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Does Education Reduce Fertility in Developing Countries? Evidence Based on Fuzzy Regression Discontinuity Design in Tanzania

by

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Does Education Reduce Fertility in a Low Income Country ? Evidence based on Fuzzy Regression Discontinuity Design in Tanzania

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Abstract

Using adoption of no-expulsion policy in primary schools in Tanzania and a fuzzy regression discontinuity design, we examine the causal effect of education on fertility and child mortality using Tanzania census data sets. A no-expulsion policy in Tanzania generates a discontinuous change of years of schooling of females by about 2 years. Using this change of years of schooling, we show that the effect of education on fertility is non-uniform in the sense that one year increase of female schooling *increases* the probability of having at least one birth by 1.55 percentage point but it *decreases* the probability of having a large number of births such as at least 8 births or 10 births by about 3 percentage points. This suggest that it is not sufficient to focus on the average number of births to examine the effect of education on fertility. We also find that one year increase of schooling decreases the number of experienced child death by 0.2 frequency and decrease the child mortality rate by 2 percentage point. Due to those several offsetting effects, the effect of additional year of schooling on the number of surviving children is very close to zero or marginally positive.

1 Introduction

It is well-known that women's education and fertility has a strong negative association in the data.(Strauss and Thomas 1995). Some policy makers and researchers suggest that educating women is one of the key important policy tools to reduce the fertility in developing countries (Schultz, 2002; Cohen, 2008; Lutz and Samir, 2011). If there is a causal relationship from education to fertility, it would implies that there would be a self-enforcing relation from higher education to lower fertility because a lower fertility would bring a higher GDP per capita and higher GDP per capita would bring a higher education. (Caldwell, 1980; Cohen, 2008; Portes, 2006). Some theoretical model of economic growth assume this negative relationship between education and fertility.

However, whether such an association between education and fertility represents a causal relationship needs careful examination. The results of the previous studies vary substantially depending on the estimation method and target countries. An initial set of studies that uses the simple cross-sectional observation shows that there is a negative relationship between female education and fertility. A study that uses sister data shows subtle results implicating there is omitted variable effect. Studies that uses the exposure of universal education, school construction program or college opening as an instrumental variable show that there is a causal negative relationship between female education and fertility (Osili and Long, 2008; Chou et al., 2010; Breierova and Duflo, 2004; Currie and Moretti, 2003; Cygan-Rehm and Maeder, 2013).

Recently, several studies have shown that there is no effect from education to fertility and some papers show that there is even a positive effect from education to fertility. For example, using the regression discontinuity design, McCrary and Royer (2011) show that there is no causal effect of female education on total fertility. Using municipality level variation of school entry policy in Norway, Monstad et al. (2008) show that there is no causal effect from schooling to total fertility.

Note that when policy makers advocate education as a policy tool to reduce the fertility, they have developing countries as target countries in their mind. On the other hand, quasi-experimental research that examine the effect of education on completed fertility is very limited and, to the best of our knowledge, no paper use the regression discontinuity design, which is thought to be most credible in the literature as a statistical tool to analyze the causality, to examine the effect of female education on completed fertility in developing countries.

The purpose of this paper is to fill this gap. More specifically, in this paper, we use the change of education policy in Tanzania as a natural experiment and apply the fuzzy regression discontinuity design to examine the effect of education on fertility. In 1971, the government of Tanzania issued an order to end the expulsion of primary pupils for non-payment of school fees. This policy change drastically increased the literacy rate and years of schooling of women. According to the Census data, literacy rate increased 20 percentage point and the years of schooling increase by two years.

This paper contributes to the previous literature in three aspects. First, as we have just mentioned, there is a few studies that analyze the causal effect of education on fertility in developing countries. Given the high population growth rate and lower years of schooling, the benefit of learning the causal effect of education in developing countries is substantial. Applying the fuzzy regression discontinuity design, we obtain the causal effect of education on fertility.

Second, this paper analyzes two waves of census data separately (Tanzania census 2012 and 1988). In the 2012 census data, the threshold age is 48 while the threshold age in 1988 census is 24. This implies that analyzing based on 2012 census data is likely to measure the effect of eduction on completed fertility and the analysis based on 1988 census is likely to measure the effect of education on early period fertility. When we analyze 1988 census, we find that one additional year of education decrease the fertility by 0.2 which is comparable to the studies by the instrumental variable while the analysis based on 2012 fertility shows that the effect of education on the number of total birth is much smaller. This suggests that the effect of education on the number of births depends on the age at which policy change is evaluated.

Third, this paper shows that the effect of education is non-uniform. We find that education decreases the probability of having a large number of births while it increase the probability of having at least one birth. Also we find that education decrease the child death experienced. In other words, educatio transform the fertlity pattern into more efficient one from large number of birth and large number of child death to smaller number of births and smaller number of child death. This transformation will make the numver of surving children unchange or slighly increases. In this sense, education does not decrease the population growth rate contray to the assumption of many models of economic growth.

The organization of this paper is as follows. In the next section, we review the related literature and summarize the contribution of this study. In the section 3, we describe the situation of education policy during 1954 and discuss the environment in those periods. In section 4, we discuss our identification strategy. In section 5, we present the results. In section 5, we provide discussion regarding our estimated result and conclusion.

2 Literature Review and Contribution of This Study

For empirical sides, there are numerous papers that examine the relationship between female education and fertility (Schultz, 1997; Cochrane, 1979). However, researchers have been cautious about interpreting the observed association between education and fertility as causal.

Researchers used different identification strategy to examine the effect of female education on fertility. Currie and Moretti (2003) used the opening of two an four year collage in 1940-1990 as the instrument to examine the effect of female education on fertility. Breierova and Duflo (2004) use the large-scaled school construction program in Indonesia as an instrument. They did not find statistically significant effect of female education on fertility. Osili and Long (2008) examine uses the regional variation of the exposure to the introduction of universal education in Nigeria as an instrument. He finds that one additional year of education reduces 0.25 birth. Monstad et al. (2008) use cross-municipality variation of school reforms in Norway to estimate the effect of education on fertility. They did not find an evidence that education decrease the fertility. Fort et al. (2016) compare the effect of education on fertility in UK and continental European countries. While they find a negative effect of education in UK, they find such a positive effect in continental Europe.

Recently, several studies have shown that there is no effect from education to fertility and some papers show that there is even a positive effect from education to fertility. For example, using the regression discontinuity design (RDD), McCrary and Royer (2011); Kan and Lee (2018); Geruso and Royer (2018) show that there is no causal effect of female education on total fertility. On the other hand, Silles (2011) applies the RDD to UK and Northern Ireland and find that education reduces teenage childbearing.

