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Beyond Chronic Absenteeism: The Dynamics and Disparities of Class Absences in Secondary School

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Student absenteeism is often conceptualized and quantified in a static, uniform manner, providing an incomplete understanding of this important phenomenon. Applying growth curve models to detailed class-attendance data, we document that secondary school students' unexcused absences grow steadily throughout a school year and over grades, while the growth of excused absences remain essentially unchanged. Importantly, students starting the school year with a high number of unexcused absences, Black and Hispanic students, and low-income students accumulate unexcused absences at a significantly faster rate than their counterparts. Lastly, students with higher growth rates in unexcused absences consistently report lower perceptions of all aspects of school culture than their peers. Interventions targeting unexcused absences and/or improving school culture can be crucial to mitigating disengagement.

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Beyond Chronic Absenteeism: The Dynamics and Disparities of Class Absences in Secondary School *

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ABSTRACT: Student absenteeism is often conceptualized and quantified in a static, uniform manner, providing an incomplete understanding of this important phenomenon. Applying growth curve models to detailed class-attendance data, we document that secondary school students' unexcused absences grow steadily throughout a school year and over grades, while the growth of excused absences remain essentially unchanged. Importantly, students starting the school year with a high number of unexcused absences, Black and Hispanic students, and low-income students accumulate unexcused absences at a significantly faster rate than their counterparts. Lastly, students with higher growth rates in unexcused absences consistently report lower perceptions of all aspects of school culture than their peers. Interventions targeting unexcused absences and/or improving school culture can be crucial to mitigating disengagement.

KEYWORDS: Student absences, racial disparities, growth curve model, school climate

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1 Introduction

School absenteeism has been widely accepted as a critical input and intermediate student outcome in educational research and policy-making. Numerous correlational (Allensworth and Easton, 2007; Balfanz and Byrnes, 2006; Gershenson et al., 2017; Henry et al., 2012; Lamdin, 1996; Nichols, 2003; Rumberger, 1995; Rumberger and Thomas, 2000) and causal (Liu et al., 2021; Tran and Gershenson, 2021) studies purport that absenteeism harms academic achievement as well as other long-run outcomes such as college enrollment. Students of color and those from low-income backgrounds accrue many more absences than their peers (Whitney and Liu, 2017). Absenteeism is also malleable, as evidenced by within-school factors such as teachers who can affect attendance (Gershenson, 2016; Liu and Loeb, 2021; Jackson, 2018) and multiple targeted interventions which have successfully decreased student absences (Robinson et al., 2018; Rogers and Feller, 2018; Bergman and Chan, 2021). As a result, reducing absenteeism disparities also has important implications for reducing troubling achievement disparities (Liu et al., 2021; Goodman, 2014).

Despite the heightened research and policy interest in absenteeism, the field still lacks conceptual coherence and measurement specificity, impeding the design of effective policies aimed at reducing absences. Seminal works on absenteeism, including Alexander et al. (1997), have long conceptualized student absenteeism simply as lost instructional time. Recent research has begun to consider absenteeism as a manifestation of a student's inability to engage in school related activities due to a range of in- and out-of-school factors (Balfanz and Byrnes, 2012; Gottfried and Hutt, 2019). In practice, schools use chronic absenteeism (typically defined as missing ten percent or more of the school year for any reason) as part of early warning systems to "flag" students who may be at-risk, despite having more detailed data on unexcused and excused absences. Several states use average daily attendance (ADA) rates as a part of their student funding formula. At the federal level, chronic absenteeism is often used in measures of accountability and school quality.

These aggregated metrics might be convenient for reporting and policy use, but risk masking important differences in the nature and the driving force behind absenteeism between two students, for example, who accrue the same number of total absences or are both labeled as chronically absent. One consequence of using an aggregated metric is that there is a limitation to understanding whether the causes and consequences of absences remain the same over time. An emerging literature that exploits more fine-grained absenteeism data than what has been typically used suggests that the *type* of absenteeism can be a useful measure that adds insight toward why absences occur relative to the black box of chronic absenteeism (Liu and Loeb, 2021; Gottfried, 2009; Gottfried et al., 2022. Other evidence suggests that the timing of absences both during Liu et al., 2021; Gottfried and Kirksey, 2017 and across school years Simon et al., 2020 might matter for future absenteeism and measures of academic performance.

