Abstract Title Page

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Title:

Evaluating the Relationship between Student Attendance and Achievement in Urban Elementary and Middle Schools: An Instrumental Variables Approach

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Abstract Body
Limit 5 pages single spaced.

Background/context:
Description of prior research and/or its intellectual context and/or its policy context.

The relationship between student attendance and academic success has been a long-standing interest to researchers, policy makers, practitioners, and parents. And yet, among the vast body of empirical research examining how student-level factors relate to academic outcomes, few investigations have honed in on the relationship between attendance and achievement. The purpose of this paper is to provide insight into this relationship. In particular, this study has evaluated the hypothesis that the number of days a student is present in school positively affects learning outcomes.

In the scant quantitative literature that exists in K-12 education on the relationship between attendance and achievement, the results are mixed. Caldas (1993) found that attendance was positively and significantly related to student performance in Louisiana's public elementary and secondary schools. His unit of observation was at the school level, and attendance was quantified as the percent of students per school that were present in a given day. As a result, the conclusions from the study are based on the relationship between the average level of school attendance and average student performance. Thus, findings from this paper can not be explained at the student level of analysis.

Lamdin (1996) also relied on aggregate data to show that student attendance had a positive and significant effect on academic performance. As with the Caldas (1993) study, the results derived from this particular paper can only be interpreted in terms of average school performance. In fact, the author asserted that conclusions about individual-level achievement outcomes cannot be drawn from this study. Borland & Howsen (1998) refuted Lamdin's (1996) findings, pointing to the lack of aincorporating a measure of ability within his analyses. They deemed this to be problematic because ability could potentially be correlated with attendance and achievement and hence would confound Lambin's (1996) results. The authors found that once ability was taken into account, attendance became an insignificant measure of student achievement. Their refutation is based on aggregated variables as well. More recently, Roby (2004) concluded that based on the analysis of educational outcomes in Ohio, there was a statistically significant relationship between attendance and achievement in fourth, sixth, ninth, and twelfth grades. Like previous studies, Roby's work only evaluated attendance the aggregated school level.

Purpose/objective/research question/focus of study:
Description of what the research focused on and why.

This paper will address several gaps in the literature. First, those studies that have attempted to hone in on the relationship between student attendance and achievement in K-12 education have been conducted only at the aggregate level of analysis. Although these papers have provided insight into how attendance may be related to achievement, aggregate data have less variability than underlying individual-level data. As a result, it is not possible with aggregate data to offer findings on the relationship between student-level inputs and student-level achievement. Thus, this paper extends upon those previous studies, which employed only aggregate data, with new analyses at the student-level. By using a large-scale, longitudinal database of all individual- and multi-level observations in all elementary and middle schools in the Philadelphia School District from academic years 1994/1995 to 2000/2001, this paper provides insight into how attendance affects student performance at a detailed level of analysis.

Second, as Borland & Howsen (1998) have suggested, there is need for quantifying a measure of ability when conducting analyses that have student achievement as the dependent variable. Because ability may be positively correlated with attendance, it is possible that there are confounding effects between attendance and achievement that will bias estimates. By using a longitudinal dataset that has multiple observations of students over time, this study avoids this issue by implementing a value added model of student achievement. As it is further explained in the methods section below, this model's feature of having a lagged achievement score at the individual-level means that it is no longer necessary to incorporate additional measures of ability or a full-historical panel of information on any particular student. Thus, in this study, student ability no longer confounds the relationship between attendance and achievement.

Finally, there is an additional issue regarding confounding variables that the literature has not entirely addressed. Even after controlling for student ability either through a direct measure or a value added model, it is still possible that there are unobserved factors affecting measures of both student attendance and academic outcomes. For instance, it might be hypothesized that unobserved student motivation or family environments can simultaneously influence both attendance patterns and student achievement. As a result, the coefficients from ordinary least squares are biased. This paper rectifies this confounding problem by implementing an instrumental variables strategy. That is, if it were possible to find a variable that embodies an exogenous source of variation affecting only student attendance but not achievement, then a quasi-experimental approach would be appropriate.

