The Heterogeneous Treatment Effect of Teenage Childbearing on Educational Attainment

Kiwoong Park
Doctoral Candidate

Department of Sociology
Center for Social and Demographic Analysis
University at Albany, State University of New York
351 AS, 1400 Washington Ave., Albany, NY 12222

Email: kpark5@albany.edu

INTRODUCTION

Although teenage mothers tend to have a lower educational attainment than non-teenage mothers (Furstenberg 2003), it remains unclear whether teen fertility has a causal effect on the educational attainment. Teenage childbearing, at first glance, is considered a "bad thing," which is detrimental to young mothers and causes social costs including increased spending on public assistance (Geronimus 1997). Supporting this view, some studies have reported the negative effects of early childbearing on teen mothers' educational and economic outcomes (Fletcher and Wolfe 2009; Kane et al. 2013; Lee 2010; Mollborn 2007). Other studies, however, found that the effects of early fertility are negligible or even positive for adolescent mothers (Ashcraft, Fernández-Val, and Lang 2013; Edin and Kefalas 2005; Geronimus and Korenman 1993; Hotz, McElroy, and Sanders 2005; Webbink, Martin, and Visscher 2011). These inconsistent findings cause even public controversy on whether campaigning to prevent teenage childbearing is necessary or harmful (Bute and Russell 2012; Geronimus 1997; Vinson 2012).

Research on the consequences of teen fertility is based on theoretical backgrounds. First, the negative consequences are supported by opportunity cost perspective (Becker and Tomes 1986). Women need to care their children and have more responsibilities associated with motherhood, which leads teen mothers to be less likely to attain their human capital like college completion. Second, the negligible or positive consequences are based on cultural norm and positive turning point arguments. That is, early childbearing for the poor may not only be a cultural rationale to reduce risks but also serve as a positive turning point in their life courses (Edin and Kefalas 2005; Geronimus 1997). The second explanations suggest that teenage childbearing itself may not necessarily lead to harmful consequences for all mothers. In addition, since some scholars argue that teenage mothers generally have disadvantaged preexisting conditions, teen fertility itself may not be a bad thing and that the negative effects result from selection bias (Furstenberg 2003; Geronimus 2003; Lee 2010).

These previous explanations imply that the effects of teenage childbearing may systematically vary by the likelihood that women have a baby during adolescence. Despite the possibility of the heterogeneity, most empirical research has assumed that the effect of teen fertility is homogeneous across population groups. While the average effect based on homogeneous assumption is simple to present the effect of treatment, it masks potential variation in the causal effect (Morgan and Todd 2008). Indeed, recent causal inference literature has found that treatment effects tend to be heterogeneous, rather than homogeneous (Angrist and Krueger 1999; Brand and Thomas 2013; Heckman, Stixrud, and Urzua 2006; Morgan and Winship 2014). Therefore, applying the heterogeneity perspective to the research on teenage childbearing and mothers' outcomes has a great potential to reconcile the existing theories and empirical findings of previous literature (Diaz and Fiel 2016).

To examine how adolescent women differently respond to teenage childbearing from the causal perspective, this study employs the smoothing-differencing (SD) method, which is a propensity score analysis developed to estimate heterogeneous treatment effects (Xie, Brand, and

Jann 2012). By using the SD method with the National Longitudinal Study of Adolescent to Adult Health (Add Health), this study not only addresses the selection bias from pre-treatment heterogeneity, but also appropriately analyzes the heterogeneous treatment effects of teenage childbearing on years of education. The heterogeneity pattern of teenage childbearing is presented by taking the differences in the years of education of the control group and the treatment group (Xie et al. 2012). I also conduct auxiliary analyses that investigate potential mechanisms that may explain the heterogeneity pattern.

BACKGROUND

Relationship between Teenage Childbearing and Educational Attainment

Despite declining trends, teen birth rates in the U.S. remain persistently high, at about 34 births per 1,000 women ages 15 to 19 (United Nations Statistics Division 2014). These rates are dramatically higher than in other developed countries. For example, US girls (29.4) are more than twice as likely as their Canadian peers (14.1), and about six times as likely as Swedish teens (5.3). Nevertheless, there are different approaches of understanding the educational consequences of teenage childbearing in the U.S. contexts.

First, teenage childbearing has been considered an issue that is related to social problems in the U.S (Furstenberg 2003). Based on the *opportunity cost theory* (Becker and Tomes 1986), many previous studies have explained the adverse effects on teen mother's lower educational attainment (Fletcher and Wolfe 2009; Klepinger, Lundberg, and Plotnick 1995; Lee 2010). Given that accumulating human capital requires substantial time and energy, women who experienced teenage childbearing are less likely to attain their human capital, such as college completion (Becker and Tomes 1986). Responsibilities related to motherhood and stresses resulting from role conflict or role transition can also be hindrances to the accumulation of human capital for teen mothers. Kane and her colleagues (2013) concluded that teen mothers tend to have 0.7 to 1.9 fewer years of schooling among teen mothers, and the estimation corresponds with other studies that found negative consequences of early fertility (Ashcraft et al. 2013; Klepinger et al. 1995; Lee 2010; Mollborn 2007).