Another consequence of lumping all absences together as a summary variable is a distorted picture of the distribution of learning opportunities between student subgroups. It is well documented that Black, Hispanic, and students from low-income backgrounds accrue substantially more absences than their peers (e.g., Goodman, 2014). Yet, progress has been relatively slow in understanding how and when these student subgroups accrue absences, as well as the extent to which such disparities are linked to within-school factors, such as poor school climate and culture, rather than individual- or family-level characteristics (Childs and Lofton, 2021). A deeper understanding of the multifaceted nature of absenteeism has the potential to provide better solutions for the school attendance issue, especially those targeted toward students who need the most support.

The current study leverages an unusually detailed daily absenteeism dataset from a large and diverse school district in California to map out longitudinal, evolving patterns of a student's excused and unexcused absences over a school year. We first describe the stark contrast between how excused and unexcused absences unfold over time in the data. Then, we estimate the growth rate of a student's *unexcused* class absences over the course of a school year, which we interpret as the rate at which student disengagement occurs in schools. Importantly, we do not intend to conceptualize disengagement rates defined here as an attribute of the student, but rather an evolving state due to both individual and contextual factors. We then explore variations in disengagement rates across grades, as well as by student race/ethnicity, income, and prior demonstrated levels of disengagement (i.e., unexcused absences). We further probe the underlying reasons for disengagement and school-level factors that might promote school engagement by leveraging students' self-reported perceptions of their school's culture and climate.

Our analysis finds that middle and high school students' unexcused absences grow steadily throughout a school year and as they progress over grades, while the level and growth of excused absences stay essentially unchanged. There are two important additional observations based on these growth patterns. First, students who initially accrue more unexcused absences tend to have a steeper growth curve later on. Second, while the growth trajectories of excused absences remain quite consistent regardless of student background, the same cannot be said for those of unexcused absences, which vary substantially from student to student. Specifically, Black and Hispanic students and students from low-income neighborhoods show much higher growth rates in unexcused absences than their White and more affluent peers in a given school year, suggesting a faster acceleration of disengagement among students of traditionally disadvantaged backgrounds. Similarly, students who start off the school year with a higher-than-average number of unexcused absences disengage much more quickly than their peers. Analysis of student self-reported school culture and climate measures indicates that students who have higher disengagement rates tend to have a poorer sense of belonging to their schools, perceive a lower level of academic support, express less agreement with the fairness of discipline, rules, and norms at their schools, and show more concerns about school safety. Lower perception of school climate and culture is especially salient for the most disengaged students. This is especially striking given that student perceptions of school climate is more strongly associated with growth rates of unexcused absences than with other conventional or aggregated absenteeism measures.

Together, our findings highlight the significance of differentiating types of absences as well as the role of timing in the development of absenteeism behavior. While not causal, our evidence implies that interventions targeting the most disengaged students early in a school year and in the lower secondary grades, as well as interventions that seek to improve school climate and culture, might be particularly promising approaches to mitigating disengagement.

2 Absenteeism in the Field

Simple intuition makes it clear that school attendance is critical for student success: Students must be present and engaged on a regular basis in order to learn and succeed in schools. Attendance has been robustly associated with high-stakes outcomes, making student absenteeism a prevalent concern among researchers, policymakers, and practitioners alike. Broadly speaking, an increase in absenteeism is linked to a decrease in academic achievement as measured by GPA (Gottfried, 2010; Gottfried and Hutt, 2019), end-of-term course grades (Liu et al., 2021), and standardized test scores in math and reading (Gottfried, 2009; Gottfried and Kirksey, 2017; Gershenson et al., 2017; Goodman, 2014; Liu et al., 2021), irrespective of grade level or student background. Absenteeism is further linked to decreased rates of long-run success such as earning a high school diploma (e.g., Neild and Balfanz, 2006; Smerillo et al., 2018), postsecondary attainment or persistence (Fraysier et al., 2020), and employment in the labor market (Kearney, 2008), as well as increased occurrences of risk factors such as drug use and criminal activity rates (Henry and Huizinga, 2007; Spencer, 2009).

