School Climate for Academic Success:
A Multilevel Analysis of School Climate and Student Outcomes

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Abstract

This multilevel study examined the relationship between school climate and academic achievement. Using the Educational Longitudinal Survey (ELS, 2002), and a sample of 16,258 students and 1954 schools nationwide, we found that student-level perception of school climate—especially the student learning environment—was highly predictive of academic success in math and reading standardized test scores. This study confirmed that, among school climate variables at the school level, worse institutional facilities have a negative impact on student achievement and higher levels of institutional surveillance negatively affected the positive effects that student perceptions of safety and their learning environments had on student success. Finally, reducing high levels of institutional surveillance was found to mitigate socioeconomic inequalities.

Keywords: school climate, surveillance, academic outcomes, multilevel analysis

Introduction

School climate is an important factor in academic achievement and performance (Battistich, Solomon, Kim, Watson, & Schaps, 1995; Stewart, 2008; Kuperminc, Leadbeater, & Blatt, 2001; Marchant, Paulson, & Rothlisberg, 2001). The first scholar to study this concept was Perry (1908), who examined the specific problems confronting principals in city schools and their effects on student learning; however, a systematic analysis of school climate did not begin until the 1980s when organized research on school effectiveness began (Center for Social and Emotional Education, 2010). Since then, research has shown that school climate is also linked to teacher commitment (Collie, Shapka, & Perry, 2011), motivation to learn (Battistich, Solomon, Kim, Watson, & Schaps, 1995), student identity development (Rich & Schacter, 2012), student dropout rates (Barile et al., 2012), sense of school community (Vieno, Perkins, Smith, &

Santinello, 2005), school satisfaction (Zullig, Koopman, Patton, & Ubbes, 2010), school violence (Leff, Power, & Costigan, 2003; Peterson & Skiba, 2001), academic achievement (Ghaith, 2003), and higher scores on standardized tests (MacNeil, Prater, & Busch, 2009).

While previous literature has linked school climate to academic success and performance, that literature has fallen short in determining concretely which dimensions of school climate are linked to academic achievement. This article provides greater clarity on how schools can focus on school climate to improve student learning and academic performance. We used a multilevel framework to test our hypotheses that: 1) positive individual-level school climate variables, like student learning environment, positively affect student academic achievement; and 2) negative school-level climate variables, such as poor institutional facilities and high surveillance, mitigate the positive effects of positive individual-level school climate variables.

Literature Review

In recent years, school climate has been a focus of an increasing number of systematic, empirical studies (Benbenisty & Astor, 2005; Cohen, McCabe, Michelli, & Pickeral, 2009). Many of these studies have highlighted the impact of a school's socioeconomic, racial (Lareau, 2003), and gender (Legewie & Diprete, 2012) demographics on academic outcomes, which resulted in increased school disorder and stress, leaving schools with higher levels of violence, teacher mobility, and racial tensions (Kim, Schwartz, Cappella, & Seidman, 2014). Not surprisingly, these schools, which are often under-resourced, were more likely to report negative school climates than their counterparts (Bellmore, Nishina, You, & Ma, 2012; Jain, Cohen, Huang, Hanson, & Austin, 2015). The above studies, however, neglected to focus on the in-school environment variables, controlling for demographics, when evaluating their impact on student academic outcomes, just like the celebrated Coleman Report (1966). Recent findings contesting Coleman suggest in-school climate factors are highly predictive of academic success (Davis & Warner, 2015).

There are multiple factors that have been found to diminish a school's climate, including: increased policing of schools, the use of metal detectors, and punitive disciplinary practices. While these methods are aimed at making schools safer, the use of surveillance technologies and full-time law enforcement has not served as an effective deterrent for problematic behaviors (Devine, 1996; Kupchik, 2010; Schreck, Miller, & Gibson 2003). Increased surveillance measures in schools are linked to decreased relational trust within the school community (Bryk, Sebring, Allensworth, Luppescu, & Easton, 2010), decreased clarity and fairness of rules (Gottfredson, Gottfredson, Payne, & Gottfredson, 2005), and decreased student perceptions of safety, respect, and socio-emotional learning (McCoy, Roy, & Sirkman, 2013). Additionally, Black students and those with particular educational disabilities, even in schools where delinquency and disorder were reported as low (Welch & Payne 2010), were disproportionately likely to be removed from the classroom for disciplinary reasons (Fabelo et al., 2011) or suspended (Hoffman, 2014). Similarly, punitive measures were found to push out students from the school community and lead to higher dropout rates (Gonzalez, 2012). An American Psychological Association Task Force (2008) concluded that these punitive measures contributed to worse school climate ratings.