Another explanation is that teenage childbearing is an adaptive practice based on a *cultural norm* for some subpopulation, especially Blacks in high poverty urban areas (Geronimus 1997, 2003). This perspective considers teenage childbearing as a rational behavior. In disadvantaged areas where life-expectancy is uncertain and economic condition is abysmal, teenage childbearing may mitigate the negative consequences of mother's health risks and unreliable labor market attachments (Geronimus 2003). In addition, extended family and kin network can provide consistent support for teen mother's children, especially when parental supports lack (DeLeire and Kalil 2002). In this circumstances, teen fertility may be socially encouraged and considered as cultural norms of success (Brand and Davis 2011; Zito 2016).

Also, *positive turning point* argument provides a clear explanation how early fertility may hold benefits for some subgroups. For example, a qualitative work suggested that disadvantaged young women tend to regard motherhood as a positive turning point in their life, motivating them to return to school, search for jobs, and avoid substance abuse or delinquency (Edin and Kefalas 2005). That is, poor teen mothers think their children recue them from disorganized life and provide them with personal benefits such as developing mother's positive identities (Edin and Kefalas 2005; SmithBattle 2007). The benefits that otherwise may not be present are considered as "advantages for the disadvantaged" (Diaz and Fiel 2016:88). These cultural norm and positive turning point arguments suggest that women differently consider and respond to early motherhood, which is practically important as opposed to conventional assumption that teenage childbearing cause negative consequences.

Causal Effects of Teenage Childbearing

Along with the different explanations above, the causal effect of teenage childbearing on mother's outcomes has been controversial. While some studies reported the negative effects of early childbearing on high school graduation and early earning (Fletcher and Wolfe 2009, Kane et al. 2013, Lee 2010), other studies found negligible adverse effects or even positive effects (Ashcraft et al. 2013; Geronimus and Korenman 1993; Hotz et al. 2005; Webbink et al. 2011). These inconsistent finding raise two important questions regarding the sources of selection bias. First, is the effect of early fertility detrimental itself or is it just a result from pretreatment heterogeneity? Second, is the effect homogeneous across the population or heterogeneous by subgroup population? To estimate the causal effect of teenage childbearing, these two questions should be addressed.

Heterogeneity in pre-existing conditions

Many scholars have criticized the opportunity cost perspective by arguing that preexisting disadvantaged conditions, rather than early childbearing itself, may be the cause of young mother's lower attainment (Geronimus 2003; Hotz et al. 2005). That is, confounding factors that affect both teen's childbearing and outcomes, such as educational attainment, are likely to estimate biased effects of teen fertility. Hotz and his colleagues (2005) concluded that pretreatment selection bias largely overstates the negative effects of teenage childbearing on educational and economic outcomes. The assignment to treatment and control group is non-random, thereby, providing selection into teenage childbearing. This issue is hard to address with conventional regression model, such as ordinary least squares (OLS). Although many studies have tried to address the pretreatment selection bias by employing different methodologies (e.g., sibling fixed-effect model, instrumental variables, and propensity scores), their findings are mixed across samples and methods (Ashcraft et al. 2013; Hotz et al. 2005; Kane et al. 2013).

Heterogeneity in treatment effects

While the heterogeneity in pre-existing conditions has been widely considered in literature, the heterogeneity in treatment effects has been rarely studied. Most of previous studies have assumed that the effect of teenage childbearing is homogeneous across groups, although theories explaining the consequences of teen fertility suggest that it may have negative effects for some subgroups but positive effects for other subgroups. The effect of teenage childbearing can be different according to teen mother's demographic factors and socioeconomic status, and family resources. For example, those who have higher potential benefits of education (i.e., college graduation) have higher cost of teenage childbearing than mothers who are less likely to attain higher education. Also, if a teen mother lives with extended family or kin, the teen mother can be more involved with her school after a birth, compared to her counterpart who do not have such family support (Martin and Brooks-Gunn 2015; Mollborn 2007). A few prior studies suggested the possibility of effect heterogeneity. For example, Kane and her colleagues (2013) acknowledged that the treatment effect of early fertility may be heterogeneous across the sample, although they did not explicitly estimate the heterogeneous treatment effect.

