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Analyzing the Causal Impact of Higher Education on Fertility and Potential Mechanisms

- Evidence from Regression Kink Designs

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Forward

Korea is experiencing an unprecedently low level of fertility. In 2016, the total fertility rate is 1.17; the second lowest level since 1970, the lowest level among OECD countries, and almost half of the world average.

While not new, policies calling for counterattacking such low fertility rate are gaining support within the country, especially with the beginning of a new government headed by President Moon Jae-in.

While many factors have been attributed for this low fertility rate, few research has been conducted on rigorously identifying and analyzing the cause of such low fertility rate. This study, conducted by Hosung Sohn, Associate Research Fellow at the Korea Institute for Health and Social Affairs, fills such research gap by analyzing the causal impact of one factor: higher education.

I hope this study enhances our knowledge regarding the role of higher education on fertility, and provides policy implications and insights on developing effective fertility-related public policies.

June, 2017

Sangho Kim, President

Korea Institute for Health and Social Affairs

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Abstract

Analyzing the Causal Impact of Higher Education on Fertility and Potential Mechanisms: Evidence from Regression Kink Designs

Little is known about what causes fertility level to go down. One factor that has been speculated to reduce fertility level is education. Theoretical arguments regarding the relationship between education and fertility are not unanimous as to whether education increases or decreases fertility. Consequently, this research question is a matter of empirical investigation.

This research, therefore, tests this hypothesis by analyzing the "causal" impact of higher education on fertility using the census data (2%) administered by Statistics Korea. In order to account for the endogeneity issue inherent in the higher education variable, this study exploits higher education reform initiated in 1993 that boosted one's likelihood of entering college with the assumption that this reform is plausibly exogenous.

Based on regression kink designs, I find that college degree reduces the likelihood of childbirths by 0.228 and the total number of childbirths by 1.32. Analyses of possible mechanisms show that one significant channel that drives the negative effects is through labor markets; female college graduates are more likely to be a wage earner and more likely to have professional occupations. I argue, therefore, that government policies should be directed more toward reducing opportunity costs of fertility induced by the increase in earning capacity.

*Key Words: Fertility Policy, Labor Market, Regression Kink Designs, Casual Inference

1 Introduction

Section 1 Research Background

Section 2 Purpose of the Research

1 Introduction

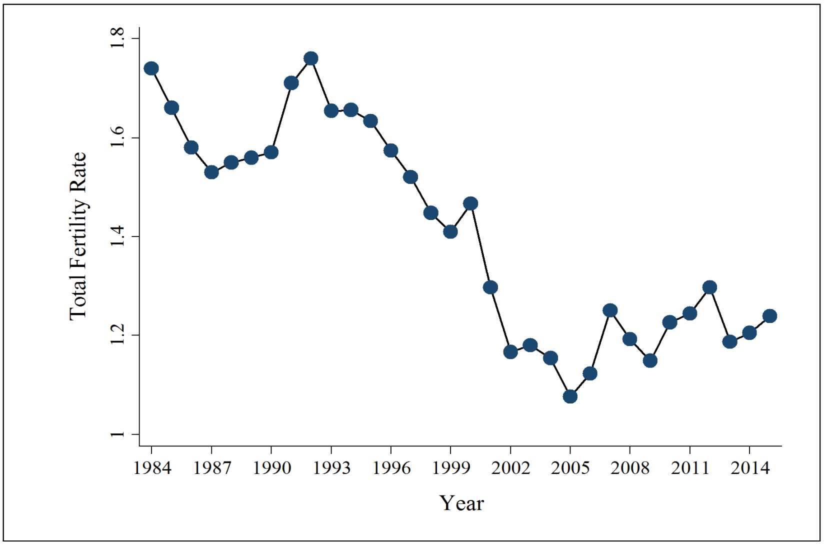
Section 1. Research Background

South Korea is experiencing a rapid decline in the total fertility rate, and finding measures to reverse this trend is considered one of the toughest challenges of the Korean government. As can be seen from Figure 1-1, South Korea's total fertility rate has declined from 1.74 births in 1984 to 1.24 births in 2015.

Opinions of researchers regarding whether a low fertility rate poses an issue is not unanimous. Lee, Mason, and NTA Network (2014), for example, show that a moderately low fertility rate and population level is favorable for the material standard of living. Bloom et al. (2010), on the other hand, show that while a low fertility rate increases income per capita in the short run as it will reduce the youth dependency ratio and increase the share of the working-age, a decline in the fertility rate will lead to an increase in the economic burden of old-age dependency in the long run.

Nevertheless, many researchers agree that a decline in the fertility rate well below the replacement level will be a serious threat to a sustained operation of government transfer programs such as unemployment insurance. As these programs are essential for promoting the social welfare of one's country, it is inevitable for a country with a fertility rate well below the replacement level to devote a high share of government spending towards raising the overall rate.

[Figure 1-1] Total Fertility Rate in South Korea from 1984 to 2015

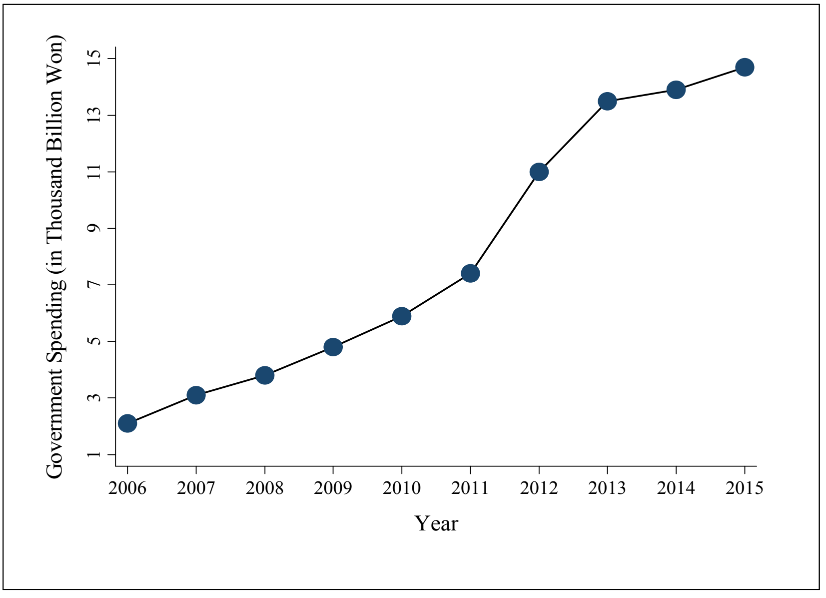


Source: National Index System (www.index.go.kr).

Figure 1-2 shows the trend of the government spending devoted for targeting low fertility. As can be seen from the figure, whereas the spending continue to increase since 2006, fertility rate remains low.

While there are many reasons that account for the ineffectiveness of government policies targeted toward boosting fertility, one reason may be that many of these policies do not attempt to address factors that actually *cause* low fertility. Developing and implementing public policies directed at factors that drive low fertility is critical for increasing the effectiveness of such policy. Identifying the 'cause' of low fertility, therefore, should precede any policy implementation.

[Figure 1-2] Share of Fertility-Related Government Spending



Source: The Third Low Fertility-Aging Master Plan (Korean Government, 2016).

Section 2. Purpose of the Research

Many research examined the potential determinants of fertility; a meta-study was conducted by Skirbekk (2008). It is difficult to conclude from these studies, however, that there is a *causal* relationship between the variables analyzed and fertility rates, because these studies engage in analyzing the 'correlation' between the two variables. Yet, Skirbekk (2008)'s study provides an insight as to which factors are potentially significant in influencing fertility rates.

One explanatory variable that most studies explore is education. Education is widely believed to be a key determinant of the fertility rate. Yet, analyzing the causal impact of education on fertility is a challenge as education level is endogenously determined. That is, even if a correlation exists between education and fertility, it does not necessarily imply that the effect is driven by education per se; the observed association may be due to confounding variables such as one's career aspiration that influences both education and fertility. If the effect of education on fertility is mostly driven by the difference in career aspirations, policies targeted merely at one's education level will be limited in influencing fertility.

This study aims to answer the following question: is there a 'causal' relationship between education and fertility? While answering this question seems interesting from a research perspective, the answer itself is limited in providing policy implications. Suppose a study finds that the increase in one's education level reduces fertility. Should the government then engage in reducing the level of education in order to raise fertility rates? As a matter of course, developing and implementing policies to reduce education levels is inappropriate; education may negatively affect fertility, but education entails many monetary and non-pecuniary benefits (Milligan, Moretti, and Oreopoulos, 2004; Oreopoulos and Salvanes, 2011).

From a policy perspective, therefore, what's more important than answering the question above is to identify the potential mechanisms that channel education and fertility. If certain causal channels are revealed and such channels are policy-relevant variables, then governments should put resources into targeting such mechanisms. In this study, therefore, I examine the potential policy-relevant mechanisms that can be tested statistically using data to help develop public policies that may increase the fertility rate.

2

Theoretical Background and Literature Review

2 Theoretical Background and Literature Review

Section 1. Theoretical Background

There are a total of eight theories that have been proposed by researchers with the aim of answering the question of why education influences fertility. The leading theory approaches the matter in regards to labor market effects. That is, education raises the earning capacity thereby affecting the opportunity cost of leaving the labor market. According to this theory which was first proposed by Becker (1965), one's education influences fertility through substitution and income effects. While substitution effects reduce fertility rates, income effects raise fertility. Becker and Lewis (1973), on the other hand, argue that income effects might be weak as there is a quality-quantity tradeoff when one's income increases. Whether education raises or reduces the fertility rate, therefore, depends on the relative magnitude of the two effects.

The second theory argues that education affects fertility through the marriage market (Whelan, 2012). More education may make an individual more or less attractive in the marriage market, and this in turn will affect the likelihood of finding a suitable spouse. Consequently, fertility rates will be affected depending on whether one favors an individual with a certain education level or not.

