Family Size and Educational Investments in Children: Evidence from Private Tutoring Expenditures in South Korea*

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Abstract
Relying on private tutoring expenditures in South Korea, this paper examines whether large family size has a strong negative impact on educational investments in children. To deal with endogeneity of family size, the paper employs a nonparametric bounding method as well as an IV method. Our primary finding is that quantity-quality trade-offs in educational investments function in a way that varies by the sex of the child. While there is a non-negligible negative effect of large family size on educational investments for girls, there is little if any impact on those for boys. Son preferences traditionally shown by Korean parents seem to underlie such empirical findings.

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1 Introduction

One of the well-established empirical regularities in economics of family is that children in large families receive small educational investments and show poor educational attainment (Blake, 1989; Hanushek, 1992; Hauser and Sewell, 1986; Rosenzweig and Wolpin, 1980). In light of a potential link between population growth and economic growth, such a tradeoff between quantity and quality of children is often promoted as strong evidence that small family and slow population growth lead to economic development (de la Croix and Doepke, 2003; Galor and Weil, 2000; Moav, 2005). Recently, however, researchers raise questions about whether the empirical negative relationship between family size and children’s education implies a true causal effect of family size on children (Angrist et al., 2006; Caceres-Delpiano, 2006; Conley and Glauber, 2006; Guo and Van Wey, 1999). For example, parents with higher socio-economic status (SES) or cognitive abilities may have smaller families and invest more in education of each child than parents with lower SES or cognitive abilities; even in the absence of true causality, this may yield a strong negative correlation between family size and educational investments (and attainment) of a child.

In order to purge spurious correlations and identify exogenous changes in family size, several recent empirical studies rely on instrumental variables (IV) methods. Despite recent intensive studies exploiting various IVs for causal estimation, however, consensus on the impacts of family size on children’s education does not seem to emerge. On the one hand, Conley and Glauber (2006), Lee (2008), Li and Zhang (2007), Li et al. (2008), Rosenzweig and Wolpin (1980) and Rosenzweig and Zhang (2009) show a strongly negative effect of large family size on children’s education. On the other hand, Angrist et al. (2006) and Black et al. (2005) present evidence of weak or negligible impacts of large family size. Qian (2006) even reports a positive causal influence of family size on children’s education in China. Given such inconclusive evidence on quantity-quality trade-offs, the current paper aims to contribute to the literature by examining causal effects of large family size on private tutoring expenditures for children in South Korea.

South Korea offers an interesting example in the current context. First, it is well known

\footnote{Angrist et al. (2006), Black et al. (2005), Black et al. (2007), Caceres-Delpiano (2006), Li et al. (2008), Rosenzweig and Wolpin (1980) and Rosenzweig and Zhang (2009) use multiple birth (e.g., twin-birth) as a source of exogenous variation in family size; Angrist et al. (2006), Black et al. (2007), Conley and Glauber (2006) and Lee (2008) employ sibling sex composition as an IV for family size; as another strand, Li and Zhang (2007), Liu (2007) and Qian (2006) rely on institutional changes that give rise to changes in fertility decisions of parents.}
that South Korea has widespread and large-scale markets for private tutoring and that Korean parents extensively use tutoring in order to improve the children’s academic performance.\textsuperscript{2} In this circumstance, tutoring expenditures can serve as a good proxy for educational investments for children. To the extent that economic theories on quantity-quality trade-offs are based on parental choices of educational resource allocation across siblings (Becker and Lewis, 1973; Becker and Tomes 1976), expenditures on tutoring are arguably more appropriate to test the theoretical predictions than, for example, private school attendance and educational attainment used in other studies (Caceres-Delpiano, 2006; Conley and Glauber 2006). Second, as an explanation of conflicting results of impacts of family size, Li et al. (2008) suggest that quantity-quality trade-offs can be hard to detect in developed countries since well-functioning welfare and public education systems in these countries may mitigate the trade-offs but they can be more pronounced in less developed countries. South Korea has relatively well-functioning welfare and public school systems. If we find evidence of non-negligible impacts of family size in South Korea, then it is an indication that quantity-quality trade-offs may not necessarily be context-specific.

Lee (2008) has first recognized the advantage of using tutoring expenditures of Korean parents as a proxy for educational investments in an analysis of family size effects. To deal with endogeneity of family size, he used the sex of the first-born as an IV. The current paper shares with Lee’s study the measure of educational investments and the first-born’s sex as an IV for family size. But it differs from Lee’s study in at least three respects. First, as Lee’s data contain information only on overall expenditures on private tutoring for all children in the family, his study fails to control for a child’s birth order in a study of family size effects. Black et al. (2005), for example, underscore the importance of controlling for birth order in examining family size effects. In contrast to Lee’s study, the current paper relies on a data set that has information on private tutoring expenditures for each child in the family, which enables us to control for birth order. Second, as we will explain later, the sex of the first-born may not be truly exogenous in the tutoring expenditure equation. It can be correlated with

\textsuperscript{2}In Korea, private tutoring is largely performed as a supplementary learning on top of the formal (public) school education. Since there are virtually no private secondary schools that are independent of the government’s control, tutoring expenditures are not confounded with costs of attending a private school. Ministry of Education (2000) reports that private tutoring expenditures constitute about 10 to 15 percent of the household income. For a detailed overview of secondary education and private tutoring in South Korea, see Kang (2007a), Kim and Lee (2001) and OECD (1998).
a determinant of tutoring expenditures. In order to address potential endogeneity of the sex of the first-born, the current study employs a different empirical approach—a nonparametric bounding method—in addition to 2SLS methods. Using the bounding method, we calculate lower and upper bounds of the treatment effect instead of obtaining traditional point estimates. Provided that the bounds are sufficiently narrow and informative to locate the causal effect, we interpret that the magnitude of the true effect is somewhere between the estimated lower and upper bounds. Third, the current paper examines private tutoring of more recent cohorts (after 2000) of children than used by Lee’s paper. Lee’s study relies on private tutoring expenditures in the mid-1990s before private tutoring markets grew rapidly in Korea at the turn of the century.

Applying 2SLS and bounding methods to the patterns of private tutoring expenditures for school-age children in South Korea, the current paper shows that large (small) family size has a strong negative (positive) impact on educational investments for girls but little impact on those for boys. Namely, quantity-quality trade-offs in educational investments function in a way that varies by the sex of the child. Son preferences traditionally shown by Korean parents seem to underlie such an empirical finding.

