

## The Seasonality of School Climate

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RESEARCH BRIEF

## The Seasonality of School Climate

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### ABSTRACT

Although several studies have focused on why school climate is important, the timing of the collection of climate measures should be considered. This is of particular interest to schools that gauge school improvement efforts within a school year and are interested in how climate changes from the beginning to the end of the academic year. We show that there is a tendency for school-level climate measures to fluctuate in a predictable, nontrivial manner ( $ds = 0.25\text{--}0.47$ ). Findings are based on data from 26 secondary schools (using over 20,000 student responses) that had school climate measures taken in fall and spring over 18 months. We show that in the fall, on average, students consistently had a more favorable outlook of the school based on five climate measures.

### IMPACT STATEMENT

School climate has been used to guide school improvement efforts and although studies have discussed why climate is important, little attention has been paid to when school climate should be measured. We show, using data from students in the sixth to the twelfth grade from 26 schools and five measures of school climate, that school-level climate fluctuates in a predictable though nontrivial manner. Climate is consistently rated more positively in the fall compared to the spring.

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The importance of school climate has been well documented in the literature. School climate is a multidimensional construct and refers to various aspects of the school environment that are related to overall perceptions of safety, sense of engagement, and the academic and physical environment (Wang & Degol, 2016). School climate often pertains to “the quality and consistency of interpersonal interactions within the school community that influence children’s cognitive, social and psychological development” (Haynes et al., 1997, p. 332).



Several studies have shown *why* climate matters (e.g., Cornell & Huang, 2019; O’Malley et al., 2012) and have shown how climate can be measured in various ways using direct observations, focus groups, administrative records, or most commonly, using student (or staff, parent, administrator) surveys (Schweig et al., 2019). Stakeholder perceptions of the school, classroom, or the general environment can be gathered and aggregated to the school level. Although the “why,” “how,” and “what” to measure have been well investigated, the question of “when” to measure school climate has not received much attention.

School climate is often a target of school improvement interventions (Bradshaw et al., 2021) and climate measured within the school year can be used to track changes from the start to the end of the school year for progress monitoring purposes (Schweig et al., 2019). Although

climate may be relatively stable from year to year, changes *within* a school year have not been explored in more detail. Surveys are often administered in the latter part of the school year as students have had more time to experience the school compared to measuring climate in the earlier half of the school year when students may still be unfamiliar or new to their environment (Brand et al., 2003). However, this potential difference in climate perceptions over the school year is an empirical question and raises the question of how much the perceptions of climate may fluctuate over the natural course of the school year.

### SEASONALITY CONSIDERATIONS

The majority of school climate studies have focused on the use of cross-sectional rather than longitudinal data (Wang & Degol, 2016). Of the studies that have used climate measures with more than one time point, climate was often measured at the same time point (e.g., in spring) across multiple years (Voight & Hanson, 2017; Wong et al., 2021). Research is lacking on studies that investigate whether school climate fluctuates depending on what time of the year measures are taken. Although studies have looked at how the prevalence of mental health disorders (Kovalenko et al., 2000) or mood (Tonetti et al., 2007) may change due to the seasons (e.g., winter vs. fall), these outcomes are

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different from school climate measures where the school, rather than the individual, is the focus.

However, one study in Finland specifically explored the seasonality of school well-being (i.e., school conditions, social relationships, and means for self-fulfillment) using responses from approximately 11,000 7th to the 9th grade students from 2007–2009 (Konu et al., 2015). School conditions focused on not only the quality of the school surroundings (e.g., temperature, air quality) but also on safety and the fairness of rules. A “social relationship” construct covered relationships with teachers, peers, and also school bullying. Findings indicated that measures were most favorable in the first half of the year compared to the second half suggesting that students may be experiencing “springtime fatigue” (p. 275) where authors suggested that students may be tired after a long school year. In the fall, students may have a more positive outlook due to having a fresh start to the school year.

## THE CURRENT STUDY

The purpose of this manuscript was to investigate differences in school climate related measures (i.e., safety, disciplinary structure, student support, prevalence of teasing and bullying, school disorder) within the same schools taken in the fall and spring using a time span of over a year. The differences in climate outcomes within a school year is a consideration for studies that may use pre-post, within-school designs to measure change (e.g., Voight, 2015; White & Warfa, 2011). If climate perceptions change naturally over time within a school year, conclusions that climate improved or declined because of some intervention (e.g., staff training) may be misinformed, depending on when climate is measured (e.g., within a school year: fall → spring vs. across school years: spring → spring or fall → fall).