A so-called assortative mating theory has been proposed to explain the relationship between education and fertility. This theory is based on the psychological notion that people tend to pick their spouse similar to themselves. With the overall increase in education levels, individuals will have higher levels of education when getting married, which also leads to a boost in their spouse's income. As can be inferred from the labor market theory, such behavior induces substitution and income effects. Note, however, that whether such assortative mating behavior affects fertility positively or negatively depends on the partner's involvement in child care activities (Behrman and Rosenzweig, 2002). If females, for example, are mostly responsible for child rearing such as in Korea, the income effect will likely dominate the substitution effect, thereby raising the fertility rate.

Education generates information effects. Education may improve one's knowledge and attitudes regarding the practice of contraception, and consequently lead to a decrease in fertility rates (Buyinza and Hisali, 2014).

Education also affects fertility through a so-called "incarceration effect" (or time effects). It is likely more education will increase one's time spent in school, and this in turn will reduce or delay opportunities to engage in fertility-related activities

(Black, Devereux, and Salvanes, 2008).

The sixth proposition argues that education affects fertility because higher education may provide bargaining power in decision-making. The increase in such power may affect the range of marriage-related activities including fertility control (Dyson and Moore, 1983).

The seventh theory states that education produces attitudinal effects. Education is likely to affect one's set of values with respect to fertility-related matters (Basu, 2002). For example, suppose more educated people conceive that education is beneficial. Then such people may engage in activities that help raise the education level of their children. Because the cost of education is high, individuals may refrain from having children.

The last theory aims to explain the link between the two variables via peer effects. Sociological theories have examined the importance of social interaction and diffusion processes for child rearing behaviors (Bongaarts and Watkins, 1996; Kohler, Behrman, and Watkins, 2001; Diaz et al., 2011). It goes without saying that education clearly affects one's social interactions. Hence, education is likely to influence fertility behavior through peer effects.

Note that many of the theories mentioned above overlap to some extent. Regardless, as can be inferred from the theoretical propositions mentioned above, education is a factor which may either increase or decrease fertility. Thus, empirical investigation should be conducted on exploring the causal impact of education on fertility. It is clear that the estimated impact of education on fertility may vary to a great extent depending on the context of the analysis sample.

Section 2. Literature Review

Many studies investigated the relationship between fertility and education. As mentioned previously, however, it is difficult to derive causality between the two variables from the results provided by these studies, as they do not address endogeneity issues inherent in the education variable. Skirbekk (2008) provides an excellent review of these studies, and therefore I resort to his meta-study for an overview of the research.

Some recent studies attempt to estimate the causal impact of education on fertility. Most of these studies exploit either the change in mandatory schooling law or educational reform within a country to overcome the endogeneity problem. In this section, I discuss only the research that analyzes the causal impact of education on total fertility.[1)]

The earliest work was conducted by Osili and Long (2008). The authors make use of the educational expansion program

1) Some research analyze the effect of education on teenage fertility. As teenage fertility is not a focus of this study, I do not discuss these research.

that was implemented in Nigeria to estimate the causal impact of education on fertility. Females who are exposed to the program received about 1.5 more years of education than those who are not exposed to the program. Exploiting such an exogenous event, the authors find that the effect of education on fertility is negative.

Grönqvist and Hall (2013) also exploit educational reform. In 1991, a major reform was implemented in Sweden, in which the two-year vocational track was extended to three years. Using this exogenous event, they find that education delays females' childbearing activities. Note, however, that they do not find any effects on males.

Monstad, Propper, and Salvanes (2008), on the other hand, exploit the change in compulsory education reform in Norway. Mandatory education was lengthened from seven to nine years due to a change in the law. Using this plausibly exogenous legislation change, they show that education has little impact on the fertility rate.

Another study that also exploits the change in compulsory education reform is Cygan-Rehm and Maeder (2013). This research makes use of the change in Germany's compulsory education reform. Following the reform, the number of years of mandatory education in Germany increased from eight to nine years, and exploiting this sudden change, the authors find that education reduces fertility.

McCrary and Royer (2011)'s study is different from the ones mentioned above in that they use each individual's exact date of birth as an instrument of the education level. Because the date of birth generates a discontinuity in one's education level, they use a regression discontinuity design to analyze the effect of education on fertility, as well as child health. The results show that education has no effects on fertility.

Rather than utilizing exogenous events, Amin and Behrman (2014) analyze fertility behavior of twins in the U.S. Educational differences are observed within twins, and exploiting such difference, they find that education reduces fertility.

As can be expected from theoretical predictions regarding the relationship between education and fertility, results of the existing empirical literature are not consistent across studies. Possible reasons for this inconsistence may be, first of all, that data from different countries have been used. Moreover, educational reform differs with respect to time and educational level across studies. Hence, more empirical studies are necessary for establishing a causal relationship between education and fertility.

This study contributes to existing literature in five ways. First, there are few research that examines the "causal" relationship between education and fertility observed for Asian countries. East Asian countries, in particular, are suffering from a rapid decline in total fertility rates. Studying the Korean case, therefore, will be helpful for understanding the relative impact of education and fertility.

Second, the effect of education on fertility may not be homogeneous. That is, it is unlikely that the effect of completing secondary education on fertility will be the same as the effect of completing tertiary education. Analyses conducted in most of the previous studies are predominantly concentrated at the elementary or secondary school levels. As this study analyzes the impact of higher education on fertility, it would clearly help complement existing literature in deriving a more complete picture of the education-fertility relationship.

Third, few studies consider the so-called sheepskin effect. The screening theory suggests that people with diplomas earn much more than those without, even if both parties have received the same amount of education (Belman and Heywood, 1991). This study is the first to take into consideration the sheepskin effect as I compare those with a four-year college degree with those with a high school degree in order to estimate the causal impact of education.

Fourth, the treatment variation (i.e., the difference in the years of education observed between the treatment and control groups) observed in previous studies is typically less than one year. If there exists increasing or decreasing returns to education with respect to fertility, exploiting this one year treatment variation may not provide a complete picture of the effect of education on fertility. Trostel (2004), for example, finds that a constant returns to scale assumption is inappropriate for analyzing the relationship between the years of education and the wage rate. The treatment variation exploited in this study is four years; i.e., college degree vs high school degree. This study may shed light on whether constant returns to scale assumption is appropriate for the education-fertility relationship.

3 Institutional Background

3 Institutional Background

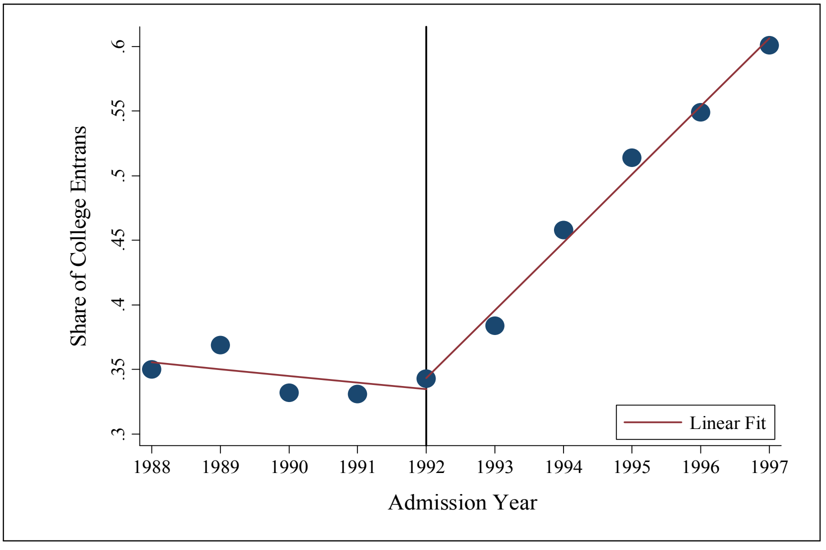
In order to estimate the causal impact of higher education on fertility, researchers need to exploit random or quasi-random variation in one's education level. In this study, I exploit higher education reform initiated in 1993.[2] Prior to 1993, the Korean government controlled the capacity of college enrollments. It further allotted an enrollment quota across colleges. Accordingly, the trend of the number of college enrollments during the 1980s and early 1990s was remarkably stable across years. Figure 3-1 shows college enrollment rates by year between 1988 and 1997. As can be seen from the figure, the enrollment rate was approximately 0.35 in 1988, and remained stable until 1992. The trend observed during this period was clearly driven by the Korean government's control over the enrollment capacity.

In 1993, the new Korean government, headed by the newly elected President Young-sam Kim, adopted a market-based approach for the higher education policy, which was strongly recommended from the Presidential Commission on Education. The new government eased higher education-related regulations. In particular, the government liberalized the enrollment capacity. Furthermore, new universities were allowed to enter the market

2) Information regarding the higher education reform implemented in 1990s is retrieved from Kim and Lee (2006) and Oh (2011).

if minimum conditions were met. Consequently, the number of college enrollments and institutions started to increase since 1993. As can be seen in Figure 3-1, the college enrollment rate increased significantly as of 1993. Whereas the enrollment rate remained stable from 1988 to 1992, it increased by more than 25 percentage points over the next five-year period. The sudden increase in the rate was clearly driven by the higher education reform measures.

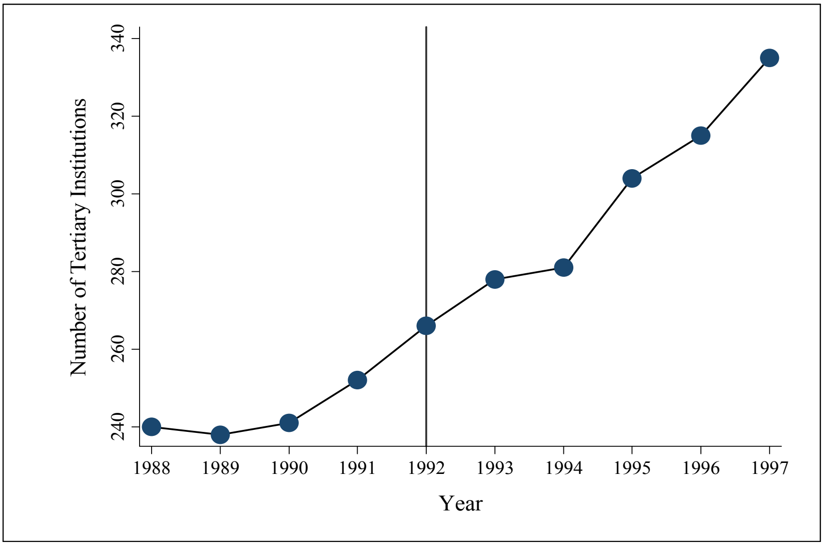
[Figure 3-1] College Enrollment Rate, by Year



Note: College enrollment rates are calculated by dividing the number of students who were admitted to college by the number of high school graduates.
Source: National Index System (www.index.go.kr).