Beyond the obvious link with student outcomes, absenteeism is a commonly-examined subject matter amongst researchers for several other reasons. First, absenteeism is a collective, prevalent issue observed across schools nationwide, justifying extensive research efforts put behind it. During the 2015-16 school year (hereafter, SY), over 7 million students or one-sixth of all K-12 students nationwide, were reported to be chronically absent, typically defined as missing 10 percent or more of school in a given year (U.S. Department of Education, 2019). Additionally, absenteeism is easily observable and measurable, making it less costly to collect compared to alternative measures designed to capture student outcomes beyond academic achievement (Schanzenbach et al., 2016a). In a typical school setting, for example, attendance is marked daily (if not multiple times a day among secondary school students) by staff and kept as administrative data in pre-existing student systems. This makes attendance measures easily accessible and analyzable relative to measures like direct classroom observation, student survey responses, or real-time measurement of behavioral engagement (e.g., hand-raising in class or disruption during a lesson). Third, absenteeism is malleable, as evidenced by multiple targeted interventions that successfully decreases student absences by leveraging various individual-level and environmental factors that can affect student engagement (e.g., Robinson et al., 2018; Rogers and Feller, 2018; Bergman and Chan, 2021). The successes of such interventions suggest that absenteeism is an academic behavior that has potential for improvement.

Educational agencies at various levels of governance also use absenteeism—particularly chronic absenteeism or other yearly absenteeism rates—to fulfill various compliance and accountability requirements. Individual schools and districts often incorporate chronic absenteeism rates into early warning indicators to flag students who may be at risk of failure or need additional intervention (Balfanz et al., 2008). At the state level, attendance is often considered in per-student funding formulas. Several states (e.g., CA, ID, IL, KY, MS, MO, and TX) account for attendance in school funding policies, using Average Daily Attendance (ADA)[1] to calculate the baseline funding a district receives per student. A number of other states use the Count Day method, where students in attendance are counted on pre-determined dates to determine baseline funding. Beyond local agencies, education poli-

[1] ADA is defined as the total number of days attended by enrolled students divided by the total number of school days

cies at the federal level have increasingly incorporated student absenteeism in recent years. The Every Student Succeeds Act (ESSA) in 2015 required states to incorporate a fifth, non-academic indicator to measure school quality and student success; by 2017, 36 states had decided on reporting average chronic absenteeism rates as their fifth indicator for federal level accountability purposes (FutureEd, 2017). These policies continue to spotlight interest in both the significance of, and stakes behind, measuring and reducing student absenteeism.

2.1 The "Black Box" of Chronic Absenteeism

The use of conventional measures of absenteeism poses a challenge counter to the aims of measuring and tracking the "black box of chronic absenteeism" (Childs and Lofton, 2021), in that it can mask variations in the driving factors behind the absences themselves. Through reviewing extant literature in the subsections below, we explain how the conceptual framework of school engagement guides our inquiry to focus on using unexcused absences as a measure of disengagement and how incorporating the type and timing of absences can help us unpack the black box of chronic absenteeism.

2.1.1 Conceptual Framework: Absenteeism as Behavioral Disengagement

School engagement is a multidimensional construct used to describe the quality of a student's involvement in the activities and context of schools (Hofkens and Ruzek, 2019). The conceptualization of school engagement guides our inquiry in two important ways. First, Scholars typically organize the concept of engagement into three types: behavioral, emotional, and cognitive (Fredricks et al., 2004). While these three aspects are dynamically related, the separation of these aspects provides a sensible approach to characterize student engagement in a nuanced way. In particular, behavioral engagement is rooted in the idea of participation and specifically refers to students' involvement in schools' academic, social, and extracurricular activities, making attendance a natural and suitable measure of behavioral engagement (Rumberger and Larson, 1998).[2] Likewise, absenteeism can be considered a measure of behavioral *dis*engagement. In contrast, emotional engagement is comprised of positive or negative interactions with peers, teachers, schoolwork, and the school. Cognitive engagement refers to the extent to which a student is willing and thoughtful to exert efforts to comprehend complex ideas and master difficult skills(Fredricks et al., 2004).

Second, another important feature about school engagement is that it can be considered as a *process* that mediates contexts and student outcomes (Connell and Wellborn, 1991; Skinner et al., 2008), which is made most clear in the extant literature that uses engagement as the primary theoretical model to explain school dropout and promote school completion. Rather than a one-time event, "dropping out itself might be better viewed as a process of disengagement from school, perhaps for either academic or social reasons, that culminates in the final act of leaving" (Rumberger and Rotermund, 2012). Thus, incorporating the dimension of timing is critical to properly characterize and measure engagement and disengagement as process variables. Similarly, this suggests that absenteeism, which has been mostly used as an outcome in both research and practice, should not be viewed as static but as an evolving phenomenon in gauging behavioral disengagement.