The rest of the paper is organized as follows. Section 2 describes the nonparametric bounding method. We explain the data in section 3 and the empirical results in section 4. Section 5 concludes the paper.

2 Empirical Framework - Nonparametric Bounding Methods

Nonparametric bounding methods were first introduced in economics by Manski (1990) and further developed in Manski (1997) and Manski and Pepper (2000, 2009). Some recent examples of this method include Blundell et al. (2007), Gerfin and Schellhorn (2006), Gonzalez (2005), Hotz et al. (1997), Kreider and Hill (2009), Kreider and Pepper (2007), Kreider et al. (2009), Lechner (1999), Manski and Nagin (1998), and Pepper (2000) among others. The basic idea of the nonparametric bounding method is that instead of obtaining point estimates that often rely on questionable assumptions, one may calculate lower and upper bounds of the treatment effect given a few weaker assumptions. A unique advantage of this approach in an estimation of family size effects is that an IV does not have to be fully exogenous. To the extent that the IV is monotonically (either positively or negatively) related with the outcome variable, the
method, in combination of some other assumptions, is able to draw fairly tight bounds of the causal effect (Manski and Pepper 2000). In this section we outline the nonparametric bounding method used for our empirical analysis. What follows heavily draws on Gonzalez (2005), Manski (1990) and Manski and Pepper (2000).

Following Angrist et al. (2006) and many others, and for clear interpretation of the results, we restrict the analysis to second-born children (boys and girls, separately) of the family that has either two or three children. We exclude families with more than three children, because the sex of the fourth-born child may compromise an identifying assumption (monotone instrumental variable) of the bounding analysis as discussed later.

Let us first define $y_i$ as a natural log of an average monthly expenditure on private tutoring (in KRW 1,000) for second-born child $i$ who attends school in grades 1 to 12. Let a treatment indicator $T_i$ be equal to zero if the total number of $i$’s siblings is equal to one, and one if it is greater than one. Note that we set large (small) family size as a treatment (control). Finally, let an indicator $D_i$ be equal to one if the first-born child of $i$’s family is a daughter, and 0 if it is a son. Below we employ $D_i$ as an (monotone) IV for family size.3

Each child receives treatment $t \in T$. The response function $y_i(\cdot) : T \rightarrow Y$ maps treatments into outcomes. The realized outcome $y_i \equiv y_i(z)$ is the level of $y$ for child $i$ who actually receives treatment $z$. The latent outcome $y_i(t)$ ($t \neq z$) describes what level of educational investments would have been made for child $i$ had he or she received treatment $t$. Of primary interest is the average causal effect of having a large number of siblings in the family (i.e., more than one as opposed to only one) on monetary educational investments for a child. That is, $E[y_i(1) - y_i(0)]$.

Following Manski (1990), in order to set up bounds for the treatment effect, we first decompose $E[y(t)]$ by

$$E[y(t)] = E[y|z = t]Pr(z = t) + E[y(t)|z \neq t]Pr(z \neq t) \quad (1)$$

To make bounds analysis feasible, let us suppose that $y$ is bounded by $[K_0, K_1]$. Since the unobservable counterfactual $E[y(t)|z \neq t]$ is also bounded by $[K_0, K_1]$, we have the worst-case

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3Son preference of parents and the presence of sex-selective abortions make it difficult to use sex composition of the first two children as an IV for family size in the Korean context. To the extent that sex selections are relatively rare for first-born children, the first-child’s sex is a more appropriate IV for family size in Korea. See section 3 of Lee (2008) for further details.
(WC) bounds of $E[y(t)]$ given by

$$E[y|z = t]Pr(z = t) + K_0 Pr(z \neq t) \leq E[y(t)] \leq E[y|z = t]Pr(z = t) + K_1 Pr(z \neq t)$$

(2)

In order to further tighten the bounds of $E[y(t)]$, a few assumptions can be invoked individually as well as jointly. The first assumption to be employed is monotone treatment response (MTR), which is specified as follows$^4$:

$$t_1 \leq t_2 \rightarrow y(t_1) \geq y(t_2)$$

(3)

This assumption is drawn from economic theories that predict negative (at least, non-positive) impacts of large family size on educational investments in a child (Becker and Lewis, 1973; Becker and Tomes, 1976). Although some studies (e.g., Qian, 2006) document positive impacts of large family size on educational attainment of children, it is hard to imagine that, given a constrained budget, parents invest more on each child’s education when the family size is large than when it is small. The MTR bounds of $E[y(t)]$ can be expressed by

$$E[y|z \geq t]Pr(z \geq t) + K_0 Pr(z < t) \leq E[y(t)] \leq E[y|z \leq t]Pr(z \leq t) + K_1 Pr(z > t)$$

(4)

The second assumption is monotone treatment selection (MTS), which is specified by:

$$t_1 \leq t_2 \rightarrow E[y(t)|z = t_1] \geq E[y(t)|z = t_2]$$

(5)

This assumption supposes that sorting into treatment is not exogenous but monotone in the sense that the expected value of latent outcome $y(t)$ is greater (or equal) for those whose family size is small ($z = 0$) than for those whose family size is large ($z = 1$). For instance, parents of high socio-economic status are more likely to form a smaller family and invest more for each

$^4$Note the reversion of the inequality on the right-hand side of the arrow compared with Gonzalez (2005) and Manski and Pepper (2000). Such a reversion is also shown in the monotone treatment selection (MTS) assumption below. Each of the nonparametric bounds under those two assumptions is adjusted in consideration of the reversed inequalities.
child’s education than those of low socio-economic status (Schultz 1997). The MTS assumption yields the bounds of $E[y(t)]$ given by

\begin{align*}
E[y|z = t]Pr(z \leq t) + K_0 Pr(z > t) \\
\leq E[y(t)] \leq \\
E[y|z = t]Pr(z \geq t) + K_1 Pr(z < t)
\end{align*}

(6)

While it specifies a source of endogeneity in a conventional OLS method of examining the impacts of family size, the MTS assumption can make an important contribution to tightening the bounds of the true effect in combination with MTR. Joining MTS with MTR, we can obtain the MTR+MTS bounds of $E[y(t)]$ given by

\begin{align*}
\sum_{h>t} E(y|z = h)Pr(z = h) + E(y|z = t)Pr(z \leq t) \\
\leq E[y(t)] \leq \\
\sum_{h<t} E(y|z = h)Pr(z = h) + E(y|z = t)Pr(z \geq t)
\end{align*}

(7)

As shown in tables later, such a union of MTR and MTS substantially tightens our estimated bounds of the family size effect.