In Figure 3-2, I plot the number of tertiary institutions by year between 1988 to 1997. The yearly trend clearly shows that the number of institutions increased significantly especially during the post-reform period. During 1988 to 1992, the number of institutions increased only by 10%, whereas the number increased by 20% between 1993 to 1997.

[Figure 3-2] Number of Tertiary Institutions, by Year



Source: Education Statistics Yearbook (Korean Educational Development Institute).

In this study, I make use of a plausibly exogenous variation induced by the higher education reform mentioned above. In particular, the abrupt increase in the number of colleges and the size of the enrollment capacity, which is driven by the reform, generated a kink in the likelihood of receiving a college degree. Exploiting such kink, I use a regression kink design, pioneered by Card et al. (2015) to causally estimate the effect of a college degree on fertility.

Note that in Figure 3-1, the kink around year 1992 is observed in the college enrollment rate. The fact that this rate increases doesn't necessarily imply that we would observe a kink in the probability of receiving a college degree. While conventional wisdom tells us that the likelihood of receiving a college degree will increase if a person enters college, it may not be true in reality. While college completion rates are fairly low in western countries such as the U.S., the case is different in Korea.[3] Therefore it is likely that we would observe a significant kink in the probability of obtaining a college degree. Nevertheless, the validity of the regression kink design is critically contingent on the existence of the kink. And I verify that the kink observed in Figure 3-1 leads to a similar kink in college graduation rates (see Chapter 5).

3) To my knowledge, there are no official statistics on college completion rates in Korea.

4 Empirical Strategy

4 Empirical Strategy

Section 1. Identification

As can be inferred from the theories mentioned above, education is one important determinant of one's fertility-related decisions. Conventional naive parametric ordinary least squares (OLS) model estimates the effect of education on fertility using the following specification:

$$Y_{ic} = \beta_0 + \beta_1 E_{ic} + \mathbb{X}_{ic}\gamma + \zeta_{ic}, \tag{1}$$

where Y_{ic} is the fertility level for person i of birth cohort c. $\mathbb{X}_{ic}$ is a vector of covariates. In equation (1), the parameter of interest is β_1, the marginal effect of one's education level (E_{ic}) on Y_{ic}.

Note, however, that the OLS estimator β_1 is biased as the specification above will likely suffer from omitted variable bias such as one's ability and career aspiration that affect both fertility and education. That is, if those who enter college consist of individuals with higher career aspirations, then we cannot determine whether the estimated effect $\hat{\beta}_1$ reflects either the effect of education or the degree of career aspiration.

This study exploits the implementation of the higher education reform initiated in 1993 in order to bypass the endogeneity in one's education level, and the identification strategy I use is the fuzzy regression kink design (RKD).

Identification in the fuzzy RKD relies on two assumptions. The first assumption requires that individuals cannot manipulate the year of birth precisely in an effort to take advantage of a future education reform. This assumption is reasonable as manipulating one's year of birth is virtually impossible. Besides, parents were unaware of the possibility of there being an education reform, and therefore it would have been impossible to consider that they would have postponed conceiving in order to take advantage of this reform.

While common sense tells us that manipulation is unlikely, I test for such behavior using a modified version of the density test proposed by McCrary (2008). The density test developed by McCrary (2008) is used for testing the manipulation of the assignment variable in the context of a regression discontinuity design (RDD). In this study, rather than testing for discontinuity in the density of the assignment variable (i.e., birth year), I test for the kink in the density of the assignment variable, as the RKD requires that there is no kink in the assignment variable.

The second assumption rules out any statistically significant kink in baseline characteristics around the cutoff point. This assumption is analogous to testing for the continuity in baseline covariates in the RDD setting, and the balance in baseline characteristics in a randomized controlled trial. The intuition behind testing for no kink in baseline covariates is that if there is a kink in baseline covariates, then we cannot determine whether the observed effect is driven by the treatment variable itself (i.e., college degree) or by other baseline characteristics such as one's career aspiration. In Chapter 6, I show that there are no kinks in baseline covariates.

Provided that the two assumptions hold, the identification of the effect of a college degree (E) on fertility (Y) is obtained by dividing the change in the slope observed for the conditional expectation function for the outcome variable Y, $E(Y|C=c)$, at the kink point $C=1974$ by the change in the slope observed for the assignment function $E=e(C)$ at the kink point $C=1974$. Here, C denotes an assignment variable (i.e., year of birth).

Formally, the RKD estimand (τ_{RKD}) is defined in the population as follows:

$$\tau_{RKD} \equiv \frac{\lim\limits_{c \to 1974^+} \dfrac{dE(Y|C=c)}{dc} - \lim\limits_{c \to 1974^-} \dfrac{dE(Y|C=c)}{dc}}{\lim\limits_{c \to 1974^+} \dfrac{de(c)}{dc} - \lim\limits_{c \to 1974^-} \dfrac{de(c)}{dc}} = \hat{\beta}_1. \quad (2)$$

In equation (2), the numerator indicates the change in the slope of the conditional expectation function at the kink point. The denominator, on the other hand expresses the change in the slope of the assignment function. To put it simply, the RKD estimand is the slope change in the outcome variable (i.e., fertility level) scaled by the slope change in the treatment variable (i.e., education level).

Section 2. Estimation

Estimation of equation (2) can be accomplished in many ways, but literature on RDD and RKD recommends estimating the equation using the nonparametric local polynomial regression techniques (Fan and Gijbels, 1996; Imbens and Lemieux, 2008; Card et al., 2016). The idea behind this local polynomial regression is to divide the data into two subsamples: the right and left of the kink point, and then a separate regression is estimated for each subsample.

Formally, this amounts to solving the following minimization problems:

$$\min_{\{\beta_j^l\}} \sum_{i=1}^{N^l} \left[e_i^l - \sum_{j=0}^{p} \beta_j^l \left(C_i^l \right)^j \right] K\left(\frac{C_i^l}{h} \right)$$

and

$$\min_{\{\beta_j^r\}} \sum_{i=1}^{N^r} \left[Y_i^r - \sum_{j=0}^{p} \beta_j^r \left(C_i^r \right)^j \right] K\left(\frac{C_i^r}{h} \right)$$

for the numerator in equation (2), and

$$\min_{\{\gamma_j^l\}} \sum_{i=1}^{N^l} \left[E_i^l - \sum_{j=0}^{p} \gamma_j^l \left(C_i^l \right)^j \right] K\left(\frac{C_i^l}{h} \right)$$

and

$$\min_{\{\gamma_j^r\}} \sum_{i=1}^{N^r} \left[E_i^r - \sum_{j=0}^{p} \gamma_j^r \left(C_i^r \right)^j \right] K\left(\frac{C_i^r}{h} \right)$$

for the denominator in equation (2), subject to

$$\beta_0^l = \beta_0^r.$$

Solving the minimization problems leads to the following RKD estimate:

$$\hat{\tau}_{RKD} = \frac{\hat{\beta}_1^r - \hat{\beta}_1^l}{\hat{\gamma}_1^r - \hat{\gamma}_1^l}.$$

Here, l and r denote left and right of the cutoff point, and p indicates the order of the polynomial. K corresponds to the kernel function that determines the relative weight. And h is the bandwidth, or the effective analysis sample used for estimation. In this setting, we can think of C as a re-centered variable at the cutoff point. Y is an outcome variable, which is the fertility level in this study, and E is an explanatory variable, which is a dummy variable indicating college degree recipients.

As can be seen from the minimization problems, researchers have to make choices on three factors: K, p, and h. While there is no unanimous agreement regarding how to make choices on these factors, majority of the RK literature use a local linear regression (i.e., a uniform kernel function for K, and $p=1$) estimator, as this estimator is known to have desirable properties for estimating the regression function at the boundary point (i.e., cutoff). Thus, I also use local linear regression estimator to derive the RKD estimate. Regarding the bandwidth choice, I report the RKD estimate based on several bandwidth choices.

Section 3. Inference

Local linear regressions are, in principle, weighted instrumental variable estimators, and accordingly, standard regression inferential procedures can be used for conducting statistical inference (Lee and Lemieux, 2010). Note that this study uses the year of birth as an assignment variable. Consequently, the data have a grouping structure. As demonstrated first by Moulton (1986), failing to account for within group dependence when calculating standard errors will underestimate true standard errors. In such a case, Lee and Card (2008) propose clustering standard errors on the assignment variable. This study, therefore, clusters standard errors at the level of the assignment variable (i.e., year of birth).

5

Data and Sample

5 Data and Sample

Section 1. Data Description

This study uses the 2010 census data (2% sample) administered by Statistics Korea. Researchers who are interested in using the census data can apply for access to the sampled data (either 1% or 2%) from the Microdata Integrated Service system.[4]

The 2010 census data contain information on one's education level, the number of births by married female (including those who are bereaved), age, place of birth, and some other variables that are useful for research purpose. Note that this study exploits the higher education reform initiated in 1993. So it is necessary that the sample should contain data regarding those who were born in or close to 1974. Fortunately, even though one can obtain the sampled data (i.e., 2%) only, the data covers all births occurring in Korea. Thus, the 2010 census data is suitable for exploiting the 1993 higher education reform. One thing to note is that the results of this analysis pertain to only married female.

4) https://mdis.kostat.go.kr

Section 2. Sample Selection

In an effort to secure research transparency, I present a series of sample restrictions steps, in Table 5-1, that has been conducted to analyze the research topic at hand. The sample size for the initial 2010 census data is 933,846. From this initial raw data, I keep only the observations whose value label for the "Relationship with the Household" variable is 'household,' 'spouse of household,' 'child,' and 'son- or daughter-in-law.' The reason for keeping these observations only is that the fertility level cannot be determined for observations with other value labels. The resulting sample size is 864,412.