In their review of the school climate research, Thapa, Cohen, Guffey, and Higgins-D'Alessandro (2013) found a continued lack of well-defined and research-based models for school climate, because fewer studies examined the effects of school climate within multilevel/hierarchical frameworks. Doing so can yield informative policy-based guidance for schools. Skiba and Williams (2014) found a significant association between school-level climate variables, especially principals' perspectives on discipline and racial disparities in out-of-school suspension and expulsion; however, their study's focus was on infraction rates, so student academic performance was beyond their scope.

Using the Educational Longitudinal Study of 2002 (ELS, 2002), Fan, Williams, and Corkin (2011) also constructed a multilevel analysis to examine the effects of social and academic risk factors on school climate. In their study, they found that individual-level behavioral and demographic predictors and school-level variables, such as school type (Catholic or Private), had a significant effect on school climate (Fan, Williams, & Corkin, 2011). These findings demonstrated the dynamic nature of school climate and how cross-level effects and interactions can significantly affect students' perceived climate. Ripski and Gregory (2009) also used the ELS (2002) to link individual perceptions of victimization and school-wide hostility to academic achievement and performance. While both are important studies of school climate, they failed to link more holistic measurements of school climate to academic success. Fan, Williams, and Corkin (2011) looked at effects of student perceptions but did not examine those perceptions' effects in relation to the students' academic success. Ripski and Gregory (2009), despite examining academic success, defined school climate too narrowly.

This paper aims to build on the current school climate literature by specifically examining the relationship between school climate variables – including increased surveillance and student learning environment – on student academic achievement. Breaking down school climate by its multiple dimensions allows the researcher to identify the interactions between these components. A much more holistic examination of school climate can develop a stronger model for school climate and inform educational stakeholders how to improve student achievement by targeting school climate policies.

Data and Research Methods

This article used the Educational Longitudinal Study of 2002 (ELS:2002)[1]. The study surveyed a nationally representative cohort of students beginning in their sophomore year of high school. There were two additional waves taken in 2004 and 2006 – when students were seniors in high school and two years after their senior years, respectively. Since the goal of this article is to evaluate the effects of school climate—at both the individual and school level—on students' academic success in high school, survey data collected during the 2002 wave is this article's focus of analysis, since this is the only year where both reading and math test scores were included in the data. This data set was specifically chosen for its nationwide scope and the diversity of variables examining multiple facets of school culture.

Table 1. Descriptive Statistics for Dependent Variables

Dependent Variable	N	Range	Median	Mean ± SD
Standardized Math Score 2002	16,258	19.38 – 86.68	50.79	50.66± 9.92

[1] We selected the ELS:2002 data set, because it is the most current data set that includes individual and school-level climate variables that we could use for our multilevel analysis.

Standardized Reading Score 2002	16,258	22.57 – 78.76	50.79	50.48± 9.87

The sample size for this study was 16,258 participants whose standardized math scores ranged from 19.38 to 86.68 and whose standardized reading scores ranged from 22.57 to 78.76 (see Table 1). The sample consisted of 7,767 men and 8,491 women. White students represented approximately 56.60 percent of the sample, Blacks 13.38 percent, Hispanics 19.57 percent, Asians 9.59 percent, and American Indians .86 percent (see Table 3). These percentages were consistent with those of the national population as reported in the 2000 Census.[2]

Procedure

The ELS:2002 surveyed students, administrators, teachers, and parents. The student questionnaire provided information on students' perceptions of the school climate within their schools, while the administrator questionnaire supplied additional aggregate information about the school in which the respective student attends. As a result, the ELS:2002 lent itself to a hierarchical linear model (HLM). This article tracks students' academic success by parsing out the different levels that contribute to students' test scores. Using HLM to evaluate the individual and school-level variables allows for greater precision in measuring error and deviance terms, enabling more effective measurements of independent variables' predictability of academic success (Luke, 2004; Raudenbush & Bryk, 2002). This study also utilized multiple imputations using multivariate normal regression from STATA to manage missing data. Unlike mean imputation methods, such as imputing using a simple regression, multiple imputation addressed the problem of overstating confidence intervals by adding randomness (Little & Rubin, 2002; Allison, 2002).