This paper claims to have found such a variable allowing for the implementation of the instrumental variables strategy. The instrument utilized in this study is the student-level geographical distance from school. This instrument has appeal because a larger geographic distance that a student lives from school should be negatively correlated with a negative pattern of school attendance. Previous studies on this relationship between geographic distance and school attendance confirm this relationship both at the K-12 level (Schlossberg, Greene, Phillips, Johnson & Parker, 2006; Schultz, 2004; Jensen & Nielsen, 1997) and for college students (Frenette, 2004). On the other hand, a researcher should not think that the distance a student lives from school would have direct impact on GPA. Moreover, the distance a student lives from school should affect only his or her attendance patterns and not the attendance of teachers. As such, this study has eliminated the often confounding issue related to student absences in which some variables that affect student absences may also be affecting teacher absences, thereby biasing estimates. Rather, the relationship between distance and GPA is only mediated through the student. With this exogenous source of variation, the methodology presented in this paper allows for the estimation of a causal relationship between attendance and achievement.

Population/Participants/Subjects:

Description of participants in the study: who (or what) how many, key features (or characteristics).

The analysis of attendance and student achievement in this study utilizes a comprehensive dataset of student, teacher, classroom, and neighborhood observations in the Philadelphia School District. This study implements data from all elementary and middle schools in the Philadelphia School District between the academic years 1994/1995 and 2000/2001. Over this time period, this amounts to 223 elementary and middle schools, with approximately N = 86,000 students in kindergarten through grade 8. In total, there are N = 332,000 student-year observations. Table 1 presents descriptive statistics for those students in the dataset. The table provides information on the overall sample as well as broken out by elementary and middle school sub-samples. There are more observations on elementary school students than on middle school students. (Insert Table 1 about here).

Research Design:
Description of research design (e.g., qualitative case study, quasi-experimental design, secondary analysis, analytic essay, randomized field trial).

As a baseline empirical model of educational outcomes, student achievement can be described using a linear relationship with a particular student measure as the dependent variable and a vector of independent variables. In the scope of this study, student GPA depends on the total days a student is present, as well as covariates for student demographics, neighborhood characteristics, family characteristics (proxied by free lunch status), teacher characteristics, and classroom characteristics.

Estimates of β_1, the coefficient on total days a student is present in a given school year, may be biased under ordinary least squares, even with the hierarchical error structure designated in equation 2. The reason is that there are unobservable student factors that may be affecting both a student's absences as well as GPA. For instance, a negative family environment or level of student motivation would affect both days present and GPA. As a first attempt to remedy this problem, a value added model strategy might mitigate this bias if the unobservable student-level influences affecting student achievement are time-invariant. In a value added model, one-year lagged GPA score serves as a proxy for individual student fixed effects. In this case, if a student's family environment is intransient over time, then this model would more accurately estimate the relationship between attendance and achievement.

The value added model proxies for individual fixed effects through the use of a lagged measure of achievement. However, these proxied fixed effects as well as the school, year, and grade fixed effects in the error are constructed under the assumption that unobserved variables are time invariant. However, there may also be unobservable factors that are time-variant, and the use of implementing fixed effects would not necessarily remedy this problem (Miller, Murnane, Willett, 2008). Thus, in conjunction with fixed effects, an instrumental variables strategy is employed as a more refined method of removing the bias on $\beta_{1.}$

To implement the instrumental variables strategy, it is necessary to utilize a two stage least squares format, in which there are two separate regression equations for each stage. Rather than immediately evaluating the relationship between days present and GPA, this approach begins with a first stage of analysis. As previously mentioned, the reason why this first stage is necessary is because unobserved, time-variant influences are affecting both independent and dependent variables. The results would yield biased estimates. However, in the first stage, PR_{it} becomes the outcome variable. The independent variables include all covariates that will be used in the second stage as well as an instrument. The instrument, or exogenous independent variable, must not be directly correlated student achievement, except through its relationship with student attendance.

Findings/Results:

Description of main findings with specific details.