As a second step, I exclude those with two-year college degrees. There are mainly three reasons for dropping these observations. First, the higher education reform initiated in 1993 did not affect two-year colleges. The second reason is to secure variation in treatment in one's education level. The resulting sample size after excluding these observations is 767,974. The third reason is that the inclusion of two-year college graduates results in statistically insignificant kink at the cutoff point that is exploited in this study.

The data also contain information regarding whether each individual completed his or her final degree. In order to account for the sheepskin effect, this study focuses on degree recipients only. This third step brings down the sample size to 490,774.

〈Table 5-1〉 Step-by-Step Restrictions to the Initial Census Data

Step	Description	Resulting Sample Size
Initial Data	Raw data: 2010 Census Sample (2%)	933,846
Step 1	Keep observations which are recorded as "household," "spouse of household," "child," and "spouse of child," in the **Relationship with the Household** variable. For other labels, it is difficult to determine the fertility level.	864,412
Step 2	Exclude individuals with a two-year college degree in order to secure treatment variation.	767,974
Step 3	Restrict to observations with degree recipients in order to account for the sheepskin effect.	490,774
Step 4	Drop observations whose value for the **number of children** variable is "99" (not applicable).	404,369
Step 5	Keep only the observations whose year of birth is between 1967 and 1979. Including observations outside this range results in unbalanced predetermined covariates, as well as insignificant kink estimates in the treatment variable.	102,185
Step 6	Keep only the female observations	57,547

The fourth step drops observations whose value for the number of childbirths variable is '99' (not applicable). The remaining sample size is 404,369. Fifth, I exclude those whose birth year is before 1967 and after 1979. There are three reasons for this. First, including observations for these years results in unbalanced baseline characteristics. Second, I no longer observe a practically significant kink in the treatment variable, if the analysis period expands to other periods, and as such, we cannot exploit the RKD. Third, South Korea experienced an economic crisis in 1998. So those who were born after 1979 were influenced by such economic crisis. Hence, these observations are less likely to be comparable with those who were born before. Finally, I drop male observations as the analysis is based on female sample.

All in all, the final sample size used in the analysis is 57,547.

Section 3. Descriptive Statistics

In Table 5-2, I provide descriptive statistics for some of the outcome variables and baseline covariates by treatment status. In the table, I also provide OLS regression estimates that test for the difference in these variables between those who have college degrees (treatment group) and those who do not (control group).

Table 5-2 shows that on average, the probability of a female college graduate having at least one child is 0.938; the probability for those who do not have a college degree is 0.958, which only differs by two percentage points. The difference in the number of childbirths between the two groups is 0.231. The differences are statistically significant.

The fact that there are differences in the outcome variables does not imply that the causal effect of education on fertility is negative. As mentioned previously, it is likely that there are many observable and unobservable differences between those who have a college degree and those who do not. This fact is easily seen in Table 5-2. As can be seen from the table, while there are differences in the outcome variables, there are other differences such as the difference in the share of people born in Seoul (6.4 percentage points).

〈Table 5-2〉 Difference in the Baseline Characteristics and Outcome Variables by Treatment Status

Variable	Untreated (A)	Treated (B)	Difference (B－A)	Sample Size
Have children (1＝yes)	0.958	0.938	－0.020*	57,547
	[0.200]	[0.240]	(0.007)	
Total no. of births	1.882	1.651	－0.231***	57,547
	[0.797]	[0.804]	(0.039)	
Age (in years)	37.764	36.509	－1.254***	57,547
	[3.207]	[3.425]	(0.349)	
Born in Seoul (1＝yes)	0.091	0.156	0.064***	57,547
	[0.288]	[0.362]	(0.003)	
Korean (1＝yes)	0.980	0.992	0.011***	57,547
	[0.138]	[0.088]	(0.001)	

Note: Tests of the difference has been conducted using OLS (for the indicator outcome variables, linear probability model has been used). The explanatory variable is a dummy variable indicating college graduates. Observations whose birth year is between 1968 and 1979 are used for the analysis sample. The results rarely change even if the comparison is based on a narrower range of period. The numbers in brackets are standard deviations. The numbers in parentheses are standard errors, clustered at the birth year level (total number of clusters is 12). *** and * indicate statistical significance at the 1% and 10% levels.

The fact that there are differences in these baseline characteristics imply that there are likely to be other confounding factors that affect both the fertility and education level. Hence, even if there are differences in the outcome variables between college degree recipients and those without a degree, we cannot conclude from such results that higher education affects the fertility rate as there are differences in other observable baseline characteristics. If there are differences in observable baseline covariates, then it may also imply that there are differences in unobservable characteristics that confound the relationship between education and fertility.

In sum, researchers need to control for these observable and unobservable differences between the treatment and control groups in order to estimate a causal impact of education on fertility. This study, therefore, exploits the higher education reform implemented in 1993 as an instrument for one's likelihood of receiving a college degree, and conducts an RKD to establish a causal relationship between higher education and fertility.

6 Validity Check for the RKD

Section 1 Kink in the Treatment Variable

Section 2 Tests of Manipulation

Section 3 Kink in Baseline Characteristics

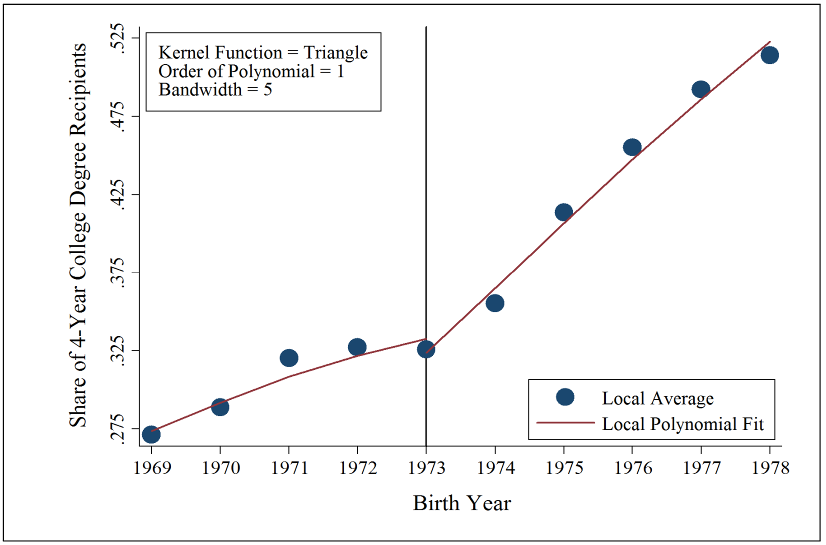
6 Validity Check for the RKD

Section 1. Kink in the Treatment Variable

The use of an RKD in estimating the causal impact of higher education on fertility is conditional on the fact that we observe a statistically and practically significant kink in the probability of receiving a college degree at the cutoff. While Figure 3-1 shows a kink that is visually clear, the figure corresponds to the population data. Moreover, the figure shows the kink in the probability of entering, not graduating, college. In order to determine whether we can exploit the RKD, therefore, I test for the kink in the treatment variable using the 2010 census data.

Panels A and B in Figure 6-1 show the shares of college degree recipients by year of birth. Note that those born after 1973 are likely to have been treated by the reform which was initiated in 1993. As can be seen from both figures, there are visually clear kinks at the cutoff. The share of college graduates increases from 0.275 to 0.325 (only five percentage points) during pre-treatment periods. The share, however, is much higher during post-treatment periods. Over the five-year period, the share increased by more than 20 percent, and the share increased in a rapid manner and continually.

[Figure 6-1] Share of 4-Year College Graduates, by Birth Year



Comparing the figure above with Figure 3-1 indicates the possibility of a significant kink in the share of college graduates at the cutoff. In Table 6-1, I statistically test for the kink in the treatment variable.

〈Table 6-1〉 Tests of Kink in the Treatment Variable

Outcome Variable	Bandwidth (h)		
	$h=4$	$h=5$	$h=6$
College degree (1=yes)	0.031***	0.024***	0.018***
	(0.004)	(0.004)	(0.003)
Sample size	38,521	48,017	57,547

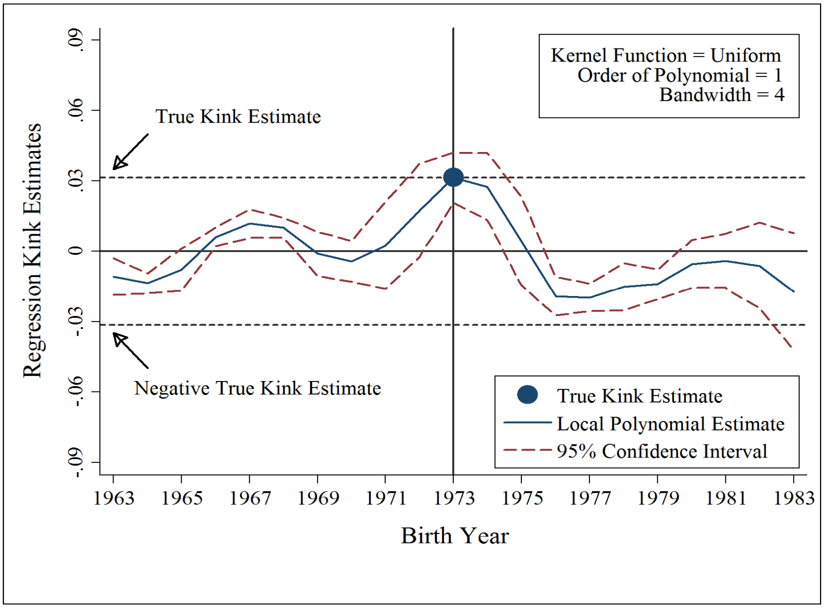
Note: The outcome variable is an indicator for whether a person holds a college degree. The numbers in parentheses are standard errors, clustered at the birth year level (there are 8, 10, and 12 clusters, depending on the bandwidth choice). *** indicates statistical significance at the 1% level.

As can be seen from the table, the regression kink estimates for the treatment variable are all statistically significant regardless of the bandwidth choice. The magnitude of the estimated kink is highest under the bandwidth choice of four.

