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Appendix to:

Gender Differences in Remote Learning amid COVID-19

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Conceptual Framework and Empirical Model

There are a variety of factors that potentially affect student academic achievement. These include student inputs, family inputs, peer inputs, teacher inputs, and school inputs. Further, each input may have persistent effects on achievement, implying that current achievement is a function of both current and prior inputs. Following the mathematical presentation of the education production function in Boardman and Murnane (1979); Hanushek (1979); Todd and Wolpin (2003); and Sass, Semykina, and Harris (2014), the relationship between inputs and current achievement can be expressed as a general cumulative achievement function:

$$A_{it} = f(S_i(t), P_i(t), X_i(t), F_i(t), I_{i0}, \epsilon_{it}) \tag{A1}$$

where A_t is a student i's academic achievement at time t, $S_i(t)$ are school-related inputs (e.g., the number of students per school, physical facilities, and teacher and principal experience) cumulative to time t. Similarly, $P_i(t)$ are cumulative peer inputs (e.g., peers' academic achievement, income and socioeconomic status of peers' parents, and peers' behavior), $X_i(t)$ are individual/student characteristics (including both demographic characteristics like race/ethnicity, gender and identified disability status, as well as cognitive and non-cognitive skills such as critical thinking, consciousness, and self-discipline), and $F_i(t)$ are cumulative family-related inputs (e.g., a parent's education, household income, the number of siblings, and so on). I_{i0} and ϵ_{it} are the student i's endowed innate ability and an idiosyncratic error term at time t. Taking this cumulative achievement function and the history of all inputs in time t and $t-1$ and rearranging them under several model assumptions produce the following cumulative achievement equation:[1]

$$A_{igst} = \alpha_1 X_{igst} + \alpha_2 P_{-igst} + \gamma_3 S_{igst} + \theta A_{igst-1} + \rho_i + \lambda_g + \sigma_s + \xi_{igst} \tag{A2}$$

where A_{igst} is an academic achievement of a student i of grade g in school s in year-semester t, X_{igst} are student characteristics, P_{-igst} are characteristics of the student i's peers, and S_{igst} are time-varying school and teacher inputs. A_{igst-1} is the academic achievement of the student i in the previous period, which is assumed to serve as a sufficient statistic for all prior school inputs. ρ_i, λ_g, and σ_s are time-invariant student/family, grade, and school/teacher inputs, respectively.

Equation (A2) is typically estimated using annual summative assessment data where there is little variation in the timing of exams between one year and the next. In our analysis we employ formative assessment data from exams given near the beginning of the school year (fall exam) and the middle of the school year (winter exam). As shown in the main text, the dates at which students take these exams can vary considerably. Therefore, it is necessary to account for the number of instructional days a student attended school between exams. To do this, we assume that θ=1 and divide the change in achievement between exams by the number of instructional days attended, D. This yields:

$$\left(A_{igst} - A_{igst-1}\right)/D_{igst} = \beta_1 X_{igst} + \beta_2 P_{-igst} + \beta_3 S_{igst} + \rho_i + \lambda_g + \sigma_s + \xi_{igst} \qquad \text{(A3)}$$

As schools switched their learning mode from traditional face-to-face instruction to remote instruction after the pandemic broke out, the pandemic-induced school closures and the consequent shift in learning mode likely reduced student achievement growth in general. Thus, we account for the proportion of time a student spends in remote instruction, R. Compared with the traditional face-to-face learning environment, students have less direct exposure to their peers while in remote instruction, which could reduce any negative influences of disruptive peers. We therefore allow the impact of remote instruction to vary with the proportion of historically disruptive peers, H. Further, effective self-regulated learning becomes more important for success in remote learning, which increases the relative importance of student self-control, C. Thus, we include an interaction term between R and C, which allows the impact of remote learning on achievement growth per day to vary with the level of self-control. Finally, we allow the effects of remote learning, peer influences, and self-control to vary by gender. The resulting empirical model is:

$$\begin{aligned}\frac{\left(A_{igst} - A_{igst-1}\right)}{D_{igst}} = {} & \gamma_1 X_{igst} + \gamma_2 C_{igst} + \gamma_3 H_{-igst} + \gamma_4 R_{igst} \\ & + \gamma_5 (C_{igst} \times R_{igst}) + \gamma_6 \left(H_{-igst} \times R_{igst}\right) \\ & + \gamma_7 \left(Female \times R_{igst}\right) + \gamma_8 \left(Female \times C_{igst}\right) \\ & + \gamma_9 \left(Female \times H_{-igst}\right) + \gamma_{10} \left(Female \times C_{igst} \times R_{igst}\right) \\ & + \gamma_{11} \left(Female \times H_{-igst} \times R_{igst}\right) + \lambda_g + \sigma_s + \tau_t + \xi_{igst} \qquad \text{(A4)}\end{aligned}$$

where X represents student characteristics (including gender) other than self-control, C. The only peer characteristic being measured is their history of disruptive behavior, H. Time-varying school/teacher characteristics are not measured. Unobserved student time-invariant characteristics are not measured, and grade, school and year fixed effects, $\lambda_g, \sigma_s, \tau_s$, account for time-invariant grade and school characteristics and year effects.

Methodology

We use multivariate regression analysis to estimate the parameters in equation (A4). We estimate the regression models over two distinct periods. First, we estimate the determinants of student achievement growth per instructional day over the two testing periods prior to the pandemic outbreak (fall to winter of SY 2018–19 and fall to winter of SY 2019–20). Since all instruction was face-to-face during this time, R=0 and all the terms that include R drop out of the equation. The resulting estimates provide a measure of the pre-pandemic relationship between the two mechanisms of interest: exposure to historically disruptive peers and (lack of) student self-control and student achievement—controlling for prior achievement, student demographics (including gender), grade level, school, and year.[2]

Second, we conduct a similar analysis for the period covering the transition from planned remote learning to in-person instruction (fall SY 2020–21 to winter SY 2020–21). We measure variation across students in their exposure to remote learning by the fraction of days attended between the fall and winter exams that were spent in remote instructional mode. Since there is only one time period, the year indicators drop out.

Because exposure to remote learning is partly determined by parental choice, the exposure measure could reflect unobserved factors like parental resources that affect both learning mode and student achievement. To address such potential selection bias, we estimate a two-stage-least-squares (2SLS) regression model, where we instrument the proportion of days attended remotely with a number of exogenous variables (parents' preference on face-to-face learning, school-level COVID-19 quarantines and positive case counts, and transportation mode to/from school) that are expected to affect exposure to remote learning days.[3] In the first stage, we estimate the determinants of exposure to remote learning. Then, in the second stage, we use the predicted exposure to remote learning to estimate the effect of learning mode on student achievement.

For both the standard ordinary-least-squares regression model and the 2SLS model, we decompose the gender achievement differential into three components: (a) the part that is "explained" by observable differences between boys and girls and their peers (i.e., differences in X, C, H, R and the interactions between C, H, and R), (b) the estimated coefficients on unobserved characteristics of boys and girls (measured by the coefficient on the female indicator), and (c) the portion that is attributable to gender differences in the marginal effects of the key variables that are hypothesized to alter the return to remote learning (the estimates of coefficients g_7–g_{11}).

Supplemental Tables

Table A1. Phase and Timing of Return to Full-time In-person Instruction

Phases	Learning Mode	Start Date
Universal remote learning	All remote	First day of school (August 17, 2020)
Phase 1	90 minutes of in-person, one day a week (Pre-K–Grade 2) 180 minutes of in-person, one day a week (special ed.) 1:1 meeting by appointment (Grades 3–12)	September 8, 2020
Phase II	1 half-day in-person, once a week	Skipped
Phase II	1 full day in-person, once a week	September 21, 2020
Phase IV	2 full days in-person	October 5, 2020
Phase V (face-to-face)	Full-time in-person or remote	October 14, 2020

Notes. The district utilized county-wide information on the level and change in the COVID-19 New Diagnosis Rate, as well as other factors, to determine transitions between phases. Data were reviewed every three weeks.