Table 2 provides parameter estimates and robust standard clustered errors for the model in equation 1. The first column uses observations from the full sample of students, whereas the second and third are broken out by elementary and middle schools, respectively. From these initial results, there are several findings related to attendance and academic achievement in both the full model and elementary and middle school models. First, days present is positive and highly significant in all three equations. The results from the baseline models suggest that attending school is correlated with a higher GPA. Furthermore, this result is consistent for the full sample and across elementary and middle school samples. In fact, a slightly larger coefficient in the middle school sample demonstrates that attendance is even more strongly correlated with a higher GPA as students advance through years of schooling (Roby, 2004).(Insert Table 2 about here)

Table 3 provides parameter estimates and robust standard errors adjusted for classroom clustering for the results of days present, the value added lagged GPA component of the full model, and student characteristics. For sake of clarity, the other covariates from table 2, although incorporated into the model, are not presented in this table. The results depict a similar explanation as before – there is evidence that the relationship between attendance and achievement is positive and highly significant, and this result slightly increases for middle school students. That is, according to both baseline and value added models, attending schools seems to be slightly more important as a student progresses through school. (Insert Table 3 about here)

Although adding a lag may account for time invariant unobservable factors affecting student achievement, it does not control for time-varying influences. To address this problem requires the use of the instrumental variables strategy described above. This approach is implemented for both baseline and value added models and for full, elementary, and middle school samples. Table 4 provides results of the first stage of the instrumental variables approach. As described by equation 4, the dependent variable is days present, and the independent variables include the instrument (i.e., the distance in exact miles a student lives from school) as well as all other covariates described in table 2. The regressions include school, year, and grade fixed effects and robust standard errors clustered at the classroom level. Again, for the sake of clarity, table 4 provides only those estimates for the instrument and for student characteristics. However, all covariates are included in the model. (Insert Table 4 about here)

The negative and statistically significant coefficient on distance indicates that as a student's distance from school increases, the days a student is present decreases. The results are consistent across models, and all coefficients hover around a value of approximately -0.50. Thus, controlling for all other student, neighborhood, classroom, and teacher characteristics, there is evidence that student attendance decreases as a function of distance from school. Briefly turning to the student characteristics in the table, having a higher GPA in the previous academic year is associated with a higher number of days present in the current year. Other demographic characteristics indicate a high association with number of days present, except for free lunch status and behavior problem indicators. Both of these coefficients are negative and highly significant.

Table 5 compares the parameters on days present from the instrumental variables regression (i.e., from the second stage of the analysis) and those from table 3. Although both sets of coefficients on days present are positive and highly significant, the results from the instrumental variables regression indicate that the causal effect of school attendance on student achievement is larger in magnitude than what the regressions in table 3 would suggest. This is consistently evident for the results in the main sample as well as for both elementary and middle school students. The effect sizes of these instrumental variable results, as defined by the standardized regression coefficient, ranges between 0.36-0.41 σ for baseline models and 0.27-0.28 σ for value added models. Consistent with the results in table 3, the lagged achievement feature of the value added model tempers the results, thereby providing evidence that the lag soaks-up a significant portion of the unobserved variation in current student achievement. (Insert Table 5 about here)

Conclusions:

This paper confirms that student performance can be influenced by higher levels of attendance. As such, district and school policies that increase attendance patterns do not go unwarranted (Lamdin, 1996). It seems possible that schools can take two paths toward strengthening the attendance-achievement relationship: limiting absences and promoting attedance. On the one hand, schools can implement policies that directly deter student absences. For example, they can decrease absence rates with suspension and expulsion rules, thereby enforcing a zero-tolerance attitude towards truancy. While these programs are specifically aimed at truant students, they may nonetheless succeed in decreasing the general level of school absences. To supplement those policies against absences, schools can simultaneously stimulate student learning in school with aims of increasing attendance patterns. That is, schools could take more proactive approach to raising student attendance rates through attractive curricular and extracurricular programs (Roby, 2004).

Policies that can prevent absence rates or increase school attendance in the early years of education are especially pertinent in urban school settings. Not only is there evidence that urban elementary school students who miss school have decreased standardized test performance in elementary years (Gottfried, 2008), but academic problems are exacerbated as students progress into later grades. For instance, Easton & Englehard (1982) found that within an urban school district, student absences are negatively correlated with reading achievement, and this relationship becomes even stronger as students enter grades 7 and 8. They attributed this heightened negative relationship to the fact that family home environments became less important in academic development compared to school settings for urban middle school students.