As a last exercise, I conduct placebo regressions for the probability of receiving a college degree in order to examine whether the estimated kink above is statistically and practically significant. To be more specific, I derive RK estimates at other birth years. Figure 6-2 shows the results of the placebo regressions.

In the figure, the black dot indicates a true RK estimate at the 1973 cutoff. And the figure presents other placebo RK estimates at the other cutoffs. Dashed lines indicate 95 percent confidence interval, and the line corresponds to each RK estimate at each cutoff. As can be seen from the figure, a true RK estimate is the highest in terms of its magnitude. None of the other RK estimates are larger than the true RK estimate. Also, most of the other RK estimates are not statistically significant at the five percent level (i.e., the 95 percent confidence interval encompasses the zero horizontal line). All in all, the placebo regression results signify that the kink observed at the 1973 birth year cutoff is statistically and practically significant, and that such kink is most likely driven by the higher education reform initiated in 1993.

[Figure 6-2] Tests of Statistical and Practical Significance of the Kink in the Treatment Variable

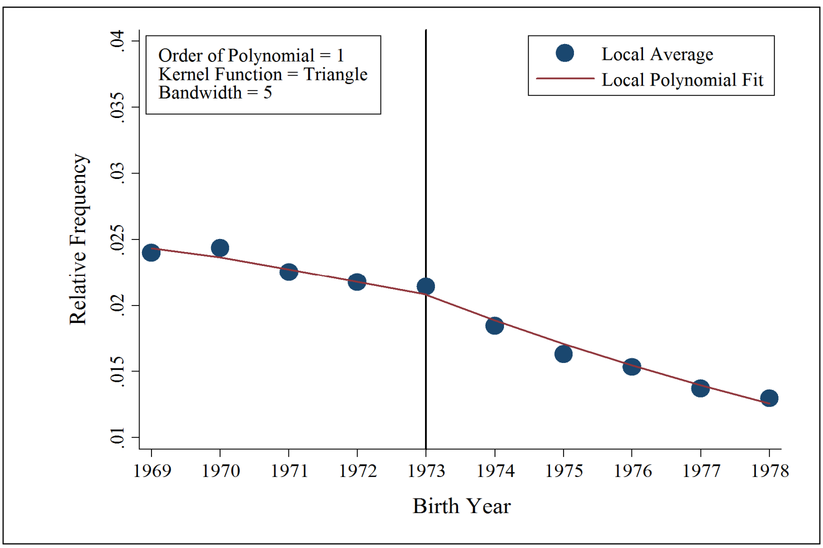


Note: The treatment variable is a dummy variable indicating college graduates. The kink estimate is derived from running a local linear regression using bandwidth of four years. Standard errors are clustered at the birth year level.

Section 2. Tests of Manipulation

One of the identification assumptions required in the context of the RKD is that individuals cannot manipulate an assignment variable. If individuals are able to manipulate, then it is likely that we would not be able to observe a quasi-random variation in the treatment variable. In this study, an assignment variable is one's year of birth, and accordingly, this assumption is reasonable as people cannot control for this. We can also statistically test for such assumption using the data. Many studies use the density test proposed by McCrary (2008). While this method is developed for the purpose of testing the prevalence of manipulation in RD designs, we can modify the test and apply it to the RKD setting. In a nutshell, a modified version of McCrary (2008)'s density test derives RK estimates using the frequency observations as data points.

[Figure 6-3] Density of the Assignment Variable



As is the case in any RDD or RKD application, graphical analyses should precede statistical analyses. Figure 6-3 shows the density of the assignment variable by birth year. The idea behind the density test is that if people can manipulate an assignment variable, then we will see statistically and practically irregular patterns in the density of the variable, especially at the cutoff point. If so, then this casts doubt on the validity of the RKD identification assumption.

Figure 6-3, however, shows no signs of such irregularity in the density of the assignment variable. In particular, we do not observe any kink (i.e., change in slope) at the 1973 cutoff point. This is well expected as people during the 1970s would have been unaware of a future higher education reform. Table 6-2 shows the results from the modified density test. For the bandwidth choice of four, five and six, the estimated kink at the cutoff point is very small; i.e., 0.004, 0.003, and 0.002, respectively. While the kink estimate under the bandwidth choice of six is somewhat statistically significant (i.e., at the 10 percent level), other kink estimates are statistically insignificant at the conventional level.

〈Table 6-2〉 Tests of Manipulation in the Assignment Variable

Variable	Bandwidth (h)		
	$h=4$	$h=5$	$h=6$
Birth year	−0.004	−0.003	−0.002*
	(0.003)	(0.002)	(0.001)
Analysis sample	8	10	12

Note: The numbers in parentheses are robust standard errors. * indicates statistical significance at the 10% level. Kink estimates are derived from conducting a local linear regression recommended by McCrary (2008).

In sum, it is reasonable that in the context of this study, the first identifying assumption is met.

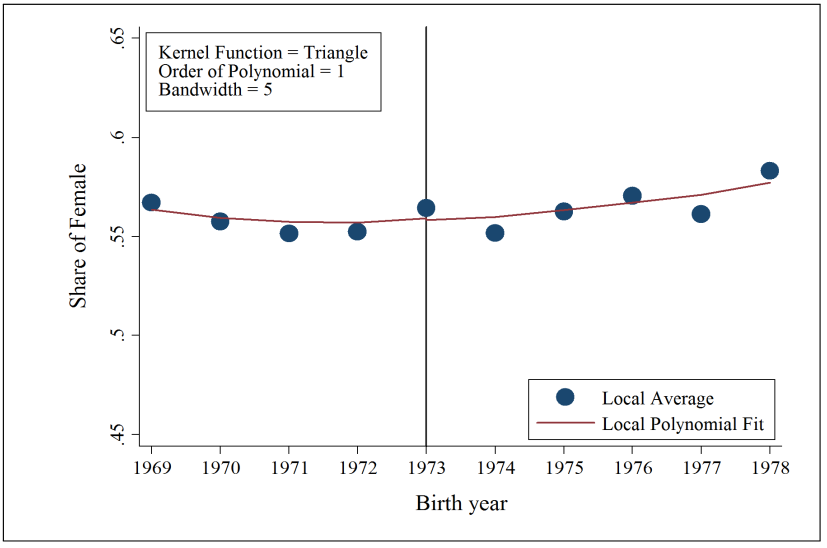
Section 3. Kink in Baseline Characteristics

The other important identifying assumption requires baseline characteristics to be balanced between the treatment and control groups. To put it differently, if baseline characteristics such as the share of people born in Seoulis different between those with a college degree and those without, then it is difficult to convincingly argue that the observed difference in an outcome variable (e.g., fertility level), if any, is driven by the difference in the treatment variable (e.g., college degree).

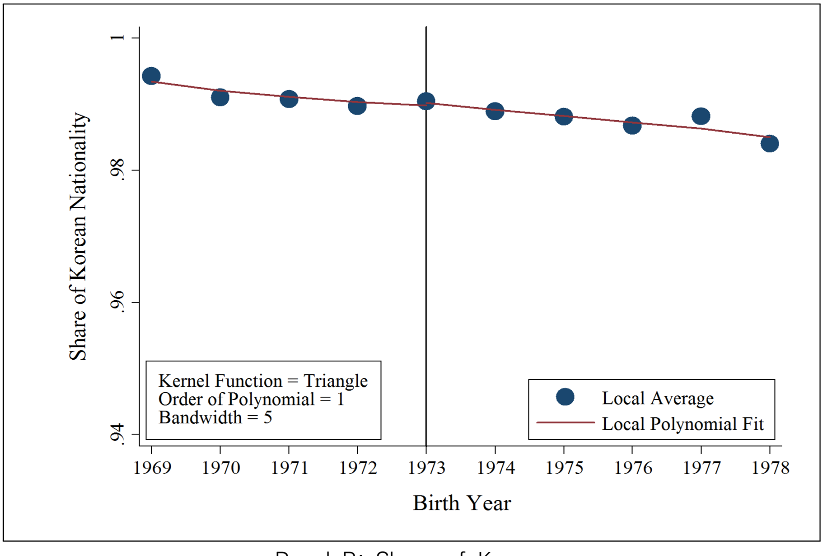
In the context of the RKD, it rules out any statistically significant kink in the baseline characteristics at the cutoff point. In this section, therefore, I test for the kink in baseline covariates available for use in the census data. Specifically, I test for the kink in the following baseline covariates: share of females, nationality, born in Seoul, Gyeonggi-do, whether individuals received their degree or not, and whether one received a college degree conditional on matriculating a college.[5)]

5) For testing the balance in the share of females, I added the male to the analysis sample.

[Figure 6-4] Kink in Predetermined Covariates I



Panel A: Share of Female



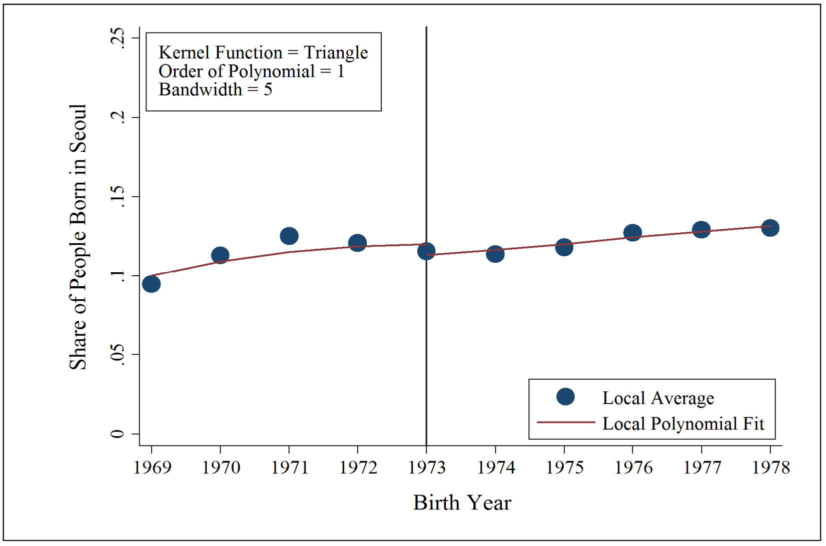
Panel B: Share of Korean

I first show graphical results. Panels A and B in Figure 6-4 correspond to the shares of females and Koreans. As can be seen from the two panels, the share of females and Koreans is smooth across birth years. In addition, we do not observe any significant change in the slope at the 1973 birth year cutoff. The share of females is approximately 57 percent, and is stable over the period being displayed. The share of Koreans is over 99 percent, also stable across years.