Variables

The article examined the relationship between school climate and student academic success; therefore, our dependent variables in this analysis were standardized math and reading scores taken during the students' sophomore year. To measure each component of school climate, four composites were created (two at the individual-level and two at the school-level) based on National School Climate Center's model for school climate. Individual-level composites were based on students' perceptions, while school-level composites were based on the aggregate data gathered from the administrative questionnaire (see tables 3 and 4).

The individual-level measurements of school climate we used for the study were: school safety and learning environment. The school safety composite consisted of seven items, including students' perceptions of their safety in school, enforcement (or the lack) of rules, and the fairness of school rules. The student learning environment composite consisted of nine items, including perceptions of school spirit, teachers' expectations for success in school, whether teaching is good, and how challenging/interesting classes are. There was high internal reliability within each composite with Cronbach's alphas of .68 and .79, respectively. Both of the final composite variables were measured on a 4-point Likert-type scale (1= disagree a lot; 2= disagree somewhat; 3=agree somewhat; 4=agree a lot).

Our school-level measurements of school climate were institutional school safety enforcement and institutional learning environment. The institutional school safety enforcement

[2] http://www2.census.gov/census_2000/datasets/demographic_profile/0_United_States/2kh00.pdf

variable consisted of eight items measuring the strictness of rules in institutions, including the enforcement of random metal detector checks, requirement of wearing badges/picture ID, use of paid security, and use of security cameras. This composite was measured on a 2-point scale (0=no; 1=yes). Institutional learning environment consisted of eleven items and measured whether the conditions of school facilities hindered learning. This composite variable was measured on a 4-point Likert-type scale; higher scores meant facilities hindered academic achievement more often. Again, there was high internal consistency within each composite with Cronbach's alphas of .70 and .90, respectively.

In addition to the individual and school-level variables, we added other individual and school-level variables to control for additional influences on academic success. At the individual-level, students' gender, race, family composition (two biological parents, at least two parents/guardians, and less than two parents), and educational track (general, college, or vocational tracks) were controlled. Most of the students were on the college track (54.76%) and had two biological parents (59.16%) (See Table 3).

Table 2. Descriptive Statistics for Continuous Variables

	N	Median	Mean ± SD
Student-Level Variable			
Parental SES	16,258	0.50	0.55± 0.35
School Climate Composites			
Student Safety	16,258	2.21	2.22± 0.42
Student Learning Environment	16,258	2.33	2.36± 0.44
School-Level Variables			
% Special Education Students	16,258	10	9.25± 8.85
% English Language Learners	16,258	1	3.90± 7.57
% Remedial Math-Reading	16,258	3	5.20± 7.01
% Full-Time Teachers Certified	16,258	100	91.72±1 9.08
School Climate Composites			
Institutional Safety	16,258	0.50	0.45± 0.23
Institutional Learning Environment	16,258	1.65	1.71± 0.53

Table 3. Descriptive Statistics for Categorical Variables

	N	%
Student-Level Variables		
Race		
American Indian	16,258	0.86
Asian	16,258	9.59
Black	16,258	13.38
Hispanic	16,258	19.57
White	16,258	56.60
Gender		
Male	16,258	49.78
Female	16,258	50.22
Family Composition		
Two biological parents/guardians	16,258	59.16
Two non-biological parents/guardians	16,258	17.27

Less than two parents/guardians	16,258	23.57
Educational Track		
General Track Student	16,258	35.23
College Track Student	16,258	54.76
Vocational Track Student	16,258	10.01

	N	%
School-Level Variables		
School Type		
Public	16,258	78.72
Catholic	16,258	12.23
Private	16,258	9.05
Urbanicity	16,258	33.91
Urban	16,258	33.91
Suburban	16,258	47.93
Rural	16,258	18.16

School-level controls included percentage of special education and English-language learners in school, percent of students in remedial reading or remedial math, percentage of full-time teachers certified (see Table 2), school type (public, catholic, or private), and school urbanicity (urban, suburban, or rural). A majority of the schools (78.72%) in the sample were public. A plurality of the schools were suburban (47.93%), while there were almost twice as many urban schools (33.91%) than rural ones (18.16%). For improved interpretability, all continuous variables were centered by grand means (see Table 3).

Plan of Analysis

A hierarchical linear model was used to address the multilevel components of the study. Two nested HLM regressions were run, one for each of our dependent variables. Each regression consisted of five models. The first model was the null model, which only included the randomized intercept. From this null model, we measured the amount of variance in the dependent variable that was associated with school-level variables. To the null model, parental socioeconomic status (SES) was added as both fixed and randomized effects. This allowed us to observe the effects of varying SES scores across schools. The other individual-level fixed effects were added to Model 3 (Equation 1) and the school-level fixed effects were added to Model 4 (Equation 2). Finally, cross-level interaction variables between three individual-level variables (Parental SES, student learning environment, and student safety) and institutional surveillance was added to Model 5 (Equation 3). The cross-level variable was important to determine the interactions between individual-level and school-level variables.