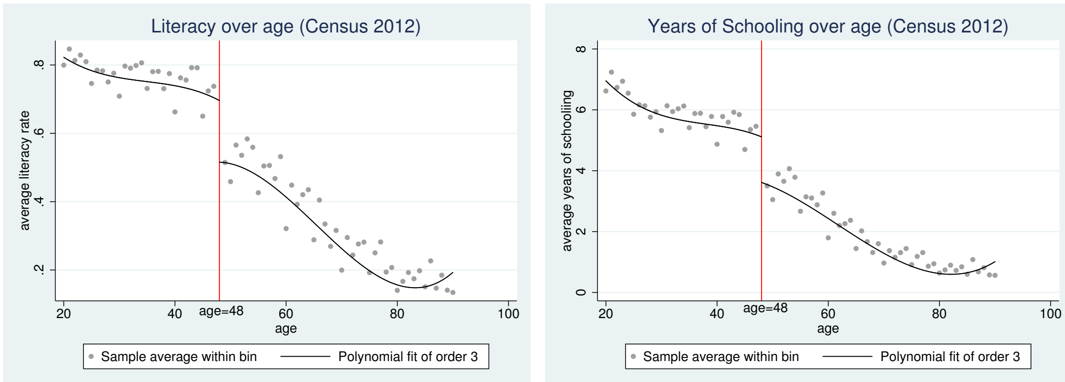
3 Background of Education Policy in Tanzania

Since becoming independent in 1961 the government of Tanzania has made education a national priority, formulating education policies and carrying out various education reforms in order to increase access to education at all levels. However, expanding the existing primary education set-up was not of primary importance to the Government. The first two development Plans (1961-1964 and 1964-1969) did not prioritize the expansion of primary education as it was believed there was no direct economic benefits from primary school growth (Bogonko, 1992). However, after ten years from the first development plan, almost as many children in 1971 as in 1961 were unable to get places in primary schools. The President Nyerere stated that this was unacceptable to a country which claims to be building socialism (Bogonko, 1992). The presidential alert caused an immediate action and in 1971 the government ordered to end the expulsion of primary pupils for non-payment of school fees. The effect of this government order (no-expulsion policy) can be seen in the current census data. Figure 1(a) and (b) show the literacy rate and years of schooling of female individuals for each age group in 2012 Population and Housing Census (PHC) for United Republic of Tanzania(PHCT). Those who were aged 47 or younger is the treatment cohorts and those whose age is more than or equal to 49 are control cohorts. Figure 1(a) and (b) show that there are discontinuous jumps in literacy rate and year of schooling between those aged 49 and 47. The literacy rate increases from 49 percent to 70 percent and the year of schooling increases about 3.5 years to 5.6 years. [1]

Figure 2 (a) and (b) show the literacy rate and years of schooling over age in 1988 Population and Housing Census of Tanzania. Those aged 23 or younger is the treatment group and cohort aged 25 or older is the control group. The cohort age 24 can be either treatment group or control group. Thus, the cohort whose age is equal to 24 is dropped from the Figure 2. Figure 2 (a) and (b) show, there is a clear discontinuous jump at

[1] For the discussion on the classification of treatment and control cohorts, see the discussion in the next sub-section.

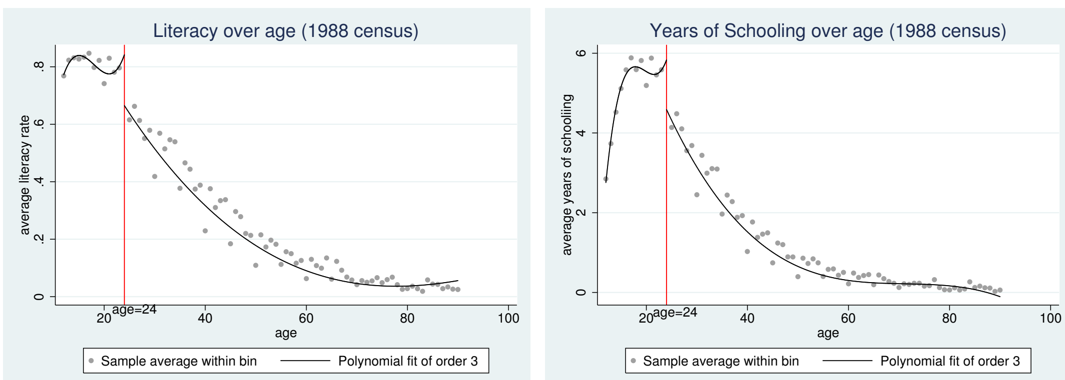
Figure 1: Literacy Rate and Years of Schooling of Different Cohorts in 2012 Census



(a) Literacy rate over age (b) Years of schooling over age

Notes: Literacy rate and years of schooling of female individuals of different cohorts in 2012 Population and Housing Census for United Republic of Tanzania (PHCT). Age shows the age in August 2012. Individuals aged 48 are dropped because those individuals cannot be uniquely classified as the treatment or the control group. See the text for the discussion. The vertical red line is drawn at age=48.

Figure 2: Literacy Rate and Years of Schooling of Different Cohorts in 1988 Census



(a) Literacy rate over age (b) Years of schooling over age

Notes: Sample is female individuals of different age group in 1988 PHCT. Age shows the age in August 1988. Female individuals aged 24 are dropped because those individuals cannot be classified uniquely as the treatment or the control group. The vertical red line is drawn at age=24.

age 24 in both literacy rate and years of schooling, which is consistent with Figure 1. In this paper, we use this discontinuous jump as identification strategy.

4 Identification Strategies and Data set

To estimate the effect of education on fertility and child mortality, we use the Fuzzy Regression Discontinuity Design, which can be implemented by two stage least squares (2SLS) with continuous control functions. Consider the following 2SLS equations:

$$\mathrm{Y}_{ci} = \beta_0 + \beta_1 \mathrm{School}_{ci} + f(c) + \epsilon_{ci} \tag{1}$$

$$\mathrm{School}_{ci} = \alpha_0 + \alpha_1 \mathrm{treat}_c + h(c) + \eta_{ci} \tag{2}$$

where i is the index of each individual and c is a index of cohort. Y_i is the outcome variable such as the number of births and the number of child death that a respondent experienced. School_{ci} is the years of schooling. treat_c is the treatment dummy. If no-expulsion policy is already implemented at age of 7 for cohort c, which is an entry age of Tanzanian educational system, treat_c is equal to one and otherwise it is equal to zero.