Table A2. List of Disciplinary Incident Codes

Incident Code	Incident Type	Frequency	Incident Code	Incident Type	Frequency
0	Continuation of incident	4,185	22	Weapons – knife^	96
1	Alcohol	89	23	Weapons – other^	132
2	Arson	15	24	Other discipline incident^	3,096
3	Battery^	3,077	25	Weapons – handgun^	17
4	Burglary	61	26	Weapons – rifle^	1
5	Computer trespass	556	27	Serious bodily injury^	80
6	Disorderly conduct^	7,964	28	Other firearms	0
7	Drugs, except alcohol and tobacco	654	29	Bullying^	447
8	Fighting^	4,927	30	Other – attendance related	3,847
9	Homicide	0	31	Other – dress code violation	48
10	Kidnapping	0	32	Academic dishonesty	535
11	Larceny or theft	549	33	Other – student incivility^	6,141
12	Motor vehicle theft	0	34	Other – Possession of unapproved items^	281
13	Robbery	14	35	Gang-related^	97
14	Sexual battery^	24	36	Repeated offenses	140
15	Sexual harassment^	221	40	Other non-disciplinary incident	214
16	Sex offenses^	172	42	Electronic smoking device*	0

17	Threat or intimidation^	1,695	44	Violence against a teacher*	0
18	Tobacco	727			
19	Trespassing	91		Total	40,681
20	Vandalism	488			

Notes. The table shows a list of disciplinary incident codes and frequency of each incident type during SY 2018–2019 and SY 2019–2020 (incidents prior to the initial school closure) from the Student Disciplinary data.
^: Identifies a student as "disruptive" if the student's incident falls into one of these disciplinary incidents.
*: These disciplinary incidents were newly listed in Georgia Department of Education Discipline Matrix table, but did not apply to any of the students in the analysis sample.

Table A3. Frequency of Disciplinary Incidents by Student

Number of Disciplinary Incidents	Frequency	Percent
0	12,080	35.35
1	6,216	18.19
2	3,846	11.26
3	2,658	7.78
4	1,932	5.65
5	1,482	4.34
6	1,139	3.33
7	884	2.59
8	689	2.02
9	553	1.62
9 <		7.87

Notes. The table shows a frequency of disciplinary incidents by student in the analysis sample during SY 2018–19 and SY 2019–20 (incidents prior to the initial school closure on March 18, 2020).

Table A4. Pre-pandemic Summary Statistics for Student Demographics, Full Sample and by Gender

	Full Sample		Girls		Boys		Mean Difference (G-B)
	Mean	SD	Mean	SD	Mean	SD	
Black	0.436	0.496	0.440	0.496	0.433	0.495	0.007
White	0.251	0.433	0.248	0.432	0.254	0.435	-0.006
Asian	0.105	0.307	0.105	0.307	0.105	0.306	0.001
Hispanic	0.175	0.380	0.173	0.378	0.178	0.382	-0.005
Other Non-White	0.033	0.177	0.034	0.181	0.031	0.174	0.003*
FRPM	0.446	0.497	0.442	0.497	0.449	0.497	-0.007*
Disability Status	0.111	0.314	0.074	0.261	0.147	0.354	-0.073***
English Learner	0.099	0.299	0.088	0.283	0.110	0.313	-0.022***
Number of Incidents (Lagged)	0.068	0.447	0.032	0.343	0.104	0.526	-0.071***
N (Math)	53,388		26,375		27,013		
N (Reading)	48,651		23,898		24,753		
Test Takers (Math)	36,091		17,817		18,280		
Test Takers (Reading)	35,593		17,492		18,073		

Notes. Analyses sample includes students in Grade 1 to Grade 7 enrolled in public schools located in the school district during the pre-pandemic semesters (fall and winter of SY 2018–19 and 2019–20 but prior to the initial school closure). The unit of the number of observations is individual in each school-year-semester.

Table A5. Mean Student Characteristics for Decomposition Calculation (2SLS) by Gender

	Math			Reading		
	Girls	Boys	G-B	Girls	Boys	G-B
Achievement Growth per Day (Fall to Winter SY 2020-21)	0.120	0.106	0.014	0.129	0.111	0.018
Proportion of Remote Days	0.593	0.578	0.015	0.597	0.583	0.014
Proportion of Disruptive Peers	0.071	0.074	-0.003	0.069	0.076	-0.007
Ever Rushed	0.115	0.195	-0.080	0.069	0.131	-0.062
Proportion of Remote Days × Proportion of Disruptive Peers	0.045	0.045	0.000	0.044	0.047	-0.003
Proportion of Remote Days × Ever Rushed	0.067	0.110	-0.043	0.042	0.076	-0.034
Black	0.376	0.369	0.007	0.369	0.366	0.003
Asian	0.142	0.144	-0.002	0.144	0.142	0.002
Hispanic	0.155	0.159	-0.004	0.158	0.160	-0.002
Other Non-White	0.039	0.035	0.004	0.039	0.036	0.003
FRPM	0.417	0.415	0.002	0.419	0.414	0.005
EL	0.064	0.077	-0.013	0.066	0.080	-0.014
Disability Status	0.071	0.141	-0.070	0.078	0.148	-0.070
N	11,571	11,726		13,040	13,480	