One can further tighten the preceding MTR+MTS bounds, if she find an IV $\upsilon$ that satisfies mean-independence—$E[y(t)|\upsilon = u_1] = E[y(t)|\upsilon = u_2]$ where $u_1 \neq u_2$. In practice, however, finding such an IV is extremely difficult, although we assume mean-independence in our 2SLS estimations as in Lee (2008). Following an idea of Manski and Pepper (2000), we employ $D_i$ as a monotone IV (MIV) for family size. The MIV assumption is specified by:

\begin{align*}
u_1 \leq u_2 \rightarrow E[y(t)|v = u_1] \leq E[y(t)|v = u_2]
\end{align*}

(8)

Under mean monotonicity, it is sufficient that for a given family size $t$, a second-born child in a daughter-first family ($D_i = 1$) receives greater educational investments than the counterpart in a son-first family ($D_i = 0$). If parents tend to prefer sons to daughters in a society such as South Korea (Park and Cho, 1995; Das Gupta et al., 2003), a second-born daughter can be as much or more advantaged in several dimensions including education in a family whose first-born is a daughter ($D_i = 1$) than in a family whose first-born is a son ($D_i = 0$). A second-born daughter is likely to receive as much or more educational investments in a daughter-daughter family than in a son-daughter family, because in the latter family a disproportionately greater
share of educational resources can be spent for a son. By the same logic, a second-born son may also receive as great or greater educational investments in a daughter-son family \((D_i = 1)\) than in a son-son family \((D_i = 0)\), since fierce competition among sons may reduce educational resources devoted to each son in the latter family. In sum, under son preference \(D_i\) may not be a good IV for family size satisfying mean-independence; nevertheless, it may serve as a good MIV satisfying mean-monotonicity.\(^5\)

If we consider a family with more than three children, the current MIV assumption can be compromised by the sex of the fourth-born. For example, a second-born son may receive smaller investments in a daughter-son-son-son family \((D_i = 1)\) than in a son-son-daughter-daughter \((D_i = 0)\) family if resource competition among sons is fierce. Thus we exclude families with more than three children from the subsequent analysis. Such a restriction, however, will not cause serious problems, because only a total of 54 expenditure observations (1.3%) are removed. Even if we include those observations and maintain the current MIV, the results are largely similar.

Under mean monotonicity, the MIV bounds of \(E[y(t)]\) are expressed by

\[
\sum_{u \in D} Pr(D = u) \{\sup_{u_1 \leq u}[E(y|D = u_1, z = t)Pr(z = t|D = u_1) + K_0 Pr(z \neq t|D = u_1)]\} \\
\leq E[y(t)] \leq \\
\sum_{u \in D} Pr(D = u) \{\inf_{u_2 \geq u}[E(y|D = u_2, z = t)Pr(z = t|D = u_2) + K_1 Pr(z \neq t|D = u_2)]\}
\]

(9)

\(^5\) Besides preferences of sibling sex composition, studies show that there are many forms of cost savings in raising same sex siblings. For example, Rosenzweig and Wolpin (2000) and Rosenzweig and Zhang (2009) find that parents of same sex siblings pay less money on clothing and others. Goux and Maurin (2005) report that same sex siblings tend to share the same room and live more often in overcrowded housing. If there are cost savings associated with siblings of same sex, they can be routed into educational investments in children. Another scenario is that under strong son preference it is possible that parents increase total educational resources in family budget with the larger number of sons. In such cases, directions of mean-monotonicity can be more complicated than equation (8) for each of second-born sons and daughters. In a working-paper version of the current paper (Kang, 2007b), we consider different directions of mean-monotonicity for each of second-born sons and daughters in estimating bounds under MIV. The empirical results of the earlier version are qualitatively similar to those reported in the current paper. The paper is available at “http://prof.cau.ac.kr/ckang/papers/Family%20size%20and%20edu%20investments%20WP.pdf”.

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Combining MIV with MTR+MTS, the MIV+MTR+MTS bounds of $E[y(t)]$ are given by

$$
\sum_{u \in D} \Pr(D = u) \cdot \{\sup_{u_1 \leq u, \sum_h > t} E(y|D = u_1, z = h) \Pr(z = h|D = u_1) + E(y|D = u_1, z = t) \Pr(z \leq t|D = u_1)\}
\leq E[y(t)] \leq 
\sum_{u \in D} \Pr(D = u) \cdot \{\inf_{u_2 \geq u, \sum_h < t} E(y|D = u_2, z = h) \Pr(z = h|D = u_2) + E(y|D = u_2, z = t) \Pr(z \geq t|D = u_2)\}
$$

(10)

Given the bounds of $E[y(t)]$ under varying assumptions, the lower bound (LB) of average treatment effects (ATE), $E[y(1)] - E[y(0)]$, is calculated by the difference between the lower bound of $E[y(1)]$ and the upper bound of $E[y(0)]$; the upper bound (UB) of ATE is obtained by the difference between the upper bound of $E[y(1)]$ and the lower bound of $E[y(0)]$. Along with the bounds of $E[y(t)]$ and ATE are calculated bootstrap 5th and 95th percentiles of the LB and UB, respectively, for testing. The interval between these percentiles shows a conservative 90% confidence interval for the estimated bounds. In addition, in order to take multiple observations for a same child into account, we generate each bootstrap sample by sampling the individual child (with replacement) first and using all expenditure observations of the child. The number of the bootstrap samples is 1,000.

There are some unusual cases where the estimated LB of $E[y(t)]$ exceeds its estimated UB due to the estimation bias for $E[\cdot]$. It arises especially when more than one assumption is jointly imposed and the bounds for $E[y(t)]$ become quite tight. In such cases the bounds of ATE can not be constructed by differencing between the estimated LB and UB of $E[y(1)]$ and $E[y(0)]$. If the estimated LB and UB of $E[y(t)]$ are reversed, we employ an alternative method of obtaining ATE, following an idea of Blundell et al. (2007, p.341). Under the null that the difference between LB and UB is zero, both LB and UB estimates are consistent estimates of $E[y(t)]$. Thus one may choose the estimate of either LB or UB as a consistent estimate for $E[y(t)]$; instead, we use a weighted combination of LB and UB, that is,

$$
\hat{E}[y(t)] = \alpha \hat{E}^L[y(t)] + (1 - \alpha) \hat{E}^U[y(t)]
$$

where $\alpha \in [0, 1]$ is a weight, and $\hat{E}^L[y(t)]$ ($\hat{E}^U[y(t)]$) is the estimated LB (UB) of $E[y(t)]$. We calculate the bounds of ATE by setting $\alpha = 0.5$, while other values of $\alpha$ yield qualitatively similar results. In tables of the results, the bounds of ATE that are obtained by such an alternative
method are presented under a different row, while those calculated with the regular method are set as missing.

