011	-0.011
	[0.042]	[0.032]	[0.057]	[0.043]	[0.061]	[0.047]
Premature	0.005	-0.020	-0.003	-0.009	0.015	-0.003
	[0.017]	[0.022]	[0.025]	[0.031]	[0.029]	[0.037]
BirthOrder	-0.069***	-0.017	-0.096***	-0.044**	-0.088***	-0.051**
	[0.007]	[0.017]	[0.009]	[0.021]	[0.012]	[0.025]
Boy x White	0.006	0.021	0.050	0.068**	-0.054	-0.024
	[0.026]	[0.023]	[0.039]	[0.034]	[0.047]	[0.041]
Age of Mother at Birth	0.019***	0.007	0.028***	0.011	0.025***	0.009
	[0.002]	[0.006]	[0.003]	[0.007]	[0.004]	[0.010]
NeverDivorce	0.009		-0.031		0.089**	
	[0.022]		[0.034]		[0.040]	
Boy x NeverDivorce	0.019		0.098**		0.053	
	[0.034]		[0.048]		[0.054]	
White	0.034**		0.057**		0.173***	
	[0.017]		[0.028]		[0.036]	
Observations	2,841	2,841	2,350	2,350	1,466	1,466
R-squared	0.100	0.566	0.114	0.616	0.121	0.620
Sibling FE	NO	YES	NO	YES	NO	YES

Note: Robust Standard errors in brackets.*** p<0.01, ** p<0.05, * p<0.1. A child is classified as premature if he/she has been born early or late. The race is that of the child

Table 13

Alternate Cutoff Educational Outcome Regression Values

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HSGrad	HSGrad	CollegeAtt	CollegeAtt	CollegeGrad	CollegeGrad
EarlyDivorce	-0.032	0.097*	-0.051	0.072	-0.087	-0.012
	[0.044]	[0.058]	[0.062]	[0.072]	[0.069]	[0.079]
Boy	-0.128***	-0.104***	-0.212***	-0.167***	-0.140***	-0.118***
	[0.026]	[0.019]	[0.036]	[0.026]	[0.036]	[0.026]
Boy x EarlyDivorce	0.085	-0.060	-0.033	-0.140*	0.140	0.092
	[0.064]	[0.072]	[0.087]	[0.083]	[0.091]	[0.092]
Premature	0.007	-0.017	-0.004	-0.007	0.017	-0.000
	[0.017]	[0.022]	[0.025]	[0.031]	[0.029]	[0.037]
Birth Order	-0.070***	-0.018	-0.097***	-0.042**	-0.088***	-0.052**
	[0.007]	[0.017]	[0.009]	[0.021]	[0.012]	[0.025]
Boy x White	0.004	0.022	0.049	0.066*	-0.058	-0.027
	[0.026]	[0.023]	[0.039]	[0.034]	[0.047]	[0.041]
Age of Mother at Birth	0.019***	0.007	0.027***	0.008	0.025***	0.009
	[0.002]	[0.006]	[0.003]	[0.007]	[0.004]	[0.010]
NeverDivorce	0.007		0.007		0.084**	
	[0.018]		[0.029]		[0.036]	
Boy x NeverDivorce	0.053*		0.099**		0.068	
	[0.028]		[0.041]		[0.048]	
Observations	2,842	2,842	2,351	2,351	1,466	1,466
R-squared	0.100	0.565	0.110	0.614	0.122	0.621
Sibling FE	NO	YES	NO	YES	NO	YES

Note: Robust Standard errors in brackets.*** p<0.01, ** p<0.05, * p<0.1. A child is classified as premature if he/she has been born early or late. The race is that of the child

Table 14

Alternate Cutoff Educational Outcome Regression Values

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	HSGrad	HSGrad	CollegeAtt	CollegeAtt	CollegeGrad	CollegeGrad
EarlyDivorce	0.009	0.020	-0.053	0.002	-0.039	-0.015
	[0.028]	[0.036]	[0.041]	[0.052]	[0.046]	[0.060]
Boy	-0.094***	-0.092***	-0.222***	-0.162***	-0.139***	-0.117***
	[0.035]	[0.020]	[0.047]	[0.028]	[0.049]	[0.029]
Boy x EarlyDivorce	-0.039	-0.051*	0.005	-0.051	0.028	0.016
	[0.043]	[0.030]	[0.058]	[0.041]	[0.061]	[0.045]
Premature	0.005	-0.018	-0.003	-0.007	0.015	-0.003
	[0.017]	[0.022]	[0.025]	[0.031]	[0.029]	[0.037]
Birth Order	-0.069***	-0.017	-0.097***	-0.042**	-0.088***	-0.051**
	[0.007]	[0.017]	[0.009]	[0.021]	[0.011]	[0.025]
Boy x White	0.006	0.020	0.050	0.066*	-0.053	-0.025
	[0.026]	[0.023]	[0.039]	[0.034]	[0.047]	[0.041]
Age of Mother at Birth	0.019***	0.007	0.028***	0.009	0.025***	0.009
	[0.002]	[0.005]	[0.003]	[0.007]	[0.004]	[0.010]
Never Divorce	0.017		-0.019		0.074*	
	[0.025]		[0.037]		[0.043]	
Boy Never Divorce	0.019		0.108**		0.065	
	[0.037]		[0.051]		[0.058]	
Observations	2,842	2,842	2,351	2,351	1,466	1,466
R-squared	0.099	0.565	0.111	0.614	0.121	0.620
Sibling FE	NO	YES	NO	YES	NO	YES

Note: Robust Standard errors in brackets.*** p<0.01, ** p<0.05, * p<0.1. A child is classified as premature if he/she has been born early or late. The race is that of the child

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