# Gender Differences in the Effect of Peer SES: Evidence from a Second Quasi-Experimental Case Study*

Joscha Legewie

(Columbia University)

Thomas A. DiPrete

(University of Wisconsin-Madison)

February 28, 2011

## Introduction

In a recent paper, Legewie and DiPrete (2011) have extended research on the effect of schools and argued that the school context effects the gender gap in education. From a theoretical perspective, they argue that the school and class environment shapes the conception of masculinity in the adolescent peer culture and thereby either fosters or inhibits the development of anti-school attitudes and behavior among boys. School resources that create a learning oriented peer culture raise the valuation of academics in the adolescent male culture and facilitate their commitment by promoting academic competition as an aspect of masculinity. This can happen through the positive influence of academically oriented peers as well as through other school resources that affect the school climate (e.g. teacher quality). Girls' peer groups, on the other hand, more readily and independently of the school context encourage attachment to teachers and school, and do not identify adolescent or pre-adolescent femininity with resistance to authority and disengagement from school. These context-dependent differences in the construction of gender identities

*Please direct correspondence to Joscha Legewie, Columbia University, Department of Sociology – MC9649, 606 W 122nd Street, New York, NY 10027 (jpl2136@columbia.edu).

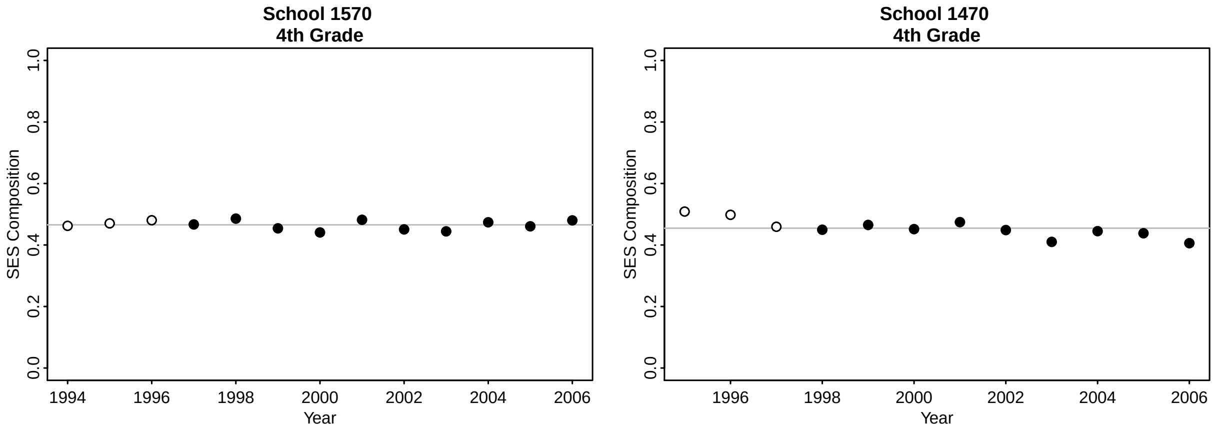
imply that boys' academic performance is particularly sensitive to school resources that stimulate a learning oriented environment in and around the school.

Using data from Germany and a quasi-experimental research design, Legewie and DiPrete (2011) present estimates of SES composition for boys and girls as a central resource in the school/class context. Their results support the claim that boys are more sensitive to resources that create a learning oriented peer culture. Their findings, however, are limited to Germany and their study only focuses on one major dimension of cognitive achievement, namely reading. In this research report, we conduct a second quasi-experimental case study using data from the Chicago Public School (CPS) system - the third largest school district in the US. Our findings extend Legewie and DiPrete's results by providing evidence from a second case using US data and by considering the effect of peer SES both for reading and math test scores.