One study provided an important implication about the effect heterogeneity by using teen pregnancy (Diaz and Fiel 2016). They found that the negative effects of teen pregnancy on educational attainment are most pronounced among women who are *least* likely to experience a teenage pregnancy. Their findings in part support positive turning point argument, in that the negative effects are significantly weaker among women who are *most* likely to experience a teen pregnancy. Despite their important findings, the Diaz and Fiel's study (2016) can be advanced in two ways. First and foremost, their outcome of interest is teen pregnancy, which does not necessarily lead to teenage childbearing. More than forty percent of unintended teen pregnancies ends in abortion (Finer and Zolna 2016), and thereby teenage childbearing is a better indicator of teen motherhood. Also, theoretical explanations, including positive turning point argument, can be only applied to teenage childbearing because raising a baby gives mothers positive meanings and motivations. Further, using teenage pregnancy makes it hard to compare with previous research on educational consequences of teenage childbearing.

Second, the data used in Diaz and Fiel's study (2016), the Child and Young Adult Cohorts of the National Longitudinal Survey of Youth (NLSY) 1979, has a couple of limitations. As they discussed, the women who experienced teen pregnancy in the sample are likely daughters of younger mothers than general population, and the number of sample is relatively small. Also, although they included a various characteristics of teen mother, NLSY data does not include important contextual factors related to fertility decision. Admittedly, it is impossible to be free from unobserved variable bias in propensity score method. However, since contextual factors (e.g., statewide public funding of abortion and presence/absence of any type of abortion Provider) are critical for adolescent's fertility decision (Fletcher and Wolfe 2009; Kane et al. 2013), the results without accounting for the contextual factors has limited implications. In sum, although the heterogeneous treatment effect of teen fertility has a potential to reconcile previous theories and empirical findings (Diaz and Fiel 2016), it is only beginning to be understood.

ANALYTIC STRATEGY

Two Sources of Selection Bias

The previous theoretical and methodological debates suggest that there may be heterogeneities in both pretreatment selection into teenage childbearing and the treatment effects of the early childbearing. Therefore, two sources of selection bias can be reiterated as (a) pretreatment heterogeneity and (b) treatment effect heterogeneity (Brand and Thomas 2013; Xie et al. 2012; Zhou and Xie 2016). First, under the pretreatment heterogeneity scenario, childbearing is a result of preexisting differences in the teen mother's individual and contextual characteristics and the bias may be captured by covariates or fixed effects. Second, however, treatment effect heterogeneity is hard to be represented by the conventional models because the effects of childbearing may vary by women among different subgroups (Zhou and Xie 2016). While many studies have addressed pretreatment heterogeneity (Fletcher and Wolfe 2009; Kane et al. 2013; Lee 2010), few studies have accounted for the effect heterogeneity of early fertility behaviors (Diaz and Fiel 2016).

As mentioned above, average treatment effect (ATE) is contaminated by the two sources of selection bias, pretreatment heterogeneity and treatment effect heterogeneity, and is decomposed and expressed as follows (Xie et al. 2012; Zhou and Xie 2016).

$$
\begin{aligned}
ATE &= E\,(Y^1 - Y^0) \\
&= E\,(Y^1_{D=1})\cdot p + E\,(Y^1_{D=0})\cdot q \;-\; E\,(Y^0_{D=1})\cdot p - E\,(Y^0_{D=0})\cdot q \\
&= E\,(Y^1_{D=1}) - E\,(Y^1_{D=1})\cdot q + E\,(Y^1_{D=0})\cdot q \;-\; E\,(Y^0_{D=1}) + E\,(Y^0_{D=1})\cdot q - E\,(Y^0_{D=0})\cdot q \\
&= [E\,(Y^1_{D=1}) - E\,(Y^0_{D=0})] - [E\,(Y^0_{D=1}) - E\,(Y^0_{D=0})] - (\mathrm{TT} - \mathrm{TUT})\cdot q, \qquad (1)
\end{aligned}
$$

where p is the proportion treated (D= 1), and q is the proportion untreated (D= 0). TT represents treatment effect of the *treated* and TUT represents treatment effect of the *untreated*. In the equation (1), $E\,(Y^1_{D=1}) - E\,(Y^0_{D=0})$ is the simple comparison estimator from observed data, $E\,(Y^0_{D=1}) - E\,(Y^0_{D=0})$ indicates pretreatment heterogeneity bias, and $(\mathrm{TT} - \mathrm{TUT})\cdot q$ represents the treatment effect heterogeneity (Xie et al. 2012; Zhou and Xie 2016). While the pretreatment heterogeneity may be captured by covariates or fixed effects, the treatment effect heterogeneity is hard to be represented by covariates or fixed effects (Zhou and Xie 2016). Due to the development of the propensity score (PS)-based methods, heterogeneous treatment effects have been studied in social science (Brand and Thomas 2013; Rosenbaum and Rubin 1983; Xie et al. 2012).