More specifically, we construct treat_c and the data set as follows. The no-expulsion policy was implemented from January of 1972 and that the academic calender of Tanzania starts from January. Thus, cohort whose age is 7 or younger in January 1st of 1972 is the treatment group and older cohort is the control group. Also note that individuals who were age 7 in January 1st in 1972 was born in January 2 to December 31 in 1964. On the other hand, all Tanzania censuses were conducted at the end of August and the censuses did not ask the birth month and birth year but the censuses asked only each individual's age at the end of August. This implies that in each census, there is one age group in which some of them belongs to treatment group and other member of this age group belong to the control group. For example, in 2012 Tanzania Census, those who were born from September to December of 1963 and from January to mid August of 1964 are aged 48. However, among those aged 48, those who were born from January to mid-August of 1964 belong to treatment group and those who were born from September to December 1963 belong to the control group. In order to make our identification strategy clear, we drop those aged 48 from the 2012 census for the analysis. For the same reason, we drop cohorts aged 24 from 1988 census.

For the selection of the bandwidth size and functional form of f(c) and g(c), note that in our data set, age is only measured by years since Tanzania census did not collect the information on birth month. This implies that running variable is discrete and we do not have so much data point near the threshold. This prevents us to use local linear regression discontinuity. Instead, we use wider window size and 3rd or 4th order polynomial to control the time trend. This global approach is quite standard in the regression discontinuity design literature and is used by researchers who examines the effect of years of schooling using a change of compulsory schooling (Oreopoulos, 2006; Devereux and Hart, 2010).[2] We use 30 years for the window size and use cubic function for f and g. We also conduct robustness check for by applying quantic function. Because the running variable is discrete, we apply the clustering robust standard error assuming that error term who has the same age are correlated. As we mentioned above, we drop individuals whose age is equal to 48.

$f(c)$ and $h(c)$ in equation (1) and (2) are continuous function of c. For the shape of $f(c)$ and $h(c)$, we use cubic functions fully interacted with treatment dummy for the census data in 2012. When we use the census data set in 1988, the threshold year is age 24. This implies that the treatment group might include those aged from 14-16. The year of schooling continuously increases as age progresses (Figure 2(b)). To capture this effect, we use quintic function for $f(c)$ and $h(c)$.

Regarding the data set, we use the IPUMS ten percent 2012 census of Tanzania. To analyze how the education affect fertility behaviors of young individual females, we also use 10 percent IPUMS sample of 1988 census of Tanzania where the threshold age is 24. Regarding other census data set, we do not use the Census data 2002 for our analysis since there is 370 thousands refugees from the neighbouring countries during the period 1989-2002. The census bureau of Tanzania itself admits that population estimate in 2002 census is biased due to the inflow of refugees from neighboring countries (National Bureau of Statistics Ministry of Planning, Economy and Empowerment Volume X, 2006).[3]

[2]For example, Oreopoulos (2006); Devereux and Hart (2010) analyze the effect of a change of compulsory schooling law in the UK when the running variable is year. They use 30 years as window size and apply quantic function to control the time trend.

[3]When we compare age-education distribution of 2002 census with 1988 and 2012 census, we also confirmed that age-education distribution in 2002 census is different from 2012 and 1988 census.

5 Results

5.1 Results based on 2012 Census Data Set

Summary Statistics

Table 1 shows the summary statistics of the data set that we use in our analysis. The Panel A is the summary statistics of the main variable in our control group where the age of female individuals are greater than or equal to 49 and less than or equal to 53. The range of the age of treatment group is from 42 to 47. In the control group, the average years of schooling is about 3.5 years and literacy rate is about 50 percent point. Those female individuals in the control group have about 6 births in their lives and the average number of surviving children is 5.9. 94 percent point women in this group has an experience of having at leat one birth and 35 percent point of those women have an experience of having 8 births in their lives.

For calculating mortality variable, we restrict the sample to female individuals who experienced at least one birth.

The Effect on Intensive and Extensive Margin of Births

Table 2 shows the first stage regression result of our 2SLS estimation which implement Fuzzy regression discontinuity design. Our instrumental variable is the dummy variable indicating the age of the respondent is lower than or equal to 47. In the first and second column, we include the cubic function interacted with treatment. In the third and fourth column, we include quadratic functions interacted with treatment dummy. In column 2 and column 4, we include the birthplace dummy and current residence dummy as additional control variables. In all cases, the Kleibergen-Papp statistics, the robust version of the first F-statistics, is great than 10, which shows that our instrumental variable is quite strong. Table 2 shows that at the threshold, individuals who are in the treatment group have about 2 years longer schooling that the individuals at the threshold in the control group. This is consistent with graph shown in Figure 1(b).

Table 3 shows the results of the second stage estimation results on birth outcomes. Panel A and Panel B show the estimated coefficient of the second stage regression when the dependent variable of the second stage is the number of births and the dummy

Table 1. Summary Statistics

Variables	Control		Treatment		All	
	mean	sd	mean	sd	mean	sd
A. Years of Schooling and Fertility						
Years of Schooling	3.046	3.620	5.509	3.547	4.662	3.759
Dummy: Literatre	0.474	0.499	0.744	0.437	0.651	0.477
Number of births	6.192	3.477	5.153	2.878	5.510	3.136
Number of surviving children	4.852	2.921	4.464	2.527	4.597	2.675
Dummy: At least 1 birth	0.942	0.234	0.961	0.194	0.954	0.209
Dummy: At least 5 births	0.671	0.470	0.557	0.497	0.596	0.491
Dummy: At least 8 births	0.363	0.481	0.202	0.402	0.258	0.437
Dummy: At least 10 births	0.182	0.386	0.0777	0.268	0.114	0.317
N	77,294		147,510		224,804	
B. Mortality Related Variables						
Number of child death	1.357	1.545	0.705	1.109	0.926	1.310
Child Mortality Rate	0.193	0.223	0.117	0.187	0.143	0.203
Dummy: At least one child death	0.579	0.494	0.389	0.488	0.454	0.498
Dummy: At least 5 child death	0.0665	0.249	0.0148	0.121	0.0324	0.177
N	72,787		141,728		214,515	

Notes: Sample is female individuals in 2012 PHCT. Individuals aged from 33 to 47 are treatment group and those individuals who were subject to no-expulsion policy. Individuals aged from 49 to 63 are control group and those individuals are not subject to no-expulsion policy. Individuals aged 48 is dropped due to ambiguity of classification between treatment group and control group. In Panel B, the sample is restricted to female individuals who experienced at least one birth among the sample used in Panel A.

variable indicating that the individual has at least one birth, respectively. Panel A shows that in all specification, additional year of schooling decrease the number of births. It shows that one year increase of schooling decrease the number of births about by 0.1 frequency. The estimated coefficient is significant at 5 percent. Since the average of the number of birth is about 5, the effect is relatively small.