# Data and Methods

We use an extensive longitudinal database from the Chicago Public Schools (CPS) system assembled by the Consortium on Chicago School Research (CCSR) at the University of Chicago. With more than 400,000 enrolled students and about 600 public elementary and high schools (2009-2010), CPS currently is the third largest school district in the US. Our database consists of different components: (a) the administrative student records for every student enrolled in CPS from the school year 1993/94 to 2005/06. These records include the school and grade identifier for the fall and spring term as well as a limited number of standard demographic characteristics such as gender, date of birth, students' race, their eligibility for free lunch as a measure of parental background, and their special education status. (b) The test file records, which contain different reading and math tests administered over the years. Most noticeable are the Iowa Test of Basic Skills (ITBS) in reading and math, which was taken by almost all students in the spring of grades 3 through 8 over the whole period, and the Tests of Achievement and Proficiency (TAP) in reading and math, which was given to different high school grades up until 2002. (c) Data from a set of school, teacher and student surveys conducted by CCSR in the spring of 1994, 1997, 1999, 2001, 2003, and 2005. These surveys include a range of measures about school related attitudes and behavior, school climate, self-evaluation of abilities, student-teacher relations and other topics. All three components can be perfectly matched over time so that we can follow students in CPS as they move through grades, change school,

Figure 1: Variation in SES composition of Adjacent Cohorts within a School within a Grade with School-Grade Average




*Note: The figure shows the average SES in 4th grade in two example schools from fall 1992 to fall 2005. The grey lines refer to the school-grade specific means so that the variation in SES composition of adjacent cohorts is the deviation of the observed means from this line. The white points indicate the years that are dropped from the final analysis because we can not construct the instrument for these years*

and improve their reading and math skills.[1]

For the main analysis presented in this paper, we restrict our sample to 4th grade students who participated in the ITBS on their grade level[2], and did not change the school or grade within 4th grade. These restrictions reduce the sample size to about 330,000. The construction of our instrument (see below) makes it necessary to exclude certain years from the analysis so that our final sample consist of about 200,000 students in grade 4 from the school year 1996/97 to 2004/05.

## Estimating Compositional Peer Effects: Analytic Strategy

Similar to Hoxby (2000) and others (e.g. Hanushek and Rivkin 2009), we exploit the variation in SES composition of adjacent cohorts within a school within a grade to estimate the causal effect of SES composition. This variation is illustrated in figure 1, which shows the average of our SES measure (for the definition see below) for 4th grade of two example schools form fall 1993 to fall 2005. The grey lines in figure 1 refer to the school-grade specific means so that the variation in SES composition of adjacent cohorts is the deviation of the observed means from this line. This variation can be decomposed in (a) the variation coming from differences between entering cohorts in first grade and

[1]Note that teachers can only be matched with schools but not individual students and can not be followed over time.

[2]A small number of students do not take the test on their grade level.

(b) the variation coming from mobility of students between schools and grades. There are good reasons to belief that in- and out-mobility is not random because parents might selectively withdraw their children based on their experiences in a certain school. It might also be the case that certain children are retained because their learning was hindered by their cohort peers. Alternatively, a good student might skip a class because the peers in his or her cohort happen to be relatively weak students. These sources of non-random selection might lead to biased estimates of peer SES effects when they are based on cohort-to-cohort variations within schools. For this reason, we focus on the variation coming from differences between entering cohorts in the fall of 1st grade before any mobility between schools and grades occurred. We can obtain estimates only based on this variation using instrumental variables. In particular, we treat 4th grade SES composition as endogenous and instrument the 4th grade SES composition in school $s$ by the composition of this cohort when it entered the school 3 years earlier. For the fall of the school year 2004/05, for example, we instrument the 4th grade SES composition at school $s$ with the composition of the 1st grade in fall 2001 at school $s$ - the year when this cohort entered the school. In the two stage framework, this can be described as