Based on previous methodological debates, the heterogeneity in treatment effect of teen fertility was suggested in a recent study (Diaz and Fiel 2016). They showed how the treatment effects of teen fertility vary by methods, OLS, PS, FE, and IV. According to their demonstration, IV and FE models put the most weights on women most likely to experience teen fertility, which

tend to yield treatment effects similar to or over the TT. In contrast, OLS and PS models provide treatment effects that exist generally between the ATE and the TT, with tending toward the TT. Since the negative effects are considered smaller among women who are more likely to have a baby as teens, TT is generally smaller than ATE and TUT (Diaz and Fiel 2016). This is consistent with mixed results of previous research, showing that OLS and PS models generally yield larger estimates than FE and IV methods do. Previous findings of different methods support the idea of heterogeneity treatment effects of teenage childbearing.

Statistical Models

The statistical analysis proceeds in three step. First, I estimate propensity score with probit regressions that predict the probability of teenage childbearing for each woman in the sample:

$$P_i = p\,(d_i = 1|X) = \ln \frac{d_i}{1 - d_i} = \sum_{k=0}^{K} \beta_k X_{ik}, \quad (2)$$

where *P* is the propensity score; d_i indicates whether individual *i* experiences teenage childbearing; and X is a vector of observed pre-treatment covariates. The propensity scores estimate the individual likelihoods of having teenage childbearing. Additionally, under an assumption of homogeneity of treatment effects, I evaluate average treatment effect (ATE) of teenage childbearing on years of education by using OLS models accounting for estimated propensity scores.

Second, I present the heterogeneous treatment effects of teenage childbearing by using the smoothing-differencing (SD) method, which is one of the PS-based approaches. SD method enables researchers to examine heterogeneous treatment effects across the probability of treatment using a nonparametric function of the propensity score, which consists of the following three steps (Xie et al. 2012): (1) The first step is to estimate propensity score for all units for the probability of treatment given a series of observed covariates. (2) The second step is to separately estimate nonparametric regressions of the dependent variable on the propensity score for two groups, the treated and the untreated. (3) The third step is to take the difference between the two nonparametric regressions, the treated and the untreated, at different levels of the propensity score. While other PS-based methods (i.e., stratification-multilevel and matching-smoothing methods) require two modeling process, SD method involves only a single-modeling procedure in the smoothing step. It enables researchers to compute confidence intervals for the treatment effects by the propensity score (Xie et al. 2012). Third, I conduct auxiliary analyses, which helps to interpret the heterogeneous treatment effect.

Contributions of this study

This study contributes to the literature on teen fertility in three ways. First, despite a substantial research on the educational consequences of teenage childbearing, no study has examined how the effect can vary by teen mothers' characteristics. This is an important gap because previous research estimating ATE has provided mixed results ranging from negative to positive effects of teenage childbearing, which not only cause public controversies but also misinform social and public health policies (Bute and Russell 2012; Geronimus 1997; Vinson 2012).

Second, compared to other data sets such as NLSY79 used in Diaz and Fiel's study (2016), Add Health data consists of a larger sample and has richer data sets including fertility-related contextual factors that may strongly influence the probability of selection into teenage childbearing. For this reason, Add Health data has been widely used to study the effects of teenage childbearing (Fletcher and Wolfe 2009; Kane et al. 2013; Lee 2010), but there is not a study investigating whether the effects vary across groups and some women differently respond to teen birth. Therefore, examining the heterogeneous treatment effects of teenage childbearing using Add Health data makes it possible to compare the results with those of previous research using the same data.

Third, the rich Add Health data enables researchers to investigate potential mechanisms explaining why and how the effect is heterogeneous. Although previous theories have suggested and explained the treatment effect heterogeneity, few studies test what factors are related to the teen mother's different response to teen fertility. For example, in contrast to Edin and Kefalas's study (2005), one recent study found that teenage childbearing is not a positive turning point for teen mothers (Zito 2016). By employing variables that capture the concepts of theoretical perspectives, this study help to understand the mechanisms underlying the heterogeneous treatment effects.

DATA, MEASURES, AND DESCRIPTIVE STATISTICS

Data

This study used Add Health data set, which is a longitudinal survey of a nationally representative sample of adolescents in grades 7-12th, during the 1994-1995 school years. The Add Health cohort has been followed into young adulthood with four in-home interviews (1994-1995, 1996, 2001-2002, 2007-2008), and 8,341 of female respondents participated in Wave 1 and 4 interviews. Analyses were limited to female respondents with a sampling weight (n = 7,860) and used a single imputation procedure in Stata 14 to handle missing data on all independent variables. More information about data structure is available on the Add Health website (http://www.cpc.unc.edu/addhealth).

Measures

***Outcomes*:** Add Health data set provided a series of ordinal categories from 1 (8^{th} grade or less) to 13 (completed post baccalaureate professional education). To follow and compare with prior research (Kane et al. 2013), this study recoded the ordinal variable as a continuous variable measuring years of completed education (8 - 26 years) at Wave 4.