Panel B shows that in all specification having additional year of schooling *increase* the probability of having at least one birth in all specification It shows that one additional year of schooling reduce the probability of having at least one birth by about 1.5 percentage point and it is statistically significant at 1 percent.

Figure 3(a) displays the average of number of births over each age group in 2012

Table 2. The Effect of Years of Schooling on Fertlity (2SLS)

First Stage Regression Results

Dependent Variable	Years of Schooling			
Explanatory Variables	(1)	(2)	(3)	(4)
Dummy(Age<48)	1.944***	1.908***	2.141***	2.188***
	(0.411)	(0.354)	(0.560)	(0.487)
Bandwidth	15	15	15	15
Order of Polynominal	2	2	3	3
Current Residene and Birthplace	No	Yes	No	Yes
Kleibergen-Paap Rank Wald	22.38	28.99	14.63	20.15
R-squared	0.105	0.174	0.106	0.174
N	224,804	224,804	224,804	224,804

Notes: Sample is female individuals in 2012 PHCT. Bandwidth k means that all female individuals aged [48-k,48+k] are used for the analysis.

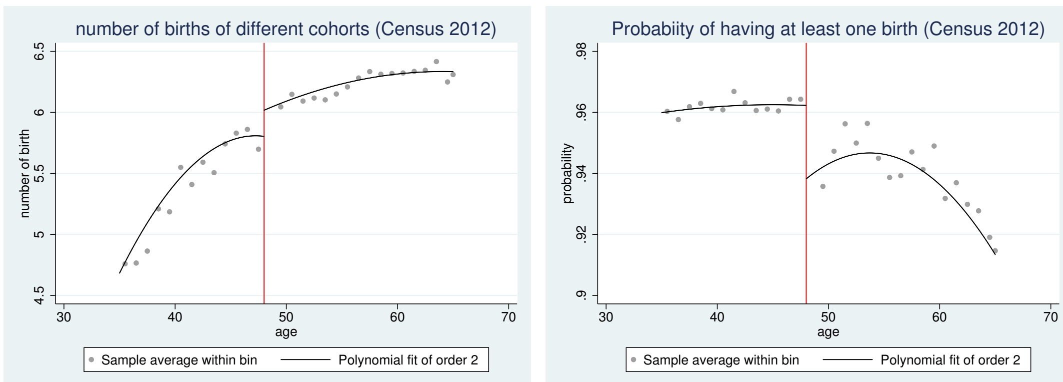
Table 3. The Effect of Years of Schooling on Number of Births and Extensive Margin: Second Stage Estimates in 2SLS

	Dependent Variable			
	(1)	(2)	(3)	(4)
Panel A.	Number of Births			
Years of Schooling	-0.160***	-0.128***	-0.113**	-0.0828**
	(0.0291)	(0.0262)	(0.0494)	(0.0416)
N	224,804	224,804	224,804	224,804
Panel B.	Dummy(at least having 1 births)			
Years of Schooling	0.0107***	0.0103***	0.0167***	0.0154***
	(0.00362)	(0.00251)	(0.00512)	(0.00345)
N	224,804	224,804	224,804	224,804
Specifications				
Bandwith	15	15	15	15
Order of Polynominal	2	2	3	3
Current Residene and Birthplace	No	Yes	No	Yes

Notes: The table displays the estimated coefficients of years of schooling and their standard errors in the second stage of 2SLS estimation when different dependent variables are used. Clustering robust standard errors are in parentheses. The sample is female individuals in 2012 PHCT whose age is between [48-k,48+k] except 48 where k is the bandwidth. For all specifications, N=224,804.

census. It demonstrates that the number of birth decreases slightly at the threshold in the treatment cohort compared with the control cohort. Figure 3(b) displays the probability of having at least one birth over each age group. Figure 3 (b) shows that, contrary to Figure 3(a), the probability of having at least one birth *increases* at the threshold in the treatment cohort. Thus, Figure 3(a) and Figure 3(b) also show contradictory effects of education on fertility outcomes, which is shown in Table 3.

Figure 3: Number of Births and Probability of Having at least One Birth over Age



(a) Number of births (b) Probability of having at least 1 birth

Notes: Sample is female individuals of 2012 PHCT. Age shows the age in August 2012. Individuals aged 48 are dropped because this age group cannot be classified uniquely as treatment or control group. The vertical red line is drawn at age=48.

To examine the contradictory effect of years of schooling on the intensive margin and extensive margin of birth outcome, we look at probabilities of having different number of births in Table 4 and Table 5. Panel A, Panel B and Panel C of Table 4 shows the effect of years of schooling on probability of having at least two births, three births and four births in 2SLS estimation. Each Panel show the estimated coefficient of years of schooling and its standard error in 2SLS.

Panel A of Table 4 shows that additional year of schooling increases the probability of having at least two birth by about 1.7 percentage point and statistically significant at one percent in all specification. Panel B that the effect of years of schooling on probability of having at least 2 birth is not robust and it is statistically significant only in column (4). Panel C shows that the effect of years of schooling have at least four births become negative in some cases and the estimated coefficients become unstable.