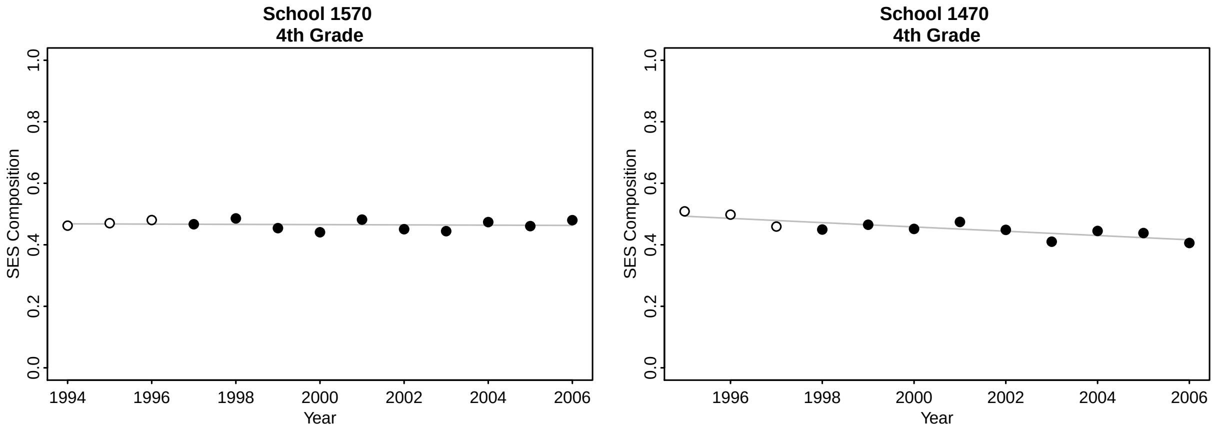
$$\widehat{D}_{sc}^{4.\,grade} = \alpha_s + \gamma_c + y_{isc}^{3.\,grade} + \delta D_{sc}^{1.\,grade} \tag{1}$$

$$y_{isc}^{4.\,grade} = \alpha_s + \gamma_c + y_{isc}^{3.\,grade} + \theta \widehat{D}_{sc}^{4.\,grade} + \epsilon_{isc} \tag{2}$$

where equation 1 represents the first stage regression of 4th grade SES composition on the school-cohort level on the instrument $D_{sc}^{1.\,grade}$ together with school as well as cohort fixed effects. Equation 2 represents the second stage regression of some measure of 4th grade educational achievement on the fitted values of $D_{sc}$ from the first stage regression together with school and cohort fixed effects. Both equations also control for prior educational achievement in 3rd grade and a set of control variables on the individual and school-cohort level $\mathbf{X}_{isc}\beta_1 + \mathbf{U}_{sc}\beta_2$, which we have omitted for simplicity. It is also important to note that the two variables of peer composition in 1st and 4th grade are measured in the fall of a school year whereas the two measure for educational achievement come from the spring term.

The problem with this strategy, however, is that the composition of adjacent entering cohorts is partly driven by naturally occurring differences between cohorts and partly by parents who select into specific schools in a specific year. Only the first source of variation is arguably random. School might, for example, exhibit a certain trend in their SES composition which is known to parents. This becomes apparent when looking at

Figure 2: Variation in SES composition of Adjacent Cohorts within a School within a Grade with Linear Trend




School 1470 in figure 2, which shows a a small downwards trend in the mean level of our SES measure within 4rd grade over the years. Such a development might occur because the school is in a 'declining' neighborhood with an increasing number of poor people. It is reasonable to argue that involved parents are aware of this trend and expect an increasing share of low SES kids, which ultimately steers them away from this specific school. In general, the trend might not only influence parents schooling decisions but might be connected to some unobserved characteristics, which are also related to achievement so that the estimate of the causal effect is biased.

We address this problem by modelling a group-specific time trend - i.e. a time trend that is specific to each school. This is illustrated in figure 2 using the same schools as in figure 1. In this case, the relevant variation is the deviation of the observed proportions from the linear trend line as illustrated on the right side for the year 1996. Statistically, this can be implemented by adding $\beta_s year$ to both the first and second stage regression for the instrumental variable model reflecting the school-grade specific linear time trend. This approach relies on the assumption that the trend on the school-grade level is linear or at least that the trend known to parents and other actors who influence the school decisions is linear. It could still be the case that high SES kids in a specific year are attracted to a specific school by some year-specific school resources (e.g., a popular teacher joined the school, or a popular principal joined the school, or something). It could also be the case that a linear trend does not adequately reflect the way in which school change is perceived by parents. These possibilities, however, seem highly unlikely especially considering that we are talking about elementary schools. To a much higher extend than for high schools, children usually attend their neighborhood school, which makes natural occurring variations between schools the more important source of variation in the cohort-to-cohort differences in SES composition within a school.