In addition to the increasing academic problems from not attending school, there are a multitude of other issues facing older students with high absence patterns in urban schools. For instance, chronically absent students have higher drop out rates, antisocial behaviors, and unemployment rates (Kane, 2006; Broadhurst, Patron, & May-Chahal, 2005; Rothman, 2001; Alexander, Entwisle, & Horsey, 1997; Gamoran, 1996). As such, a lack of school attendance not only has negative academic implications but also spurs economic problems for the student, school, and community. For instance, a rise in drop out rates leads to a decline in school quality and subsequent school funding. In turn, this has additional negative effects on the valuation of local neighborhoods. This problem is even further exacerbated because high drop out rates lead to high unemployment rates in despondent urban neighborhoods, and this may cause unemployed high school drop outs to take up illicit activities as a source of income (Anderson, 1990). Therefore, policies geared at curbing truancy and increasing attendance in early years of education can have future consequences not only for the individual student but also for the school, neighborhood, and local urban economy.

Appendixes
Not included in page count.

Appendix A. References
References are to be in APA format. (See APA style examples at the end of the document.)

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Appendix B. Tables and Figures
Not included in page count.

Table 1

Descriptive Statistics for All Students, Academic Years 1994/1995 through 2000/2001

	Total Sample		**Elem School Students**		**Middle School Students**	
	Mean	***Std dev***	**Mean**	***Std dev***	**Mean**	***Std dev***
N	332,924		293,449		39,475	
Academic outcome measure						
GPA	2.44	*1.10*	2.44	*1.10*	2.44	*1.08*
Attendance measures						
Total days present	165.26	*17.20*	165.64	*16.98*	162.40	*18.51*
Distance from school (in miles)	1.65	*2.08*	1.66	*2.10*	1.54	*1.93*
Student Characteristics, in percent						
Male	49.26	*49.99*	49.44	*50.00*	47.90	*49.96*
White	17.96	*38.38*	17.77	*38.23*	19.34	*39.50*
Black	67.51	*46.83*	67.98	*46.66*	64.01	*48.00*
Latino	10.73	*30.95*	10.66	*30.86*	11.26	*31.61*
Asian	3.60	*18.64*	3.39	*18.11*	5.16	*22.13*
Other	0.20	*4.47*	0.20	*4.44*	0.22	*4.66*
Dummy: kindergarten in Philadelphia school system	75.58	*42.96*	76.26	*42.55*	70.51	*45.60*
Dummy: special education	0.58	*7.57*	0.50	*7.02*	1.19	*10.82*
Dummy: free or reduced lunch	61.39	*48.69*	61.73	*48.60*	58.88	*49.21*
Dummy: english language learner	4.38	*20.46*	4.21	*20.08*	5.58	*22.96*
Dummy: behavior problem	10.41	*30.54*	10.75	*30.97*	8.73	*28.23*
Student's Neighborhood Block Characteristics						
Percent of block, white	30.56	*32.95*	30.15	*32.93*	33.64	*32.94*
Percent of block, below poverty	14.16	*8.71*	14.22	*8.72*	13.68	*8.65*
Household vacancy rate for block	12.75	*9.32*	12.81	*9.32*	12.28	*9.31*
Log of average block income	10.16	*0.45*	10.15	*0.45*	10.19	*0.46*
Teacher Demographics						
Male	6.21	*24.13*	5.27	*22.35*	13.15	*33.80*
White	84.09	*36.58*	83.63	*37.00*	87.44	*33.15*
Black	15.10	*35.80*	15.55	*36.24*	11.71	*32.15*
Latino	0.51	*7.14*	0.52	*7.22*	0.43	*6.53*
Asian	0.23	*4.83*	0.21	*4.59*	0.40	*6.31*
Other	0.07	*2.68*	0.07	*2.68*	0.03	*1.67*
	0.07	*2.68*	0.08	*2.79*	0.03	*1.67*
Teacher Skills						
Years of experience	1.55	*5.45*	1.47	*5.33*	2.09	*6.26*
Has a master's degree	4.43	*20.58*	4.22	*20.11*	12.01	*32.51*
Class charactersitics						
Class size	28.02	*3.93*	27.93	*3.84*	28.68	*4.53*

