Nonparametric Bounds Analysis of Intergenerational Transmission of Human Capital in Korea

Joonhong Ahn*

University of Missouri, Columbia

Abstract

This study estimates the average causal effects of parents' educational attainment on the educational attainment of children in Korea using a new method, the nonparametric bounds approach. This approach does not require the assumption of homogeneous and linear effects of parental schooling. It also uses relatively weaker assumptions, monotone treatment response and monotone treatment selection, than assumption underlying other methods and is more amenable to testing. With the additional assumption of monotone instrumental variables, it provides the tightest bounds on the average treatment effects (ATE) that an increase in parents' education increases children's educational success. It also shows the effects are overestimated in simple regression models.

*Department of Economics, University of Missouri, Columbia, 118 Professional Building, Columbia, Missouri 65211, joonhong.ahn@mail.missouri.edu.

1 Introduction

Parents' schooling level is one of the most important determinants of children's educational outcomes. An extensive empirical literature has examined the association between parental education and children's schooling. Haveman and Wolfe (1995) and Black and Devereux (2011) review the relevant studies and confirm that parents' schooling is positively related to children's educational outcomes in different surveys of the U.S. Blanden et al. (2007) and Grönqvist et al. (2017) find that parent's cognitive and noncognitive abilities are positively related to a child's labor market outcomes. However, the positive relationships that are observed are not necessarily causal because unobserved characteristics such as genetic endowments, acquired personal characteristics, and acquired abilities may underlie observed relationships (Holmlund et al., 2011).

There have been a variety of approaches used to estimate the causal effects of parental education. One approach uses an adoptee sample in order to remove the genetic factors shared by parents and their birth children in estimating intergenerational schooling effects (Björklund et al., 2006; Sacerdote, 2007). A second identification strategy uses a sample of identical twins (Behrman and Rosenzweig, 2002; Bingley et al., 2009), allowing a model of the process of attainment for individuals who have the same genetic makeup. Another method is the use of instrumental variables, taking advantage of a change in the environment such as that due to compulsory schooling reform, a change in university admission policy, or college tuition (Black et al., 2005; Oreopoulos et al., 2006; Maurin and McNally, 2008; Carneiro et al., 2013). However, the findings of these studies do not reach a consensus on the effects of parental education. Some studies suggest large positive effects of a father's schooling, but other studies find that a mother's schooling has significant impacts on a child's educational attainment whereas father's education has minimal effects.

Holmlund et al. (2011) give an overview of the relevant empirical literature on intergenerational causal schooling effects and present estimates of causal impacts with these three identification specifications using Swedish registry data to verify the reason for different results. They point out that estimates differ because of differences between datasets and differences in empirical methods. The estimates using families of adoptees and twins represent the effects of parental schooling in a subpopulation rather than representing the whole population. The instrumental variables approach relies on satisfying the requirements of an instrument to estimate the causal effects. If an instrument violates the requirements, the estimates may not be consistent. They find that the differences in estimates across the three methods using Swedish data are not as big as between other studies, although the estimates are consistent with patterns of results in other studies. Holmlund et al. (2011) also conclude that the causal effects of parental education represent a small part of the determinants of a child's schooling in Sweden, although parental schooling plays a substantial role in a child's success in school in the reviewed studies. In other words, parental schooling is associated with children's outcomes because of parents' experience and parenting skills, not primarily through causal channels.

This article applies an alternative empirical method, the nonparametric bounds approach, to identify the intergenerational causal relation using Korean data, following from the work of Manski (1989, 1990, 1997), and Manski and Pepper (2000, 2009). A detailed empirical explication of the method is provided in the next section. There are two important advantages of using this method. The method provides the bounds on the average treatment effects by imposing nonparametric assumptions, in particular monotone treatment response, monotone treatment selection, and monotone instrumental variables. It does not require the assumption of homogeneous effects of parental schooling. Another advantage is that the nonparametric assumptions are relatively weaker than assumption underlying other methods and are more amenable to testing.

There are many recent studies applying the nonparametric bounds approach to obtain bounds on average treatment effects, most of them focused on the economic return to skills (Lechner, 1999; Pepper, 2000; Gonzalez, 2005; de Haan, 2011; Giustinelli, 2011; Gundersen et al., 2012; Kang, 2014; Hof, 2014; Okumura and Usui, 2014; Kikuchi, 2017). Closely paralleling the work here, de Haan (2011) applies the nonparametric bounds approach to identify the true average treatment effect of parents' educational levels on the child's years of schooling using U.S. data. She obtains bounds implying that an increase in both fathers' and mothers' educational level have positive impacts on children's educational outcomes. Also, she finds that the lower bounds are significantly greater than zero, and the least upper bounds are substantially lower than the OLS results. Kikuchi (2017) uses the nonparametric bounds approach to analyze the causal effects of the intergenerational schooling effects in Japan. His findings with Japanese data are consistent with those of de Haan.

The educational structure in Korea has changed substantially with economic growth over the last several decades. The proportion attending college has increased drastically since the beginning of the 1990s, and so there is a substantial difference between parents' and children's average educational attainment. According to Ministry of Education (2008), only 27% of high school graduates attended a college in 1980, but the attendance rate of college has been around 85% since 2000. Looking at recent entrants into the labor market, the low college attendance rate in their parents' generation suggests that factors other than parental education may be more important in leading their children to attend a college. More generally, insofar as parents guide their children according to their own experiences in a particular level of schooling, if parents who attend college are able to prepare their children for college, we might expect that effects would be weaker in an environment with large differences in educational achievement between parents and children. As a result, the intergenerational transmission of education may show different patterns than in western countries where children's educational achievements are more similar to those of their parents.

Most studies of intergenerational status transmission in Korea have focused on the effects of parents' income or wealth on economic outcomes of children (Kim, 2009; Ueda, 2013; Ma and Kwon, 2013; Richey and Jeong, 2014; Lee, 2014; Kang, 2014; Kim, 2017) or parents' educational investment in children (Lee, 2008; Kang, 2011) rather than the educational transmission process itself (Nam, 2008; Kim, 2015). Nam (2008) finds a strong positive association between parents' and children's education in Korea, a relationship that is much stronger than in the central and western European countries (Iannelli, 2002). These empirical studies, however, have focus on the zero-order relationship between parents' and children's education but have not considered the causal effects of parental education.

Using the nonparametric bounds approach, we find that the estimated tightest bounds on the average treatment effects are informative. We estimate lower bounds that are significantly different from zero and upper bounds that are less than the OLS estimates. These are consistent with findings for the U.S. and for Japan (de Haan, 2011; Kikuchi, 2017).

The remainder of this study is organized as follows: Section 2 presents the detailed empirical specification. Section 3 describes the Korean Labor and Income Panel Study (KLIPS) dataset, which is used in this study. We discuss the results in section 4. Section 5 summarizes and concludes.

2 Empirical Specification

To identify the causal intergenerational effects of education, this study uses a nonparametric bounds approach developed by Manski (1989, 1990, 1997) and Manski and Pepper (2000). We assume there is a function $y_j(\cdot) : T \to Y$ that maps the parental education level t into education of child j. j is contained in population J. Also, we assume that children's education, y and the treatment set T is an ordered set. Following de Haan (2011) and Kikuchi (2017), we take either years of schooling or college completion of a child as the dependent variable, so I denote $y_j \equiv y_j(z_j)$ as a child's outcome with a parent's realized completed schooling, z_j and $y_j(t)$ as the counterfactual that cannot be observed if a parent has a schooling level, $z_j \neq t$. Also, y_{min} (y_{max}) represents the lowest (greatest) value of a child's educational outcome. In the analysis examining years of education, the minimum is 8 years and the maximum is 16 years, and in the analysis examining college graduation, coded on the 0-1 scale. I will drop the subscript j from here to simplify notation.

The main interest in this analysis is the average treatment effect (ATE) with an increase in parent schooling from t_1 to t_2 ($t_1 \leq t_2$), that is,[1]

$$\Delta(t_2, t_1) \equiv E[y(t_2)] - E[y(t_1)]. \tag{1}$$

This provides the ATE of increasing a parent's schooling level from t_1 to t_2, averaged across all individuals in the sample. One approach to identifying this latent outcome is to assume exogenous treatment selection (ETS), meaning that y is mean independent of z, observed parental schooling level. In our example, assuming observable measures x were controlled, the relevant conditional independence assumption would be written $E[y(t)|x] = E[y(t)|z = t_1, x] = E[y(t)|z = t_2, x]$, implying that the mean child's educational outcome would be the same if parental educational levels were equalized, controlling for measured characteristic x.

