# Heterogeneous Cognitive Development: Parental Divorce, Gender and Socioeconomic Status

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# Abstract

Previous literature has identified negative effects of parental divorce on children's cognitive achievements, yet the heterogeneous effects of parental divorce haven't been examined thoroughly given the uneven distributions of parents' propensity to divorce. Moreover, boys and girls from various social backgrounds not only have separated growth trajectories of cognitive abilities but also experience parents' marital transition in divergent ways. This paper uses Distributed Fixed Effects Models to account for the temporal heterogeneities associated with parental separation. Based on National Longitudinal Survey of Youth and Mothers between 1979 and 2006, I found that the cognitive trajectories of boys and girls raised in different SES backgrounds are affected by parental separation differently. The negative effects of parental divorce exist only in the most disadvantaged socioeconomic backgrounds, and are stronger for readings than math. Boys whose mothers have less than high school degrees are more likely to suffer from parental divorce across years, while girls' cognitive abilities are more constant.

# **Key Words**

Cognitive, Parental Divorce, Gender, SES

## Heterogeneities Associated with Parental Divorce

Past studies have identified significant negative effects of parental divorce on children's psychological well-being (Mandemakers & Kalmijn 2014), cognitive skills (Kim 2011) and academic achievements (Anthony et al. 2014). However, the causal effect of parental divorce is not so straightforward, since people from lower social origins or through less advantageous life events are more likely to get divorced. If we omit the larger propensity of disadvantageous families to have disruptive events, we are in the danger of overestimating the causal effect of parental divorce effect. Even if we include pretreatment characteristics such as income, socioeconomic status as well as children's status, we are still vulnerable in arguing the causality of divorce effect. Meanwhile, whether the potential bias of family background is positive or negative is not at all clear from previous findings. It could be that children from higher class or highly educated families are less likely to be exposed to the negative effects of parental separation (Mandemakers & Kalmijn 2014; Grätz 2014), while it is also possible that the "penalty" of divorce is larger for advantageous families (Bernardi et al. 2014).

Building on above studies, in this paper I mainly approach the gender gap among children in response to the family's socioeconomic status whose parents are divorced. The key question I intend to answer is: is the negative effect of disruptive family structure larger for boys than girls, and why? Using longitudinal NLSY children and mothers' data (1979-2014), I used a distributed fixed effects model to test not only whether gender and SES would affect how negatively children experienced parental separation, but also whether the long-run effects of parental separation existed.

While OLS coefficient is not robust to the causal identification, what scholars have been doing for years is to introduce lagged variables (Cherlin et al. 1998). However, controlling child's pre-separation well-being is not sufficient because divorce is something that might start to begin its process years before it takes place. This strategy is also sensitive to other life-course event within the family that happens between two measured time periods. We should also be aware that the bias between long-term and short-term effect of divorce. Growth curve model (Magnuson & Berger's 2009) is used to distinguish the cause and consequence of divorce by incorporating more time points. This is a lot better than LDV though it is not perfect at avoiding unmeasured bias (McLanahan et al. 2013).

Gennetian (2005) takes a fixed-effects approach to reduce potential bias by comparing the effect of divorce on siblings within the same family who have different lengths of exposure due to their age or embrace separate experiences in terms of of living with bio or step parent. However, dynamics of sibling structure introduces heterogeneity of cooperations in response to parental divorce, and a blended family cannot be treated the same as a traditional two-parent family (McLanahan et al. 2013). More advanced methods to predict this causal effect is a natural experiment case with instrumental variables such as change of divorce low in several states (Gruber 2004), as well as propensity score matching (Frisco et al. 2007). The problem of a more rigorous model is that we lose the power of generalizability in a sense (McLanahan et al. 2013).

## **Quantitative Strategy and Data**

I followed the models from Dougherty (2006) and found the results from FE models are more reasonable than the OLS ones. Here  $Y_{it}$  are the PIAT Math and English standardized scores measured at certain years of survey.  $D_{it}$  represent the length to the year of parental divorce as well as the year span after parental divorce, thus  $\beta$  is an average estimate of yearly effect of parental divorce. Among  $X_{jit}$  there are key variables such as gender and SES (measured by parental highest educational level and income percentiles) as well as other control variables that might be causing the correlation between children's cognitive ability and parental marital status. A common strategy to treat with potential concerns with distributed fixed effects models is to recode the years too far before the divorce as the reference group (no divorcing), thus the graphs I presented below has a time span of 4 years before parental divorce to 10 years after parental divorce.

$$Y_{it} = \beta D_{it} + \sum_j \delta_j X_{jit} + \alpha_i + \varepsilon_{it}, \qquad \text{OLS}$$

$$Y_{it} - \overline{Y}_i = \beta (D_{it} - \overline{D}_i) + \sum_j \delta_j (X_{jit} - \overline{X}_{jt}) + (\varepsilon_{it} - \overline{\varepsilon}_i), \text{ DFE}$$

Given my focus on gender and SES heterogeneities, and based on the rightful model to disentangle divorce effects, here the question to be answered is not whether or how much parental marriage transitions affect children's educational outcomes for the general population, but rather how the effects on cognitive development could be hugely different across different social origins, separately for boys and girls.