In sum, the rich theory of school engagement provides a useful framework to conceptualize and empirically examine absenteeism. However, the multi-faceted nature of absenteeism renders it difficult to interpret all absences as behavioral disengagement without knowing the reasons behind each absence. We thus turn to explaining the differences between excused and unexcused absences in relation to disengagement, and why we focus most markedly on unexcused absenteeism as a defensible indicator of behavioral disengagement.

[2] At the most fine-grained level, behavioral engagement can be observed within the context of a given task, like verbally answering a teacher's question or completing one's homework assignment (Woodward and Munns, 2003), but behaviors like showing up to math class or participating in a school event/activity can also be considered a measure of engagement.

2.1.2 Excused vs. Unexcused Absences

The vast majority of local educational agencies often go beyond chronic absenteeism to categorize absences as either excused or unexcused. Typically, the difference between the two hinges primarily upon whether the parent or caregiver communicates a reason for missing school. Students may accrue excused absences, for example, due to unavoidable reasons—illness, religious holidays, and funerals are some examples—as well as avoidable ones, such as doctor's appointments. Students can also miss school due to issues beyond their control such as family responsibilities, unstable housing, unreliable transportation to school, and hazards or violence in the neighborhood (Chang and Romero, 2008; Gottfried and Kirksey, 2017; Gottfried and Hutt, 2019). These are often indicative of systemic issues beyond the school that further drive absenteeism rates, and are the same issues that also pose as barriers toward student engagement and perpetuate educational inequalities (Balfanz and Byrnes, 2012, 2013; Chang and Romero, 2008; Ehrlich et al., 2014).

Of the myriad reasons why students accrue absences for unexcused reasons, one possibility is that students "disengage" or skip school. While the term school skipping may inherently suggest this is driven solely by individual-level behavior, emerging evidence suggests that absences stem from a mix of individual and environmental factors. For example, literature cites disinterest in schools and delinquent behavior as two key, individual-level reasons for missing school for unexcused reasons (Hess et al., 1989; Rumberger, 1995). Some sources of school disinterest may include a lack of a sense of belonging or inability to feel connected to their academic environment. As for the former, evidence suggests that students who report feeling connected to their peers and adults at the school are more likely to attend and be engaged in schools (Berabei, 2014). Even one supportive non-parental adult at a school can improve a student's sense of belonging as well as student outcomes overall (Johnson et al., 2012; Osher et al., 2020; Ryan and Patrick, 2001). Therefore, it is possible that a student lacking healthy, positive relationships at school may avoid being in such an environment. This process has the potential to become cyclical in nature, where students fail to develop positive relationships with peers and adults due to frequent absenteeism, which can then go on to affect their existing relationships with others (Finn, 1989; Gottfried, 2014; Johnson, 2006).

Similarly, schools with higher student-reported ratings for school climate and culture tend to report lower rates of absenteeism (Schanzenbach et al., 2016b), suggesting that a student's perception of the community present in their schools is essential for regular attendance and engagement. Likewise, some students may miss school because they simply find their learning experience to be unwelcoming and disagreeable to them for various reasons. This could be applicable to students who attend schools with harsh discipline practices, which can prevent them from learning effectively (Balfanz and Legters, 2004). Often, academically struggling students perceive school to be a place of failure rather than a place for growth (Darling-Hammond, 2015), and this belief may lead them to choose not to attend.

It is important to note that unexcused absences can often be due to legitimate but involuntary factors that are far outside of the control of the student. For example, a prerequisite for good attendance habits consists of conditions for learning (Osher and Kendziora, 2010; Cantor et al., 2019) such as safety, well-being, positive relationships, and an appropriate level of academic content. Students with a high number of absences are also more likely to have a number of health- or family-related risk factors (Hancock et al., 2018) or come from communities with fewer resources or low-income families (Attwood and Croll, 2006; Crowder and South, 2003; Galloway, 1983). This is not surprising given that the risk of violence, bullying, harassment, or other threats to safety generally increase the incidence of absences (Balfanz and Byrnes, 2012). Likewise, schools and communities that provide physically and emotionally safe conditions and practices have also been shown to improve student engagement and attendance overall (Gottfried, 2014; Resnick et al., 1997; Berabei, 2014).