### Alternative Identification Strategy

Hanushek and Rivkin (2009) rely on a different strategy, which makes use of variations in adjacent cohorts within a school within a grade coming both from differences between incoming cohorts as well as mobility over time. Bla bla... We replicate their estimation strategy to compare the results obtained with the two different identification strategy.

## Variables

Our analysis uses reading and math test scores in 4th grade from the Iowa Test of Basic Skills (ITBS) as the main outcome variables (see table 1 for descriptive statistics). The ITBS was designed by Riverside Publishing and was given to all students in grade 3 through grade 8 up until the spring of 2005. The test scores are measured on a common scale using item response theory and are standardized with a mean of zero and a standard deviation of one.

Our focal treatment variable is the socioeconomic (SES) composition of the student body, which is measured at the school-grade-year-level as the average social status on a scale constructed from three indicators. The most common measure of family background used in administrative datasets is the student's eligibility for free or reduced-price lunch as defined by the federal state. In the context of CPS, however, this measure is not satisfying because the extraordinary high concentration of poverty. In more than 50% of the schools, for example, the proportion of students who receive free lunch is above 85% so that the measure does not show a lot of variation across schools. To address this problem, we have constructed a SES measure from a set of indicators and averaged these separate indicators weighting each one equally. For the first indicator, we averaged the free lunch eligibility of a student across the different years the student is observed in order to get a more stable measure of family background. Accordingly, a student who received free lunch in two years but not in the third gets a value of 0.66. We then averaged this more stable indicator of family background on the school-grade-year level. The second indicator is the proportion of minority students in a school-grade-year defined as the proportion of black students. The third indicator is a seven point scale for mothers education obtained from the student questionnaires. This variable only exists for a subset of the students in our sample and was imputed for the other cases using the three other indicators. Before averaging, all of the four indicators were scaled from 0 to 1 and oriented so that a higher value reflects an lower average status.

Table 1: Variables in Main Analysis at Individual and Class Level

| Variables | Description | Mean | SD | Mean (Male) | Mean (Female) | Std. Diff. in Means |
|---|---|---|---|---|---|---|
| *Dependent Variables* | | | | | | |
| Reading Test Scores | 4th grade reading test scores | 196.19 | 24.15 | 194.46 | 197.86 | .14 |
| Math Test Scores | 4th grade math test scores | 198.77 | 19.32 | 198.58 | 198.95 | .02 |
| *Independent Variables (Individual Level)* | | | | | | |
| Prior Achievement | 3rd grade reading test scores | 182.12 | 21.13 | 180.74 | 183.45 | .13 |
| Prior Achievement | 3rd grade math test scores | 184.08 | 16.44 | 184.11 | 184.05 | 0 |
| Female | 0 - Male; 1 - Female | 0.51 | 0.50 | | | |
| Family Background | 0 - not eligible for free lunch; 1 - eligible for free lunch | 0.78 | 0.41 | 0.78 | 0.79 | .03 |
| | avg. free lunch across years | 2.58 | 0.54 | 2.57 | 2.58 | .04 |
| | mother's education (7-point scale) | 3.39 | 1.75 | 3.42 | 3.35 | -.04 |
| Race | 1 - White | 0.10 | 0.30 | 0.10 | 0.10 | -.01 |
| | 2 - African-American | 0.53 | 0.50 | 0.52 | 0.54 | .03 |
| | 3 - Native American | 0.00 | 0.04 | 0.00 | 0.00 | .01 |
| | 4 - Asian | 0.03 | 0.17 | 0.03 | 0.03 | -.01 |
| | 5 - Latino | 0.34 | 0.47 | 0.34 | 0.33 | -.02 |
| Mover | 0 - did not change school; 1 - changed school | 0.30 | 0.46 | 0.31 | 0.30 | -.01 |
| Age | continuous variables | | | | | |
| Interaction Terms | School x Year (School specific time trend | | | | | |
| Fixed Effects | School Fixed Effects | | | | | |
| | Year Fixed Effects | | | | | |
| *Independent Variables (School-Grade-Year Level)* | | | | | | |
| SES Comp. 4th grade | 4th grade (fall) avg. SES at school-grade-year level (aggregated) | 0.65 | 0.16 | 0.65 | 0.66 | .02 |
| SES Comp. 1st grade (Instrument) | 1st grade (fall) avg. SES at school-grade-year level (aggregated) | 0.65 | 0.17 | 0.65 | 0.65 | .03 |