I match National Longitudinal Survey of Youth (NYLS) Child and Young Adults Data to their mothers in the original cohorts. Variables on year before divorce and year after divorce are created from all marital status of the young women available between 1979 to 2014. Marital history before 1979 is also retrieved to know whether the mother has divorce experiences prior to being surveyed. For the original sample of 11,521 young adults of all ages in the data, I use the observations when they were at the ages between 5 and 14 during which period their cognitive scores are measured most frequently and have fewer missing rates. In order to have multiple data points of cognitive scores, I constrain observations to children who have PIAT-Math and PIAT-Reading scores measured at least 2 times in the data. I also restrict my analysis to children who keeps residing with mothers, which is the majority of the sample. The remaining sample size after I create maternal marital status and cognitive scores are described in Table 1 in Appendix.

Following Grätz (2014) I define socioeconomic status by highest educational level attained by mother across years. Since my analyses are very much dependent on the time structure, and variations in family characteristics would bias the divorce effects, I control for various maternal and household characteristics that explain children's cognitive development. Other than age and race of the child, yearly household income, I also include whether the mother has been a single mother, mother's age, mother's employment status, number of siblings in the household, geographical regions.

### Results

From Graph 1.1-1.4 I present the cognitive variations for boys and girls by whether their mother has divorced or separated with their mothers after they were born. The graphs show the parental divorce gap at different years of old from separate socioeconomic backgrounds. While it is clear that children with parental divorce from are generally worse off, children from an intact family from lower socioeconomic backgrounds won't be better off than children from higher social origins. Distributed Effects Models results (as in Table 2.1 and 2.2) show what is similar to what Aughinbaugh et al. (2005) has found, that parental divorce effects are not significant overall. However, the negative effects are significantly large for boys from the bottom two social classes, and take place before the divorce actually takes place.

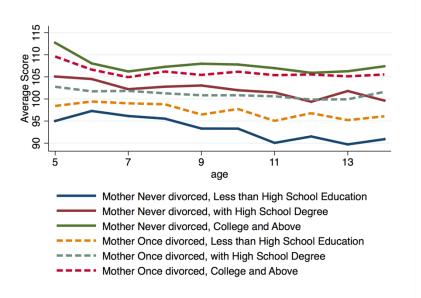
Although NLSY is one of the best data sources to learn about young children's cognitive development, selection bias due to the sample attrition issues. There is reason to believe that children whose mothers drop out of sample and whose information never get to be recollected could have more disadvantaged family characteristics and educational outcomes (Aughinbaugh 2003). Thus the current estimates I obtained omit the children at the bottom whose growth trajectories are subject to different life course functions. Thus the following step would be to impute on missing data and test the robustness of the results. Another long-existing problem for the literature is also that what we call parental divorce effects usually also point to the maternal sides (Grätz 2014). NLSY data also shows very few percentages of children reside with their fathers after parental separation, and thus limits our ability to explore the variation of parental divorce by the co-resident parent. More robustness tests are going to be needed to support this finding.

# Appendix

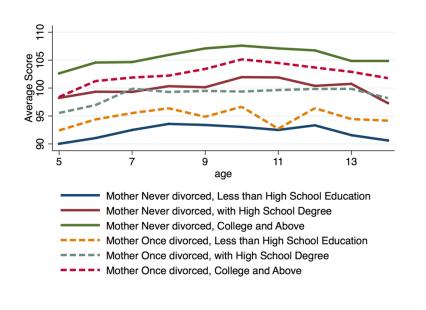
Table 1 Sample Restriction

	Number of Children
Original sample	11495
Stays with Mother	11225
Between age 5-14	10023
PIAT Math measured at least twice	8015
PIAT Read measured at least twice	7968
Analytic Sample Size	7968

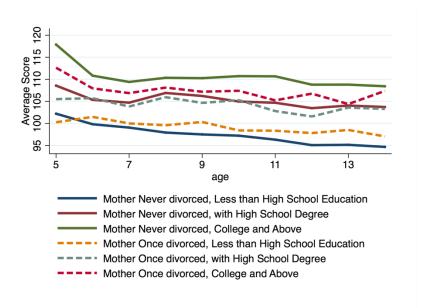
Figure 1.1 Average PIAT-Read for Boys, by Social Origins