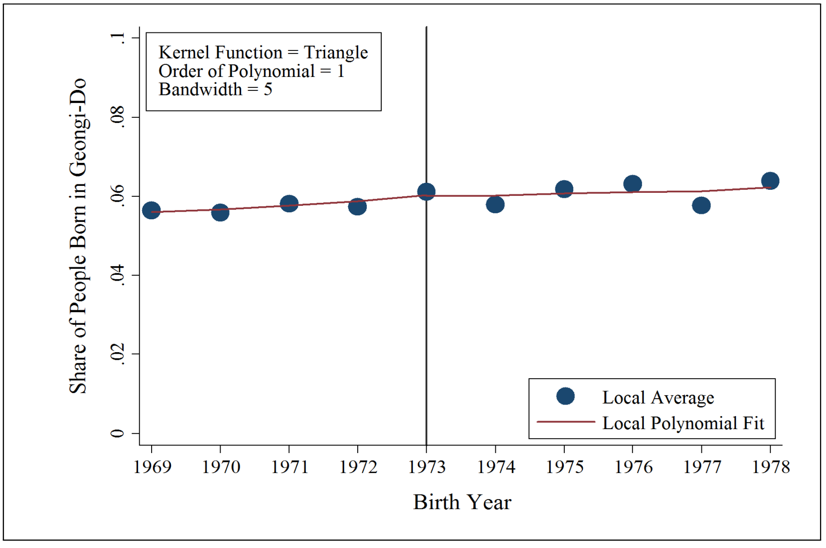
Figure 6-5 presents another two set of predetermined characteristics: the place of birth is either Seoul or Gyeonggi-do. Examining the kink in these two variables is useful for testing for the baseline characteristics of the two groups, as it is likely that those who were born in Seoul or Gyeonggi-do come from more advantageous environments in terms of socio-economic factors.

Panel A of Figure 6-5 shows the share of individuals born in Seoul by the assignment variable. The share is approximately 10 percent, and we do not observe any significant kinks at the cutoff. Furthermore, the magnitude of the share is relatively consistent across years. Panel B on the other hand shows the share of individuals born in Gyeonggi-do. The overall share is slightly lower than for Seoul; approximately six percent. Regardless, the share of individuals born in Gyeonggi-do is stable. Besides, we do not see any shift in the slope at the cut-off point.

[Figure 6-5] Kink in Predetermined Covariates II

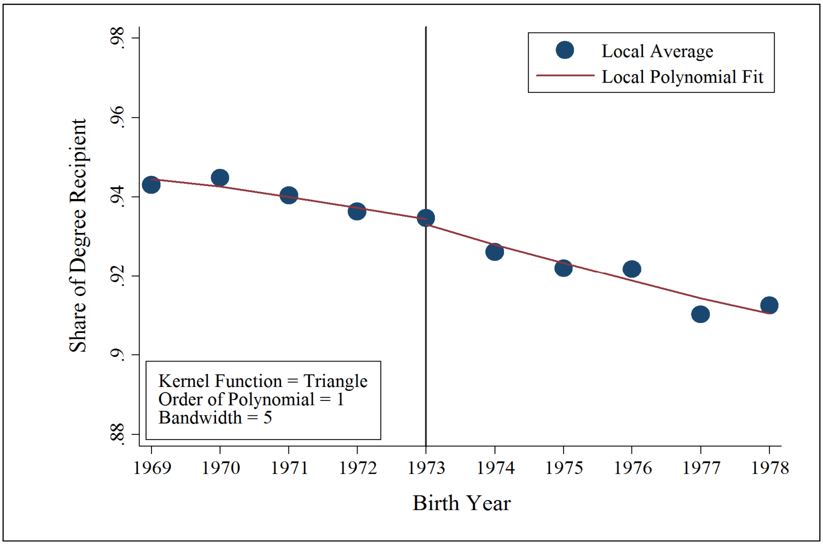


Panel A: Share of Individuals Born in Seoul

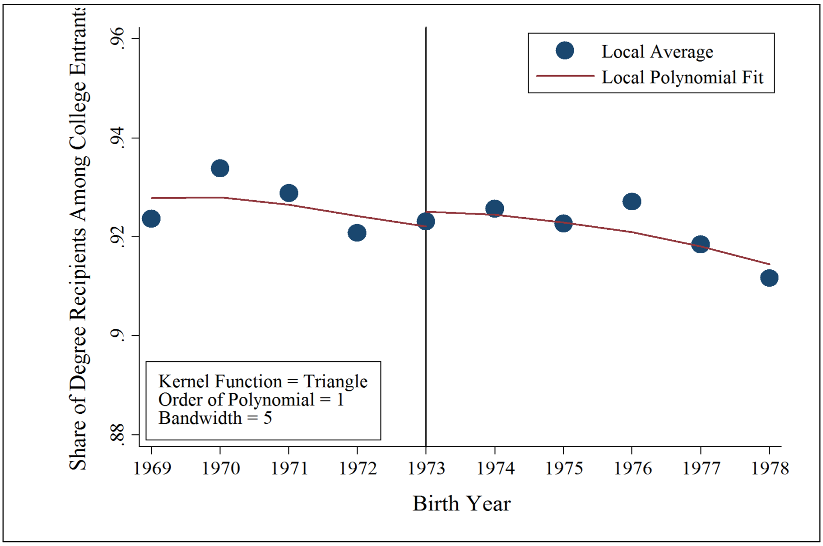


Panel B: Share of Individuals Born in Gyeonggi-Do

[Figure 6-6] Kink in Predetermined Covariates III



Panel A: Share of Degree Recipient



Panel B: Share of College Degree Recipients Among College Entrants

The two panels in Figure 6-6 present the shares of people who received a degree, and the share of college entrants who obtained college degree. The two variables are examined in an effort to determine whether the two groups are different unobservably. Obtaining a degree requires many kinds of factors such as motivation, effort, and other unobservable characteristics. Therefore, if we do see a difference in terms of the two variables mentioned above, it is unlikely that the unobservable characteristics are similar between the two groups.

Panel A displays the share of those who received a degree among all education levels. The mean share is approximately 94 percent for those born before 1974. The mean share of those born in 1974 or later is approximately 93 percent. And no significant kink is observed at the cutoff point. Panel B shows the share of those who received college degrees among those who entered college. There is little difference in the mean shares between the two groups, and again, we do not observe any visually salient kinks at the cutoff point.

In sum, all six figures indicate that there are no kinks that are visually clear at the cutoff point. They point toward the fact that the two groups are comparable in terms of predetermined characteristics. Note, however, that we cannot derive any statistical conclusions from graphical results. In Table 6-3, I present regression kink estimates for the variables examined above.

〈Table 6-3〉 Tests for the Kink in Baseline Characteristics

Outcome Variable	Bandwidth (h)		
	$h=4$	$h=5$	$h=6$
Female (1=yes)	0.001	0.006	0.008**
	(0.004)	(0.004)	(0.003)
Korean (1=yes)	−0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)
Born in Gyeonggi-do (1=yes)	0.001	0.000	0.001
	(0.001)	(0.000)	(0.001)
Born in Seoul (1=yes)	0.006	0.000	−0.001
	(0.003)	(0.003)	(0.002)
Degree (1=yes)	−0.002	−0.003**	−0.002**
	(0.002)	(0.001)	(0.001)
College degree (1=yes)	0.005	−0.002	0.002
	(0.003)	(0.003)	(0.003)
Analysis sample	38,521	48,017	57,547

Note: Each variable analyzed is an indicator variable. The number of observations used for analyzing the "Female," "Degree," and "College degree" variable is 68,988, 40,873, and 13,146 (for $h=4$), 85,569, 50,976, and 16,418 (for $h=5$), 109,721, 61,070, and 19,532 (for $h=6$). The numbers in parentheses are standard errors, clustered at the birth year level (there are 8, 10, and 12 clusters, depending on the bandwidth choice). ** indicates statistical significance at the 5% level.

Two points stand out from the results in Table 6-3. First, as can be expected from graphical analyses, the estimated kinks at the cutoff point are mostly statistically and practically negligible. The results are, therefore, favorable for the identifying assumption of the RKD. While some estimates are statistically significant, the magnitude of the estimates is extremely small, and it is quite likely that the statistical significance is achieved by the precision driven by large sample size and small variance, not because there is imbalance in unobservable characteristics. Note that the results from the density test produce a significant kink in the density of the assignment variable when the choice of bandwidth is six (see Table 6-2). And two estimates are statistically significant in Table 6-2, though all of these estimates are close to zero. Moreover, the estimated kink in the assignment variable is little bit small under the bandwidth choice of six (i.e., 0.018). When analyzing the effect of a college degree on fertility, therefore, we focus on the bandwidth choice of four or five and derive conclusions and policy implications from the results obtained from such choice.

7 Results

7 Results

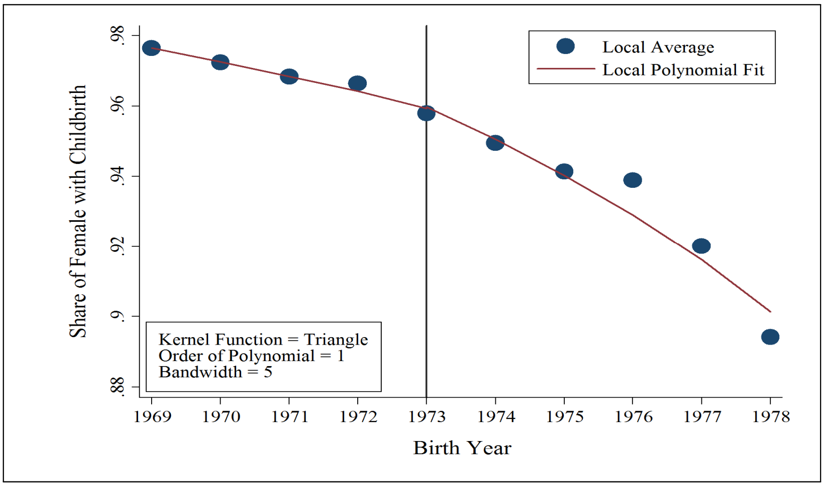
Section 1. Effects of a College Degree on Fertility

In this section, I present the analysis of the effect of a college degree on fertility. Two sets of outcome variables are analyzed for examining the causal impact of college degrees on fertility. The first outcome is an indicator variable that is equal to one, if a female has given birth, and zero, if not.