Treatment: this study treats teenage childbearing as treatment, determined by whether the respondent's first child birth occurred prior to 19^{th} birthday. The Add Health Wave 1 data has 10,480 females, and 4,943 of whom reported at least one pregnancy before Wave 3 survey when the respondents were, on average, 22 years old. The analytic sample consists of 7,860 adolescent females who were surveyed at Wave 1 and 4, and 920 of whom (11.7%) were treated as teenage mothers. Teenage pregnancy is also used as a treatment, and results are similar to teenage childbearing (results not shown but available upon request).

***Covariates**:* This study includes common observable variables, following prior research using Add-Health (Fletcher and Wolfe 2009, Kane et al. 2013, Lee 2010). The sociodemographic covariates consist of age, race/ethnicity (non-Hispanic Blacks, non-Hispanic Others, Hispanics, reference category= non-Hispanic Whites), country of birth (1= foreign born), parent's education, family structure (1= two parent family), household income-to-needs ratio, respondents' cognitive ability (age standardized score on the Add Health Picture Vocabulary Test, AHPVT), how much knowledgeable about how to use a condom, whether to receive public assistance (1= yes), whether to smoke (1= have smoked cigarettes regularly), depressive symptoms (1= yes) and self-efficacy ("compared with other people your age, how intelligent are you?") at Wave 1. Family support is constructed from eight questions measuring how much adolescents feel supported in their family relationships (8 - 40).

Childbearing-related contextual factors, which were used in prior research, are also added. Statewide abortion laws regarding parental consent for abortion, public funding of abortion, and the average Medicaid payment per recipient; per capita income in census tract level; the abortion rate among women aged 15 - 44 in county, the number of Ob/Gyn physicians per 100,000 women aged 15 - 44, and the percentage of family planning clients younger than age 20 in county level. Finally, the type of school where respondents were enrolled in Wave 1 is coded as public school (= 1) and private school (= 2).

RESULTS

Descriptive Statistics

[Table 1 here]

Table 1 presents weighted descriptive statistics. Conforming with prior Add Health research (Kane et al. 2013), approximately 12 % of young women had a birth before age 19 in this sample. As Fletcher and Wolfe (2009) pointed out, since Add Health survey employed

computer-assisted personal interview (CAPI) technology, there could be a potential bias in self-reports of pregnancy outcomes. Respondents of Add Health answered sensitive questions using a laptop, which makes a difference from other surveys using verbal interview. Fletcher and Wolfe argued that the self-reported pregnancy outcomes in Add Health are more close to official vital statistics.

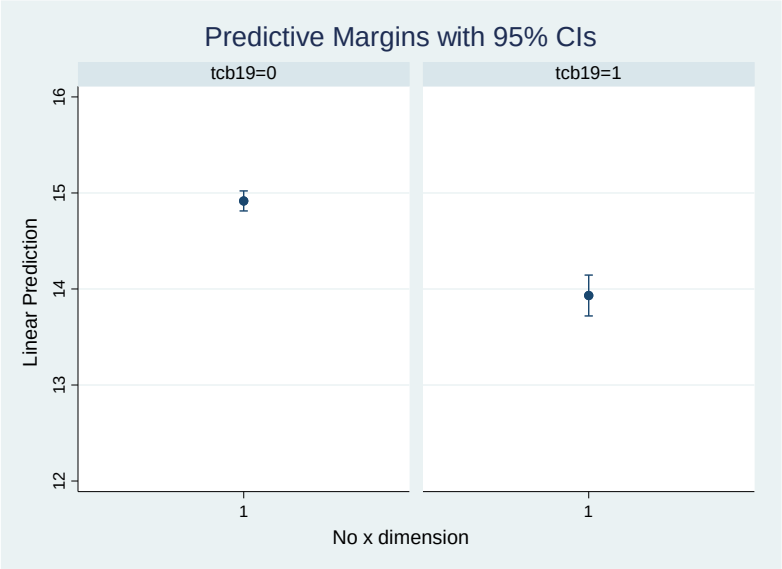

Figure 1. Predicted Years of Education among Controlled Group (tcb19=0) and Treatment Group (tcb19=1)

Probit Regression

[Table 2 here]

A probit regression model is used to estimate propensity scores for each women for the probability of teenage childbearing given a set of observed covariates. Table 2 provides results for the propensity model, which yields similar results to prior literature on the effects of teen birth on educational attainment. There are several points worth noting. First, non-Hispanic black women are roughly 37% more likely to have teenage childbearing, compared to non-Hispanic white women [=100*(exp(.314)-1)]. Hispanic women exhibit 21% greater odds of having a teen birth relative to non-Hispanic white women [=100*(exp(.189)-1)]. Second, women living with two biological parents or having higher educated parents exhibit lower odds than those residing with their counterparts. Receiving public assistance and lower social support are related to increased odds of having a teen birth. Third, after holding constant individual background characteristics, contextual factors including higher per capita income or abortion rate are associated with lower odds of having teenage childbearing. Also, women enrolled in public school exhibit 49% more likely to have teenage childbearing, compared to women in private school.