Table 5 displays the effect of years of schooling on large number of births such as at

Table 4. Effect of Years of Schooling on Probability of Having at least Few Births : Second Stage Estimates of 2SLS

	Dependent Variable			
	(1)	(2)	(3)	(4)
Panel A.	Dummy (having at least 2 births)			
Years of schooling	0.00910**	0.00871***	0.0186**	0.0171***
	(0.00401)	(0.00261)	(0.00747)	(0.00518)
Panel B.	Dummy (having at least 3 births)			
Years of schooling	0.00233	0.00184	0.0169	0.0148**
	(0.00492)	(0.00342)	(0.0104)	(0.00732)
Panel C.	Dummy (having at least 4 births)			
Years of schooling	-0.0102**	-0.00934*	0.0122	0.0116*
	(0.00485)	(0.00529)	(0.00904)	(0.00610)
Specifications				
Bandwith	15	15	15	15
Order of Polynominal	2	2	3	3
Current Residene and Birthplace	No	Yes	No	Yes

Notes: The table displays the estimated coefficients of years of schooling and their standard errors in the second stage of 2SLS estimation when different dependent variables are used. Clustering robust standard errors are in parentheses. The sample is female individuals in 2012 PHCT whose age is between [48-k,48+k] except 48 where k is the bandwidth. For all specifications, N=224,804.

least having 8 births in 2SLS estimation. Note that as seen summary statistics, in our sample, 26 percent of our sample have at least 8 births. Thus, having a large number of births for this sample is not uncommon. Panel A of Table 5 displays the estimated coefficients of years of schooling in 2SLS estimation when the dependent variable is a dummy variable indicating a respondent has at least 8 births. Panel A shows that increasing one year of schooling decreases the probability of having at least eight births by about 3 percentage point and the estimated coefficients are statistically significant at one percent in all specifications. Panel B and Panel C of Table 5 display the estimated coefficients of years of schooling when the dependent variable is a dummy variable indicating whether a responding has nine birth or ten births, respectively. Panel B and Panel C shows that one additional year of schooling will decrease the probability of having at least nine births and ten births by 2.7 percentage point and 2.2 percentage point, respectively. In all specification, the estimated coefficient are statistically signif-

Table 5. Effect of Years of Schooling on Probability of
Having a Large Number of Birtths : Second Stage Estimates of 2SLS

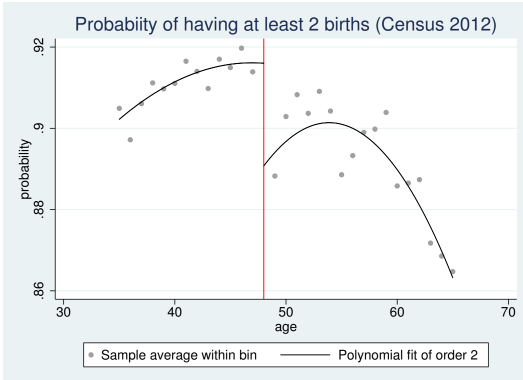
	Dependent Variable			
	(1)	(2)	(3)	(4)
Panel A.	Dummy (having at least 8 births)			
Years of schooling	-0.0295***	-0.0237***	-0.0365***	-0.0297***
	(0.00527)	(0.00473)	(0.00637)	(0.00583)
Panel B.	Dummy (having at least 9 births)			
Years of schooling	-0.0216***	-0.0165***	-0.0334***	-0.0274***
	(0.00554)	(0.00508)	(0.00641)	(0.00527)
Panel C.	Dummy (having at least 10 births)			
Years of schooling	-0.0172***	-0.0135***	-0.0272***	-0.0227***
	(0.00401)	(0.00361)	(0.00460)	(0.00344)
Specifications				
Bandwith	15	15	15	15
Order of Polynominal Controls	2	2	3	3
Current Residene and Birthplace	No	Yes	No	Yes

Notes: The table displays the estimated coefficients of years of schooling and their standard errors in the second stage of 2SLS estimation when different dependent variables are used. Clustering robust standard errors are in parentheses. The sample is female individuals in 2012 PHCT whose age is between [48-k,48+k] except 48 where k is the bandwidth. For all specifications, N=224,804.

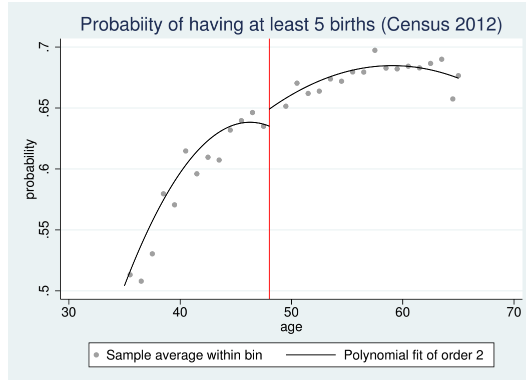
icant at one percent. Those results explain why we have conflicting results regarding the effect of years of schooling on the intensive margin and extensive margin. Those results demonstrates that additional years of schooling reduce the probability of having a large number of births such as 8 births but it increase the probability of having at least one and 2 births. Those skewed effect of years of schooling on birth outcomes results in conflicting results in intensive and extensive margin of the birth outcomes.

Figure 4 shows that graphical relationship of the probability of having different number of birth for each cohorts. Figure 4(c) and Figure 4(d) shows that a there is substantial discontinuous drop for younger cohort at the threshold regarding having at least 8 birth or 10 births, respectively.

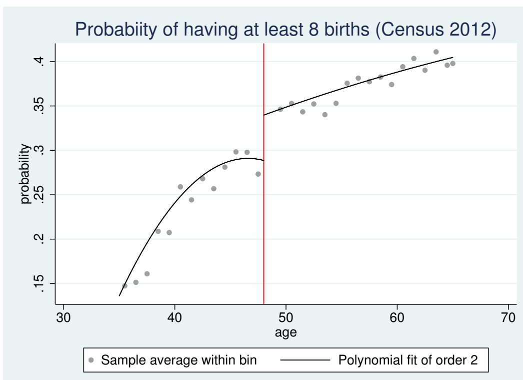
Figure 4: Probability of Having Multiple Births in 2012 census



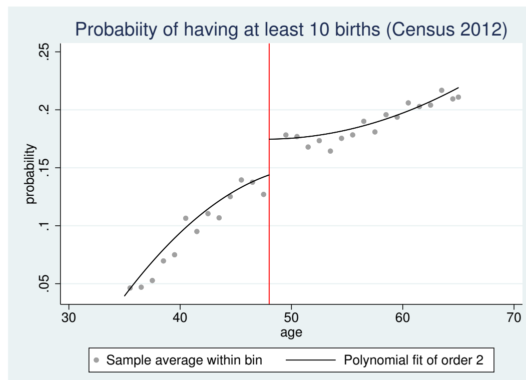
(a) At least 2 births



(b) At least 5 births



(c) At least 8 births



(d) At least 10 births

Notes: Sample is female individuals of the Tanzania Population and Housing census 2012. Age show the age at August 1988. Individuals aged 48 are dropped because this age group cannot be classified as treatment or control group. The vertical red line is drawn at age=48.