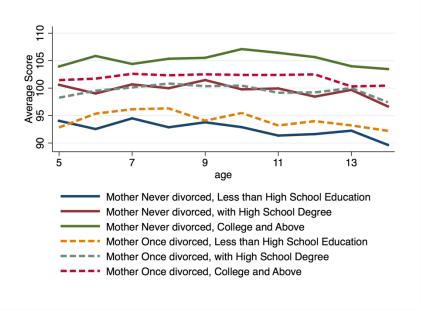
Graph 1.2 Average PIAT-Math for Boys, by Social Origins



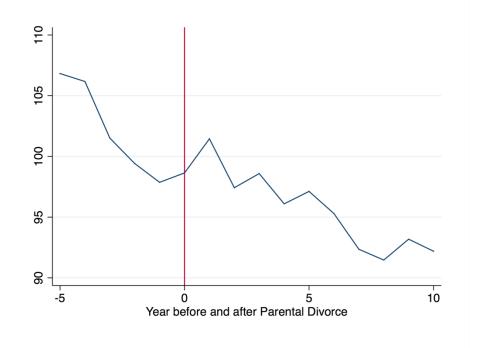
Graph 1.3 Average PIAT-Read Score for Girls, by Social Origins



Graph 1.4 Average PIAT-Math Score for Girls, by Social Origins



Graph 2 Predicted Reading Skills for Boys from Bottom Class, By Parental Divorce Year



High School - -0.1266 (1.7187) -5.0358 (3.8806)	High School Degree -0.8671 (1.2493) -0.5566	College + 0.4023 (1.1743)	High School - 0.6717	High School Degree 0.1328	College + -0.4841
(1.7187) -5.0358	(1.2493)			0 1328	0 19/1
-5.0358		(1.1743)		0.1520	-0.4041
	-0.5566		(1.7382)	(1.3009)	(1.0670)
(3.8806)		-5.8077	6.3719	5.1130	-2.3373
	(3.4773)	(3.3436)	(5.1539)	(3.0627)	(2.4278)
-6.071847**	-2.6674	-1.6698	1.0735	0.1586	0.8684
(2.0740)	(1.5337)	(1.4430)	(2.1049)	(1.4898)	(1.2283)
-8.573671*	-2.2748	-1.6611	7.2531	-2.8270	-0.1894
(3.5566)	(2.8386)	(3.0658)	(5.0011)	(2.9650)	(2.3966)
-6.811151**	-0.7065	-1.2688	1.4915	0.1140	1.4680
(2.4670)	(1.7717)	(1.6977)	(2.3723)	(1.8138)	(1.4317)
-5.9938	-0.0343	-0.6456	0.1028	-4.5638	0.5444
(3.4785)	(2.7384)	(2.9733)	(4.2284)	(2.8388)	(2.2022)
-7.549825**	-1.8247	0.2833	1.8117	1.9601	0.8205
(2.8795)	(2.0065)	(1.9562)	(2.7665)	(2.0652)	(1.6760)
-8.397987*	0.7706	0.9806	1.3491	-1.5100	0.3989
(3.6847)	(2.7566)	(2.7992)	(4.4004)	(2.7873)	(2.2659)
-8.129426**	-3.0300	-0.1876	2.1893	1.8534	0.0023
(3.1116)	(2.2874)	(2.2223)	(3.0731)	(2.3475)	(1.9059)
-9.76015**	1.7986	1.5688	0.0472	-1.2007	1.1227
(3.7282)	(2.8316)	(2.8609)	(4.2534)	(2.9056)	(2.3333)
-10.67669**	-1.6375	-0.8719	3.9404	0.0391	1.7971
(3.4643)	(2.5477)	(2.4950)	(3.4159)	(2.6164)	(2.1339)
-13.51289***	-1.5225	2.6610	2.8437	-0.9538	2.2805
(3.7213)	(2.9037)	(2.9026)	(4.0722)	(2.9568)	(2.4291)
-14.22393***	-3.5168	-0.1938	1.5855	-1.0817	2.5333
(3.7761)	(2.7986)	(2.7237)	(3.7861)	(2.8803)	(2.3440)
-13.02781***	-3.1918	0.7750	0.5658	-1.7670	1.5719
(3.9387)	(3.0884)	(2.9684)	(4.2532)	(3.1154)	(2.5347)
-14.59355***	-3.0980	-0.5026	-0.0803	0.9194	1.9772
(4.1844)	(3.1902)	(3.0692)	(4.2739)	(3.2695)	(2.6821)
	$\begin{array}{r} (2.0740) \\ -8.573671^* \\ (3.5566) \\ -6.811151^{**} \\ (2.4670) \\ -5.9938 \\ (3.4785) \\ -7.549825^{**} \\ (2.8795) \\ -8.397987^* \\ (3.6847) \\ -8.129426^{**} \\ (3.1116) \\ -9.76015^{**} \\ (3.7282) \\ -10.67669^{**} \\ (3.4643) \\ -13.51289^{***} \\ (3.7213) \\ -14.22393^{***} \\ (3.7761) \\ -13.02781^{***} \\ (3.9387) \\ -14.59355^{***} \\ (4.1844) \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$