Table 2

Baseline Model Parameter Estimates

	Full Sample	Elementary	Middle
Days present	0.015 ***	0.015 ***	0.018 ***
	(0.000)	*(0.000)*	*(0.001)*
Male	-0.286 ***	-0.275 ***	-0.368 ***
	(0.006)	*(0.006)*	*(0.015)*
Black	-0.328 ***	-0.328 ***	-0.347 ***
	(0.011)	*(0.012)*	*(0.025)*
Hispanic	-0.220 ***	-0.223 ***	-0.218 ***
	(0.015)	*(0.017)*	*(0.034)*
Asian	0.177 ***	0.159 ***	0.229 ***
	(0.016)	*(0.017)*	*(0.034)*
Other	-0.268 ***	-0.265 ***	-0.302 *
	(0.050)	*(0.053)*	*(0.158)*
Attended K in Philadelphia	0.103 ***	0.108 ***	0.085 ***
	(0.008)	*(0.009)*	*(0.020)*
Special ed	-0.164 ***	-0.173 ***	-0.143 *
	(0.040)	*(0.043)*	*(0.082)*
Free lunch eligible	-0.205 ***	-0.208 ***	-0.187 ***
	(0.006)	*(0.006)*	*(0.016)*
ELL	-0.196 ***	-0.210 ***	-0.118 ***
	(0.015)	*(0.017)*	*(0.036)*
Behavior problem	-0.552 ***	-0.572 ***	-0.373 ***
	(0.011)	*(0.011)*	*(0.025)*
Census block: percent white	0.021 *	0.029 **	-0.036
	(0.012)	*(0.014)*	*(0.035)*
Censuc block: percent poverty	-0.188 ***	-0.158 ***	-0.349 ***
	(0.046)	*(0.047)*	*(0.107)*
Census block: vacancy rate	-0.122 ***	-0.121 ***	-0.141
	(0.032)	*(0.032)*	*(0.112)*
Census block: log(mean income)	0.022 **	0.022 **	0.035
	(0.010)	*(0.010)*	*(0.026)*
Teacher male	0.071 ***	0.066 ***	0.079 **
	(0.017)	*(0.019)*	*(0.037)*
Teacher black	-0.030 **	-0.029 **	-0.026
	(0.012)	*(0.013)*	*(0.033)*
Teacher hispanic	-0.084	-0.093	0.060
	(0.059)	*(0.065)*	*(0.148)*
Teacher asian	0.029	0.021	0.085
	(0.070)	*(0.089)*	*(0.143)*
Teacher other	-0.170 **	-0.160 **	-0.180 **
	(0.071)	*(0.074)*	*(0.079)*
Teacher experience	-0.002	-0.001	-0.013 **
	(0.000)	*(0.003)*	*(0.006)*
Teacher experience - squared	0.000	0.000	0.000 **
	(0.000)	*(0.000)*	*(0.000)*
Teacher has master's degree	-0.002	0.002	-0.006
	(0.018)	*(0.019)*	*(0.040)*
Class size	-0.037 ***	-0.030 ***	-0.081 ***
	(0.001)	*(0.007)*	*(0.021)*
Class size - squared	0.001 ***	0.000 ***	0.001 ***
	(0.000)	*(0.000)*	*(0.000)*
School, year, grade fixed effects	Yes	Yes	Yes
n	167,553	147,831	19,722
R^2	0.22	0.22	0.25