Manski and Pepper (2000, 2009) and Kreider and Pepper (2007) caution that there exists finite-sample bias in estimated bounds of $E[y(t)]$ that involve MIV, because they take sups and infs in calculations; the estimated bounds tend to be narrower than the true bounds. To address the concern, Kreider and Pepper (2007) propose to use a nonparametric bootstrap correction by calculating $2T_n - E^*(T_n)$ where $T_n$ is a consistent analog estimator of a parameter and $E^*(\cdot)$ is the expectation operator with respect to the bootstrap distribution. We rely on Kreider and Pepper’s method based on 1,000 bootstrap samples, and report biased-corrected bounds of $E[y(1)] - E[y(0)]$ along with the biased-uncorrected bounds.

3 Data

3.1 Descriptions of Data

The data that we use for empirical analysis are drawn from a longitudinal household survey of South Korea entitled “the Korean Labor and Income Panel Study (KLIPS)”. This survey has been often employed to study issues of South Korea (e.g., Cho and Keum, 2004; Kang et al., 2007; Lee and Tae, 2005). KLIPS is a nationally representative annual survey of Korean households that started in 1998 with 5,000 households and 13,783 individuals aged 15 or older. It is modeled after the National Longitudinal Surveys (NLS) and the Panel Study of Income Dynamics (PSID) of the U.S., and administered by the Korea Labor Institute (KLI), a government-sponsored research institute (Korea Labor Institute 1998).

The KLIPS survey collects a wide range of information on families and individuals such as labor market status, earnings, family background, and demographic characteristics. From the household questionnaire of the survey, we obtain a household’s sibling composition and a child’s birth order. Staring from the third wave (survey year 2000), KLIPS collects unique information on private tutoring for children. The data contain private tutoring expenditures for each and every child in a household who attends educational institutions (including daycares) below college. We construct our measure of educational investments for a child from this information. Specifically, we employ the monthly average expenditure on private tutoring for

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6We thank a referee for bringing the finite-sample bias and papers that suggest a correction to our attention.
each individual child, which is collected in waves three to seven of KLIPS (survey years 2000 to 2004). Such a private tutoring expenditure does not include expenses on school supplies, reference books, school fees, etc. Although not verifiable using the KLIPS data, these expenses will not vary substantially by different households in the nation due to Korea’s unique system of primary and secondary education. In Korea schooling is almost exclusively publicly provided under national education financing and even distribution of public educational resources (OECD, 1998). Variations in private tutoring expenditure are likely to be a good proxy for those in total monetary educational investment for Korean children.

For subsequent analysis we impose several restrictions on the raw KLIPS data. First, we exclude children below elementary school age (age 7), because private tutoring expenditures for these young children may be confounded with child care expenditures. With such a restriction, we have the total number of tutoring expenditure observations for first to twelfth graders as following: 2,437 in 2000; 2,205 in 2001; 2,168 in 2002; 2,179 in 2003; 2,282 in 2004; and a total of 11,271 between 2000 and 2004. Second, those students who live in single-parent families or whose guardian is not one of the parents are also excluded, because patterns of educational investments in such families may be far from normal. However, students who cohabit with grandparents as well as both parents are included. Third, we exclude children whose mother is younger than 35 years of age, because the mother may not have completed fertility. Fourth, we focus our analysis on second-born children alone (but boys and girls, separately), who have no missing information for variables employed. The above restrictions leave us with a total of 1,942 observations for 616 second-born girls and 2,231 observations for 721 second-born boys from years 2000 to 2004. Finally, if we further exclude the observations of those whose family size is greater than three, a total of 1,893 observations are left for 603 second-born girls, and a total of 2,226 observations are left for 720 second-born boys.

3.2 Descriptive Statistics

Descriptive statistics of the main samples and their differences between daughter-first and son-first families are documented in Table 1. First three columns report statistics for second-born girls; last three columns those for second-born boys.
As for second-born girls, the monthly average expenditure on private tutoring is W123,800 (in 2000 constant)—approximately $98.2. This value is fairly close to the national monthly average expenditure on tutoring (W111,750) reported by Ministry of Education (2000) for female students attending school from grades 1 to 12 (W111,917 for male students). If the sample is divided by the sex of the first-born, second-born girls in daughter-first families receive smaller educational investments than those in son-first families; the average expenditure is W114,028 in the daughter-first family and W131,624 in the son-first family. The difference is significantly different from zero. Note that such a difference is obtained with no control for family size; hence it is not inconsistent with MIV, since MIV is defined for a given family size \( t (= 0, 1) \). The proportion of those who receive private tutoring, having a positive expenditure, is also lower among girls in daughter-first families (68.4%) than those in son-first families (72.2%). Such a difference is also significant. Namely, the sex of the first-born seems to affect educational investments for second-born girls. Yet it remains to be seen whether such a difference in educational investments is mediated through and caused by the difference in family size.

Family sizes are significantly different between the two types of families. As expected by son preference, the average number of children in daughter-first families (2.48) is greater than that in son-first families (2.08). The proportion of girls who have more than one sibling is also higher in daughter-first families (0.483) than in son-first families (0.084). Namely, the sex of the first-born child yields a significant difference in family size for a second-born girl.

Given the differences in family size and \( y \) between daughter-first and son-first families, we can calculate a Wald estimate of the effect of increased family size on tutoring expenditures. Such an estimation supposes that the sex of the first-born child is truly exogenous to \( y \) when \( T \) is controlled for. The estimate can be calculated by

\[
\frac{E(y_i | D_i = 1) - E(y_i | D_i = 0)}{E(T_i | D_i = 1) - E(T_i | D_i = 0)}.
\]

The Wald estimate implies that a second-born girl receives 46.3% (s.e. 23.3) smaller educational investments if she has more than one sibling than if she has only one sibling. In section 4.1, we extend this simple analysis to 2SLS by controlling for other characteristics of the girl and her family.