Findings

Math Achievement

In predicting standardized math test scores in 2002 (see Table 4), based on the null model, the intra-class coefficient (ICC) was .1855, which meant at least 18 percent of the variance in the math scores was associated with school-level variables. This justified the inclusion of school-level variables in the study. The log likelihoods increased significantly from Model 1 to Model 5, indicating that each subsequent model improved the fit with the data. Parental SES, race, gender, family composition, and student academic tracks all proved to be statistically significant predictors of standardized math test scores during the students' sophomore year of high school. Further**,** students with higher parental SES backgrounds had higher math test scores (Hursh, 2007). A statistically significant variance on the randomized-slope for parental SES also demonstrated that different levels of parental SES of a school impacted a student's standardized math score. Because the randomized slope was positive, we inferred that higher parental SES positively impacted a students' standardized math score, but that impact lessened in schools with lower parental SES averages across the student population.

Of the individual-level school climate measurements, student safety and student learning environment were statistically significant. For each point increase in positive perception of learning environment, the model found an increase in math score by 2.061 points. Likewise, the model showed that each point of increase in student perception of school safety correlated with an increase in math score by 1.806 points.

Regarding the school-level student climate variables, the models predicted students to perform worse in schools with stricter safety enforcement and worse facilities. The cross-level interaction between SES and institutional surveillance was statistically significant. We found schools with more school surveillance modified the effect of parental SES on standardized math scores by 3.122 points. Additionally, both cross-level interaction effects between the student-level school climate variables and institutional surveillance were statistically significant. The model showed that greater institutional surveillance dramatically decreased the effect of students' perception of safety (-1.755 points) and learning environment (-2.087 points) on the standardized math scores.

Table 4: Models based on HLM Regression of School Level Effects Predicting Students' Standardized Math Test Scores in 2002 (Standard Errors in Parentheses)

	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed effects					
Parental SES^		9.406***	7.118***	6.956***	5.601***
		(.222)	(.210)	(.214)	(.430)
Race (Ref. White)					
American Indian or			-4.569***	-4.402***	-4.383***
Alaska Native			(.749)	(.744)	(.744)
Asian			.234	.687**	.684**
			(.247)	(.252)	(.251)
Black			-6.300***	-5.896***	-5.873 ***
			(.223)	(.227)	(.227)
Hispanic			-4.226***	-3.814***	-3.817***
			(.186)	(.191)	(.190)
Male (Ref. Female)			1.327***	1.335***	1.330***
			(.128)	(.128)	(.128)
Family composition (Ref. 2 Biological Parents)					
At least two			-1.034***	-1.014***	-.996***
parents/guardians			(.176)	(.176)	(.176)
Less than two parents			-.666***	-.623***	-..602***
			(.163)	(.163)	(.162)
Student school program (Ref. College Track)					
General track			-3.526***	-3.447***	-3.456***
			(.149)	(.150)	(.150)
Vocational, technical,			-4.383***	-4.225***	-4.219***
or business track			(.235)	(.235)	(.235)
Student Safety			.789***	.871***	1.806 ***
			(.182)	(.182)	(.392)
Student Learning			1.233***	1.274***	2.061***
Environment			(.175)	(.175)	(.377)
Percent in Special				-.054***	-.054**
Education^				(.013)	(.013)
Percent English-language				-.065***	-.066***
learners^				(.014)	(.014)
Type of school (Ref. Public schools)					
Catholic				.489	.535
				(.383)	(.382)

Private				.714 (.458)	.805⁺ (.456)
Urbanicity (Ref. Suburban)					
Urban				-.687** (.241)	-.684** (.240)
Rural				-.592* (.289)	-.616* (.289)
Percent of school in remedial math-reading^				-.056*** (.015)	-.056*** (.015)
Percent of full-time teachers certified^				.019** (.006)	.019** (.006)
Institutional Surveillance				-1.292* (.501)	6.248⁺ (.691)
Institutional Facilities				4.795*** (1.319)	4.718*** (1.315)
Parental SES X Institutional Surveillance					3.122*** (.864)
Student learning environment X Institutional Surveillance					-1.755* (.748)
Student safety X Institutional Surveillance					-2.087** (.771)
Intercept	50.497 *** (.141)	50.679*** (.119)	48.673*** (.783)	44.669*** (1.452)	40.596*** (2.052)
Random effects (variance components)					
Between schools:					
Intercept	16.638*** (.854)	10.376*** (.613)	6.584*** (.407)	4.885*** (.368)	4.851*** (.366)
Parental SES		8.148*** (1.804)	3.994** (1.436)	4.091** (1.473)	3.271* (1.437)
Within schools	73.024*** (.803)	65.735*** (.736)	59.816*** (.669)	59.556*** (.666)	59.571*** (.666)
Log Likelihood	-62993.889	-62006.894	-60989.780	-60914.195	-60903.977