This may not be appropriate to identify the intergenerational causal educational relationship, although this assumption can be valid in a particular model of a structure.

[1] Equations (1) and (2) are adapted from equations (1) and (2) in de Haan (2011). In addition to, equation (2) corresponds to equation (1) in Manski (1989).

Manski (1989, 1990, 1997) and Manski and Pepper (2000) suggests estimating the average treatment effect without imposing the ETS assumption. By imposing weaker and testable assumptions, this approach allows us to look at the more reliable average treatment effects.

2.1 No Assumption Bounds

Manski (1989, 1990) proposes an analysis method of treatment response that can identify bounds on treatment effects without imposing any assumptions if the support of a dependent variable is bounded. In our analysis, the dependent variable is either a child's years of schooling or college completion. The dependent variable is bounded between $[y_{min}, y_{max}]$, where obviously $y_{min} < y_{max}$. To build the basic bounds on $E[y(t)]$, we can expand $E[y(t)]$ using the law of iterated expectations and the fact that $E[y(t)|z = t] = E[y|z = t]$:

$$E[y(t)] = E[y|z = t] \cdot P(z = t) + E[y(t)|z \neq t] \cdot P(z \neq t). \tag{2}$$

With the data set this study uses, we can observe $E[y|z = t]$, $P(z = t)$, and $P(z \neq t)$. An issue is that we cannot observe $E[y(t)|z \neq t]$. Because y must be in a range of $[y_{min}, y_{max}]$, $E[y|z \neq t]$ also should be bounded by $[y_{min}, y_{max}]$: $y_{min} \leq E[y|z \neq t] \leq y_{max}$.

We can derive the bounds of $E[y(t)]$ by replacing $E[y|z \neq t]$ in equation (2) with y_{min} to obtain a lower bound and by replacing $E[y|z \neq t]$ with y_{max} to obtain a upper bound. Using these values, Manski (1989, 1990) derives "no assumption" bounds:

$$
\begin{aligned}
&E[y|z=t]\cdot P(z=t)+y_{min}\cdot P(z\neq t)\\
&\leq E[y(t)] \leq \qquad (3)\\
&E[y|z=t]\cdot P(z=t)+y_{max}\cdot P(z\neq t).
\end{aligned}
$$

The no-assumption bounds on $E[y(t)]$ allow us to calculate the bounds on the average treatment effect (ATE), $\Delta(t_2, t_1)$, by subtracting a upper(lower) bound of $E[y(t_1)]$ from a lower(upper) bound of $E[y(t_2)]$. The no-assumption bounds on ATE are:[2]

$$
\begin{aligned}
&E[y|z=t_2]\cdot P(z=t_2)+y_{min}\cdot P(z\neq t_2)-\{E[y|z=t_1]\cdot P(z=t_1)+y_{max}\cdot P(z\neq t_1)\}\\
&\leq \Delta(t_2,t_1) \leq \qquad (4)\\
&E[y|z=t_2]\cdot P(z=t_2)+y_{max}\cdot P(z\neq t_2)-\{E[y|z=t_1]\cdot P(z=t_1)+y_{min}\cdot P(z\neq t_1)\}.
\end{aligned}
$$

Although no-assumption bounds are meaningful to identify bounds on $E[y(t)]$, these are generally not informative. Imposing some weak assumptions on the no-assumption bounds can tighten the bounds and provide informative results: I will consider (1) monotone treatment response (MTR), (2) monotone treatment selection (MTS), and (3) monotone instrumental variables (MIV).

2.2 Monotone Treatment Response

Manski (1997) and Manski and Pepper (2000) introduce MTR and MTS assump-

[2] This equation (4) is taken from an equation on page 4 in Kikuchi (2017), and an error has been corrected.

tions. In this paper, we apply that the MTR assumption, implying that outcomes are weakly increasing in a parent's education. The MTR assumption is:

$$t_1 \leq t_2 \;\;\Rightarrow\;\; y(t_1) \leq y(t_2). \tag{5}$$

Equation (5) assumes that child's educational outcomes (either years of schooling or college completion) are an increasing function of a parent's. This assumption is consistent with models based on human capital theory, which posits a positive relationship between parents' and children's schooling (Becker and Tomes, 1979, 1986; Solon, 1999). Parental education could be transmitted to children through several channels, as more educated parents are more likely to invest in educational environments and create an educational atmosphere for a child than those who have less education. Empirically, we observe a strong association between parents' and children's education. However, it does not allow us to conclude that parental schooling has causal impacts on the child's outcomes due to the selection problem. It is for this reason that the MTR assumption does not rule out a zero effect.

To tighten the no assumption bounds using the MTR assumption, children in the sample can be divided to three groups: (1) children who have a parent with realized schooling level below t ($z < t$), (2) children who have a parent with schooling level t ($z = t$), and (3) children who have a parent with realized schooling level greater than t ($z > t$). This relationship is:[3]

[3] The approach presented here was first developed in Manski (1997).

$$
\begin{aligned}
t < z \quad &\Rightarrow \quad y_{min} \leq y(t) \leq y \\
t = z \quad &\Rightarrow \quad \quad y(t) = y \\
t > z \quad &\Rightarrow \quad y \leq y(t) \leq y_{max}.
\end{aligned} \tag{6}
$$

The outcomes $y(t)$ for $z > t$ and $z < t$ are counterfactuals, and so are not observed. $y(t)$ for $z = t$ is the value of the educational outcome observed for parents with education level z. To obtain more informative bounds, we need to consider what children's education would have been for values of parents' education that are not observed. MTR implies that for $z < t$ the observed mean educational outcome of a child with a parent who has actual schooling level z is greater than the mean outcome a child would have had if a parent had the educational level t. The child's observed mean educational outcome can be used to tighten the upper bound. We already know that the mean educational outcome of a child is the same when a parent has an educational level of $z = t$. For $t > z$, when a parent's actual schooling level z is less than schooling level t, it is certain that a child's observed mean educational outcome would be less than a child with a parent who has educational attainment $z = t$. The observed mean educational outcome of a child when a parent has schooling level z can tighten the lower bound. A combination of the no assumption bounds and the MTR assumption provides (equation (5) in de Haan (2011)):

$$
\begin{gathered}
E[y|z < t] \cdot P(z < t) + E[y|z = t] \cdot P(z = t) + y_{min} \cdot P(z > t) \\
\leq E[y(t)] \leq \\
y_{max} \cdot P(z < t) + E[y|z = t] \cdot P(z = t) + E[y|z > t] \cdot P(z > t).
\end{gathered} \tag{7}
$$

2.3 Monotone Treatment Selection

The next assumption imposed in our analysis is the monotone treatment selection (MTS) assumption (Manski and Pepper, 2000). The MTS assumption is:

$$\begin{gathered} for\ \ each\ \ t \in T\ \ and\ \ \forall (u_1, u_2) \in T \times T \\ u_1 \leq u_2 \ \ \Rightarrow \ \ E[y(t)|z = u_1] \leq E[y(t)|z = u_2]. \end{gathered} \tag{8}$$

The MTS assumption asserts that a child who has a parent with higher levels of education has a weakly greater mean function of education. This means that a child with a more educated parent would obtain more (or at least as much) education even if the parent did not have more schooling. There is (or may be) something other than parental education that makes a child of a more educated parent obtain more schooling. This assumption is consistent with economic models that parents who have higher ability are likely to have higher education and obtain greater average earnings, factors that contribute to children's educational achievement.

We divide the sample into three groups again to apply the MTS assumption: (1) children with a parent with an educational level lower than schooling t ($z < t$), (2) children with a parent who has educational level equal to t ($z = t$), and (3) children with a parent who has greater schooling than educational level t ($z > t$). Outcomes for the three groups can be written as:[4]

[4]Equations (9) and (10) in this paper are adapted from equations (12) and (13) in Manski and Pepper (2000).

$$
\begin{aligned}
u < t \;&\Rightarrow\; y_{min} \leq E[y(t)|z=u] \leq E[y(t)|z=t] \\
u = t \;&\Rightarrow\; E[y(t)|z=u] = E[y(t)|z=t] \\
u > t \;&\Rightarrow\; E[y(t)|z=t] \leq E[y(t)|z=u] \leq y_{max}.
\end{aligned} \tag{9}
$$

Considering the first case ($u > t$), we know that the mean educational outcome for a child with a parent who has educational level less than t would be less than or equal to that for one who has a parent with schooling t, even if the former parent had obtained schooling level t. We also know that the mean outcome of a child whose parent's education is greater than t is greater than or equal to the outcome for a child who has a parent with education t, even if the former parent had obtained schooling level t. The MTS bounds obtained by combining the no assumption bounds and the MTS assumption are:

$$
\begin{gathered}
y_{min} \cdot P(z < t) + E[y|z=t] \cdot P(z=t) + E[y|z=t] \cdot P(z > t) \\
\leq E[y(t)] \leq \\
E[y|z=t] \cdot P(z < t) + E[y|z=t] \cdot P(z=t) + y_{max} \cdot p(z > t).
\end{gathered} \tag{10}
$$

Manski and Pepper (2000) suggest combining the MTR and MTS assumptions to obtain more informative bounds. As assuming that the MTS and MTR assumptions hold, we obtain the MTR-MTS bounds (equation (7) in de Haan (2011)):

$$
\begin{gathered}
E[y|z < t] \cdot P(z < t) + E[y|z=t] \cdot P(z=t) + E[y|z=t] \cdot P(z > t) \\
\leq E[y(t)] \leq \\
E[y|z=t] \cdot P(z < t) + E[y|z=t] \cdot P(z=t) + E[y|z > t] \cdot p(z > t).
\end{gathered} \tag{11}
$$

The combined assumption substantially tightens the bounds compared to the no assumption bounds or the single assumption bounds.