For the current study, we used data from over 20,000 sixth- to twelfth-grade student (middle and high school) survey responses from 26 schools. We hypothesized that fall scores (i.e., measured in the first half of the school year) would be more favorable than climate scores measured in the spring (i.e., in the second half of the school year). Given that students have had less time and experiences at school in the fall (vs. spring), their outlook may be more positive (e.g., students are not yet fatigued) and have had less time to form negative experiences (e.g., being bullied, being disciplined) which could affect their perceptions of the school climate.

## METHODS

### Sample and Procedure

Data for the current study come from two separate, ongoing cluster randomized (wait-list) controlled trials (RCTs) being conducted in Missouri (MO) and Oklahoma (OK). The

RCTs focus on evaluating separate interventions to improve school climate. The RCTs employed an open enrollment recruitment strategy whereby any public school in the respective states was eligible to participate (K–12 in Missouri; 6–12 in Oklahoma). We emailed study descriptions to every principal in each state with information on how to enroll and we also presented at school leadership conferences in each state to recruit schools. We obtained informed consent from each principal who expressed interest in participating. Participating schools were then randomized to the intervention or control/business-as-usual (BAU) conditions. We provided descriptions of the study purpose at the start of each survey and schools sent home this information to parents prior to survey completion.

For the current study, we limited the analytic sample to only those schools with students from grade 6 to 12 (as these were common in both RCTs) and we only used the control/BAU schools (as the intervention was designed to improve school climate). In OK, the study used data from 17,486 students from 13 middle, 3 combined, and 4 high schools (20 schools). In MO, data came from 13,693 students from 11 middle and 2 high schools (13 total). Out of a total of 31,179 responses, students who indicated, based on validity screening items (Cornell et al., 2012) in the survey (i.e., “I am telling the truth on this survey”), that they had responded dishonestly (6.8%;  $n = 2,146$ ) or responded too quickly were excluded from the sample (0.4%,  $n = 118$ ).<sup>1</sup> The remaining sample had 28,915 student responses ( $N_{OK} = 16,052$ ;  $N_{MO} = 12,863$ ) from 33 schools.

School climate surveys (which contained measures of climate as well as respondent sociodemographic questions) were administered anonymously online to the students under the guidance of their teachers. Data were collected over several cohort waves of the RCT (i.e., schools entered the RCT in different years). Student response rates (based on state, semester, and cohort) ranged from 59%–91%. Due to the differences in timing of the RCTs and the requirements of the funding agencies, in OK, repeated surveys were administered in spring-fall-spring-fall<sup>2</sup> while in MO, surveys were administered in fall-spring-fall-spring. As a result of the different starting and ending semesters of the survey by state, we excluded the first spring measure in OK and the last fall measure in MO resulting in a sample of 21,454 student responses. This allows us to compare measures using fall-spring-fall data (at the school level) and does not use the spring measures collected either at the start (in OK) or at the end (in MO) of the data collection cycle.

The analytic sample was composed of students from schools that had responses from at least two or three time points. Seven schools only had data for one time point (within the fall-spring-fall timeframe) and were excluded as this would not allow for a comparison across time.

A few schools had data from two time points and were included in the analyses: five schools were not able to administer the survey in spring 2020 due to the Coronavirus pandemic and only had fall<sub>1</sub>-fall<sub>2</sub> measures.<sup>3</sup> One school had fall<sub>1</sub>-spring<sub>1</sub> measures and did not collect data in fall<sub>2</sub>. The final analytic sample consisted of 20,831 students from 26 schools ( $N_{MO} = 12$ ,  $N_{OK} = 14$ ) with data collected (over several cohorts) from fall 2017 to fall 2020.

In both states, based on student self-reported data, respondents were 52% female, 13–14% had a disability, and 33% were in high school. In OK, respondents were 49% White, 27% Hispanic, 2% Black, and 20% were of some other race/ethnicity. In comparison, in MO respondents were 63% White, 15% Hispanic, 6% Black, and 16% were of some other race/ethnicity. In terms of free or reduced price lunch status, 68% and 54% were eligible in MO and OK, respectively.<sup>4</sup> Based on the Common Core of Data classification,<sup>5</sup> of the schools, three were in cities, nine were in rural areas, six were in suburbs, and eight were in towns.