Figure 7-1 shows the graphical result. The share of females born in 1969, who have given birth, is almost 98 percent. The share continues to decline until 1978. One thing to emphasize regarding the observed trend is that this decline is driven by aging. That is, younger generation is less likely to give birth than older generation. Note, however, the degree of the slope observed for both groups is quite different. While the slope observed for the control group (i.e., those born in 1973 or before) is relatively flat and barely negative, the slope observed for the treated group is relatively steep and more negative. The RKD used in this study makes use of this slope change to estimte the treatment impact.

Interestingly, the observed pattern in Figure 7-1 is very similar to the pattern observed in Figure 6-1. Specifically, we observe an opposite pattern in Figure 6-1. In Figure 6-1, the slope observed for the share of college graduates is relatively flat during the pre-treatment period. The slope observed for the post-treatment period, however, is steep and positive.

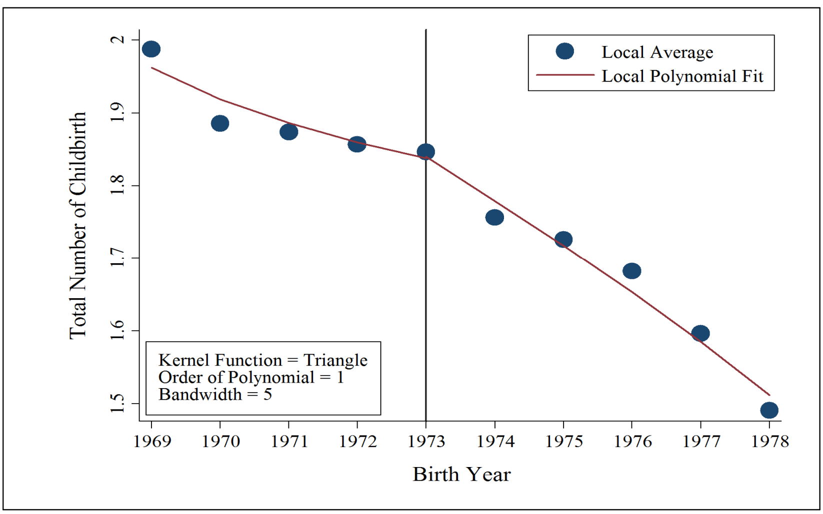
[Figure 7-1] Share of Females Who Have Given Birth, by Birth Year



In Figure 7-2, I present graphical results for the other outcome variable: the total number of female childbirths. Again, the pattern observed for the number of childbirths is quite similar to that observed in Figure 6-1.

Hence, the graphical results in Figures 7-1 and 7-2 indicate that the patterns of the treatment and outcome variables are closely and negatively related. That is, it seems that a college degree is negatively associated with the fertility rate. To get a sense of the extent to which a college degree influences fertility, I conduct a fuzzy regression kink analysis to estimate the causal impact. As explained in Section 2 of Chapter 4, this requires estimating the two conditional functions; one for the treatment variable and the other for the outcome variable. And the fuzzy RKD estimand is obtained by estimating the slope change in the outcome variable which is scaled up by the slope change in the treatment variable. Table 7-1 presents the results of the fuzzy RKD method.

[Figure 7-2] Total Number of Childbirths, by Birth Year



In Table 7-1, I present the RKD estimates separately by gender. As explained in Section 3 of Chapter 4, standard errors are clustered at the birth year level. Panel A presents the results for the female sample. The estimated effect of a college degree on the probability of giving birth is 0.138 under the bandwidth choice of four and 0.319 under the bandwidth choice of five.

The estimates are statistically significant at the 5 and 1 percent levels. Therefore, compared with those who do not have a college degree, the probability of a female giving birth is, on average, 0.228 lower for those who have college degrees.

〈Table 7-1〉 Effects of College Degree on Fertility: Fuzzy RK Estimates

Outcome Variable	Bandwidth (h)		Mean of Estimates
	$h=4$	$h=5$	
Given birth (1=yes)	−0.138**	−0.319***	−0.228
	(0.056)	(0.121)	
Total number of births	−1.347***	−1.293***	−1.320
	(0.326)	(0.478)	
Sample size	38,521	48,017	

Note: The numbers in parentheses are standard errors, clustered at the birth year level (there are 8 or 10 clusters, depending on the bandwidth choice). *** and ** indicate statistical significance at the 1% and 5% levels.

The estimated effect of a college degree on the total number of births is −1.347 and −1.293, both of which are statistically significant at the 1 percent level. So, on average, females with a college degree have about 1.34 children less than those without a college degree.

All in all, it seems that college degree reduces fertility

Section 2. Identifying the Mechanisms

The regression kink estimates derived in the previous section indicate that a college degree reduces the fertility rate. Note that merely deriving the causal impact of a college degree on fertility provides few policy implications unless one speaks to the underlying mechanisms that induce the causal channel between a college degree and fertility. In Section 1 of Chapter 2, I presented the leading theories that address why education is related to fertility. While testing for each of these theories is difficult because of data availability, I examine some of the theories that can be tested for using the census data, in an effort to shed light on the causal mechanisms.

Table 7-2 presents the regression kink estimates for the potential mechanism variables. The estimation method used in deriving such estimates is the same as the one we used for estimating the effect of education on fertility. The only difference here is that the outcome variable (i.e., fertility) is replaced with other possible moderating variables, so that the estimated regression kink estimates reflect the effect of a college degree.

The first set of moderating variables is intended to test for the labor market theory. According to the labor market theory, education increases earning capacity and thereby generates substitution and income effects. And depending on the relative magnitude of the two effects, education may increase or reduce fertility. To test whether education affects females' labor market-related status, I estimate the effect of a college degree on three outcomes: unemployment status, whether a person is a wage earner, and whether a person has a professional occupation, e.g., lawyer.

〈Table 7-2〉 The Effects of College Degree on Possible Moderating Variables (Mechanisms): Fuzzy RK Estimates

Outcome Variable	Bandwidth (h)		Mean of Estimates
	$h=4$	$h=5$	
Unemployed (1=yes)	−0.151**	−0.220***	−0.185
	(0.067)	(0.051)	
Wager earners (1=yes)	0.211**	0.482***	0.346
	(0.090)	(0.186)	
Professional occupation (1=yes)	0.143*	0.226***	0.184
	(0.079)	(0.076)	
Married (1=yes)	−0.026	−0.099**	−0.062
	(0.037)	(0.044)	
Age at first marriage is 35 or higher (1=yes)	−0.151***	−0.205***	−0.178
	(0.037)	(0.072)	
Spouse's education level is equal or higher (1=yes)	−0.223***	−0.178**	−0.200
	(0.067)	(0.075)	
Sample size	38,521	48,017	

Note: The numbers in parentheses are standard errors, clustered at the birth year level (there are 8 or 10 clusters, depending on the bandwidth choice). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

According to the estimated results, a college degree reduces the likelihood of being unemployed. The estimated effect is, on average, −0.185, indicating that the unemployment rate is higher for females who do not have a college degree. In terms of the opportunity cost, therefore, it is reasonable that college degree increases the opportunity cost of fertility.

Regarding the effect of a college degree on one's likelihood of becoming a wage earner, female college graduates are, on average, 34.6 percentage points more likely to be wage earners.

The result is reasonable because in Korea, most males are wage earners, regardless of whether one holds a college degree. For females, however, it is more likely for a college graduate to enter the labor market compared with those without a degree. And that is why we observe a positive impact of a college degree on a female's likelihood of being a wage earner. Hence, a college degree is more likely to affect a female's earning capacity.

A college degree also has an impact on a female's occupation. It is estimated that female college graduates are about 18.4 percentage points more likely to have a professional occupation compared with those without a college degree. In Korea, while exact numbers are not available, the overall wage level of a professional occupation is relatively higher than that of other occupations. Having a professional occupation is likely to increase the earning capacity. Thus, it is likely that a college degree will affect a female's opportunity cost of fertility.

Note that from the estimated effects above, it is difficult to draw conclusions regarding the relative size of substitution and income effects induced by college degrees. But because the effect of college degrees on fertility is negative, and a college degree raises the earning capacity, I argue that substitution effects are larger than income effects, which coincides with the conclusion provided by Becker and Lewis (1973).

The next possible mechanism I test for is marriage market-related variables. Specifically, I test whether a college degree influences one's marriage status and the probability of getting married later in life. First, contrary to the belief that education negatively affects a female's marital status, the estimated effect of a college degree on the probability of being married is practically small; 0.062, on average. Second, I find that a college degree in fact reduces the probability of being a late marriage. Here, the late marriage is defined as those whose age at first marriage is equal to or greater than 35. For female college graduates, the probability of getting married late is 17.8 percentage points lower than those without a college degree. Typically, Korea's high educational level have been regarded as one of the culprits that induce late marriage. I do not, however, find this to be the case; it reduces the probability of getting married late.

The last causal channel that I examine is related to the assortative mating theory. The theory predicts that individuals with a college degree are more likely to choose spouses with a similar or higher level of education. In order to test such theory, I create an indicator variable which is equal to one if a spouse's education level is equal to or higher than the individual. The results show that the estimated difference in the probability that a spouse's education level is equal or higher is 0.200. To put in context, the results imply that, in Korea, females with a college degree are less likely to choose a spouse with an equal or higher level of education. At least in Korea, therefore, the data do not support the assortative mating theory, and I argue that the estimated negative effect of a college degree on fertility is not driven mainly by the assortative mating behavior.