Manski and Pepper (2000) suggest that we can test the validity of the joint MTR-MTS assumptions. The joint MTR-MTS assumptions imply:[5]

$$\begin{aligned} u_1 \leq u_2 \;\;\Rightarrow\;\; & E[y|z=u_1] = E[y(u_1)|z=u_1] \\ & \leq E[y(u_1)|z=u_2] \leq E[y(u_2)|z=u_2] = E[y|z=u_2]. \end{aligned} \tag{12}$$

The first inequality comes from the MTS assumption and the second inequality follows from the MTR assumption. In other words, a child's mean educational outcome has to be weakly increasing in parent actual educational attainment. If $E[y|z=u]$ in not weakly increasing in parent realized education, the joint hypothesis MTR-MTS is rejected.

The main interest in this analysis is the average treatment effects (ATE). Under the MTR-MTS assumption, it is possible to obtain bounds on each of $E[y(t_1)|z=u]$ and $E[y(t_2)|z=u]$. The upper (lower) bound on the ATE ($\Delta(t_2,t_1)$) can be calculated by subtracting the lower (upper) bound on $E[y(t_1)|z=u]$ from the upper (lower) bound on $E[y(t_2)|z=u]$. The MTR-MTS bounds on ATE is:[6]

$$\begin{aligned} & E[y|z<t_2]\cdot P(z<t_2) + E[y|z=t_2]\cdot P(z\geq t_2) - \{E[y|z=t_1]\cdot P(z\leq t_1) + E[y|z>t_1]\cdot P(z>t_1)\} \\ & \leq \Delta(t_2,t_1) \leq \\ & E[y|z=t_2]\cdot P(z\leq t_2) + E[y|z>t_2]\cdot P(z>t_2) - \{E[y|z<t_1]\cdot P(z<t_1) + E[y|z=t_1]\cdot P(z\geq t_1)\}. \end{aligned} \tag{13}$$

[5] This equation (12) is adapted from equation (19) in Manski and Pepper (2000).

[6] To obtain the $\Delta(t_2,t_1)$, we follow the method of Manski and Pepper (2000, page 1005).

It is possible that these calculations yield a non-positive lower bound on $\Delta(t_2, t_1)$ if the upper bound on $E[y(t_1)|z = u]$ is greater than the lower bound on $E[y(t_2)|z = u]$. As Manski (1997) notes, however, the lower bound on $\Delta(t_2, t_1)$ has to be a non-negative value because of the MTR assumption (equation (5)). We use zero as the lower bound on the average treatment effects when equation (13) implies a negative value.

2.4 Monotone Instrumental Variables

Many studies of intergenerational educational effects have adapted standard Instrumental Variables (IV) methods to identify causal effects (Black et al., 2005; Oreopoulos et al., 2006; Holmlund et al., 2011). The standard IV assumption of the mean-independence can be written as (Manski and Pepper, 2000):

$$\begin{gathered} For \;\; each \;\; t \in T, u \in V \;\; and \;\; \forall(u_1, u_2) \in V \times V, \\ E[y(t)|\upsilon = u_1, z = t] = E[y(t)|\upsilon = u_2, z = t]. \end{gathered} \tag{14}$$

However, it is often difficult to find a useful instrument that satisfies the mean-independence assumption. Even when an instrument satisfies the requirements, IV methods identify the local average treatment effect (LATE), the effect for compliers, distinct from the average treatment effect (ATE). In many cases, this is of relatively little interest, as it may include few or no cases. Huber et al. (2017) construct IV bounds to estimate the average treatment effect (ATE) while using an instrumental variable, although their derivation is limited to the case of a binary instrumental variable and a binary treatment. As an alternative, Manski and Pepper (2000, 2009) propose the monotone instrumental variable (MIV) assumption, which is weaker and more credible, replacing the equality in equation (14) with an inequality. The assumption indicates that the mean response function is weakly monotone in specific sub-samples. Assuming that V is an order set, we may write this assumption as:

$$u_1 \leq u_2 \quad \Rightarrow \quad E[y(t)|\upsilon = u_1] \leq E[y(t)|\upsilon = u_2]. \tag{15}$$

We can use paternal schooling level as a treatment and maternal schooling level as an MIV to illustrate how the MIV assumption works. To satisfy standard IV assumptions, mother's schooling level would have to have no direct effect children's educational outcome except through paternal schooling. It is hard to believe that maternal schooling is an appropriate IV, as it would appear to affect a child's education through a variety of channels. However, the maternal schooling would be acceptable as an MIV if there is a positive effect of mother's education on children's education. Maternal education as an MIV is useful to determine bounds.

To obtain identifying power from the MIV assumption, $E[y(t)|\upsilon]$ also can be expanded in an identical way to equation (2):[7]

$$\begin{aligned} E[y(t)|\upsilon = u] = E[y|\upsilon = u, z = t] \cdot P(z = t|\upsilon = u) + \\ E[y(t)|\upsilon = u, z \neq t] \cdot P(z \neq t|\upsilon = u). \end{aligned} \tag{16}$$

$E[y(t)|\upsilon = u, z \neq t]$ must be in a range of $[y_{min}, y_{max}]$. The bounds can be written as

[7] Equations (16) to (21) are adapted from Manski and Pepper (2000, equation (4) to (9)).

follows,

$$\begin{aligned} &E[y|\upsilon = u, z = t] \cdot P(z = t|\upsilon = u) + y_{min} \cdot P(z \neq t|\upsilon = u) \\ &\leq E[y(t)|\upsilon = u] \leq \\ &E[y|\upsilon = u, z = t] \cdot P(z = t|\upsilon = u) + y_{max} \cdot P(z \neq t|\upsilon = u). \end{aligned} \tag{17}$$

The MIV assumption implies a monotone relationship, that is,

$$u_1 \leq u \leq u_2 \Rightarrow E[y(t)|\upsilon = u_1] \leq E[y(t)|\upsilon = u] \leq E[y(t)|\upsilon = u_2]. \tag{18}$$

Under equations (17) and (18), $E[y(t)|\upsilon = u]$ is not smaller than the lower bound on $E[y(t)|\upsilon = u_1]$ and not greater than upper bound on $E[y(t)|\upsilon = u_2]$ for all $u_1 \leq u$ and $u \leq$u$_2$ (Manski and Pepper, 2000; de Haan, 2011). Then, we have bounds under the MIV assumption, written as follows,

$$\begin{aligned} &\sup_{u_1 \leq u} [E(y|\upsilon = u_1, z = t) \cdot P(z = t|\upsilon = u_1) + y_{min} \cdot P(z \neq t|\upsilon = u_1)] \\ &\leq E[y(t)|\upsilon = u] \leq \\ &\inf_{u \leq u_2} [E(y|\upsilon = u_2, z = t) \cdot P(z = t|\upsilon = u_2) + y_{max} \cdot P(z \neq t|\upsilon = u_2)]. \end{aligned} \tag{19}$$

The MIV bounds on $E[y(t)]$ are sharp without adding other restrictions on $E[y(t)|\upsilon = u]$. Using the law of iterated expectation, $E[y(t)]$ can be written as

$$E[y(t)] = \sum_{u \in V} P(\upsilon = u) \cdot E[y(t)|\upsilon = u]. \tag{20}$$

Then, combining equation (21) with the lower and upper MIV bounds provides the following equation.