## Measures

Three measures (i.e., discipline structure, student support, prevalence of teasing and bullying) for the current study came from the Authoritative School Climate Survey (ASCS; Cornell et al., 2013). The ASCS has studies investigating its multilevel factor structure, predictive ability, and longitudinal invariance (e.g., Konold et al., 2014, 2021) which makes it well-suited for the current study. In addition, two scales (i.e., safety and school problems) were taken from the U.S. Department of Education tool for measuring school climate (EDSCLS; **ED School Climate Surveys**).<sup>6</sup> For all measures, the response options ranged from 1 to 4 indicating “strongly disagree”, “disagree”, “agree”, and “strongly agree” and mean scores were created using all scale items. Reliability measures (alphas) and intraclass correlation coefficients (ICCs) are presented as a range to represent the different time points studied.

### Disciplinary Structure Scale

Disciplinary structure was measured using a seven-item scale (e.g., “The school rules are fair”, “Students are treated fairly regardless of their race or ethnicity”) to evaluate whether school discipline was strict but fair (Gregory et al., 2010) ( $\alpha = .72$  to  $.75$ ; ICC =  $.06$  to  $.11$ ).

### Student Support

Student support consisted of eight items (e.g., “Most teachers and other adults care about all students”, “There are adults at this school I could talk with if I had a personal

problem”) designed to measure how supportive staff at the school were and the willingness of students to seek help (Gregory et al., 2010) ( $\alpha = .85$  to  $.88$ ; ICC =  $.06$  to  $.11$ ).

### Prevalence of Teasing and Bullying (PTB)

Consisted of five items (e.g., “Bullying is a problem at this school”, “Students in this school are teased about their clothing or physical appearance”) to measure student perceptions of teasing and bullying activity at the school (Cornell et al., 2013) ( $\alpha = .83$  to  $.86$ ; ICC =  $.09$  to  $.17$ ).

### School Problems Scale

Four items from the EDSCLS measured the prevalence of school problems. Items included: “The following types of problems occur at this school often: 1) profanity, 2) classroom disturbance, 3) students arrive late, 4) absenteeism” ( $\alpha = .74$  to  $.78$ ; ICC =  $.10$  to  $.15$ ).

### School Safety

Eight items from the EDSCLS were used (e.g., “I feel safe at this school”, “I feel safe going to and from school”) to measure perceptions of students’ feelings of safety ( $\alpha = .82$  to  $.84$ ; ICC =  $.14$  to  $.20$ ).

## Analytic Strategy

All student-level measures were aggregated to the school level as the unit of analysis was the school (as school climate is a school-level, not student-level, construct) (Cornell & Huang, 2019; van Horn, 2003). A longitudinal, school fixed effects growth model was constructed using a tall dataset with each school appearing approximately three times (once per time point). Five models were run separately, one for each outcome (which was standardized). The school fixed effects model is appropriate because this controls for all observed and unobserved school-level characteristics (Huang, 2016). As the responses across time points (i.e., fall-spring-fall) are nested within schools, we used CR2 cluster robust standard errors designed to be used with a limited number of clusters (Huang & Li, 2022).<sup>7</sup> The model can be expressed as  $SC_{st} = F1_{st} \beta_1 + F2_{st} \beta_2 + c_s + \varepsilon_{st}$  where  $SC$  is a measure of school climate,  $s$  is school,  $t$  refers to the time period (i.e., fall<sub>1</sub>, spring<sub>1</sub>, fall<sub>2</sub>),  $c_s$  is a school specific intercept that accounts for the effects of omitted variables at the school level,  $F1$  and  $F2$  are two dummy coded measures for time periods of fall<sub>1</sub> and fall<sub>2</sub> (spring<sub>1</sub> is the reference category), and the  $\beta$ s are the regression coefficients of interest. The  $\beta$ s represent how much higher or lower the school climate measures were in the fall compared to the spring (the reference group). All statistical analysis were done using

R 4.2 (R Core Team, 2022). Supplementary analyses performed at the student (not school) level are also included in the online appendix.