⁺p<.10, *p<.05, **p<.01, ***p<.001; ^ = centered variable

Table 5: Models based on HLM Regression of School Level Effects Predicting Students' Standardized Reading Test Scores in 2002 (Standard Errors in Parentheses)

	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed effects					
Parental SES^		8.708*** (.220)	6.852*** (.213)	6.661*** (.219)	5.711*** (.444)
Race (Ref. White)					
American Indian or Alaska Native			-5.269*** (.760)	-5.070*** (.754)	-5.044*** (.754)
Asian			-2.836*** (.250)	-2.284*** (.255)	-2.285*** (.255)
Black			-5.325*** (.226)	-4.940*** (.230)	-4.918*** (.230)
Hispanic			-3.926*** (.189)	-3.476*** (.193)	-3.475*** (.193)
Male (Ref. Female)			-1.147*** (.130)	-1.140*** (.129)	-1.143*** (.129)
Family composition (Ref. 2 Biological Parents)					
At least two parents/guardians			-.975*** (.178)	-.943*** (.177)	-.933*** (.177)
Less than two parents			-.565** (.165)	-.521** (.164)	-.505** (.164)

Student school program (Ref. College Track)					
General track			-3.275*** (.151)	-3.157*** (.151)	-3.161*** (.151)
Vocational, technical, or business track			-4.600*** (.238)	-4.406*** (.238)	-4.402*** (.238)
Student Safety			.301 (.184)	.400* (.184)	.850* (.396)
Student Learning Environment			1.050*** (.177)	1.086*** (.177)	1.898*** (.381)
Percent in Special Education^				-.037** (.013)	-.037** (.013)
Percent English-language learners^				-.094*** (.014)	-.094*** (.014)
Type of school (Ref. Public schools)					
Catholic				1.836*** (.395)	1.866*** (.395)
Private				1.345** (.472)	1.400** (.472)
Urbanicity (Ref. Suburban)					
Urban				-.367 (.250)	-.367 (.249)
Rural				-.283 (.300)	-.290 (.300)
Percent of school in remedial math-reading^				-.042** (.015)	-.042** (.015)
Percent of full-time teachers certified^				.025*** (.007)	.025*** (.007)
Institutional Surveillance				-.786 (.517)	5.032 (3.356)
Institutional Facilities				4.213*** (1.361)	4.175** (1.359)
Parental SES X Institutional Surveillance					2.191* (.892)
Student learning environment X Institutional surveillance					-1.826* (.756)
Student safety X Institutional surveillance					-1.002 (.780)
Intercept	50.493*** (.140)	50.647*** (.121)	51.431*** (.792)	47.271*** (1.489)	47.315*** (1.487)
Random effects (variance components)					
Between schools:					
Intercept	16.443*** (.843)	10.806*** (.628)	6.413*** (.439)	5.423*** (.392)	5.406*** (.391)
Parental SES		7.160** (1.759)	4.213* (1.518)	4.924* (1.605)	4.513* (1.582)
Within schools	72.245*** (.795)	65.916*** (.739)	61.032*** (.683)	60.668*** (.680)	60.691*** (.680)
Log Likelihood	-62899.890	-62035.853	-61196.734	-61108.541	-61105.811

$^{+}$p<.10, *p<.05, **p<.01, ***p<.001; ^ = centered variable

Reading Achievement

Like the standardized math tests, most independent-level variables in the reading achievement regression were statistically significant in predicting standardized reading scores for the base year. According to the ICC (=.1854) of the null model, approximately 18.5 percent of the variance was associated with the school-level variables (see Table 5). The improvement in log likelihoods from Models 1 to 5 and the decrease in the variance of the residuals inform us that our full model improved the fit with the data.