$$\sum_{u \in V} P(\upsilon = u)\{\sup_{u_1 \leq u}[E(y(t)|\upsilon = u_1, z = t) \cdot P(z = t|\upsilon = u_1) + y_{min} \cdot P(z \neq t|\upsilon = u_1)]\}$$

$$\leq E[y(t)] \leq \tag{21}$$

$$\sum_{u \in V} P(\upsilon = u)\{\inf_{u \leq u_2}[E(y(t)|\upsilon = u_2, z = t) \cdot P(z = t|\upsilon = u_2) + y_{max} \cdot P(z \neq t|\upsilon = u_2)]\}.$$

Manski and Pepper (2000) introduce not only the MIV bounds but also the combined bounds of the MTR, MTS and MIV assumptions (MTR-MTS-MIV bounds), which provide the tightest bounds. We already know that the combined MTR and MTS assumption yields relatively more informative and tighter bounds than no-assumption bounds and single-assumption bounds. Following Kang (2011, equation (10)), equation (10), we can write the MTR-MTS-MIV bounds as,

$$\sum_{u \in V} P(\upsilon = u)\{\sup_{u_1 \leq u}[E[y(t)|\upsilon = u_1, z < t] \cdot P(z < t|\upsilon = u_1) +$$

$$E[y(t)|\upsilon = u_1, z = t] \cdot P(z \geq t|\upsilon = u_1)]\}$$

$$\leq E[y(t)] \leq \tag{22}$$

$$\sum_{u \in V} P(\upsilon = u)\{\inf_{u \leq u_2}[E[y(t)|\upsilon = u_2, z = t] \cdot P(z \leq t|\upsilon = u_2)] +$$

$$E[y(t)|\upsilon = u_2, z > t] \cdot P(z > t|\upsilon = u_2)]\}.$$

As mentioned above, this analysis is interested in the bounds on the average treatment effects, the effects of an increase in a parent's schooling level from t_1 to t_2 on a child's educational outcomes. We obtain the bounds on the average treatment effect by subtracting an upper(lower) bound of $E[y(t_1)]$ from a lower(upper) bound of $E[y(t_2)]$. Also, the lower bound on the average treatment effects should be non-negative due to the MTR assumption.

The MTR-MTS-MIV bounds on the average treatment effects are,

$$
\begin{aligned}
&\sum_{u\in V} P(v=u)\{\sup_{u_1\le u}[E(y(t_2)|v=u_1, z<t_2)\cdot P(z<t_2|v=u_1)\\
&+E(y(t_2)|v=u_1, z=t_2)\cdot P(z\ge t_2|v=u_1)] - \{\inf_{u\le u_2}[E(y(t_1)|v=u_2, z=t_1)\cdot P(z\le t_1|v=u_2)\\
&\qquad +E(y(t_1)|v=u_2, z>t_1)\cdot P(z>t_1|v=u_2)]\}\}\\
&\le \Delta(t_2,t_1)\le \qquad (23)\\
&\sum_{u\in V} P(v=u)\{\inf_{u\le u_2}[E(y(t_2)|v=u_2, z=t_2)\cdot P(z\le t_2|v=u_2)\\
&+E(y(t_2)|v=u_2, z>t_2)\cdot P(z>t_2|v=u_2)] - \{\sup_{u_1\le u}[E(y(t_1)|v=u_1, z<t_1)\cdot P(z<t_1|v=u_1)\\
&\qquad +E(y(t_1)|v=u_1, z=t_1)\cdot P(z\ge t_1|v=u_1)]\}\}.
\end{aligned}
$$

This study uses two variables as MIVs in the analysis. The first is the educational level of the other parent. For example, when father's schooling is the treatment, we use mother's educational attainment as an MIV. Also, a father's education plays the role as the MIV when a mother's schooling is used to obtain informative bounds. Both parents' schooling levels are categorized in five groups: (1) no education, (2) education less than 12th grade, (3) high school graduate, (4) some college (junior college dropouts and graduates, and college dropouts), and (5) college graduates and above. The MIV assumption is that the mean educational outcome of a child is weakly increasing in the other parent's educational level.[8]

Father's occupation is the second MIV in this analysis. This is a dummy variable that is coded as 0 for lower-skilled jobs and as 1 for upper-skilled jobs based on Korea's

[8]For further discussion, please see a Kikuchi (2017).

standard job classification. The upper-skilled jobs include managers, professionals, lower levels of white-collar workers, and sales jobs; the lower-skilled jobs consist of personal service, agriculture (including fisheries), technicians, and laborers.[9] We assume that if a father works in an upper-skilled job rather than lower-skilled job, it weakly increases the mean schooling of a child. Before we use a father's occupation as an MIV, we also test whether it shows the mean-monotone relation with children's education that is a necessary result of this assumption.

We consider the possibility that the OLS method overestimates the effects relative to the true causal relationship. We must address the possibility that differences between the OLS estimate and the bounds we obtain are due to sampling error. We apply a bias-corrected method on the least upper bounds using a bootstrap method proposed by Kreider and Pepper (2007) to estimate standard errors.[10] We also conduct a one-sided test of whether the OLS overestimates causal effects employing a bootstrap method. In particular, to look into the possibility that observed differences are due to sampling error, the estimated least upper bound is subtracted from OLS estimates as follows and estimated for 1,000 bootstrap replications of random selection from the base sample.

$$OLS_i - Least\,UB_i > 0, \;\; \forall\, i = 1, 2, 3, \cdots, 1000. \tag{24}$$

[9] High school graduates are the overwhelming majority educational category for sales workers. Nonetheless, college graduates account for approximately 32 percent of sales workers, according to the Korean Statistical Information Service 2011 report. The proportion of college graduates in sales jobs is greater than in other lower-skilled jobs.

[10] Manski and Pepper (2000) and Kreider and Pepper (2007) indicate that finite-sample bias can be generated by taking sups and infs on the MIV estimation. If the finite-sample bias is severe in the analyses, bounds under the MTR-MTS combined assumptions may have greater power because the bounds based on the combined assumptions of MTR and MTS are free from the bias.

OLS_i and $LeastUB_i$ are the OLS estimates and the least upper bounds under the MTR-MTS-MIV combined assumption, respectively, and i indicates the bootstrap replication. This allows us to conclude that the difference between the upper bound and the OLS is not attributed to the sampling error if the difference is positive for 95% (90%) of the replications. Furthermore, following Manski and Pepper (2000) and de Haan (2011), we also compute and report 95% confidence intervals on each estimated lower and upper bounds using the bootstrap method.

3 Data: Korean Labor and Income Panel Study (KLIPS)

This study uses the Korean Labor and Income Panel Study (hereafter KLIPS) conducted by the Korean Labor Institute to identify the effects of parents' educational attainment on children's years of schooling.[11] KLIPS provides information on the Korean labor market and income structure of households and individuals who lived in urban and suburban areas from 1998 to 2016. This is a longitudinal survey and samples 5,000 households with 13,321 individuals aged 15 and older in 16 metropolitan areas in 1998. An additional 1,415 households were included in the survey in 2009 to improve the representativeness of the data and to overcome limitations of attrition and concentration of urban residence.

KLIPS provides extensive information related to labor market outcomes and in-

[11] The KLIPS is the first Korean longitudinal survey focusing on labor issues. These data are available on a site of the Korea Labor Institute: *https://www.kli.re.kr/klips_eng/index.do*

Table 1: Summary Statistics

	Mean	Std. dev.
Child's years of schooling	13.926	1.923
Child's college completion	0.361	0.480
Child's age	31.254	7.829
Child's gender (son = 0)	0.448	0.500
Father's education:		
1. No education	0.062	0.106
2. Less than 12th grade	0.292	0.463
3. High school	0.411	0.496
4. Some college	0.072	0.259
5. College	0.163	0.369
Mother's education:		
1. No education	0.084	0.205
2. Less than 12th grade	0.425	0.499
3. High school	0.385	0.487
4. Some college	0.042	0.200
5. College	0.064	0.245
Father's occupation		
Upper-skilled jobs (=1)	0.473	0.499
N	5,722	

dividual and family characteristics such as education, earnings, type of job, family background, and demographic characteristics. To identify the intergenerational transmission of human capital using a nonparametric bounds analysis, a dataset must contain at least two generations' completed educational level and enough observations. For the bounds analysis, I include respondents who responded to questions regarding both father's and mother's completed educational attainment. Individuals who answered questions regarding both parental final educational levels are included, including those that lost a father or mother after entering a college. However, I drop the respondents if either father or mother were absent before they attended college because single-parent families may have substantially different educational environments than two-parent families. I also omit individuals who are still in school, and I only include those who were born before 1966. This restriction provides a final sample, containing 5,722 individuals who are aged 15 to 50 at the survey date.