## RESULTS AND DISCUSSION

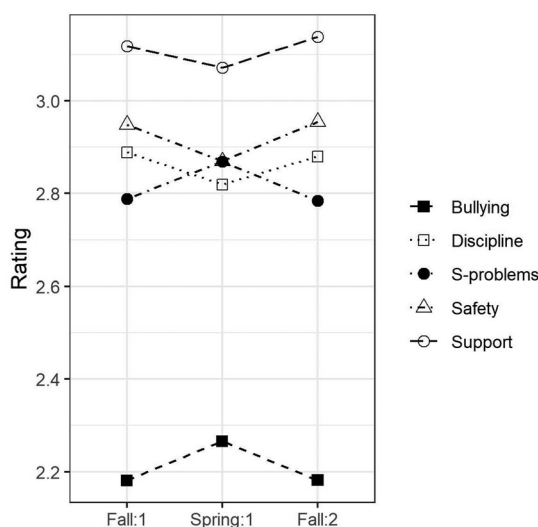
### Visualizing Seasonality

Prior to consulting the statistical models, we show results graphically using the raw metric of the scales by plotting the average scores of all measures for all schools combined (see Figure 1). Unambiguously, a zig-zag pattern is consistent and evident for the measures. Disciplinary structure, school safety, and student support measures are higher in the fall compared to the spring. The negative outcomes of bullying (PTB) and school problems are lower in the fall compared to the spring. These patterns are consistent across the three semesters and for all measures.

### Regression Model Results

Analyzing the measures over time, the graphical results are supported statistically using the fixed effect models (see Table 1). In comparison with the spring measure, measures taken in the fall of the school year and fall of the succeeding school year align with the graphical depiction of results. Outcome variables are standardized so that the regression coefficients can be interpreted as effect size measures (i.e., standardized mean differences). The absolute differences between fall to spring measures are size-

**Figure 1.** School-Level Climate Measures Across Different Time Points



Discipline = school discipline structure. Bullying = prevalence of teasing and bullying. S-problems = school problems. Support = student support.

**Table 1.** School Fixed Effects Regression Results (N = 72; 26 Schools)

	PTB	School Probs	Support	Discipline	Safety
Fall:1 <sup>1</sup>	-0.312* (0.119)	-0.392** (0.125)	0.251 (0.149)	0.379* (0.146)	0.329** (0.100)
Fall:2 <sup>1</sup>	-0.380* (0.151)	-0.470** (0.160)	0.372* (0.160)	0.315+ (0.177)	0.402** (0.120)
R <sup>2</sup> Adj.	.723	.717	.769	.681	.827

Notes. All outcomes standardized. <sup>1</sup>Spring is the reference group. PTB = prevalence of teasing and bullying. School Probs = school problems. Support = student support. Discipline = disciplinary structure. Cluster robust standard errors (CR2) within parenthesis.

+ $p < .10$ , \* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .001$ .

able ranging from a low of 0.25 (for student support,  $p = .11$ ) to a high of 0.47 (for school problems,  $p < .01$ ). For example, students' perception of safety is higher in the fall (compared to spring) by 0.33 to 0.40 *SD*. Students report less bullying in the fall (compared to the spring) by a magnitude of  $-0.31$  to  $-0.38$  *SD*. In other words, the differences in climate measures taken in the fall and spring are not trivial and fluctuate by measurement occasion. The effects can be considered small to moderate in size (e.g., 0.20 = small, 0.50 = moderate).

As a robustness check, we performed the analysis with only the schools that had complete data for all three time points ( $N = 20$ ). Results (see Table 2) are similar to the original analyses conducted. Descriptively, all the models with the smaller sample had even higher adjusted  $R^2$ s (.73 to .88), implying better model fit. In addition, the student-level analyses (both visual and regression analyses) are shown in the online appendix and display a similar pattern.

## DISCUSSION AND CONCLUSION

As indicated by Bradshaw et al. (2021), "school psychologists and school mental health practitioners play a central role in school climate research, practice, and policy; they are often unofficial and occasionally explicitly named school climate leaders or coordinators in their schools and districts" (p. 230). School psychologists, as well as other individuals assessing school improvement efforts, should recognize that school climate as a measure, fluctuates through the natural course of the school year. Findings suggest that schools looking at school climate improvement efforts should base their results on measures taken within the same term (fall-to-fall or spring-to-spring) instead of comparing fall and spring measures within the same school year. Schools expecting improvements in fall to spring may be discouraged to see climate worsen.