Notes. Sample includes students in Grade 2 to Grade 8 enrolled in public schools located in the school district during the transitional period (fall and winter of SY 2020–21). The unit of the number of observations is individual in each school-year-semester. Gender differences are computed by first rounding the gender-specific means to the nearest 0.001. The unrounded means are used for the decomposition calculation presented in Table 7.

Table A6. Decomposition of the Achievement Growth per Day Difference between Girls and Boys on 2SLS, Transitional Period (Fall to Winter of SY 2020–21)

	Math		Reading	
	Amount	% of Total	Amount	% of Total
Total Gender Achievement Growth Gap	0.014	100.0	0.018	100.0
Total Gap Due to:				
Mean Difference in:				
Unobserved Student Characteristics	-0.009	-65.2	-0.015	-83.1
Observed Student Demographics	0.002	14.6	0.003	9.4
School/Grade Enrolled In	-0.000	-1.7	-0.001	-5.1
Proportion of Disruptive Peers	0.000	-0.2	0.000	-0.3
Ever Rushed	-0.001	-10.3	-0.001	-4.9
Proportion of Remote Days	0.000	-2.6	-0.001	-6.2
Proportion of Remote Days × Proportion of Disruptive Peers	0.000	-0.7	0.000	-0.6
Proportion of Remote Days × Ever Rushed	0.001	4.6	0.000	-1.4
Impact Difference in:				
Proportion of Disruptive Peers	0.000	0.4	-0.001	-3.6
Ever Rushed	-0.001	-4.6	-0.001	-4.6
Proportion of Remote Days	0.000	2.6	0.001	5.3
Proportion of Remote Days × Proportion of Disruptive Peers	0.000	1.0	0.001	3.5
Proportion of Remote Days × Ever Rushed	0.002	14.7	0.002	13.1

Notes. Sample includes students in Grade 2 to Grade 8 enrolled in public schools located in the school district during the transitional period (fall and winter of SY 2020–21). The unit of the number of observations is individual in each school-year-semester. Decomposition calculation is based on 2SLS estimates from Table 5 (columns 1 and 3) and mean statistics of girls and boys in the analysis sample.

References

Boardman, A. E., & Murnane, R. J. (1979). Using panel data to improve estimates of the determinants of educational achievement. *Sociology of Education.*, *52*(2), 113–121. doi.org/10.2307/2112449

Hanushek, E. A. (1979). Conceptual and Empirical Issues in the Estimation of Educational Production Functions. *The Journal of Human Resources*, *14*(3), 351–388. doi.org/10.2307/145575

Sass, T. R., Semykina, A., & Harris, D. N. (2014). Value-added models and the measurement of teacher productivity. *Economics of Education Review*, *38*, 9–23. doi.org/10.1016/j.econedurev.2013.10.003

Todd, P. E., & Wolpin, K. I. (2003). On the Specification and Estimation of the Production Function for Cognitive Achievement. *The Economic Journal*, *113*(485), F3–F33.

Endnotes

1. See Sass, Semykina and Harris (2014) for a detailed discussion of the assumptions required to obtain equation A2 and the validity of those assumptions.

2. In the pre-pandemic period, prior-semester values are used to measure peer disruptive behavior. For example, when measuring the determinants of standardized test scores in winter SY 2019–20, the proportion of disruptive peers is calculated based on the peers' disciplinary records in the fall semester of SY 2019–20.

3. Given our achievement model includes interactions with exposure to remote learning, these interactions are treated as potentially endogenous as well, and the list of instruments include the corresponding interaction terms. The use of school-level quarantines/case counts precludes the use of school fixed effects in the 2SLS model.