Admittedly, the differentiation of excused vs. unexcused absences is far from perfect. Unexcused absences can occur for the exactly same reasons that excused absences do, but could be marked as such due to lack of parental communication with schools or educators' unequal treatment of different students. For example, evidence suggests that parents of students with high absences tend to be less informed (or misinformed) about their child's education (Rogers and Feller, 2018; Sheldon and Epstein, 2004) relative to those of low-absence students. Additionally, if there are systematic biases in the reporting process of absenteeism that is in favor of more affluent students (i.e., absences due to legitimate reasons are more likely to be excused for affluent or White students than their less advantaged or minoritized peers - see McNeely et al., 2021), exploiting the differences of the two types of absences risks wrong interpretations of the results and false policy implications.

With the above caveat in mind, our study differentiates unexcused absenteeism from excused absences as a measure of behavioral disengagement for several reasons. First, it allows us to distinguish, to some extent, why absences may occur. Several empirical studies highlight the importance of differentiating between unexcused and excused absences when examining academic engagement among students (Gottfried, 2009; Liu and Loeb, 2021; Pyne et al., 2021). For instance, Pyne et al. (2021) found that unexcused absences are detrimental toward yearly academic growth, while excused absences are only modestly associated with declines in academic growth. Similarly, Gottfried (2009) reported that among students with an equal number of absences, those with a higher proportion of unexcused absences (relative to excused ones) had lower math achievement relative to those with a higher proportion of excused absences. Additionally, absences can have varying levels of malleability depending on their type, and emerging evidence suggests unexcused absences are more malleable than excused ones. Using data from the same district as this study, Liu and Loeb (2021) examine teacher value-add in increasing student attendance and finds that high-quality teachers can effectively reduce unexcused absences, but not excused absences. This finding adds nuance to evidence from various student absenteeism interventions that leverage teachers or other adults in the school to reduce absenteeism (e.g., Guryan et al., 2017), and also provides some validation of the precision of the data used in the current study. Lastly, an understanding of the relationship between unexcused absences (in particular) with school climate can shed light on strategies to mitigate these incidences. If we assume that unexcused absences stem from a mix of individual- and environmental-level factors, gauging the association between the incidence of these types of absences and how students perceive their schools is a natural first step toward deciding whether and how to improve the environmental factors that can drive up absenteeism.

To conclude, despite its flaws, the cause of an absence (or the *legitimacy* of an absence), matters in measuring and mitigating absenteeism. Of the studies above, only Liu and Loeb (2021) examine absenteeism in a granular manner—partial-day, class-level absences—and within secondary schools, an understudied student population when it comes to attendance research. The latter context is especially important, as secondary school students are situated in an environment and developmental stage where their absenteeism behaviors can be substantively influenced by their peers, teachers, and classroom settings (Youth Justice Board, 2013). Further, secondary school students must attend multiple classes a day, and thus have been observed to miss school for unexcused reasons at higher rates than those at younger grade levels (Whitney and Liu, 2017). This presents a key opportunity to examine secondary school students and their absence patterns more closely. Lastly, secondary school students have a higher locus of control relative to elementary school students. This implies that a bigger share of secondary school absences could be driven by lack of caregiver communication about the absence relative to elementary school absences. As such, this study gives closer attention to secondary school absences, their type and timing.

2.1.3 Absenteeism as a Dynamic Phenomenon

Literature on attendance as a measure of academic engagement supports the notion that attendance is a dynamic habit that evolves over many intervals of time. School attendance, like reading or teeth brushing, is considered a daily habit that is malleable but also persistent over time (Jordan and Chang, 2015; Connolly and Olson, 2012; Ehrlich et al., 2013).

Indeed, absenteeism starts as early as kindergarten (Chang and Romero, 2008) and worsens as students enter secondary schools, where academic stakes increase (Corville-Smith et al., 1998; Whitney and Liu, 2017). School transitions also pose challenges for some students. Yearly absence counts are often higher when tumultuous schooling transitions occur, such as the transition to middle school in sixth grade and the transition to high school in the ninth grade (Garrison et al., 2006). Additional studies suggest that high rates of absenteeism in years as early as kindergarten were positively associated with higher rates of absenteeism in the advanced elementary grades (Connolly and Olson, 2012) as well as in high school (Ansari et al., 2021). Several studies also have examined patterns and consequences of absenteeism between elementary and secondary school and found that chronic absenteeism is cumulative in nature, and persistently affects students' academic achievement (London et al., 2016).