Once again, students' reading scores benefited from higher parental SES. The randomized slope for parental SES was also statistically significant for reading scores, suggesting that the impact of parental SES on students' scores was affected by school level variables. Similar to the model predicting standardized math test scores, a point of increase in students' perceptions of school safety and of their learning environment showed an improvement to students' reading test scores by .850 points and 1.898 points, respectively.

At the school level, although institutional safety was not a statistically significant predictor in the model, worse institutional learning environment affected students' reading scores negatively. A point of increase in institutional learning environment correlated with an increase of 4.175 points in reading test scores. Finally, a significant cross-level interaction effect between parental SES and institutional surveillance suggested that parental SES becomes more important in determining higher school outcomes in schools with more surveillance. We found schools with more school surveillance modified the effect of parental SES on reading test scores by 2.191 points. Institutional surveillance, once again, had a negative impact on student-level school climate variables in the cross-level interaction effects. Greater institutional surveillance diminished the positive effect that improved student learning had on students' standardized reading test scores. Interestingly, our model did not find institutional surveillance to have any effect on students' perception of safety in the cross-level interaction.

Discussion and Conclusion

Our findings confirmed the research about the prevalence of educational inequalities across American schools and point to the salience of student perception of school climate and the institutional learning environment in predicting academic achievement. Consistent with the findings of the NSCC, our student learning environment composite variable was a highly significant predictor of academic success in both reading and math test scores. As we found, the more students felt supported and encouraged to excel by their peers, teachers, and parents, the more likely they were to enjoy their school and succeed academically.

We also found that higher students' perceptions of safety were associated with higher standardized test scores. Advocates for increasing school safety have called for policy changes to reduce bullying in schools and fostering more supportive educational communities for students to thrive in (Farrington & Ttofi, 2010; Olweus, 1993). As our models showed, increased institutional surveillance did not achieve this goal. Rather, it reduced the positive academic impact of students' learning environment and perceptions of school safety. In this environment, students often felt imprisoned in their school by going through metal detectors daily or being subject to drug sniffing dogs, which did not instill a motivation to excel academically for the students (Tuzzolo & Hewitt, 2006/7). Moreover, the focus on criminalization within schools often resulted in the negative perception of minority students and their exclusion from the educational process (Hirschfield, 2008). Further, as Skiba et al. (2003) found, "As the statewide rate of school suspension increases, average achievement scores decline" (p. 17).

As we found, a school's institutional facilities were significantly predictive of math and reading score outcomes. These findings indicated the importance of school facilities in fostering a positive learning environment for its students (Schneider, 2002). Such effects pointed to a larger educational issue: the achievement gap between rich and poor schools. Hedges, Laine, and Greenwald (1994) confirmed that the quality of educational facilities is directly related to a positive school climate and positive academic outcomes. Moreover, this pointed to the fact that the inequality of funding between rich and poor schools had a direct impact on student academic performance. Funding inequality can compound the individual-level inequalities that students may already face at home. As a result, while schools can help equalize some learning inequalities *within* schools (Downey et al., 2004), unmitigated inequalities *between* schools continue to contribute to the achievement gap.

The implications of our cross-level interactions are very telling. When we examined our interaction between institutional surveillance and student learning environment, we found that the more securitized a school was, the less helpful positive learning environment was on school outcomes. At the same time, increased institutional surveillance exacerbated the academic inequality caused by socioeconomic status. In other words, students with low socioeconomic status performed even worse in their academics in highly policed schools. Such a finding signaled the negative effects increasing surveillance had on students—not just in terms of its own effects, but the multiplicative effect it has in lessening the positive impact of positive student learning environments and increasing the negative impact of socioeconomic status on academic outcomes. As a result, schools should consider focusing more on instilling positive learning environments and less on employing increased surveillance and punitive disciplinary measures.

We acknowledge that our data from 2002 does not account for the drastic educational reforms in the last decade; therefore, we hope that new data sets surface to tackle the same type of multilevel analysis of school climate that the ELS:2002 provides; such data could help corroborate our findings and demonstrate the continued need for schools to focus on improving their school climate. As some school systems begin to implement restorative justice practices, new data sets can provide needed analysis of these practices' effects on school climate and student academic achievements (Gonzalez, 2012).

School climate is a critical factor in academic achievement. As we demonstrated, the sooner schools focus on creating these types of climates – that student perceive as safe, encouraging, challenging, and empowering – the better students will perform in school. Thus, additional research is needed to corroborate the important relationship between early interventions in fostering positive school climate for students. Such research will provide educational policy makers data focusing on building a positive school climate to foster academic success.

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