\footnote{In order to examine an intent-to-treat estimate for tutoring expenditures, we run a reduced-form regression of a log of tutoring expenditures \( (y_i) \) against the sex of the first-born and other individual and family variables. The estimate for \( D_i \) is \(-0.120\) (s.e. 0.073). Provided that \( T_i \) is significantly positively with \( D_i \) in a similar regression, family size is found to have a negative impact on \( y_i \), as will be shown below in 2SLS.}

\footnote{For a combined sample of boys and girls, Lee (2008, Col (2) of Table 6) documents that the average family size of daughter-first families is greater by 0.177 than that of son-first families. If we experiment with a similar specification of Lee’s using our combined sample of second-born boys and girls, we find that daughter-first families have 0.181 (s.e. 0.021) more children than son-first families.}
Concerning other variables, a student’s age, grade level and parents’ education level are similar between daughter-first and son-first families. Parents of daughter-first families, however, are slightly older and worse-off than those of son-first families. Nonetheless, if \( D_i \) is regressed against all of the individual and family variables jointly, neither single variable nor entire set of variables is significant at the 10% level (p-value of the F-statistic = 0.476). The proportion of the daughter-first family is 0.447, which fails to be significantly different from 0.5.

As for second-born boys on the other hand, it is notable that boys in daughter-first families receive greater educational investments than those in son-first families. And it is in sharp contrast to the case of girls that family sizes fail to be significantly different between daughter-first and son-first families. Provided that the second-born child is a boy, the sex of the first-born child does not give rise to differences in the fertility decision of Korean parents; the likelihood of giving birth to more than two children in a family is quite low around an average of 6% regardless of the sex of the first-born. Other variables such as a student’s age, grade level, parents’ education level, age and family income are also similar between daughter-first and son-first families. Because the sex of the first-born fails to vary significantly the family size of second-born boys, Wald and 2SLS estimates cannot be convincingly produced for the boys sample; we focus on the bounds analysis in order to explore the causal impact of large family size on educational investments for second-born boys.

4 Estimation Results

4.1 OLS and 2SLS Results

As an intermediate step, we estimate the following conventional model of family size effects by OLS and 2SLS:

\[
y_i = \beta_0 + \beta_1 T_i + \beta_2 X_i + \epsilon_i \tag{11}
\]

where \( y_i \) is a natural log of an average monthly expenditure for child \( i \); \( T_i \) takes 0 if the total number of \( i \)'s siblings is equal to one, and 1 if greater than one; and \( X_i \) is a vector of \( i \)'s measured

\footnote{In the data raw values of tutoring expenditures vary from 0 to 1,743.7. To deal with zero expenditures in the log transformation, a value of 10 is added to every child’s raw value of expenditure before a log is taken. The value of 10 is chosen because it is the smallest accounting unit reported in the survey (W10,000) and it is about 7 to 8% of the mean expenditure on private tutoring. If a smaller value (e.g., 1) is added to every expenditure, however, the results are qualitatively similar.}
characteristics. In 2SLS, $D_i$ is employed as an IV for $T_i$. Table 2 presents the estimation results for girls and boys separately.

**INSERT TABLE 2 HERE.**

First, family size is strongly associated with the size of tutoring expenditures for girls. The OLS estimate in column (1) suggests that a second-born girl receives on average a 29.5% smaller educational investment if she lives with more than one sibling than if she lives with only one sibling in the family. This amount is significant statistically as well as economically. However, it may not be a causal estimate due to endogeneity of $T_i$. If we rely on 2SLS so as to draw better causal estimates for the effect of large family size, the 2SLS estimate in column (3) suggests that a second-born girl receives a 29.2% smaller educational investment if she lives with more than one sibling.

As suggested by MIV, even this estimate is likely to understate negative impacts of large family size than overstate them: for second-born girls $D_i$ is likely to be positively rather than negatively correlated with $\epsilon_i$ while being also positively correlated with $T_i$.

The first-stage estimate in column (2) shows that the sex of the first-born child is a strong predictor of family size for a second-born girl. She is more likely to live in a large family if the first-born child is a girl than if it is a boy. A second-born girl has a 41.2 percentage point higher probability of getting more than one sibling (as opposed to only one sibling) if the first-born child is a girl than if it is a boy.

---

10. If the first-born sibling attends college, this may greatly affect parents’ spending on a second-born girl’s tutoring. While such an impact can be in part captured by a control of the child’s own age given that age differences between the first and second-born child are similar across families, we add three variables (age of the first-born child, a dummy for whether he or she attend primary, middle or high school, and a dummy for whether he or she attends college or university) in order to consider potential impacts of the first-born sibling. In such a case, the 2SLS estimate is $-0.283$ (s.e. 0.172), which is similar to the current 2SLS estimate. A referee is concerned that the first-born sibling not living with the parents may indicate an atypical family configuration and affect education spending for a second-born girl. (About 5.6% of the girls sample has the first-born sibling not living with the parents.) To address such a concern, we add a dummy for whether the first-born sibling cohabits with the parents. In this case, the 2SLS estimate for $\beta_3$ is $-0.260$ (s.e. 0.174), which is also similar to the current 2SLS estimate. Moreover, in order to consider the fact that about 30% of expenditure observations are zeros, we run an IV-Tobit model using the same specification as in column (3) and $D_i$ as an IV for $T_i$. The IV-Tobit estimate is $-0.534$ (s.e. 0.426), which is not inconsistent with the current 2SLS result.

11. Besides a limitation from a failure to control for a child’s birth order in a study of family size effects, Lee’s (2008) interpretation of potential bias of his 2SLS estimates is wrong-signed. He argues that postnatal son preference yields an overstatement of the true causal effect of family size (p.865). However, as is clear from our setting which measures the effect on second-born boys and girls separately, using the sex of the first-born child ($D_i$) is more likely to understate the true effect of family size rather than overstate it for second-born girls. In addition, if we rule out cost-savings associated with same sex siblings, using $D_i$ as an IV for family size is more likely to understate rather than overstate the true effect on second-born boys as well, because competition among sons within the family is likely to yield a positive (rather than negative) correlation between $D_i$ and $\epsilon_i$, while $D_i$ is positively correlated with $T_i$. 

---
Second, family size is also strongly associated with the amount of tutoring expenditures for boys. The OLS estimate in column (4) suggests that a second-born boy receives on average a 22% smaller educational investment if he lives with more than one sibling than if he lives with only one sibling. This amount is, however, marginally significant.