The Effect on Child Mortality and Number of Surviving Children

In Table 3, we have shown that additional year of schooling will reduce the number of births. On the other hand, the number of surviving children, which eventually determine the population growth rate, is affected not only by the total number of births but also by child mortality. Table 6 examines the effect of years of schooling on several child mortality related variables. To estimate the child mortality, we restrict the sample to female individuals who experience at least one birth. Panel A of Table 6 examines the effect of years of schooling on the number of child death a respondent experienced. Panel A shows that one year increase of schooling reduces the number of child death about 0.18 frequency. The estimated coefficients are stable and they are significant at 1 percent in all specifications. Panel B of Table 6 examines the probability of having at least one child death. Panel B of Table 6 shows that one additional years of schooling reduces the probability of experiencing at least one child death by about 3.4 percentage point. Panel C, D, E and F of Table 6 display the effect of additional year of schooling on the probability of experiencing at least two, three, four or five children death, respectively. In our sample, five child death is the maximum number. In all specifications, the those panel show that one additional year of schooling reduce the probability of two, three, four or five children's death about 2-3 percentage points.

Figure 4 show the graphical relationship between child death of different cohort. Figure 4 shows that for a the number of child death, probability of experiencing at least one child death, experiencing two child death, four child death, there is a discontinuous jump at the threshold cohort.

Table 7 examines the effect of years of schooling on the number of surviving children and the probability of having at least certain number of surviving children (child). Panel A of Table 7 show that additional year of schooling on the number of surviving children is unstable. It is worth noticing that the coefficient is positive when we control the birthplace, current residence and apply cubic polynomial function to control the time trend. Thus, we do not find a compelling evidence that additional years of female education decrease the number of surviving children. Panel B show the effect of years of schooling on the probability of having at least one surviving child. As expected from the results of Table 5 and Table 6, the estimated coefficient is positive in all specification and it is statically significant. Panel B show that one additional year of schooling increase the probability of having at least one surviving child and two surviving children by 1.8 percentage point and 2.4 percentage points, respectively.

Panel D and Panel E show that effect of years of schooling on the probability of having a very large number of surviving children. Panel D shows that additional years of schooling will decrease the probability of having at least 8 surviving children by 1.8 percent point. Panel E shows that additional year of schooling does not affect the probability of having at least 10 surviving children.

Over all, Table 7 shows that we do not find a strong evidence that additional year of schooling reduces the number of surviving children in a compelling way. This is

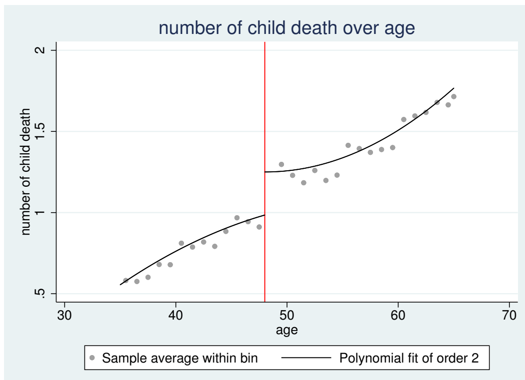
Table 6. Effect of Years of Schooling on Number of Child Death and Child Mortality
Second Stage Estimates of 2SLS

	Dependent Variable			
	(1)	(2)	(3)	(4)
Panel A.	Number of Child Death			
Years of Schooling	-0.162***	-0.157***	-0.191***	-0.179***
	(0.0361)	(0.0304)	(0.0440)	(0.0349)
Panel B	Dummy (having at least one child death)			
Years of Schooling	-0.0344***	-0.0326***	-0.0370***	-0.0339***
	(0.00915)	(0.00823)	(0.0103)	(0.00867)
Panel C	Dummy (having at least 2 child death)			
Years of Schooling	-0.0448***	-0.0433***	-0.0528***	-0.0493***
	(0.00879)	(0.00729)	(0.0110)	(0.00872)
Panel D	Dummy (having at least 5 child death)			
Years of Schooling	-0.0173***	-0.0172***	-0.0209***	-0.0200***
	(0.00418)	(0.00350)	(0.00520)	(0.00405)
Panel E	Child mortality			
Years of Schooling	-0.0181***	-0.0177***	-0.0225***	-0.0210***
	(0.00519)	(0.00413)	(0.00619)	(0.00463)
F. Specifications				
Bandwith	15	15	15	15
Order of Polynominal Controls	2	2	3	3
Current Residene and Birthplace	No	Yes	No	Yes

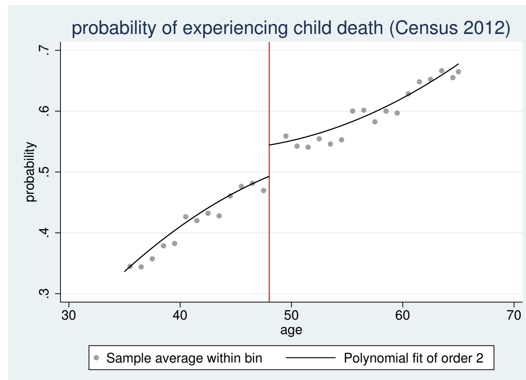
The above table displays the estimated coefficients of years of schooling and their standard errors. Clustering robust standard errors are in parentheses assuming that the error term are correlated within each age cell. The sample is female individuals in 2012 PHCT who experienced at least one birth and whose age is within [48-k,48+k] except age being 48 where k is the bandwidth. In all cases, N=214,515

due to several factors. First additional year of schooling will increase the probability of having at least one child but decrease a large number of birth. Second, additional years of schooling reduces the child mortality.

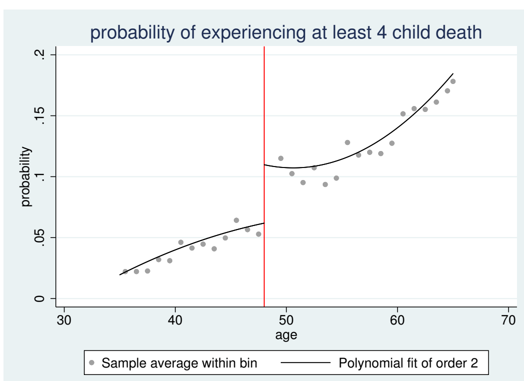
Figure 5: Number of Experienced Child Death and Other Probabilities (2012 census)