However, limitations in the current literature make it difficult to gauge actual patterns of absenteeism–for example, denoting exactly when students accrue absences during the school year. Conventional measures of yearly absences or yearly chronic absenteeism rates do not allow for an understanding of within-year absences. Causal studies suggest that missing any day of school is considered equally detrimental to student success, regardless of whether it is the student's first or tenth absence (Liu et al., 2021; Gershenson et al., 2017; Gottfried, 2009). Nonetheless, if absenteeism is a habitual practice that can beget subsequent absenteeism (Gottfried, 2017), it is possible that every absence, beginning with those that accrue at the onset of the school year, poses a risk to a student's ability to remain academically engaged in the later part of the school year, leading to future absences. One study supports this notion: Gottfried (2017) found that students who accrue unexcused absences in the first semester are more likely to accrue them in the next semester.

Additionally, no studies to date have extended this knowledge to examine whether students accrue absences at the same rate across multiple years of a student's schooling experience. While it is possible that high-absence students in one year may be more likely to have more absences in a future year, it's not clear whether the pattern of absenteeism accrual evolves over a student's educational experience. Within the framework of academic engagement, it is possible that attendance, as a habit, can evolve and change as a pattern over time. At the same time, it also seems arguable that, for example, students who start out missing many days of school at the beginning of one school year might continue on in this pattern in later school years.

2.1.4 Consequences of Using Conventional Absenteeism Measures

There are two potential, relevant ramifications of using conventional measures of absenteeism that further "the black box" of chronic absenteeism in research and policy. The first is that current absenteeism measures mask the shifts in type and timing of absences, which hinder our ability to have a nuanced understanding of absenteeism trends across various student subgroups. Unsurprisingly, absenteeism is particularly pervasive among minoritized student populations and students from disadvantaged communities, who are more likely to face barriers to attending school relative to White and wealthy students (Whitney and Liu, 2017). We know that Black, Hispanic, Native, and Pacific Islander students consistently experience higher rates of chronic absenteeism relative to their White and Asian peers, as do students who attend urban schools or reside in high-poverty neighborhoods (Gottfried and Hutt, 2019; Sheldon and Epstein, 2004; Attendance Works, 2021; McNeely et al., 2021). Low-performing schools also tend to have higher absenteeism rates than high-performing counterparts (Balfanz and Byrnes, 2012). However, coarse and static measures such as chronic absenteeism rates provide little information on when and how these gaps appear–for instance, whether there is a point in time during the school year when racial gaps emerge or whether these attendance gaps persist from the onset of the school year.

A second and related consequence is that measures such as chronic absenteeism indicators can impede the design of effective interventions aimed at reducing absences in a timely and relevant manner. In Guryan et al. (2017), student attendance improved as a result of a high-touch intervention using in-school mentors trained to support students directly in tailored ways and to engage with parents on a regular basis. It is possible that such an intervention, if scaled, would be extremely useful for reducing student absences caused by a reluctance to attend schools or extenuating family circumstances that pose barriers to regular attendance. We, however, do not have knowledge on whether such an intervention would be useful for students who, for example, start off with a high number of absences at the beginning of the school year, relative to students who miss more school at the end of the school year, given the way absenteeism is measured for this particular intervention. Others, such as those by Robinson et al. (2018) and Rogers and Feller (2018), engaged parents and guardians with increased communications in order to decrease student absenteeism. While this may have helped caregivers receive more information about the number of school days their student had missed thus far, the use of yearly absence counts is insufficient for understanding whether such an intervention would be effective for all students with various driving factors behind absences. Knowing when and how students accrue absences and how these patterns evolve can better inform the many interventions currently present nationwide in an effort to reduce chronic absenteeism.

In practice, understanding the nuance of absence reasons and trends behind the face of chronic absenteeism can also contribute to an increased understanding of whether policies and programs are fully effective and meet their intended goals. One such example is September Attendance Awareness Month (Attendance Works, 2014), which targets absence reduction in the early weeks of the school year. While it is important for students to build habits and relationships at the beginning of the school year, it is not clear whether such interventions contribute effectively toward reduced absences later on in the year, and whether they have similar effects for unexcused and excused absences alike. Similarly, the use of chronic absenteeism indicators in the policy arena to gauge school quality can also be better served with this type of understanding of the evolving nature of absenteeism. By unpacking absenteeism, one can retrieve foundational information such as what is driving the increase in chronic absenteeism, which student group contributes the most to it, and when in the school year absences accrue the most. In turn, this knowledge has the powerful potential to inform what aspect of school quality can be improved.