To find the causal impact of increasing parental education on child's years of schooling, I consider child's years of final schooling, coded as: 8 years (no more than primary education), 10 years (high school dropout), 12 years (high school graduate), 14 years (some college, or two or three year degree), and 16 years (bachelor's degree and above). As mentioned in the previous section, this study considers five educational levels for parents and two categories for father's occupation. In some of the analyses, we use the other parent's education or father's occupation as a monotone instrumental variable (MIV). Table 1 provides descriptive statistics.

4 Results

This section shows the results of applying the nonparametric bounds approach to examining the effects of parental education on a child's educational outcomes. As stated in the Methods section, in order to determine whether the MTR-MTS combined assumption is rejected by the data, I test whether the means of the child's education are non-decreasing in parents' schooling and in father's occupation, a requirement for the MTR and MTS

Table 2: Child's Mean Years of Schooling by Parent's Education and Father's Occupation

Panel A:	**Father's Education**				
Child's Educational Achievement	No Education	Less Than 12th-Grade	High School	Some College	College
Year of Schooling	12.333	13.637	13.736	14.362	14.913
College Completion	0.106	0.287	0.320	0.403	0.614
Panel B:	**Mother's Education**				
Year of Schooling	13.075	13.716	14.067	14.377	14.896
College Completion	0.237	0.322	0.366	0.461	0.634
Panel C:	**Father's Occupation**				
	Lower-level Jobs			Upper-level Jobs	
Year of Schooling	13.581			14.309	
College Completion	0.294			0.436	

assumptions to be met. Table 2 shows that the MTR-MTS combined assumption is not rejected since the mean of child's schooling outcomes is weakly increasing both in the level of father's and mother's education, and outcomes are weakly increasing function in father's occupation.

4.1 Treatment Effects on Child's Years of Schooling

Table 3 reports bounds on the average treatment effects of increasing father's or mother's educational attainment to the next educational level on a child's years of schooling, i.e., $E[y(t_2)] - E[y(t_1)]$. Table 3 also shows confidence intervals at a 95% significance level obtained by 1,000 replications using the bootstrap method. In Table 3, all bounds are shown although the bounds under a single assumption (MTR, MTS, or MIVs) are wide and not very informative compared to the tightest bounds from the MTR-MTS-MIV combined assumption. According to Table 1, most parents graduate high school: 41% of fathers and 39% of mothers had a high school degree only. Parents who have some schooling but did not graduate from a high school account for the next biggest group. In this paper, we focus on the average treatment effect of increasing a parent's education from less than high school to college graduation, or from high school to college graduation.

Columns (1) and (10) show the results of simple OLS, for father's and mother's education, respectively, which provide an unbiased estimate of the effect of parental education if we assume exogenous treatment selection. It indicates that if a father (mother) holds a college degree, it is associated with an increase in child's schooling of 1.38 (1.28) years relative to a father (mother) who did not graduate high school. When a father's (mother's) education increases from high school to college, a child has 1.18 (0.93) more years of schooling. Overall, based on the OLS results, father's schooling has a stronger positive relationship to a child's education than mother's education.

Columns (2) to (4) and (11) to (13) show what the estimated bounds would be under the case of no assumptions and bounds imposing single assumptions. Although all bounds are very wide and uninformative, imposing either MTR or MTS tightens lower and upper bounds compared to the no assumption bounds. A combination of the two assumptions, MTR and MTS (columns (7) and (16)) provides substantially tighter bounds than the no assumption cases. An increase of father's (mother's) schooling from high school to college shows bounds on the average treatment effects from 0 to 1.62 years (0 to 1.34

years) of a child's schooling. Since the bounds, however, include the OLS estimates, the bounds analysis based on the MTR-MTS combined assumptions does not challenge the OLS results.

Bounds under an MIV assumption itself yields slightly tighter bounds compared to the no assumption bounds, but they are still wide enough and largely uninformative (columns (5), (6), (14), and (15)). Table 3 also gives the bounds under the joint MTR-MTS-MIV assumption (columns (8), (9), (17), and (18)). These three combined assumptions yield the tightest bounds on average treatment effects, and they lead to informative bounds. When I use the mother's (father's) education as an MIV, we obtain the bounds between 0.25 (0.27) and 1.06 (1.07); OLS point estimates fall outside of the bounds in most cases. The exception is that our bounds analysis implies that an increase of father's schooling from some college to college leads to as much as 0.76 more years of schooling for the child, but we cannot reject the OLS point estimate, 0.55. Although the bounds do not contain the OLS estimates, they contain zero effects.

With the father's occupation as an alternative MIV, the bounds estimates are similar to the bounds using the other parent's education as an MIV. We look at the effects of parents' education comparing the lower levels of education to college graduation, i.e., $E[y(t = Coll)] - E[y(t = Less12^{th})]$ and $E[y(t = Coll)] - E[y(t = HS)]$. For these effects, the lower bounds do not contain zero, and the upper bounds are significantly lower than the OLS point estimates. A father (mother) who graduated from a college as compared to not graduating from high school would increase a child's years of schooling at least 0.19 years

Table 3: ETS Point Estimates and Bounds of A Parent's Education on Child's Years of Schooling

Panel A:	Father's Educational Attainment																	
Assumption	OLS		No Assumption		MTR		MTS		MIV		MIV		MTR-MTS		MTR-MTS-MIV		MTR-MTS-MIV	
MIV	No		No		No		No		Father's Education		Father's Occupation		No		Mother Education		Father's Occupation	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB
	0.206		-4.730	5.243	0.000	4.898	-3.354	1.697	-3.736	3.128	-4.340	4.525	0.000	0.851	0.000	0.250	0.000	0.275
$E[y(t=HS)] - E[y(t=Less12th)]$	(0.118	0.307)	(-4.774	5.284)	(0.000	4.947)	(-3.413	1.801)	(-3.872	3.208)	(-4.936	4.595)	(0.000	1.102)	(0.000	0.391)	(0.000	0.416)
	[0.120	0.305]	[-4.738	5.254]	[0.000	4.908]	[-3.369	1.718]	[-3.765	3.145]	[-4.355	4.539]	[0.000	1.016]	[0.000	0.354]	[0.000	0.354]
	0.626		-6.540	5.348	0.000	3.364	-4.773	2.747	-6.085	3.904	-6.486	5.345	0.000	1.163	0.000	0.513**	0.000	0.352**
$E[y(t=SMC)] - E[y(t=HS)]$	(0.448	0.804)	(-6.574	5.384)	(0.000	3.413)	(-4.846	2.889)	(-6.124	4.038)	(-6.536	5.381)	(0.000	1.350)	(0.000	0.622)	(0.000	0.473)
	[0.449	0.798]	[-6.547	5.357]	[0.000	3.373]	[-4.790	2.776]	[-6.094	3.933]	[-6.498	5.352]	[0.000	1.234]	[0.000	0.579]	[0.000	0.430]
	0.551		-6.757	7.363	0.000	3.022	-5.504	5.417	-5.533	7.139	-6.753	7.351	0.000	1.077	0.000	0.761	0.000	0.835
$E[y(t=Coll)] - E[y(t=SMC)]$	(0.258	0.752)	(-6.776	7.383)	(0.000	3.070)	(-5.639	5.521)	(-5.595	7.176)	(-6.773	7.372)	(0.000	1.329)	(0.000	0.846)	(0.000	0.952)
	[0.260	0.748]	[-6.761	7.367]	[0.000	3.032]	[-5.539	5.438]	[-5.547	7.147]	[-6.759	7.356]	[0.000	1.243]	[0.000	0.808]	[0.000	0.908]
	1.383		-6.138	6.066	0.000	6.016	-6.111	2.341	-5.365	3.181	-5.748	5.391	0.000	1.791	0.000	1.056**	0.188	1.091**
$E[y(t=Coll)] - E[y(t=Less12th)]$	(1.293	1.425)	(-6.171	6.098)	(0.000	6.049)	(-6.145	2.476)	(-5.430	3.262)	(-5.797	5.442)	(0.000	1.876)	(0.000	1.138)	(0.072	1.189)
	[1.295	1.422]	[-6.145	6.073]	[0.000	6.022]	[-6.120	2.368]	[-5.380	3.199]	[-5.762	5.402]	[0.000	1.842]	[0.000	1.104]	[0.127	1.162]
	1.177		-5.876	5.290	0.000	3.482	-5.144	3.031	-5.534	3.959	-5.821	5.278	0.000	1.624	0.000	0.977**	0.119	0.945**
$E[y(t=Coll)] - E[y(t=HS)]$	(1.052	1.301)	(-5.913	5.327)	(0.000	3.528)	(-5.204	3.145)	(-5.593	4.089)	(-5.872	5.315)	(0.000	1.778)	(0.000	1.065)	(0.000	1.077)
	[1.053	1.298]	[-5.883	5.299]	[0.000	3.492]	[-5.159	3.055]	[-5.547	3.988]	[-5.834	5.287]	[0.000	1.688]	[0.000	1.020]	[0.065	1.004]

Table 3: ETS Point Estimates and Bounds of A Parent's Education on Child's Years of Schooling (cont.)