As observed in Table 1, the sex of the first-born child fails to be a strong predictor of family size for a second-born boy. It has little correlation with the family size. Thus 2SLS methods cannot be convincingly applied to the case of boys. As expected from the extreme weakness of the IV in the first stage, the 2SLS estimate in column (6) shows an unrealistic figure of negative 11.6 (s.e. 35.6). Therefore, we rely on the bounds analysis in order to explore the causal impact of large family size on boys.12

4.2 Results of Bounds Analysis

Figure 1 graphically shows the bounds of the average treatment effect (ATE, \(E[y(1) - y(0)]\)) estimated under varying individual and joint assumptions. The bounds of ATE under each of individual MTR, MTS and MIV assumptions are fairly large, hence they fail to be informative. In order to further tighten the bounds, we put together the individual assumptions. The estimated bounds of \(E[y(t)]\) and ATEs based on joint assumptions are presented in Table 3. Together with MTR+MTS and MIV+MTR+MTS bounds, we report other joint assumptions bounds (MIV+MTR and MIV+MTS bounds) in the table for comparison. The estimates of the girls sample are shown in Panel A; those of the boys sample in Panel B.

In our specification \(y\) is a natural log of a tutoring expenditure that may vary from negative infinity to positive infinity in principle. In the data the observed \(y\) varies from 2.302 to 7.943 after a value of 10 is added to the raw value of the expenditure (see footnote 9).13 In order to make bounds analysis feasible, we arbitrarily impose lower and upper bounds of \(y\). We set \(K_0\)

---

12 Using total spending on education as well as on private tutoring, and a combined sample of boys and girls for years 1993 to 1998, Lee’s (2008) 2SLS methods find that an additional child of the two-children family decreases per-child educational investments by about 14.5 to 18.5%. A 2SLS estimate based on our combined sample of second-born girls and boys yields the estimated effect comparable to Lee’s, although ours is more imprecisely estimated. Our 2SLS estimate suggests that an additional child decreases educational investments for a second-born child by about 10.1% (s.e. 27.1).

13 If a value of 1 is added to the raw expenditure before a log is taken, the results are qualitatively unaffected. They are available in Appendix Tables of Kang (2007b).
equal to 2.3, which corresponds to a zero expenditure, and $K_1$ equal to 10, which corresponds to a monthly expenditure of W22,016,466.\footnote{Such bounds are somewhat arbitrary. Thus we have explored how the estimated bounds vary with alternative values of $K_0$ and $K_1$. (This sensitivity analysis is unnecessary for the MTR+MTS and MIV+MTR+MTS bounds because they are not a function of $K_0$ and $K_1$.) Nonetheless, the primary findings of the paper are qualitatively unaffected. The results based on alternative values of $K_1$ are available upon request.}

At first, if we look at the results for girls, MIV+MTR bounds suggest that ATE could be anywhere between $-3.065$ and $-0.185$. Such bounds imply that the average amount of tutoring expenditures for a second-born daughter can decrease by a maximum of 307\% and a minimum of 18.5\% if she has one more sibling in the family. MIV+MTS bounds imply that ATE could be anywhere between $-0.342$ and 2.929. In contrast to these two joint bounds, the joint MTR+MTS assumption considerably tightens the bounds of ATE to a range between $-0.344$ and 0.

Manski and Pepper (2000, p.1004) propose an informal method to check the validity of the joint MTR+MTS hypothesis. Under MTR+MTS, it should be satisfied that $E[y|z = u]$ must be a weakly decreasing function of $u$, namely,

$$u_1 \leq u_2 \rightarrow E[y|z = u_1] \geq E[y|z = u_2]$$

(12)

In our data, it is found that $\hat{E}[y|z = 0] = 4.307$ and $\hat{E}[y|z = 1] = 3.963$ for the girls sample. Since a T-test strongly rejects equality of the two means at the 1\% level, it seems unlikely that the joint MTS+MTR assumption is violated.

Finally, the joint MIV+MTR+MTS assumption yields the tightest bounds of ATE between $-0.383$ and $-0.144$.\footnote{Note that the LB of MIV+MTR+MTS bounds is below that of MIV+MTS bounds ($-0.342$), which is inconsistent with the theory. Such inconsistency arises probably because a modified method of calculating ATE is used when there is a reversal of the estimated LB and UB of $E[y(t)]$. In contrast to the bounds of the girls sample, the LB of MIV+MTR+MTS bounds is equal to that of MIV+MTS bounds ($-0.121$) in the boys sample, for which there is no reversal of the LB and UB of $E[y(t)]$.}

If one accepts the three assumptions of MIV, MTR, and MTS jointly to occur due to estimation errors for $u$. In any case, the MIV+MTR+MTS bounds of $E[y(0)]$ under equation (8) in such a case, the estimated LB and UB of $E[y(0)]$ are not reversed. Nevertheless, the estimated

\[ E[y(0)] = 3.770 < E[y(1)|D = 1] = 3.997, \quad E[y(0)|D = 0] = 4.348 > E[y(0)|D = 1] = 4.218 \text{ for the girls sample from the data, although the latter difference is insignificantly different from zero. In order to investigate potential changes in the estimated bounds of ATE that arise from a failure of MIV to be uniformly true for the whole girls sample, we calculate the MIV+MTR+MTS bounds of $E[y(0)]$ under a different version of MIV (MIV') such that $u_1 \leq u_2 \rightarrow E[y(t)|v = u_1] \geq E[y(t)|v = u_2]$, while estimating the MIV+MTR+MTS bounds of $E[y(1)]$ under equation (8). In such a case, the estimated LB and UB of $E[y(0)]$ are not reversed. Nevertheless, the estimated}
estimate the effect of large family size, she can infer that the true size of the effect is somewhere between \(-0.383\) and \(-0.144\). Bias-corrected MIV+MTR+MTS bounds indicate a slightly wider range of ATE between \(-0.401\) and \(-0.142\). It is reassuring that the 2SLS estimate (i.e., \(-0.292\)) in Table 2 is located within such an interval that is obtained via a different empirical approach.\(^{17}\)

The bootstrap confidence interval for the MIV+MTR+MTS bounds suggests that the UB of ATE is strictly smaller than zero at the 10% level of significance. Therefore, statistical evidence suggests that there exists a negative (positive) causal impact of large (small) family size on educational investments for second-born girls. If we rely on our (possibly upward-biased) 2SLS estimate as a point estimate, a 29.2% decrease in tutoring expenditure due to a one child increase in family size is both statistically and economically significant for second-born girls. A more conservative estimate, the UB of ATE (\(-0.144\)), also suggests a fairly strong impact of family size on educational investments for second-born girls.