*Note: *** p<.01; **p<.05; *p<.1*

Robust standard errors, corrected for classroom clustering, are in parentheses

Table 3

Selected Parameter Estimates for Baseline Model (Table 2) and Value Added Model

	Full Sample		Elementary School Sample		Middle School Sample	
	Basline	**Value Added***	**Baseline**	**Value Added**	**Baseline**	**Value Added**
Days present	0.015 ***	0.010 ***	0.015 ***	0.010 ***	0.018 ***	0.014 ***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.001)*
One-year lagged GPA		0.503 ***		0.512 ***		0.437 ***
		(0.003)		*(0.003)*		*(0.009)*
Male	-0.286 ***	-0.181 ***	-0.275 ***	-0.176 ***	-0.368 ***	-0.228 ***
	(0.006)	*(0.005)*	*(0.006)*	*(0.005)*	*(0.015)*	*(0.014)*
Black	-0.328 ***	-0.203 ***	-0.328 ***	-0.208 ***	-0.347 ***	-0.210 ***
	(0.011)	*(0.009)*	*(0.012)*	*(0.009)*	*(0.025)*	*(0.022)*
Hispanic	-0.220 ***	-0.121 ***	-0.223 ***	-0.123 ***	-0.218 ***	-0.137 ***
	(0.015)	*(0.011)*	*(0.017)*	*(0.013)*	*(0.034)*	*(0.033)*
Asian	0.177 ***	0.123 ***	0.159 ***	0.121 ***	0.229 ***	0.128 ***
	(0.016)	*(0.014)*	*(0.017)*	*(0.014)*	*(0.034)*	*(0.030)*
Other	-0.268 ***	-0.154 ***	-0.265 ***	-0.167 ***	-0.302 *	-0.118 ***
	(0.050)	*(0.048)*	*(0.053)*	*(0.052)*	*(0.158)*	*(0.124)*
Attended K in Philadelphia	0.103 ***	0.034 ***	0.108 ***	0.036 ***	0.085 ***	0.028
	(0.008)	*(0.006)*	*(0.009)*	*(0.007)*	*(0.020)*	*(0.017)*
Special ed	-0.164 ***	-0.085 ***	-0.173 ***	-0.093 ***	-0.143 *	-0.068
	(0.040)	*(0.034)*	*(0.043)*	*(0.036)*	*(0.082)*	*(0.069)*
Free lunch eligible	-0.205 ***	-0.106 **	-0.208 ***	-0.107 ***	-0.187 ***	-0.100 ***
	(0.006)	*(0.004)*	*(0.006)*	*(0.004)*	*(0.016)*	*(0.014)*
ELL	-0.196 ***	-0.065 ***	-0.210 ***	-0.063 ***	-0.118 ***	-0.066 **
	(0.015)	*(0.014)*	*(0.017)*	*(0.016)*	*(0.036)*	*(0.029)*
Behavior problem	-0.552 ***	-0.133 ***	-0.572 ***	-0.137 ***	-0.373 ***	-0.066 **
	(0.011)	*(0.009)*	*(0.011)*	*(0.010)*	*(0.025)*	*(0.025)*
Neighborhood chacteristics	Yes	Yes	Yes	Yes	Yes	Yes
Teacher characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Classroom characteristics	Yes	Yes	Yes	Yes	Yes	Yes
School, year, grade fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
n	167,553	162,552	147,831	143,709	19,722	18,829
R^2	0.22	0.40	0.22	0.41	0.25	0.38
P-value of Likelihood Ratio Test		0.00		0.00		0.00

*Note: *** p<.01; **p<.05; *p<.1*

Robust standard errors, corrected for classroom clustering, are in parentheses

**As a test of robustness, the dependent variable in the value added model was changed to A_{it} -$A_{i(t-1)}$. The results of those models are consistent with the value added results here.*

Table 4

Selected Parameter Estimates for the First Stage Instrumental Variables Approach - Baseline and Value Added Models