Visually, the fall-to-fall measures are relatively stable (see Figure 1) unlike the within school variation. For experimental studies that use spring outcomes and include

**Table 2.** School Fixed Effects Regression Results (N = 60; 20 Schools)

	PTB	School Probs	Support	Discipline	Safety
Fall:1 <sup>1</sup>	-0.419** (0.114)	-0.502*** (0.115)	0.332* (0.151)	0.494** (0.149)	0.434*** (0.094)
Fall:2 <sup>1</sup>	-0.340* (0.155)	-0.444* (0.162)	0.288+ (0.160)	0.231 (0.184)	0.320* (0.117)
R <sup>2</sup> Adj.	.804	.804	.801	.725	.883

Notes. Only using schools with data from all three time periods. All outcomes standardized. <sup>1</sup>Spring is the reference group. PTB=prevalence of teasing and bullying. School Probs=school problems. Support=student support. Discipline=disciplinary structure. Cluster robust standard errors (CR2) within parenthesis.

+ $p < .10$ , \* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .001$ .

control groups, that may be less of an issue as (fall) baseline measures are often used as covariates to improve power. However, for schools that are looking at measuring climate over several time points in efforts to evaluate school improvement efforts, the seasonality of school climate measures should be considered as the fluctuations occur in a predictable but nontrivial manner.

The findings that perceptions of school climate change from the start to the end of the school year may not be surprising though have not been specifically investigated by prior studies. In the latter part of the school year, students may be tired and more restless compared to the start of the academic year (Konu et al., 2015). Teachers may also be more stressed as the year progresses. Misbehaving students (who may have been warned already in the earlier part of the year) combined with emotionally exhausted teachers can result in more disciplinary sanctioning (Eddy et al., 2020) which in turn may affect how students view their relationships with teachers (e.g., teachers do not care about me) and the overall school (e.g., school rules are not fair). A study in one of the largest school districts in the U.S. indicated that a majority (>40%) of disciplinary incidents and sanctioning (e.g., suspensions, office referrals) occurred from March to the end of the school year (Huang et al., 2023).

A few limitations should be considered when interpreting results. Although we had schools from two different states, we do not know how findings may generalize to the larger population of K-12 schools. In addition, although we had used a broad range of constructs (e.g., bullying, safety, support), other instruments or factors may demonstrate greater stability when used in the same school year. As a result, our findings may be worth replicating with a different sample and with different school climate measures. Finally, for the student-level analysis shown in the appendix, results do not consider that the same student may have taken the survey more than once as the surveys were anonymous and not linked by any student identifier. Overall, we present preliminary evidence that measures

of school climate may differ depending on when surveys are administered.

## NOTES

1. Two graduate students went through the survey and timed how long it would take to complete if reading and responding very quickly. As a result, a five-minute cut-off was adopted. The mean completion time for the survey was approximately 17 minutes ( $SD = 8$ ).
2. Most of the fall surveys were completed in October/November. For the spring, these were completed in late March to early May.
3. One school was able to complete the school climate survey in spring 2020 and was retained.
4. For a comparison with state characteristics, see the online appendix.
5. <https://nces.ed.gov/ccd/schoolsearch/>
6. See <https://safesupportivelearning.ed.gov/edscls>
7. An alternative would be to use a growth model using multilevel modeling though has the disadvantage of not controlling for school-level predictors which might bias results.

## DISCLOSURE

The authors have no conflicts of interest to report.

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**Bixi Zhang** is a postdoctoral fellow in the Missouri Prevention Science Institute at the University of Missouri. Her methodological work focuses on the applications of robust methods in causal inference and multilevel modeling (including meta-analysis) for both experimental data and large-scale assessments. She is also interested in investigating the associations between learning-related behaviors and academic achievement in childhood.

**Wendy M. Reinke** is a Professor in the Department of Education, School, & Counseling Psychology at the University of Missouri. She is the Co-Founder and Co-Director of the Missouri Prevention Science Institute. She has an extensive grant and publication record including over 140 peer-reviewed publications and over \$60 million in grant funding in the areas of prevention and early intervention of child emotional and behavior disturbances. She is also the Director of the National Center for Rural School Mental Health and the co-developer and leadership team member for the Family Access Center for Excellence and the Boone County Schools Mental Health Coalition.

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**James Sebastian** is an Associate Professor in the Department of Educational Leadership & Policy Analysis at the University of Missouri. He received his Ph.D. in Educational Leadership & Policy Analysis from the University of Wisconsin-Madison. His research interests include the study of school leadership, organizational theory and behavior, organizational learning, and urban school reform.