Heterogeneous treatment effects

Figure 2 uses the SD model to plot the predicted years of education by the propensity of teenage childbearing. Regardless of the covariates, two graphs provide similar patterns of the heterogeneous treatment effect of childbearing. The SD results show the most negative treatment effects on years of completed education for women least likely to become teenage mothers. Also, as the propensity score increases within a range between 0 – 0.4, women those who are more likely to experience teenage childbearing have weaker (or negligible) treatment effects on outcomes. That is, teenage women who are most likely to have a child experience smaller consequences in terms of years of completed education (i.e., more disadvantages for the advantaged). However, this study cannot find evidence on "advantages for the disadvantaged", which was found in a prior research (Diaz and Fiel 2016).

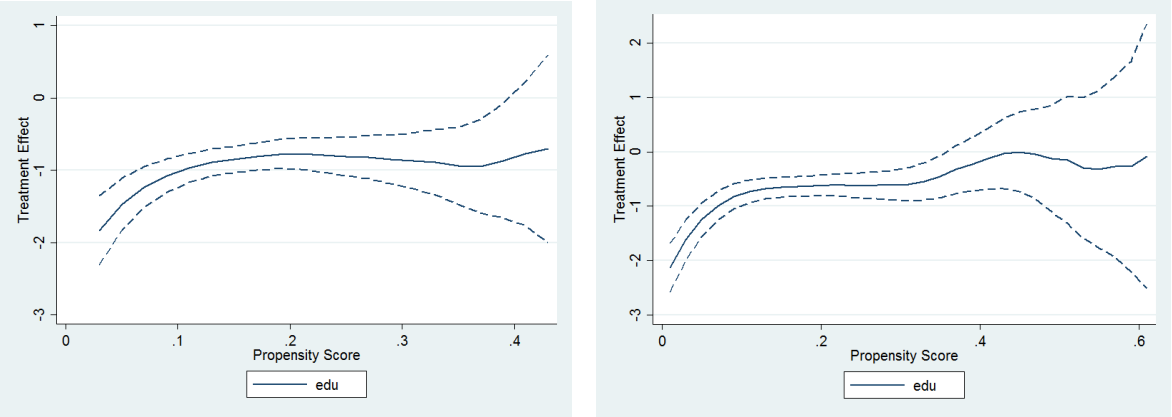

Figure 2. Teenage Childbearing Effects on Years of Education: using individual characteristics (left) and both individual and contextual characteristics (right)

Subgroup analysis by race/ethnicity

However, there are racial/ethnic differences in the heterogeneous treatment effects among women who are most likely to have a baby in adolescents as shown in Figure 3. To be specific, among white women at high risk of teen fertility, teen mothers are likely to have higher educational attainment, compared to white women who do not have a baby. This echoes the "advantages for the disadvantaged" argument, which suggests teen fertility can be a positive turning point for some young women. In contrast, among Hispanic women at high risk of teen fertility, teen mothers are likely to have lower educational attainment, compared to Hispanic women who do not have a baby. This supports the opportunity cost perspective, which indicates the disadvantages who Hispanic mothers experience. Therefore, examining the heterogeneous treatment effects by race/ethnicity have potential to reconcile the existing theories and inconsistent findings.

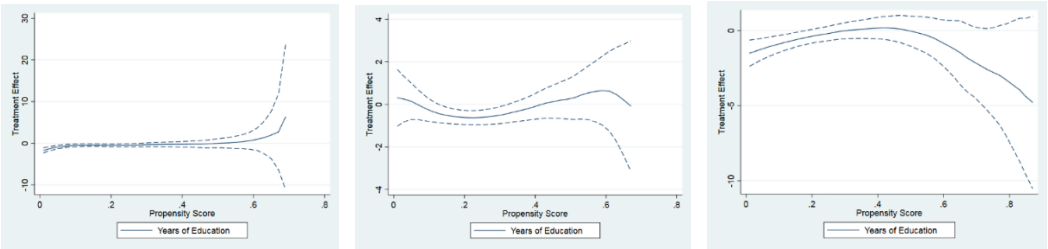

Figure 3. Heterogeneous treatment effect of teen fertility on the years of education by race/ethnicity: Whites (left), Blacks (middle), and Hispanics (right). Dotted lines represent 95% confidence interval.