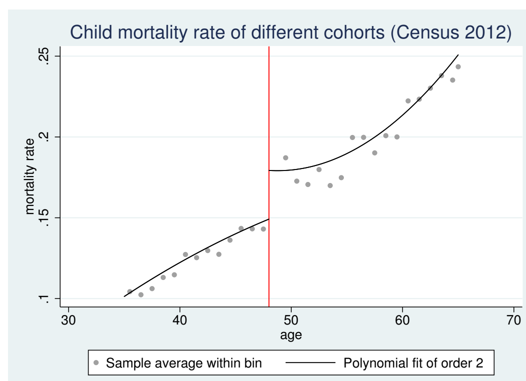
(a) Number of experienced child death



(b) Probability of experiencing at least one child death



(c) probability of experiencing at least 4 child death



(d) child mortality rate

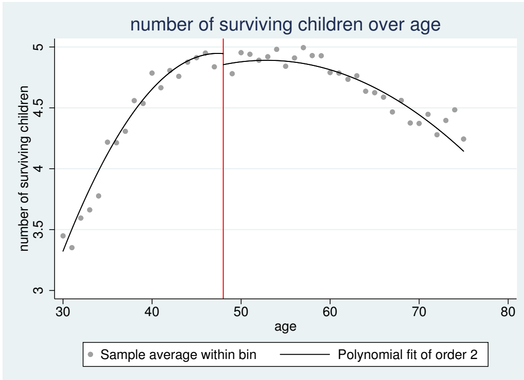
Notes: The sample is female individuals of 2012 PHCT. Age shows the age at August 2012. Female individuals aged 48 are dropped because this age group cannot be classified uniquely as treatment or control group. The vertical red line is drawn at age=48.

Table 7. Effect of Years of Schooling on Number of Surviving Children
Second Stage Estimates of 2SLS

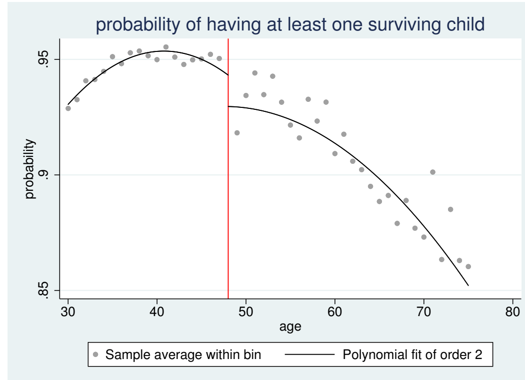
	Dependent Variable			
	(1)	(2)	(3)	(4)
Panel A.	Number of Surving Children			
Years of Schooling	-0.00693	0.0217	0.0704	0.0902*
	(0.0395)	(0.0253)	(0.0663)	(0.0473)
Panel B.	Dummy (having at least one surviving child)			
Years of Schooling	0.0125**	0.0118***	0.0196***	0.0178***
	(0.00497)	(0.00344)	(0.00675)	(0.00462)
Panel C.	Dummy (having at least 2 surviving children)			
Years of Schooling	0.0136**	0.0128***	0.0265***	0.0239***
	(0.00594)	(0.00364)	(0.00981)	(0.00651)
Panel D.	Dummy (having at least 8 surving children)			
Years of Schooling	-0.00853**	-0.00333	-0.0163***	-0.0107***
	(0.00381)	(0.00357)	(0.00365)	(0.00313)
Panel E.	Dummy (having at least 10 surviving children)			
Years of Schooling	-0.00229*	7.62e-05	-0.00492***	-0.00227
	(0.00135)	(0.00132)	(0.00168)	(0.00147)
F. Specifications				
Bandwith	15	15	15	15
Order of Polynominal	2	2	3	3
Current Residene and Birthplace	No	Yes	No	Yes

Notes: The table displays the estimated coefficients of years of schooling and their standard errors in the second stage of 2SLS estimation when different dependent variables are used. Clustering robust standard errors are in parentheses. The sample is female individuals in 2012 PHCT whose age is between [48-k,48+k] except 48 where k is the bandwidth. For all specifications, N=224,804.

Figure 6: Number of Surviving Children over Age



(a) Number of surviving children



(b) Probability of having at least one survived child

Notes: Sample is female individuals of 2012 PHCT. Age shows the age at August 2012. Those aged 48 are dropped because this age group cannot be classified uniquely as the treatment or as the control group. The vertical red line is drawn at age=48.

5.2 Analysis based on 1988 Census

In the previous sub-section, we have shown that additional years of schooling reduces the probability of having a large number of births and the number of child death and child mortality rate. One natural question is the generalizability of our result. Since the threshold age of our 2012 census data is 48, it is possible that our results are driven by the change of fertility behavior of women after the age of 35. For example, literature on health research shows that birth after 35 have risks such as low birth weight of new born babies (Jacobsson et al., 2004). It is possible that a woman who have longer years of schooling knows the risk of having birth after 35 and decide to birth before 35 and as a result, such women experience lower child mortality. If this is so, then it implies that the effect of longer years of schooling can be replaced with much cheaper intervention such as giving female individual knowledge on the risk of childbirth after 35.

To examine whether such a case occurred, we use the census data in 1988 in which the threshold age is 24. The following table shows our regression results. As Figure 2(b) shows, that the years of schooling increases with very steep slope between age 14 to age 18. To apply the regression discontinuity design, I restrict the sample from age 16 to 34 except age 24. As in the previous analysis that use the 2012 census, cohort whose age equal to 24 cannot be classified into one group. To make our identification clear, we drop the cohort whose age is equal to 24. Since the increase of years of schooling during age 16-23 is very steep, we use cubic or quintic function to control the time trend.

Table A1 is the summary statistics of the census data in 1988. Table 8 is the regression results. Panel A of Table 8 shows that additional year of schooling reduces the number of birth by about 0.4 units. This number is larger than the estimate that uses 2012 census data set. This is likely to the fact that the estimate that use 2013 cuneus measure the effect f years of schooling on completed fertility while the estimates that use the 2012 census estimate the effect of years of schooling on the number of birth during young periods. Panel B show the effect of years of schooling on the probability of having at least one birth. The estimates are unstable and depends on the order of control function and controlling covariates. This is perhaps due to the fact that education increases the extensive margin of fertility but reduces the number of births. Panel C, D, E show the effect of years of schooling on the probability of having at least two births, three births and four births. It shows that additional years of schooling reduces those probabilities. Panel E and F show the effect of years of schooling on the number of child death experienced and the child mortality. They show that additional years of schooling reduce the number of child death and child mortality by 0.18 frequency and 3 percentage points. Table 8 show that effect of years of schooling on the number of birth, the number of child death and child mortality is consistent with estimates obtain using 2012 census data sets.