Table 2.1 Distributed Effects of Parental Divorce on Children's Reading Recognition Outcomes, By Gender and Social Origins

\* p<0.05, \*\* p<0.01, \*\*\* p<0.001

	Boys			Girls				
PIAT-Math	High School -	High School Degree	College +	High School -	High School Degree	College -		
4 or more years before	-1.4820	-2.3586	-1.7514	-1.6335	0.2044	-0.0978		
	(1.8473)	(1.3801)	(1.1827)	(1.6975)	(1.4051)	(1.1727)		
3 years before divorce	2.4421	-6.6419	0.0376	8.1800	2.7359	-1.4263		
	(4.1966)	(3.8801)	(3.3739)	(5.3763)	(3.3290)	(2.6990)		
2 years before divorce	-3.6480	-2.9901	0.1774	-0.9950	-0.5114	-0.0986		
	(2.2428)	(1.6983)	(1.4511)	(2.0418)	(1.6112)	(1.3525)		
1 year before divorce	3.8391	-4.0828	-2.3703	-6.0437	-3.4197	-0.7035		
	(3.8415)	(3.1275)	(3.1488)	(4.8503)	(3.2363)	(2.6629)		
Divorce year	-6.59982*	-1.2375	2.2861	-0.7110	0.0071	-0.6534		
	(2.6687)	(1.9623)	(1.7027)	(2.3071)	(1.9595)	(1.5738)		
1 year after divorce	-1.0775	-4.1177	-0.2784	2.0190	-1.8678	-2.4389		
	(3.8292)	(3.0484)	(3.0092)	(4.1537)	(3.0869)	(2.4316)		
2 years after divorce	-6.364665*	-3.8616	-0.4475	-1.0954	0.3954	0.4843		
	(3.1327)	(2.2238)	(1.9682)	(2.6810)	(2.2358)	(1.8455)		
3 years after divorce	-2.9357	-6.367535*	-1.1715	4.6894	1.9684	0.0802		
	(3.9916)	(3.0541)	(2.8335)	(4.2896)	(3.0170)	(2.5017)		
4 years after divorce	-4.8338	-3.6728	-0.7422	1.2332	1.3478	2.1662		
	(3.3691)	(2.5394)	(2.2396)	(2.9813)	(2.5361)	(2.0966)		
5 years after divorce	-0.6891	-1.7344	0.1803	0.0988	-0.0710	-1.7595		
	(4.0397)	(3.1471)	(2.8856)	(4.1462)	(3.1430)	(2.5725)		
6 years after divorce	-7.2058	-1.9380	0.1224	3.0325	-0.0690	-1.1154		
	(3.7500)	(2.8350)	(2.5091)	(3.3047)	(2.8256)	(2.3474)		
7 years after divorce	-6.2128	-5.7815	0.7145	0.5605	-1.1202	-4.7419		
	(4.0239)	(3.2213)	(2.9235)	(3.9607)	(3.1956)	(2.6727)		
8 years after divorce	-6.9195	-4.1982	-2.8825	1.7952	1.6383	-1.8674		
	(4.0874)	(3.1177)	(2.7428)	(3.6656)	(3.1098)	(2.5794)		
9 years after divorce	-7.9945	-4.2002	-0.3398	1.2998	-1.0810	-3.1534		
	(4.2603)	(3.4187)	(2.9905)	(4.1270)	(3.3623)	(2.7885)		
10 or more years after divorce	-9.992732*	-3.8920	-2.4416	0.3584	-1.0029	-2.6429		
	(4.5276)	(3.5490)	(3.0991)	(4.1414)	(3.5267)	(2.9478)		

Table 2.2 Distributed Effects of Parental Divorce on Children's Math Outcomes, By Gender and Social Origins

\* p<0.05, \*\* p<0.01, \*\*\* p<0.001

Table 2.3 Distributed Effects of Parental Divorce on Children's Reading Recognition Outcomes, By Gender and Social Origins, Controlling Parent-Children Relationships

Table 2.4 Distributed Effects of Parental Divorce on Children's Math Recognition Outcomes, By Gender and Social Origins, Controlling Parent-Children Relationships

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