TABLES

Table 1. Weighted Descriptive Statistics after Imputation Procedure (n= 7,860[1])

	Mean or Proportion	Std.	Min	Max
Outcome				
Years of completed education (W4)	14.80	.10	8	26
Treatment				
Teen birth (by age 19)	.12	-	0	1
Individual Covariates				
Two-parent family (= 1)	.54	-	0	1
Parental education	5.32	.10	1	9
Income-to-needs ratio	2.49	.08	0	65.98
Race				
NH-Black	.16	-	0	1
Hispanic	.12	-	0	1
NH-Other	.04	-	0	1
NH-White	.67	-	0	1
Foreign-born	.05	-	0	1
AHPVT score	100.59	.67	15	146
Age	15.40	.12	11	21
Knowledge about how to use a condom	2.00	.03	1	5
Social support	32.13	.13	8	40
Self-efficacy	3.83	.03	1	6
Have ever smoked (= 1)	.22	-	0	1
Depressive symptoms (= 1)	.29	-	0	1
Whether to receive public assistance (= 1)	.10	-	0	1
Public school (= 1)	.94	-	0	1
Contextual Covariates				
Per capita income (tract level)	12.95	.41	0	68.82

Note: This study follows the same imputation procedure as Kane et al.(2013)'s study to compare the results, which is shown in Appendix Table 1. Contextual covariates are omitted in Table 1 but are available upon request. Income-to-needs ratio and per capita income are truncated at 0.

[1] The number of observation in this study is different from that of Kane et al. (2013) because I dropped the observations in Add-Health Wave 1 full sample, which are trans-genders or men who were not sure their gender identity in Wave 1.

Table 2. Propensity Score Probit Regression Model Predicting Teenage Childbearing (go to Appendix)

Childbearing before age 19	Coef.	Std. Err.	Sig.
Two-parent family (= 1)	-0.259	0.043	***
Parental education	-0.043	0.009	***
Income-to-needs ratio	-0.020	0.010	+
Race			
Non-Hispanic Black	0.314	0.057	***
Hispanic	0.189	0.070	**
Non-Hispanic Other	-0.048	0.104	
Foreign-born (= 1)	-0.332	0.097	**
AHPVT score	-0.005	0.001	**
Knowledge about how to use a condom	-0.085	0.021	***
Whether to receive public assistance (= 1)	0.174	0.059	**
Social support	-0.012	0.004	**
Self-efficacy	-0.095	0.019	***
Have ever smoked	0.427	0.049	***
Depressive symptoms (= 1)	0.069	0.045	
Contextual covariates			
Public school (= 1)	0.398	0.123	**
Per capita income in census tract	-0.027	0.005	***
Laws regarding parental consent for abortion	0.101	0.060	+
Laws regarding public funding of abortion	0.004	0.054	
Percentage of family planning clients younger than age 20	0.664	0.447	
Abortion rate among women aged 15 – 44	-0.077	0.024	**
Average Medicaid payment per recipient	-0.000	0.000	***
Number of Ob/Gyn physicians per 100,000 women aged 15 – 44	0.001	0.001	
Presence of any type of abortion provider (= 1)	0.271	0.079	**
Constant	0.208	0.300	
N		7,860	

Note: *** p<0.001, ** p<0.01, and * p<0.05 + p<0.1 (two-tailed tests)

REFERENCES

Angrist, Joshua D. and Alan B. Krueger. 1999. "Empirical Strategies in Labor Economics." Pp. 1277–1366 in *Handbook of labor economics*. Vol. 3. Elsevier.

Ashcraft, Adam, Iván Fernández-Val, and Kevin Lang. 2013. "The Consequences of Teenage Childbearing: Consistent Estimates When Abortion Makes Miscarriage Non-Random." *The Economic Journal* 123(571):875–905.

Becker, Gary S. and Nigel Tomes. 1986. "Human Capital and the Rise and Fall of Families." *Journal of Labor Economics* 4(3, Part 2):S1–39.

Brand, Jennie E. and Dwight Davis. 2011. "The Impact of College Education on Fertility: Evidence for Heterogeneous Effects." *Demography* 48(3):863–887.

Brand, Jennie E. and Juli Simon Thomas. 2013. "Causal Effect Heterogeneity." Pp. 189–213 in *Handbook of Causal Analysis for Social Research*, edited by S. L. Morgan. Springer, Dordrecht.

Bute, Jennifer J. and Laura D. Russell. 2012. "Public Discourses About Teenage Pregnancy: Disruption, Restoration, and Ideology." *Health Communication* 27(7):712–22.

DeLeire, Thomas and Ariel Kalil. 2002. "Good Things Come in Threes: Single-Parent Multigenerational Family Structure and Adolescent Adjustment." *Demography* 39(2):393–413.

Diaz, Christina J. and Jeremy E. Fiel. 2016. "The Effect (s) of Teen Pregnancy: Reconciling Theory, Methods, and Findings." *Demography* 53(1):85–116.