Table 8. Effect of Years of Schooling on Birth Outcome Using 1988 Census Data
Second Stage Estimates of 2SLS

	Dependent Variable			
	(1)	(2)	(3)	(4)
Panel A.	Number of births			
Years of Schooling	-0.416***	-0.428***	-0.372***	-0.377***
	(0.0504)	(0.0512)	(0.0675)	(0.0647)
N	161,279	161,279	161,279	161,279
Panel B	Dummy (having at least one birth)			
Years of Schooling	-0.0731***	-0.0754***	0.0163	0.0178
	(0.0178)	(0.0189)	(0.0174)	(0.0174)
N	161,279	161,279	161,279	161,279
Panel C.	Dummy (having at least 2 births)			
Years of Schooling	-0.0520***	-0.0529***	-0.0319**	-0.0313*
	(0.0108)	(0.0113)	(0.0161)	(0.0165)
N	110,777	110,777	110,777	110,777
Panel D.	Dummy (having at least 3 births)			
Years of Schooling	-0.0500***	-0.0512***	-0.0354***	-0.0358***
	(0.00879)	(0.00907)	(0.0129)	(0.0130)
N	161,279	161,279	161,279	161,279
Panel E.	Number of Child Death			
Years of Schooling	-0.106***	-0.106***	-0.119***	-0.117***
	(0.0198)	(0.0191)	(0.0305)	(0.0286)
N	110,777	110,777	110,777	110,777
Panel F.	Child morality rate			
Years of Schooling	-0.0107***	-0.0106***	-0.00804**	-0.00762*
	(0.00266)	(0.00296)	(0.00369)	(0.00406)
N	110,777	110,777	110,777	110,777
G. Specifications				
Bandwith	[8, 15]	[8, 15]	[8, 15]	[8, 15]
Order of Polynominal	3	3	4	4
Current Residene and Birthplace	No	Yes	No	Yes

Notes: The table displays the estimated coefficients of years of schooling and their standard errors in the second stage of 2SLS estimation when different dependent variables are used. Clustering robust standard errors are in parentheses Bandwidth [a,b] implies that for the left side of the threshold, bandwidth a is used and for the right side of the threshold bandwidth b is used. The sample is female individuals whose age is within [24-a, 24+b] except 24 where a and b are parameters of bandwidth. For Panel D and E, the sample is restricted further to those who experienced at least one birth.

6 Discussion and Conclusion

This study examines the effect of years of schooling on fertility and child mortality using no-expulsion policy in Tanzania as a quasi-natural experiment in the fuzzy regression discontinuity design framework. We obtain several important findings from the analysis. First, the effect of years of schooling is non-uniform. Additional years of schooling *increases* the probability of having at least one birth by 1.5 percentage point but decreases the probability of having a large number of births such as at least 8 births or 10 birth about 2-3 percentage points. With two effects combined, additional year of schooling reduces the number of births by about 0.08 frequency which is equivalent to about 2 percent reduction of the number of births. Second, additional year of schooling reduces the number of child death by about 0.2-0.3 frequency and child mortality rate by 3-4 percent point. Third, as a result, the effect of years of schooling on the number of surviving children become zero or marginally *positive*. Fourth, we find a similar pattern when we use the 1988 census data where the threshold age of the regression discontinuity is 24. This implies that the reduction of the total number of births, the number of child death and child mortality are observed when the sample is restricted to young female individuals.

The finding of this paper has several implications. First, as a policy tool to reduce a higher population growth rate of developing country, encouraging education is not the solution. Our analysis shows that education is not likely to reduce the population growth rate since the education does not decrease the number of surviving children. On the other hand, if the objective of a policy maker is to find a tool transform fertility pattern from many births and many child death into less birth and less child death, our analysis shows that encouraging education is a very effective tool. We find that additional increase of one year will reduce the probability of having at least 8 birth by 2 percentage point and reduce the child mortality by 3 percentage point. This pattern is observed even when we restrict our sample to relatively young female individuals. This transformation of fertility pattern seems more beneficial to mothers since it will give less physical burden with the similar number of surviving children. Thus education can transform fertility pattern into more efficient pattern.

Second, our finding could suggest one reason why different studies regarding the effect of education on fertility have different results. In the previous literature, regarding the effect of education on fertility, some studies find zero effect and other studies find negative effect. Our study shows that the effect of education on fertility is non-uniform. Education increase the probability of having at least one birth but it decreases the probability of having a large number of births. Since the previous studies focus on the average number of births, they might have had different results. This suggest that for studying the effect of education on fertility, it is not sufficient to focus on the average number of births. A new study need to examine how the distribution of births are affected.

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Appendix

Table 1. Summary Statistics of 1988 Census

	Control		Treatment		All	
Variables	mean	sd	mean	sd	mean	sd
A. Years of Schooling and Fertility						
Years of Schooling	3.484	3.467	5.585	2.841	4.602	3.320
Dummy: Literatre	0.559	0.496	0.809	0.393	0.692	0.462
Number of births	3.805	2.498	0.893	1.278	2.256	2.429
Number of surviving children	3.163	2.103	0.759	1.095	1.884	2.037
Dummy: At least 1 birth	0.914	0.281	0.487	0.500	0.687	0.464
Dummy: At least 2 births	0.816	0.388	0.229	0.420	0.504	0.500
Dummy: At least 3 births	0.679	0.467	0.0952	0.293	0.368	0.482
Dummy: At least 4 births	0.516	0.500	0.0406	0.197	0.263	0.440
N	75,506		85,773		161,279	
B. Mortality Related Variables						
Number of child death	0.670	1.120	0.202	0.590	0.493	0.982
Child Mortality Rate	0.128	0.189	0.0643	0.163	0.104	0.182
Dummy: At least one child death	0.384	0.486	0.149	0.356	0.295	0.456
Dummy: At least 2 child death	0.168	0.374	0.0353	0.184	0.118	0.322
Dummy: At least 3 child death	0.0668	0.250	0.00940	0.0965	0.0452	0.208
Dummy: At least 4 child death	0.0273	0.163	0.00321	0.0565	0.0182	0.134
Dummy: At least 5 child death	0.0114	0.106	0.00148	0.0385	0.00767	0.0873
N	68,988		41,787		110,775	

Notes: Sample is female individuals in 1988 PHCT. Control cohorts is female individuals aged from 25 to 33 and treatment cohorts is female individuals aged from 15 to 23. In Panel B, the sample is restricted to female individuals who experienced at least one birth among the sample used in Panel A.