In contrast to the findings for second-born girls, the primary results for second-born boys are somewhat different, while patterns of changes in bounds with varying assumptions for boys are similar to those for girls. From Panel B, the joint MIV+MTR assumption suggests that ATE could be anywhere between \(-2.219\) and 0. The MIV+MTS bounds imply that ATE could be between \(-0.121\) and 5.467. The MTR+MTS assumption considerably tightens the bounds of ATE. Based on equation (12), it seems unlikely that the joint MTS+MTR assumption is violated for the boys sample, since \(\hat{E}[y|z = 0] = 4.300\) and \(\hat{E}[y|z = 1] = 4.075\) and a T-test rejects equality of the two means (p-value= 0.066). Finally, the joint MIV+MTR+MTS assumption yields the tightest bounds of ATE between \(-0.121\) and 0.\(^{18}\) Bias-corrected MIV+MTR+MTS bounds indicate a slightly wider range of ATE between \(-0.153\) and 0.

LB and UB of ATE do not vary substantially. The new MIV’+MTR+MTS bounds of ATE, which correspond to MIV+MTR+MTS bounds in Table 3, are \([-0.414, -0.102]\) and their 90% CI is \([-0.633, -0.023]\).

\(^{17}\)Provided that mean-independence rather than mean-monotonicity is assumed in 2SLS, one may wonder how the bounds will change if mean-independence is also employed in our bounding analysis. Theoretically, the bounds under mean-independence will be narrower than those under mean-monotonicity (Manski and Pepper, 2000). As expected, independence+MTR+MTS bounds of ATE are \([-0.253, -0.144]\) and their 90% CI is \([-0.412, -0.025]\) for the girls sample. For the boys sample, such bounds are \([-0.108, -0.055]\) and their 90% CI is \([-0.376, -0.005]\). Other bounds under mean-independence are available upon request.

\(^{18}\)Figure 1 reveals that for the girls sample bounds of ATE that involve MIV are somewhat tighter than the corresponding bounds that does not involve MIV: MIV, MIV+MTR, MIV+MTS and MIV+MTR+MTS bounds are tighter than WC, MTR, MTS and MTR+MTS bounds, respectively. This suggests that MIV has some identifying power in the girls sample, as \(D_i\) has a strong correlation with treatment levels. However, \(D_i\) does not contribute to tightening the bounds involving MIV in the boys sample, since it has little correlation with treatment levels. Such weakness of \(D_i\) may be a reason why the bounding method fails to reveal non-zero impacts of family size on boys. With a stronger and more exogenous IV than \(D_i\), one may be able to find statistically significant effects of family size on boys. Nonetheless, it seems difficult to deny that effects of family size are weaker for boys than for girls in Korea.
The bootstrap confidence interval for the MIV+MTR+MTS bounds suggests that the UB of ATE fails to be strictly smaller than zero at the 10% significance level. Although the estimated LB suggests a negative level of ATE, its 95th percentile is equal to zero; the LB also fails to be significantly different from zero. Therefore, it seems doubtful that there exist strong negative causal impacts of large family size on educational investments for boys. Even if one takes the LB of the MIV+MTR+MTS bounds of ATE seriously, the estimate suggests that second-born boys receive at most 12.1% smaller educational investments if they live with more than one sibling than if they live with only one sibling.

Compared with the results for girls, negative (positive) impacts of large (small) family size for second-born boys seem much weaker. Although a statistical test does not confirm a significant difference, the estimated bounds of ATE for second-born girls exceed those for second-born boys in absolute magnitude. Hence, an arguable summary of the preceding results would be that while there is a non-negligible negative (positive) effect of large (small) family size on educational investments for second-born girls, there is little if any effect of family size on educational investments for second-born boys.

5 Concluding Remarks

Applying 2SLS and nonparametric bounding methods to patterns of private tutoring expenditures in South Korea, this paper examines whether large family size has a strong negative impact on educational investments for children. Our primary finding is that quantity-quality trade-offs in educational investments function in a way that varies by the sex of the child. While there is a non-negligible negative (positive) effect of large (small) family size on educational investments for second-born girls, there is little if any effect of family size for second-born boys. Son preferences traditionally shown by Korean parents seem to underlie such empirical findings.

In a working-version of the current paper (Kang, 2007b), we infer that second-born girls are likely to suffer more in education from increased family size if a younger brother is born to the

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19We extend the current bounds analysis based on second-born children alone to each of the boys and girls samples that include first-born as well as second-born children. A major disadvantage of such an extension is that MIV, which tightens bounds of ATE in combination with MTR+MTS, cannot make sense to the first-born children. Hence we calculate the WC, MTR, MTS and MTR+MTS bounds alone, failing to obtain bounds based on MIV. Not surprisingly, MTR+MTS yields the tightest bounds of ATE. For the girls sample, the MTR+MTS bounds are \([-0.330,0]\); for the boys sample, they are \([-0.285,0]\). Although both bounds are fairly tight and the LB of ATE for girls are larger in absolute value than that for boys, it seems difficult to draw firm conclusions about the size of the impacts of family size and the difference in impacts between girls and boys.
family than if a younger sister is born; in contrast, second-born boys suffer as little—or slightly less due to reduced competition among sons—when they have a younger sister as when they have a younger brother. The statistical evidence on such an inference, however, remains only suggestive, since there is an overlap of relevant tightest bounds of ATEs.

Several recent papers (e.g., Angrist et al., 2006; Black et al., 2005; Caceres-Delpiano, 2006; Qian, 2006) show that family size has negligible effects on the quality of children. Besides the doubts raised about exogeneity of IVs frequently employed, Liu (2007) shows that the causal relationship between quantity and quality of children depends on the measure of quality. Liu (2007) and Caceres-Delpiano (2006) empirically find the sensitivity of the estimated relationship to measures of children’s quality. Although the current paper sheds light on quantity-quality trade-offs with respect to educational inputs, it does not examine a more traditional issue of whether family size has an impact on an ultimate quality such as educational outcomes of children. Such an issue may be of great interest because parents will ultimately care about the output (quality) of children rather than an input. Employing different quality measures to examine the family size effects in various dimensions would be a topic for future research.
References


Korea Labor Institute, 1998. Reports on the Korean Labor and Income Panel Study (various years), Korea Labor Institute, Seoul: Korea.


Kreider, B., Pepper, J.V., Gundersen, C., Jolliffe, D., 2009. Identifying the Effects of Food Stamps on Children’s Health Outcomes When Participation is Endogenous and Misreported, Unpublished manuscript.