Edin, Kathryn and Maria Kefalas. 2005. *Promises I Can Keep: Why Poor Women Put Motherhood before Marriage*. Univ of California Press.

Finer, Lawrence B. and Mia R. Zolna. 2016. "Declines in Unintended Pregnancy in the United States, 2008–2011." *New England Journal of Medicine* 374(9):843–52.

Fletcher, Jason M. and Barbara L. Wolfe. 2009. "Education and Labor Market Consequences of Teenage Childbearing Evidence Using the Timing of Pregnancy Outcomes and Community Fixed Effects." *Journal of Human Resources* 44(2):303–325.

Furstenberg, Frank F. 2003. "Teenage Childbearing as a Public Issue and Private Concern." *Annual Review of Sociology* 29(1):23–39.

Geronimus, Arline T. 1997. "Teenage Childbearing and Personal Responsibility: An Alternative View." *Political Science Quarterly* 112(3):405–430.

Geronimus, Arline T. 2003. "Damned If You Do: Culture, Identity, Privilege, and Teenage Childbearing in the United States." *Social Science & Medicine* 57(5):881–893.

Geronimus, Arline T. and Sanders Korenman. 1993. “The Socioeconomic Costs of Teenage Childbearing: Evidence and Interpretation.” *Demography* 30(2):281–290.

Heckman, James J., Jora Stixrud, and Sergio Urzua. 2006. “The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior.” *Journal of Labor Economics* 24(3):411–482.

Hoffman, Saul D. 1998. “Teenage Childbearing Is Not so Bad after All... or Is It? A Review of the New Literature.” *Family Planning Perspectives* 30(5):236–243.

Hotz, V. Joseph, Susan Williams McElroy, and Seth G. Sanders. 2005. “Teenage Childbearing and Its Life Cycle Consequences Exploiting a Natural Experiment.” *Journal of Human Resources* 40(3):683–715.

Kane, Jennifer B., S. Philip Morgan, Kathleen Mullan Harris, and David K. Guilkey. 2013. “The Educational Consequences of Teen Childbearing.” *Demography* 50(6):2129–2150.

Klepinger, Daniel H., Shelly Lundberg, and Robert D. Plotnick. 1995. “Adolescent Fertility and the Educational Attainment of Young Women.” *Family Planning Perspectives* 23–28.

Lee, Dohoon. 2010. “The Early Socioeconomic Effects of Teenage Childbearing: A Propensity Score Matching Approach.” *Demographic Research* 23(25):697–736.

Martin, Anne and Jeanne Brooks-Gunn. 2015. “Has Adolescent Childbearing Been Eclipsed by Nonmarital Childbearing?” *Societies* 5(4):734–743.

Mollborn, Stefanie. 2007. “Making the Best of a Bad Situation: Material Resources and Teenage Parenthood.” *Journal of Marriage and Family* 69(1):92–104.

Morgan, Stephen L. and Jennifer J. Todd. 2008. “A Diagnostic Routine for the Detection of Consequential Heterogeneity of Causal Effects.” *Sociological Methodology* 38(1):231–281.

Morgan, Stephen L. and Christopher Winship. 2014. *Counterfactuals and Causal Inference*. Cambridge University Press.

Rosenbaum, Paul R. and Donald B. Rubin. 1983. “The Central Role of the Propensity Score in Observational Studies for Causal Effects.” *Biometrika* 70(1):41–55.

SmithBattle, Lee. 2007. “‘I Wanna Have a Good Future’: Teen Mothers’ Rise in Educational Aspirations, Competing Demands, and Limited School Support.” *Youth & Society* 38(3):348–371.

United Nations Statistics Division. 2014. *Demographic Yearbook 2013*. New York, NY: United Nations.

Vinson, Jenna. 2012. “Covering National Concerns about Teenage Pregnancy: A Visual Rhetorical Analysis of Images of Pregnant and Mothering Women.” *Feminist Formations* 24(2):140–62.

Webbink, Dinand, Nicholas G. Martin, and Peter M. Visscher. 2011. “Does Teenage Childbearing Reduce Investment in Human Capital?” *Journal of Population Economics* 24(2):701–730.

Xie, Yu, Jennie E. Brand, and Ben Jann. 2012. “Estimating Heterogeneous Treatment Effects with Observational Data.” *Sociological Methodology* 42(1):314–47.

Zhou, Xiang and Yu Xie. 2016. “Propensity Score–Based Methods Versus MTE-Based Methods in Causal Inference: Identification, Estimation, and Application.” *Sociological Methods & Research* 45(1):3–40.

Zito, Rena Cornell. 2016. “Children as Saviors? A Propensity Score Analysis of the Impact of Teenage Motherhood on Personal Transformation.” *Youth & Society* 0044118X16653872.