Panel B:	Mother's Educational Attainment																	
Assumption	OLS		No Assumption		MTR		MTS		MIV		MIV		MTR-MTS		MTR-MTS-MIV		MTR-MTS-MIV	
MIV	No		No		No		No		Father's Education		Father's Occupation		No		Mother Education		Father's Occupation	
	(10)		(11)		(12)		(13)		(14)		(15)		(16)		(17)		(18)	
	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB
	0.352		-4.603	4.597	0.000	4.234	-3.860	1.808	-2.893	4.198	-4.214	3.974	0.000	1.046	0.000	0.266*	0.000	0.298*
$E[y(t=HS)]-E[y(t=Less12th)]$	(0.245	0.457)	(-4.648	4.642)	(0.000	4.285)	(-3.910	1.907)	(-3.109	4.326)	(-4.276	4.038)	(0.000	1.225)	(0.000	0.344)	(0.000	0.372)
	[0.246	0.456]	[-4.612	4.607]	[0.000	4.245]	[-3.871	1.827]	[-2.941	4.228]	[-4.228	3.987]	[0.000	1.147]	[0.000	0.325]	[0.000	0.346]
	0.310		-6.990	5.597	0.000	2.643	-5.597	3.504	-5.991	4.301	-6.985	5.594	0.000	0.850	0.000	0.270	0.000	0.265
$E[y(t=SMC)]-E[y(t=HS)]$	(0.179	0.539)	(-7.021	5.628)	(0.000	2.691)	(-5.668	3.709)	(-6.125	4.372)	(-7.015	5.624)	(0.000	1.345)	(0.000	0.364)	(0.000	0.349)
	[0.183	0.535]	[-6.996	5.604]	[0.000	2.653]	[-5.614	3.546]	[-6.024	4.316]	[-6.992	5.600]	[0.000	1.176]	[0.000	0.320]	[0.000	0.316]
	0.620		-7.491	7.663	0.000	2.445	-6.039	6.222	-1.977	6.502	-7.487	7.658	0.000	1.004	0.000	0.584	0.000	0.786
$E[y(t=Coll)]-E[y(t=SMC)]$	(0.313	0.917)	(-7.505	7.678)	(0.000	2.494)	(-6.248	6.386)	(-2.113	6.577)	(-7.501	7.673)	(0.000	1.755)	(0.000	0.679)	(0.000	0.904)
	[0.315	0.915]	[-7.494	7.666]	[0.000	2.455]	[-6.086	6.254]	[-2.005	6.517]	[-7.490	7.662]	[0.000	1.623]	[0.000	0.646]	[0.000	0.863]
	1.282		-6.496	5.270	0.000	5.046	-6.395	2.433	-0.568	4.708	-6.107	4.647	0.000	1.809	0.000	1.065**	0.237	1.130**
$E[y(t=Coll)]-E[y(t=Less12th)]$	(0.991	1.417)	(-6.532	5.306)	(0.000	5.086)	(-6.434	2.616)	(-0.811	4.770)	(-6.162	4.703)	(0.000	1.964)	(0.000	1.167)	(0.142	1.214)
	[0.992	1.416]	[-6.504	5.278]	[0.000	5.054]	[-6.403	2.465]	[-0.623	4.722]	[-6.120	4.659]	[0.000	1.889]	[0.000	1.124]	[0.179	1.182]
	0.930		-6.815	5.595	0.000	2.711	-5.831	3.919	-1.511	4.346	-6.810	5.590	0.000	1.336	0.000	0.889**	0.105	0.849**
$E[y(t=Coll)]-E[y(t=HS)]$	(0.746	1.011)	(-6.845	5.626)	(0.000	2.759)	(-5.898	4.085)	(-1.694	4.415)	(-6.840	5.621)	(0.000	1.487)	(0.000	0.976)	(0.023	0.926)
	[0.747	1.008]	[-6.821	5.601]	[0.000	2.721]	[-5.846	3.952]	[-1.550	4.361]	[-6.818	5.597]	[0.000	1.455]	[0.000	0.927]	[0.053	0.890]

Note: Numbers in the parenthesis are confidence limits for lower and upper bounds for bounds estimates. The square brackets present 95% confidence intervals, obtained by applying a bootstrap method with 1,000 time replications. An astrisk (*) denotes the OLS results fall outside statistically the estimated bounds at 90%, and two astrisks (**) represent 95%.

(0.24 years) or as much as 1.1 years (1.13 years). A child whose a father (a mother) obtained a college degree rather than graduating only from high school is estimated to experience increases in schooling ranging from 0.12 (0.11) years to 0.95 (0.85) years. These bounds imply that OLS results are overestimated.

We undertake a test of the significance of the difference between the OLS estimates and the least upper bounds, as indicated in equation (25) above. We employ a bootstrap method with 1,000 replications, estimating the difference between the OLS and the upper bound under the combined MTR-MTS-MIV assumptions. Asterisks in Tables 3 and 4 indicate that we can reject the null hypothesis, which is that the OLS estimates is not greater than the estimated upper bound: Two asterisks indicate that the difference is statistically significant at a 95% level, and one asterisk indicates the 90% level. We can confirm that the OLS estimates are greater than the least upper bounds of the average treatment effects of an increment of either a father's or a mother's education from high school to college, at the 95% level of significance. However, we cannot reject the OLS estimates for an increase in education of a father from some college to college graduation, which is not surprising given the small sample size for some college limits the precision of estimates.

4.2 Treatment Effects on Child's College Completion

Only small proportion of parents obtained a college degree, but many children do so. It is interesting to estimate the effects of an increase in parental education on the probability of a child's college graduation. College completion is of particular interest since it has become more important in the modern labor market environment. Table 4 provides the bounds of increasing parental educational level on the probability of a child's graduating from college along with its confidence intervals based on a bootstrap with 1,000 replications.

The OLS results indicate that an increase in father's schooling from *Less than 12th grade* to *College* increases the chance that a child graduates from college by 33 percentage points, and an increase from *High school* to *College* increases this chance by 30 percentage points. Table 4 displays the bounds for every set of assumptions, although bounds for single assumptions (MTR, MTS, or MIVs) are wide and not very informative. The joint MTR-MTS assumption tightens the bounds significantly compared to the no assumption bounds, but the bounds include the OLS point estimates in all cases.

When I use the other parent's education as an MIV, the upper bounds under the MTR-MTS-MIV joint assumptions are lower than the OLS estimate in most cases. The effect of an increase in father's schooling from *High school* to *College* increases a child's chance of completing a college degree by up to 25 percentage points. However, the bounds on the treatment effects still include zero. Instead of using the other parent's education, we can also consider father's occupation as an alternative MIV. Columns (9) reports that the bounds under the MTR-MTS-MIV assumption do not contain the OLS results in any treatment effects. Similar to results presented in Table 3, the lower bounds do not include zero effects when we consider the parental schooling effects from less than high school or from high school to college. When a father's schooling increases from high school to college, the upper bound indicates that the maximum effect on the chance that a child graduates

Table 4: ETS Point Estimates and Bounds of A Parent's Education on Child's College Completion