Source: CPS Data data; n=XXXX; * $p < 0.05$, ** $p < 0.01$

*Note: The descriptive statistics show in this table are based on the same sample as the final analysis. The difference in means refers to the mean for boys minus the mean for girls divided by the pooled standard deviation. Note that all the continuous variables are standardized for the final analysis.*

In addition, we use a number of control variables both at the individual and at the school-grade level. These variables are described in table 1 together with some descriptive statistics. All independent, continuous variables are standardized to have a mean of 0 and a standard deviation of 1 across the combined sample of males and females in both dataset.

# Results

Table 2 presents the results for the instrumental variable-fixed effect regressions of 4th grade reading test and math scores on school-grade level SES composition, gender and other control variables. The table also shows separate models with and without a control variable for prior performance. Across the four models, the results for SES composition indicate a positive effect of about 0.15 standard divisions for the raw score and of about 0.08 (reading) and 0.11 (math) for the gain scores. These results are in line with Legewie and DiPrete's findings (2011) and also other studies such as Crosnoe (2009). More importantly, the interaction between peer SES and female is negative and significant for all four models. Compared to the German results reported by Legewie and DiPrete (2011), the size of the interaction effect is slightly smaller but still substantial considering the the gain scores accumulate over the years.

# Conclusion

In this paper, we have presented results from a second quasi-experimental case study for the gender differences in the effect of peer SES. In an earlier paper, we have argued that boys are more sensitive to school resources that create a learning oriented environment because of context-dependent differences in the construction of gender identities. The results presented in this paper reconfirm our earlier findings (Legewie and DiPrete 2011) and provide further evidence for our argument. Using data from the Chicago Public Schools (CPS), they reveal the same pattern for the US and also extend them to math test scores.

Table 2: Gender Differences in the Effect of Peer SES

| | | Female | | SES Comp. | | SES Comp. x Female | |
|---|---|---|---|---|---|---|---|
| Model | Prior Perf. | coef. | (se) | coef. | (se) | coef. | (se) |
| 1. IV/FE - Estimate (Outcome: Reading) | yes | 0.055*** | (0.00) | 0.077*** | (0.02) | -0.010*** | (0.00) |
| 2. IV/FE - Estimate (Outcome: Reading) | no | 0.139*** | (0.00) | 0.157*** | (0.03) | -0.021*** | (0.00) |
| 3. IV/FE - Estimate (Outcome: Math) | yes | -0.023*** | (0.00) | 0.105*** | (0.02) | -0.024*** | (0.00) |
| 4. IV/FE - Estimate (Outcome: Math) | no | 0.026*** | (0.00) | 0.140*** | (0.03) | -0.052*** | (0.00) |

n=192,014; Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Note: The first stage results show that the two instruments are highly correlated with SES composition as the treatment. The F-statistics are over XXX (highly significant), which is far above the commonly used threshold of 10. The additional control variables are described in table 1. The number of cases is 192,014.*

# References


Crosnoe, Robert. 2009. "Low-Income Students and the Socioeconomic Composition of Public High Schools." *American Sociological Review* 74:709–730.

Hanushek, Eric A. and Steven G. Rivkin. 2009. "Harming the best: How schools affect the black-white achievement gap." *Journal of Policy Analysis and Management* 28:366–393.

Hoxby, Caroline. 2000. "Peer Effects in the Classroom: Learning from Gender and Race Variation." NBER Working Paper 7867, National Bureau of Economic Research.

Legewie, Joscha and Thomas A. DiPrete. 2011. "School Context and the Gender Gap in Educational Achievement." *American Sociological Review* (forthcoming).