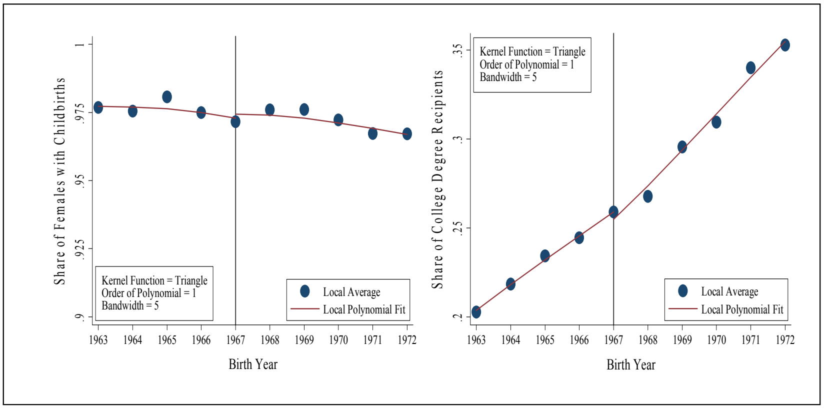
Section 3. Robustness Check: Placebo Tests

To examine the robustness of the findings regarding the relationship between college degrees and fertility, I conduct placebo tests in this section. If the estimated effects we observed at the 1973 year cutoff can convincingly be attributed to the effect of a college degree on fertility, we should not observe such effects when we apply the same method to the pre-treatment periods. If we observe similar significant effects from such placebo tests, this calls into question whether the true observed effects indeed reflect treatment effects. To examine the issue at hand, I create a placebo cutoff at six and ten years before the true cutoff, and examine whether we observe similar kinks. Figure 7-3 presents graphical results.

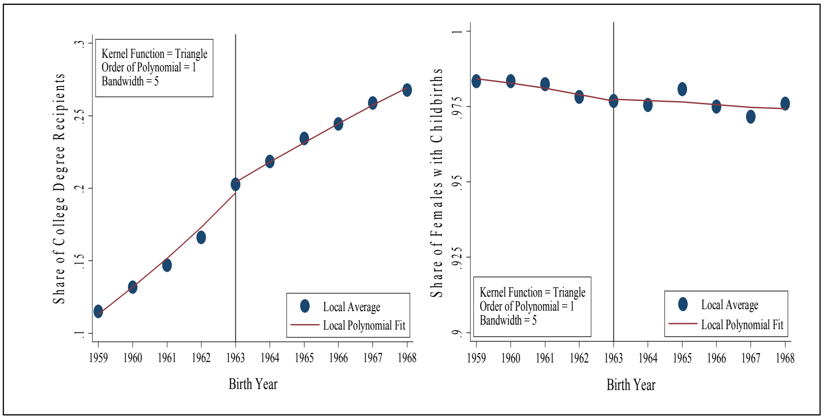
In Panel A of Figure 7-3, the placebo cutoff is set at the 1967 birth year. As can be seen from the panel, there are no visually significant kinks observed for either the share of college degree recipients or the share of females with childbirths. In Panel B, the placebo cutoff is set at the 1963 birth year. Again, we do not observe any visually clear kinks in either of the variables.

Hence, the graphical results for the placebo cutoffs support the results.

[Figure 7-3] Placebo Cutoffs: 6 and 10 Years Before the True Cutoff



Panel A: Cutoff = 1967



Panel B: Cutoff = 1963

Table 7-3 presents statistical results obtained for placebo tests. In the table, I present the fuzzy regression kink estimates that reflect the effect of a college degree on the likelihood of having a child that is obtained from using other birth years as placebo cutoffs.

〈Table 7-3〉 Placebo Tests: Fuzzy Regression Kink Estimates

Placebo Birth Year Cutoff	Bandwidth (h)	
	$h=4$	$h=5$
Birth year =1964	−0.070	−0.178
	(0.096)	(0.110)
	[53,770]	[68,034]
Birth year =1965	0.067	−0.045
	(0.214)	(0.170)
	[52,693]	[66,779]
Birth year =1966	−0.053	−11.028
	(0.382)	(390.047)
	[51,792]	[65,803]
Birth year =1967	−0.062	−0.174
	(0.196)	(0.139)
	[50,901]	[63,408]

Notes: The numbers in brackets are the sample size. The numbers in parentheses are standard errors, clustered at the birth year level (there are 8 or 10 clusters, depending on the bandwidth choice).

The estimated results all support the true observed estimates in Table 7-1. There is one significantly large estimate observed for the 1966 birth year cutoff under the bandwidth choice of five (i.e., −11.028), though the estimate is not statistically significant. Note that the RKD estimand is obtained by dividing the slope change in an outcome variable by the slope change in a treatment variable. And because the slope change in the treatment variable is almost zero for the 1966 birth year cutoff under the bandwidth choice of five, the small slope change observed for the outcome variable resulted in a very large point estimate. Nevertheless, most of the placebo effects are practically and statistically insignificant, and accordingly, I argue that the placebo test results support the conclusion that college degree reduces fertility.

8 Discussion and Conclusions

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Section 1. Discussion

Application of the RKD shows that, on average, college education reduces the probability of childbirth by 22.8 percentage points for females. This study also finds that a college degree reduces the total number of births by 1.3. It is reasonable to conclude that a college degree reduces the probability of childbirth, in general.

The magnitude of the findings above coincides with previous literature that estimates the causal impact of education on fertility. While the exact size of the estimated effects presented in previous literature vary to some extent, most studies find that, on average, one year of education reduces fertility by 0.3. This study compares individuals who have four-year college degrees with those who have high school or lower degrees. The estimated impact in this study is slightly higher than those presented in previous studies. This is reasonable, as this study takes into account the sheepskin effect. Moreover, this research examines the effect of higher education, so the size of the impact is likely to be different from those observed for the lower tail of the education levels.

Provided that a college degree reduces fertility, it is important to identify, from a policy perspective, the factors that drive such effects (i.e., mechanisms). This study analyzes the possible mechanisms that channel the relationship between the two variables in an effort to derive policy implications.

One possible mechanism found from the analysis is that a college degree affects labor market-related outcomes of females. In particular, I find that a college degree reduces the likelihood of being unemployed. Furthermore, a female college graduate is more likely to be a wage earner and is more likely to have a professional occupation than those with only a high school degree. This implies that a college degree increases the earning capacity of females, thereby increasing the opportunity cost of fertility.

From a policy perspective, therefore, I argue that governments should focus more on reducing or eliminating the opportunity costs of fertility faced by females that are most likely to be induced by the increase in the earning capacity, if it were to increase fertility rates or at least to stop any further decline.

To fulfill such goal, it is necessary to investigate the opportunity costs of fertility that are created by such increase in the earning capacity. Income may not be the only opportunity cost. Unfortunately, this study does not shed light on non-income-related aspect and therefore future research should be directed at identifying such opportunity costs of fertility induced by the increase in the earning capacity of females so that relevant policy alternatives can be developed and implemented to reduce such costs.

External validity of the research should also be discussed. While the effect estimates based on quasi-random variation may provide an estimate that is internally valid, that doesn't mean that such estimate is externally valid. This study basically uses the cohorts who are born between 1969 to 1978. The results obtained for these cohorts may not be applicable to other recent cohorts such as those who are born after 1979. Thus, the results of this study should be interpreted with this limitation in mind.

Another limitation of this study is the use of cohorts who are not considered to have reached childbearing years. The childbearing years are not unanimously agreed upon by researchers; female whose age is between 45 to 49 is normally considered as having reached the childbearing years. Because the cohorts that are analyzed in this study are those whose age is between 32 to 41, the estimated results may be different if cohorts who reached the childbearing years are used for the analysis. So the results should also be accounted for with this important limitation.

Section 2. Conclusions

Using the higher education reform initiated in 1993 as an exogenous variation for the probability of holding a college degree, I apply the RKD to estimate a causal impact of a college degree on fertility as well as to identify possible mechanisms that channel the relationship between college degrees and fertility. The results show that, on average, college degrees reduce fertility rates. Specifically, it reduces the likelihood of childbirths by 0.228 and the total number of childbirths by 1.320.

An analysis of the possible mechanisms shows that one significant channel that drives the negative effects of a college degree on fertility is through labor markets. It is estimated that a college degree increases the earning capacity of females, in particular; compared with a high school graduate, a female college graduate is more likely to be a wage earner and also more likely to have a professional occupation, and less likely to be unemployed. I argue, therefore, that government policies should be directed more toward reducing opportunity costs of fertility induced by the increase in earning capacity.

Note, however, that there are other possible channels through which a college degree affects fertility. This study, for example, finds that a college degree does not induce individuals to marry late. Rather, it reduces this probability (defined as those whose first marriage is at age 35 or older). Hence, I argue that a college degree is not detrimental to fertility in that it reduces the instance of getting married late.

With today's high educational levels, a decline in the fertility rate may be inevitable. But as many people agree, high educational level is extremely valuable for any society, in general (e.g., reductions in crime rates and governmental dependency). From the policy perspective, therefore, measures to decrease such high educational levels should ‘never’ be adopted. Then is the decline in the fertility rate is a phenomenon that cannot be resolved? This study sheds light on possible policy measures that may be helpful for relieving such a trend such as by eliminating the increase in the opportunity cost induced by high educational levels. Future studies, therefore, should engage more into investigating the possible mechanisms inherent in the education-fertility relationship. After investigating the mechanisms inherent in the relationship, policy measures should be directed more toward such mechanisms.

In addition to identifying the possible mechanisms, analyzing the causal impact of existing policies intended to counterattack the decline in fertility rates is valued. At this point, the Korean government has adopted many programs intended to resolve this problem. To my knowledge, however, research that analyzes the “causal” impact of such programs on fertility is rare. Analyzing the causal impact of such programs would help identify the programs that work and those that do not. Moreover, such an effort is extremely valuable for developing new policies and for increasing the efficacy of existing programs. I therefore hope that future research puts more effort into analyzing the causal impact of many of these fertility-related programs. One last thing to note is that this paper does not necessarily imply that existing policies aimed at promoting fertility are ineffective. This paper emphasizes that more efforts may be helpful for raising the fertility level, if more resources are devoted to mitigating the opportunity costs of women with respect to labor market.

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Chapter 6. Validity Check for RKD

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Chapter 7. Results

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