Panel A:	Father's Educational Attainment																	
Assumption	OLS		No Assumption		MTR		MTS		MIV		MIV		MTR-MTS		MTR-MTS-MIV		MTR-MTS-MIV	
MIV	No		No		No		No		Father's Education		Father's Occupation		No		Mother Education		Father's Occupation	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB
	0.033		-0.636	0.610	0.000	0.503	-0.553	0.195	-0.419	0.566	-0.531	0.577	0.000	0.088	0.000	0.035	0.000	0.020
$E[y(t=HS)] - E[y(t=Less12^{th})]$	(0.000	0.164)	(-0.647	0.628)	(0.000	0.515)	(-0.568	0.221)	(-0.456	0.596)	(-0.544	0.592)	(0.000	0.127)	(0.000	0.104)	(0.000	0.090)
	[0.000	0.145]	[-0.640	0.620]	[0.000	0.509]	[-0.556	0.209]	[-0.426	0.583]	[-0.533	0.585]	[0.000	0.115]	[0.000	0.086]	[0.000	0.052]
	0.084		-0.670	0.816	0.000	0.662	-0.385	0.284	-0.641	0.771	-0.663	0.814	0.000	0.131	0.000	0.070	0.000	0.065
$E[y(t=SMC)] - E[y(t=HS)]$	(0.032	0.135)	(-0.679	0.832)	(0.000	0.674)	(-0.403	0.329)	(-0.681	0.789)	(-0.674	0.822)	(0.000	0.184)	(0.000	0.182)	(0.000	0.176)
	[0.034	0.134]	[-0.673	0.825]	[0.000	0.669]	[-0.388	0.307]	[-0.649	0.781]	[-0.665	0.818]	[0.000	0.165]	[0.000	0.129]	[0.000	0.115]
	0.211		-0.857	0.908	0.000	0.676	-0.401	0.520	-0.388	0.884	-0.855	0.903	0.000	0.288	0.000	0.194	0.000	0.182*
$E[y(t=Coll)] - E[y(t=SMC)]$	(0.122	0.299)	(-0.863	0.920)	(0.000	0.688)	(-0.444	0.552)	(-0.433	0.914)	(-0.862	0.909)	(0.000	0.333)	(0.000	0.310)	(0.000	0.297)
	[0.124	0.298]	[-0.858	0.914]	[0.000	0.682]	[-0.409	0.537]	[-0.395	0.900]	[-0.857	0.907]	[0.000	0.318]	[0.000	0.241]	[0.000	0.235]
	0.328		-0.678	0.848	0.000	0.846	-0.670	0.330	-0.354	0.810	-0.572	0.817	0.000	0.329	0.000	0.283*	0.015	0.191**
$E[y(t=Coll)] - E[y(t=Less12^{th})]$	(0.302	0.394)	(-0.686	0.863)	(0.000	0.855)	(-0.678	0.368)	(-0.395	0.826)	(-0.584	0.829)	(0.000	0.378)	(0.000	0.395)	(0.000	0.318)
	[0.305	0.391]	[-0.680	0.856]	[0.000	0.851]	[-0.671	0.351]	[-0.345	0.818]	[-0.574	0.823]	[0.000	0.361]	[0.000	0.358]	[0.000	0.249]
	0.295		-0.600	0.796	0.000	0.705	-0.380	0.398	-0.261	0.787	-0.592	0.791	0.000	0.307	0.000	0.246*	0.011	0.189**
$E[y(t=Coll)] - E[y(t=HS)]$	(0.257	0.332)	(-0.609	0.813)	(0.000	0.717)	(-0.395	0.431)	(-0.310	0.806)	(-0.604	0.801)	(0.000	0.352)	(0.000	0.352)	(0.000	0.312)
	[0.258	0.330]	[-0.602	0.806]	[0.000	0.711]	[-0.383	0.416]	[-0.269	0.796]	[-0.594	0.797]	[0.000	0.337]	[0.000	0.307]	[0.000	0.251]

Table 4: ETS Point Estimates and Bounds of A Parent's Education on Child's College Completion (Cont.)

Panel B: Mother's Educational Attainment

Assumption	OLS		No Assumption		MTR		MTS		MIV		MIV		MTR-MTS		MTR-MTS-MIV		MTR-MTS-MIV	
MIV	No		No		No		No		Father's Education		Father's Occupation		No		Father's Education		Father's Occupation	
	(10)		(11)		(12)		(13)		(14)		(15)		(16)		(17)		(18)	
	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB
	0.044		-0.544	0.606	0.000	0.550	-0.475	0.125	-0.478	0.529	-0.438	0.583	0.000	0.069	0.000	0.055	0.000	0.024
$E[y(t=HS)] - E[y(t=Less12^{th})]$	(0.017	0.071)	(-0.555	0.626)	(0.000	0.562)	(-0.489	0.149)	(-0.497	0.549)	(-0.453	0.597)	(0.000	0.149)	(0.000	0.174)	(0.000	0.090)
	[0.018	0.070]	[-0.546	0.618]	[0.000	0.556]	[-0.477	0.138]	[-0.479	0.541]	[-0.441	0.591]	[0.000	0.137]	[0.000	0.126]	[0.000	0.069]
	0.094		-0.737	0.836	0.000	0.623	-0.385	0.315	-0.608	0.717	-0.734	0.835	0.000	0.131	0.000	0.081	0.000	0.075
$E[y(t=SMC)] - E[y(t=HS)]$	(0.027	0.160)	(-0.745	0.849)	(0.000	0.665)	(-0.404	0.374)	(-0.618	0.738)	(-0.743	0.843)	(0.000	0.249)	(0.000	0.156)	(0.000	0.143)
	[0.027	0.159]	[-0.739	0.845]	[0.000	0.659]	[-0.388	0.345]	[-0.610	0.727]	[-0.736	0.839]	[0.000	0.219]	[0.000	0.124]	[0.000	0.098]
	0.173		-0.937	0.957	0.000	0.656	-0.454	0.585	-0.745	0.923	-0.935	0.955	0.000	0.284	0.000	0.145	0.000	0.118**
$E[y(t=Coll)] - E[y(t=SMC)]$	(0.054	0.294)	(-0.941	0.965)	(0.000	0.668)	(-0.511	0.635)	(-0.764	0.934)	(-0.939	0.959)	(0.000	0.390)	(0.000	0.230)	(0.000	0.237)
	[0.056	0.293]	[-0.938	0.961]	[0.000	0.662]	[-0.463	0.612]	[-0.748	0.929]	[-0.936	0.957]	[0.000	0.367]	[0.000	0.196]	[0.000	0.188]
	0.311		-0.644	0.827	0.000	0.816	-0.614	0.326	-0.606	0.745	-0.539	0.804	0.000	0.315	0.000	0.250*	0.040	0.204**
$E[y(t=Coll)] - E[y(t=Less12^{th})]$	(0.231	0.393)	(-0.653	0.842)	(0.000	0.825)	(-0.624	0.379)	(-0.624	0.766)	(-0.551	0.817)	(0.000	0.422)	(0.000	0.327)	(0.000	0.287)
	[0.232	0.391]	[-0.646	0.836]	[0.000	0.821]	[-0.616	0.353]	[-0.609	0.756]	[-0.541	0.811]	[0.000	0.399]	[0.000	0.294]	[0.000	0.256]
	0.267		-0.716	0.836	0.000	0.675	-0.393	0.454	-0.648	0.735	-0.713	0.833	0.000	0.294	0.000	0.231*	0.032	0.177**
$E[y(t=Coll)] - E[y(t=HS)]$	(0.214	0.321)	(-0.724	0.850)	(0.000	0.687)	(-0.411	0.504)	(-0.665	0.755)	(-0.721	0.842)	(0.000	0.399)	(0.000	0.324)	(0.000	0.243)
	[0.215	0.320]	[-0.717	0.844]	[0.000	0.681]	[-0.396	0.481]	[-0.651	0.745]	[-0.714	0.838]	[0.000	0.376]	[0.000	0.281]	[0.000	0.202]

Note: Numbers in the parenthesis are confidence limits for lower and upper bounds for bounds estimates. The square brackets present 95% confidence intervals, obtained by applying a bootstrap method with 1,000 time replications. An astrisk (*) denotes the OLS results fall outside statistically the estimated bounds at 90%, and two astrisks (**) represent 95%.

from college is 19 percentage point, whereas the OLS point estimate is 30 percentage points. This suggests that the linear probability model overestimates the effect.

We observe a similar pattern when we consider the mother's schooling as a treatment. The MTR-MTS-MIV joint assumption yields the tightest and most informative bounds, and the bounds exclude the point estimates (columns (17) and (18)) for the bottom two comparisons in the table. With the father's schooling as an MIV, the bounds include zero, while the lower bounds of the changes from less than high school or from high school to college do not contain the zero effects when we use father's occupation as an MIV. The upper bounds using the MIV father's occupation are also significantly lower than the upper bounds when father's schooling is used as an MIV. If a mother graduated from a college rather than obtaining only a high school diploma, it would increase the probability that a child obtains a college degree from 3 to 18 percentage points. The one-tailed test is conducted in this analysis as well. The null hypothesis is rejected at the 95% (90%) significant level because the OLS estimates are greater than the least upper bounds on the average treatment effects for an increase in both a father's and a mother's schooling when we use father's occupation (the other parent's education) as an MIV.

5 Conclusion

Parental education is positively associated with a child's educational outcomes. Although previous studies apply manifold empirical methods to identify the causal effects of parental education, it is not clear there is a general consensus on the causal effects of father's and mother's education on a child's schooling. Holmlund et al. (2011) review the recent literature on the intergenerational transmission of education, and they indicate that empirical evidence differs significantly across studies. Because of different data and different empirical approaches, it is challenging to achieve the consensus of the intergenerational schooling effects across previous studies.