In our paper, we answer the following three research questions:

1. How do different types of class absences among secondary school students evolve over the course of a school year and across grade levels?

2. How do disengagement rates vary by students' first month of absenteeism, their race/ethnicity, and socioeconomic status?

3. How do students with varying disengagement rates, especially those who are the most disengaged in schools, perceive their school's climate and culture?

3 Data

Our paper uses a rich administrative dataset from a large, urban school district across three school years, from 2015-16 through 2017-18. There are three different samples that we examine in our paper. Our full sample consists of all secondary school students (i.e., students in grades 6-12) ever enrolled across the three years we are able to observe. Additionally, we examine two different cohorts of students within our full sample. The first is the middle school cohort, which consists of students who were enrolled in sixth grade in the 2015-16 SY and continued enrollment in the district throughout middle school or through the end of the 2017-18 SY. The second is the high school cohort, which is the same except students were enrolled in the ninth grade in the 2015-16 SY and observed through their junior year in the 2017-18 SY. Examining these two cohorts separately allows us to see how absenteeism evolves within students over time and how the patterns vary in middle and high school (Whitney and Liu, 2017).

For all students observed in our sample, we are able to observe detailed course-by-day-level attendance data, which we link to students' demographic information which includes student gender, race/ethnicity, neighborhood income, grade level, Special Education status, and English Learner status. We are also able to link students' attendance records to their responses to the annual school climate survey administered by the school district. For the middle and high school cohorts, we restrict our sample to those who enrolled continuously; for the full sample, no specific restrictions are made. The full analytic sample data consists of 39,145 unique students across the three academic school years. We further narrow down to the middle school cohort and high school cohort, which include 3,517 and 3,416 students, respectively.

3.1 Variables

3.1.1 Measures of Attendance

The fine-grained manner in which attendance is recorded in the administrative dataset allows us to leverage these records to describe the temporal patterns of different types of absenteeism. In this particular school district, teachers mark student attendance daily using an electronic student information system. In effect, the raw attendance data indicate whether, for example, a student was present, marked absent for an excused reason, or marked absent for an unexcused reason in every period and day during which the student is enrolled in the district.[3] Several peer-reviewed papers have validated the reliability of this data (Liu and Loeb, 2021; Whitney and Liu, 2017).

In the district pertaining to our study, student absences were considered excused if a parent/guardian notified the school with a reason for missing school, via written note or in verbal communication with a school representative. Reasons falling under the excused absence category as outlined by the district were aligned with the state education code and include health reasons, family emergencies, and religions or personal reasons.[4] Unexcused

[3]While tardies and suspensions are also part of the choice set for why a student may be marked absent, we do not include them in our analyses as our interest lies in unexcused and excused absences. Tardies and suspensions make up a trivial amount (less than five percent) of the attendance data overall.

[4]While it is possible to assume that excused absences consist of one of these reasons, the authors lack

absences were defined as missing school or being tardy for longer than 30 minutes without a valid excuse from a parent/guardian. While the district does not have particular protocol for excessive excused absences, accruing three unexcused absences would typically lead to district actions, such as a letter informing the parent/guardian that the student has been classified as truant, as well as school-parent conferences and/or referral to the School Attendance Review Board.

We reshape our class absence data in two key ways. First, we collapse the data to the weekly level, generating for each student the total number of classes missed in each week of the school year, separately for excused and unexcused reasons.[5] This supports our ability to analyze students' absenteeism patterns across time without the issue of excessive zeros in the data and makes the modeling process more computationally feasible; we discuss this issue in greater detail in Section 4. Additionally, we exclude from analysis any absences that students accrue during the last two weeks of fall semester and the last two weeks of spring semester. The final weeks of each semester and the school year often involve unique activities for both students (e.g., final exams, graduation/promotion ceremonies, or field trips) and teachers (i.e., grading). Absences that occur during this period of time may therefore be inconsistent in terms of motivation or rationale relative to absences that occur during other times of the school year.

3.1.2 Race/Ethnicity and Neighborhood Income

To address our second research question, we disaggregate and examine absenteeism rate trends across groups of different sociodemographic backgrounds. Our five race categories are defined as follows: non-Hispanic Asian, non-Hispanic Black, non-Hispanic White, Hispanic, and Other Race. Other Race consists of students who identify as multi-race, students from

data that include the specific reasons of each absence and are unable to differentiate across various types of excused absences.