	Full Sample		Elementary School Sample		Middle School Sample	
	Basline	**Value Added[(a)]**	**Baseline**	**Value Added**	**Baseline**	**Value Added**
Instrument: distance in school (in miles)	-0.506 ***	-0.484 ***	-0.510 ***	-0.495 ***	-0.514 ***	-0.470 ***
	(0.017)	*(0.017)*	*(0.017)*	*(0.017)*	*(0.060)*	*(0.065)*
One-year lagged GPA		2.033 ***		1.967 ***		2.570 ***
		(0.039)		*(0.037)*		*(0.122)*
Male	-0.004	0.408 ***	-0.049	0.342 ***	0.266	0.971 ***
	(0.067)	*(0.064)*	*(0.071)*	*(0.069)*	*(0.207)*	*(0.211)*
Black	2.592 ***	2.935 ***	2.206 ***	2.577 ***	4.163 ***	4.596 ***
	(0.150)	*(0.132)*	*(0.146)*	*(0.137)*	*(0.464)*	*(0.425)*
Hispanic	0.784 ***	1.155 ***	0.484 **	0.942 ***	2.136 ***	2.184 ***
	(0.180)	*(0.171)*	*(0.201)*	*(0.187)*	*(0.556)*	*(0.508)*
Asian	7.409 ***	6.729 ***	7.057 ***	6.529 ***	8.797 ***	7.572 ***
	(0.195)	*(0.169)*	*(0.214)*	*(0.204)*	*(0.508)*	*(0.449)*
Other	1.026 ***	1.339 *	0.717	0.793	2.534	4.356 **
	(0.745)	*(0.719)*	*(0.853)*	*(0.860)*	*(1.963)*	*(1.842)*
Attended K in Philadelphia	2.722 ***	2.340 ***	2.733 ***	2.401 ***	2.688 ***	1.999 ***
	(0.112)	*(0.102)*	*(0.134)*	*(0.122)*	*(0.351)*	*(0.352)*
Special ed	2.500 ***	2.969 ***	2.349 ***	2.839 ***	3.056 **	3.583 ***
	(0.647)	*(0.601)*	*(0.660)*	*(0.644)*	*(1.481)*	*(1.153)*
Free lunch eligible	-3.153 ***	-2.677 ***	-3.018 ***	-2.602 ***	-3.891 ***	-3.121 ***
	(0.065)	*(0.066)*	*(0.070)*	*(0.074)*	*(0.219)*	*(0.220)*
ELL	0.687 ***	0.956 ***	0.514 **	0.874 ***	1.514 **	1.280 **
	(0.184)	*(0.197)*	*(0.197)*	*(0.216)*	*(0.591)*	*(0.605)*
Behavior problem	-4.305 ***	-2.363 ***	-4.089 ***	-2.293 ***	-5.832 ***	-3.076 ***
	(0.142)	*(0.139)*	*(0.134)*	*(0.138)*	*(0.584)*	*(0.569)*
Neighborhood chacteristics	Yes	Yes	Yes	Yes	Yes	Yes
Teacher characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Classroom characteristics	Yes	Yes	Yes	Yes	Yes	Yes
School, year, grade fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
n	173,871	164,740	149,483	145,022	24,388	19,718
R^2	0.09	0.10	0.08	0.09	0.15	0.17

*Note: *** p<.01; **p<.05; *p<.1*

Robust standard errors, corrected for classroom clustering, are in parentheses

(a)As a test of robustness, the dependent variable in the value added model was changed to A_{it}-$A_{i(t-1)}$. The results of those models are consistent with the value added results here.

Table 5

Parameter Estimate for Days Present, Instrumental Variable and Regression Reults from Table 3, Baseline and Value Added Models

	Full Sample		Elementary School Sample		Middle School Sample	
	Basline	**Value Added**	**Baseline**	**Value Added**	**Baseline**	**Value Added**
Instrumental variables strategy[(a)]	0.026 ***	0.018 ***	0.026 ***	0.018 ***	0.021 ***	0.016 **
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.007)*	*(0.006)*
Results from Table 3	0.015 ***	0.010 ***	0.015 ***	0.010 ***	0.018 ***	0.014 ***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.001)*

*Note: *** p<.01; **p<.05; *p<.1*

Robust standard errors, corrected for classroom clustering, are in parentheses

(a) All models' post-estimation tests of significance reject the null hypothesis (at p<0.000) that the parameter on student distance is zero.

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Sample Citation: Journal Article

Hypericum Depression Trial Study Group. (2002). Effect of Hypericum perforatum (St John's Wort) in major depressive disorder: A randomized controlled trial. *JAMA, 287,* 1807–1814.

Sample Citation: Newsletter/Newspaper Article

Brown, L. S. (1993, Spring). My research with oranges. *The Psychology Department Newsletter*, *3*, 2.

Sample Citation: Book

American Psychiatric Association. (1990). *Diagnostic and statistical manual of mental disorders* (3rd ed.). Washington, DC: Author.

Booth, W. C., Colomb, G. G., & Williams, J. M. (1995). *The craft of research*. Chicago: University of Chicago Press.

Sample Citation: Chapter or Section in a Book

Stephan, W. G. (1985). Intergroup relations. In G. Lindzey & E. Aronson (Eds.), *The handbook of social psychology* (3rd ed., Vol. 2, pp. 599–658). New York: Random House.

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Dewey, R. A. (2004). *APA Style Resources by Russ Dewey*. Retrieved September 8, 2004, from http://www.psywww.com/resource/apacrib.htm