This study investigates the causal intergenerational effects of education by adapting an alternative empirical method, the nonparametric bounds approach proposed by Manski and Pepper (2000). The method provides bounds on the causal effects of parents' educational level on a child's educational outcomes, years of schooling, and college completion, under nonparametric assumptions: MTR, MTS, and MIV. The assumptions are relatively weaker than the standard mean-independence assumption of IV method and partly testable. This article also combines multiple assumptions to obtain informative bounds on treatment, e.g., combining MTR with MTS or combining MTR, MTS, and MIV. We look at the causal effect of an increase in a parent's education without assuming homogeneous treatment of parental education.

While the bounds under single assumptions are wide and uninformative, we can obtain the tightest bounds by combining all three assumptions, MTR, MTS, and MIV. In particular, when we look at the average treatment effect of increasing a parent's schooling from either less than 12th grade or from high school to college, the highest lower bounds are positive and significantly different from zero when we use father's occupation as a MIV. Also, the least upper bounds on the average treatment effect are substantially lower than the estimates obtained from OLS. This allows us to conclude that the OLS results are overestimated relative to the true causal relationship between a parent's and a child's education. This is consistent with previous studies using the nonparametric bounds analysis to examine causal effects of parental education in the U.S. and Japan.

References

Becker, G. S. and N. Tomes (1979): "An Equilibrium theory of the distribution of income and intergenerational mobility," *Journal of Political Economy*, 87(6), 1153–1189.

——— (1986): "Human capital and the rise and fall of families," *Journal of Labor Economics*, 4(3), S1–S39.

Behrman, J. R. and M. R. Rosenzweig (2002): "Does increasing women's schooling raise the schooling of the next generation?" *American Economic Review*, 92, 323–334.

Bingley, P., K. Christensen, and V. M. Jensen (2009): "Parental schooling and child development: Learning from twin parents," *Danish National Centre for Social Research Social Policy and Welfare Services Working Paper 07:2009*.

Björklund, A., M. Lindahl, and E. Plug (2006): "The origins of intergenerational associations: Lessons from Swedish adoption data," *The Quarterly Journal of Economics*, 121, 999–1028.

Black, S. E. and P. J. Devereux (2011): "Chapter 16 - Recent Developments in Intergenerational Mobility," Elsevier, vol. 4 Part B of *Handbook of Labor Economics*, 1487 – 1541.

Black, S. E., P. J. Devereux, and K. G. Salvanes (2005): "Why the apple doesn't fall far: Understanding intergenerational transmission of human capital," *American Economic Review*, 95, 437–449.

Blanden, J., P. Gregg, and L. Macmillan (2007): "Accounting for intergenerational income persistence: Noncognitive skills, ability and education," *The Economic Journal*, 117, C43–C60.

Carneiro, P., C. Meghir, and M. Parey (2013): "Maternal education, home environments, and the development of children and adolescents," *Journal of the European Economic Association*, 11, 123–160.

de Haan, M. (2011): "The effect of parents' schooling on child's schooling: A nonparametric bounds analysis," *Journal of Labor Economics*, 29(4), 859–892.

Giustinelli, P. (2011): "Non-parametric bounds on quantiles under monotonicity assumptions: with an application to the Italian education returns," *Journal of Applied Econometrics*, 26, 783–824.

Gonzalez, L. (2005): "Nonparametric bounds on the returns to language skills," *Journal of Applied Econometrics*, 20, 771–795.

Grönqvist, E., B. Öckert, and J. Vlachos (2017): "The intergenerational transmission of cognitive and noncognitive abilities," *Journal of Human Resources*, 52, 887–918.

Gundersen, C., B. Kreider, and J. Pepper (2012): "The impact of the National School Lunch Program on child health: A nonparametric bounds analysis," *Journal of Econometrics*, 166, 79–91.

Haveman, R. and B. Wolfe (1995): "The determinants of children's attainments: A review of methods and findings," *Journal of Economic Literature*, 33, 1829–1878.

Hof, S. (2014): "Does private tutoring work? The effectiveness of private tutoring: A nonparametric bounds analysis," *Education Economics*, 22, 347–366.

Holmlund, H., M. Lindahl, and E. Plug (2011): "The causal effect of parents' schooling on children's schooling: A comparison of estimation methods," *Journal of Economic Literature*, 49, 615–51.

Huber, M., L. Laffers, and G. Mellace (2017): "Sharp IV bounds on average treatment effects on the treated and other populations under endogeneity and noncompliance," *Journal of Applied Econometrics*, 32, 56–79.

Iannelli, C. (2002): "Parental Education and Young People's Educational and Labour Market Outcomes: A Comparison across Europe," MZES Working Papers 45, MZES.

Kang, C. (2011): "Family size and educational investments in children: Evidence from private tutoring expenditures in South Korea," *Oxford Bulletin of Economics and Statistics*, 73, 59–78.

Kang, E. (2014): "A study on the intergenerational mobility of migration to the Seoul metropolitan area," *[in Korean] Journal of Korea Real Estate*, 32(1), 75–92.

Kikuchi, N. (2017): "Intergenerational transmission of education in Japan: Nonparametric bounds analysis with multiple treatments," *ISER Discussion Paper No. 1011.*

Kim, H. (2009): "An analysis of intergenerational economic mobility in Korea," *[in Korean] Korea Development Institute*, 3.

——— (2015): "Resetting education policy to restore social mobility," *KDI FOCUS*, 18.

Kim, S. (2017): "Intergenerational earnings mobility in Korea," *IZA Journal of Development and Migration*, 7, 21.

Kreider, B. and J. V. Pepper (2007): "Disability and employment: Reevaluating the evidence in light of reporting errors," *Journal of the American Statistical Association*, 102, 432–441.

Lechner, M. (1999): "Nonparametric bounds on employment and income effects of continuous vocational training in East Germany," *The Econometrics Journal*, 2, 1–28.

Lee, J. (2008): "Sibling size and investment in children's education: An Asian instrument," *Journal of Population Economics*, 21, 855–875.

Lee, Y. S. (2014): “Exams, districts, and intergenerational mobility: Evidence from South Korea,” *Labour Economics*, 29, 62–71.

Ma, K. and O. Kwon (2013): “A study on intergenerational mobility of housing asset,” *[in Korean] Housing Studies Review*, 21, 169–188.

Manski, C. F. (1989): “Anatomy of the selection problem,” *Journal of Human Resources*, 24(3), 343–360.

——— (1990): “Nonparametric Bounds on Treatment Effects,” *The American Economic Review*, 80, 319–323.

——— (1997): “Monotone treatment response,” *Econometrica*, 65(6), 1311–1334.

Manski, C. F. and J. V. Pepper (2000): “Monotone instrumental variables: With an application to the returns to schooling,” *Econometrica*, 68(4), 997–1010.

——— (2009): “More on monotone instrumental variables,” *The Econometrics Journal*, 12, S200–S216.

Maurin, E. and S. McNally (2008): “Vive la revolution! Long-term educational returns of 1968 to the angry students,” *Journal of Labor Economics*, 26, 1–33.

Ministry of Education (2008): “2008 Brief Statistics on Korean Education,” Seoul, Korea: Ministry of Education, Republic of Korea.

Nam, K. (2008): “The effect of parents’ education level on children’s education level and occupational status: International comparative analysis,” *[in Korean] The Journal of Economics and Finance of Education*, 17, 61–92.

Okumura, T. and E. Usui (2014): “Concave-monotone treatment response and monotone treatment selection: With an application to the returns to schooling,” *Quantitative Economics*, 5, 175–194.

Oreopoulos, P., M. Page, and A. Stevens (2006): “The intergenerational effects of compulsory schooling,” *Journal of Labor Economics*, 24(4), 729–760.

Pepper, J. V. (2000): “The intergenerational transmission of welfare receipt: A nonparametric bounds analysis,” *Review of Economics and Statistics*, 82, 472–488.

Richey, J. and K. Jeong (2014): “Intergenerational economic mobility in Korea using a quantile regression analysis,” *Journal of the Korean Data and Information Science Society*, 25(4), 715–725.

Sacerdote, B. (2007): “How large are the effects from changes in family environment? A study of Korean American adoptees,” *The Quarterly Journal of Economics*, 122, 119–157.

Solon, G. (1999): “Intergenerational mobility in the labor market,” in *Handbook of Labor Economics*, New York: Elsevier, vol. 3, 1761–1800.

Ueda, A. (2013): "Intergenerational mobility of earnings in South Korea," *Journal of Asian Economics*, 27, 33–41.