Figure 1: Bounds of the Average Treatment Effect

![Graph showing bounds of the average treatment effect for girls and boys with different treatments and their combinations.](image-url)
Table 1: Descriptive Statistics of the Main Samples

<table>
<thead>
<tr>
<th>Variables</th>
<th>Girls Sample (N=1,893)</th>
<th>Boys Sample (N=2,226)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total Sample</td>
<td>Daughter-first family</td>
</tr>
<tr>
<td>Spending on tutoring (W1,000)</td>
<td>123.8 (151.5)</td>
<td>114.0 (153.6)</td>
</tr>
<tr>
<td>Log(spending on tutoring)</td>
<td>4.217 (1.343)</td>
<td>4.115 (1.339)</td>
</tr>
<tr>
<td>Any tutoring (Yes=1)</td>
<td>0.705 (0.456)</td>
<td>0.684 (0.465)</td>
</tr>
<tr>
<td>Family size</td>
<td>2.263 (0.440)</td>
<td>2.483 (0.500)</td>
</tr>
<tr>
<td>More than one sibling (Yes=1)</td>
<td>0.263 (0.440)</td>
<td>0.483 (0.500)</td>
</tr>
<tr>
<td>Age</td>
<td>12.485 (3.346)</td>
<td>12.496 (3.355)</td>
</tr>
<tr>
<td>Grade</td>
<td>6.598 (3.383)</td>
<td>6.617 (3.383)</td>
</tr>
<tr>
<td>Father’s education</td>
<td>12.311 (2.762)</td>
<td>12.306 (2.751)</td>
</tr>
<tr>
<td>Mother’s education</td>
<td>11.288 (2.463)</td>
<td>11.320 (2.525)</td>
</tr>
<tr>
<td>Father’s age</td>
<td>43.795 (3.975)</td>
<td>44.141 (4.098)</td>
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<tr>
<td>Mother’s age</td>
<td>40.640 (3.674)</td>
<td>40.848 (3.877)</td>
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<tr>
<td>Family income (W1,000)</td>
<td>2.145 (1.351)</td>
<td>2.134 (1.441)</td>
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<tr>
<td>Log(family income)</td>
<td>7.528 (0.695)</td>
<td>7.483 (0.780)</td>
</tr>
<tr>
<td>Live with grandparents (Yes=1)</td>
<td>0.024 (0.152)</td>
<td>0.017 (0.128)</td>
</tr>
<tr>
<td>Daughter-first family (Yes=1)</td>
<td>0.447 (0.497)</td>
<td>0.519 (0.500)</td>
</tr>
</tbody>
</table>

Note: * significant at the 10% level; ** significant at the 5% level
Table 2: OLS and 2SLS estimates of the Average Treatment Effect

<table>
<thead>
<tr>
<th>Estimation method:</th>
<th>Girls Sample (N=1,893)</th>
<th>Boys Sample (N=2,226)</th>
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<tbody>
<tr>
<td>Dependent variable:</td>
<td>OLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>Log(Tutoring Expenditure)</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>More than one sibling (Yes=1)</td>
<td>-0.295 (0.084)**</td>
<td>-0.292 (0.174)*</td>
</tr>
<tr>
<td>Daughter-first (Yes=1)</td>
<td>0.412 (0.036)**</td>
<td>-0.008 (0.009)</td>
</tr>
<tr>
<td>Father’s education</td>
<td>0.047 (0.018)**</td>
<td>-0.008 (0.009)</td>
</tr>
<tr>
<td>Mother’s education</td>
<td>0.083 (0.021)**</td>
<td>0.015 (0.010)*</td>
</tr>
<tr>
<td>Father’s age</td>
<td>-0.014 (0.016)</td>
<td>-0.026 (0.007)**</td>
</tr>
<tr>
<td>Mother’s age</td>
<td>-0.008 (0.016)</td>
<td>-0.007 (0.007)</td>
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<tr>
<td>Log(family income)</td>
<td>0.504 (0.048)**</td>
<td>-0.027 (0.019)</td>
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<tr>
<td>Grandparents (Yes=1)</td>
<td>-0.216 (0.225)</td>
<td>0.103 (0.074)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.005 (0.644)</td>
<td>1.478 (0.277)**</td>
</tr>
<tr>
<td>F(excluded IV)</td>
<td>130.22</td>
<td>0.11</td>
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<tr>
<td>R-square</td>
<td>0.268</td>
<td>0.258</td>
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</table>

Note: * significant at the 10% level; ** significant at the 5% level

Each regression controls for dummies for a student’s grade, residential region and the wave of KLIPS in addition to the variables reported.
Table 3: Bounds of $E[y(t)]$ and the Average Treatment Effect

Panel A: Girls sample ($N = 1,893$)

<table>
<thead>
<tr>
<th>Assumptions:</th>
<th>MIV+MTR</th>
<th>MIV+MTS</th>
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<tbody>
<tr>
<td>$E[y(0)]$</td>
<td>4.299</td>
<td>4.176</td>
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<tr>
<td>$E[y(1)]$</td>
<td>2.737</td>
<td>3.875</td>
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<tr>
<td>$E[y(1) - y(0)]$</td>
<td>-3.065</td>
<td>-0.342</td>
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<tr>
<td>Bias-corrected</td>
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<td>-0.593</td>
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Assumptions: MTR+MTS

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<tr>
<td>$E[y(0)]$</td>
<td>4.286</td>
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<td>$E[y(1)]$</td>
<td>3.963</td>
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<td>$E[y(1) - y(0)]$</td>
<td>-0.344</td>
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Panel B: Boys sample ($N = 2,226$)

<table>
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<th>Assumptions:</th>
<th>MIV+MTR</th>
<th>MIV+MTS</th>
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<tbody>
<tr>
<td>$E[y(0)]$</td>
<td>4.286</td>
<td>4.181</td>
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<tr>
<td>$E[y(1)]$</td>
<td>2.419</td>
<td>4.179</td>
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<tr>
<td>$E[y(1) - y(0)]$</td>
<td>-2.219</td>
<td>-0.121</td>
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<tr>
<td>Bias-corrected</td>
<td></td>
<td>0.138</td>
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Assumptions: MTR+MTS

<table>
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<th>Assumptions:</th>
<th>MIV+MTR+MTS</th>
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<tbody>
<tr>
<td>$E[y(0)]$</td>
<td>4.286</td>
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<tr>
<td>$E[y(1)]$</td>
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<tr>
<td>$E[y(1) - y(0)]$</td>
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