[5]Readers who may be interested in potential variations of absence occurrences by period/time of day may refer to Whitney & Liu (2017) which documents this variation among secondary school students.

American Indian/Alaskan Native backgrounds, and students who decline to state their race (fewer than 5% of students per year). We derive income by using the 2007-2012 American Community Survey data, where we can use students' residential addresses to identify the median income of that census tract. We use this rather than eligibility for free or reduced price lunch, which can be problematic in accurately determining income (Fazlul et al., 2021).

3.1.3 Survey of School Climate and Culture

Each year between February and April, the partnering school district administers a school climate and culture survey to all students in upper elementary through high school grades. The survey consists of multiple-choice items that measure four constructs: Climate of support for academic learning; sense of belonging and school connectedness; knowledge and fairness of discipline, rules, and norms; and sense of safety. See Table A1 for a full copy of the survey with a complete list of all items under each construct and item response choices. Prior work has systematically examined the psychometric properties of this survey, showing high reliability (ranging between 0.77 and 0.88) and validity of the four constructs(Hough et al., 2017; Marsh et al., 2016). We link these survey constructs to our full sample at the student-year level; the average response rate is about 67% over the three years we examine. For the purposes of our analysis, we produce a mean score for each construct using all items under each construct.[6]

3.2 Descriptive Statistics

Table 1 presents the descriptive statistics of these three samples. In our main sample, which consists of all middle and high school students, slightly less than half are female. Given this is a large urban school district in California, it is not surprising to see that 44% of the students are Asian. While the share of Black students is only 8%, the share of Hispanic students, the fastest growing ethnic group in the U.S., is over a quarter of the student population.

[6] We also tried using item response theory (IRT) scales and found substantively similar results.

The median household income is around $70,000, which is higher than the U.S. median level ($64,000); however, there is a tremendous amount of variation between students, as suggested by the large standard deviations. In terms of weekly absences, an average secondary school student only has 0.01 full-day absences during a week. Notably, class absences are much more prevalent. An average student missed 2.16 class periods per week. The large standard deviation (4.79) suggests that some students miss far more classes than others. Importantly, class absences are mainly composed of unexcused rather than excused absences, which is consistent with prior findings by Whitney and Liu (2017).

When comparing the two cohorts examined for our paper, there are few differences by sociodemographic characteristics. The high school cohort has a smaller gender gap and is slightly less racially dispersed (with about 5 percentage higher of Asian but 3 percentage fewer Black students) than the middle school cohort, but otherwise the samples look remarkably similar to one another. A notable exception is that the middle school cohort has a lower mean total weekly class absence and unexcused absence count compared to the high school cohort. On the other hand, there is minimal difference in excused absences and full-day absences between the two cohorts.

4 Methods

We apply a growth curve model (GCM) to estimate how class-absences change over the course of a school year.[7] Widely used in developmental research, GCM provides several advantages for modeling how absences evolve over time using the longitudinal data we have (Singer et al., 2003). First, GCM allows us to adequately characterize the start points, the growth trajectories, and how these patterns of absences vary between individual students in a parsimonious manner. Second, GCM enables us to directly derive individual parameters (e.g., slopes) using empirical Bayes methods, which provide the Best Linear Unbiased Predic-

[7]We use a multilevel linear model approach to estimate GCM. The estimation is conducted using Stata and we use the maximum likelihood estimator.

tor (BLUP) for further analysis. Third, GCM provides sufficient modeling flexibility in how we specify the functional form of the time variable. Thus, we can introduce nonlinearities, for example, by using a quadratic term, to better fit our data. Lastly, compared to Ordinary Least Square (OLS) estimates which were commonly used prior to the prevalence of GCM, GCM greatly improves the precision of the estimates because they require estimation of fewer parameters and "borrow strength" from all the data.

As mentioned, we first aggregate our student-by-day class absence data to the student-by-week level, which lowers the computational burden compared with a dataset at the student-by-day level but still preserves the fine-grained nature of the data. Another benefit of this aggregation is that we avoid excessive zeroes in the data, as students are more likely to have some class absences during a week rather than in a single day. Thus, the data are shaped in a way that each student i has about 40 observations (i.e., one per instructional week) in a year, each indicating the total number of absences in a given week j; the variable indicating the week of the school year effectively serves as the time variable in our model. We center the week variable at week one, such that the intercept would estimate absences that occur in the first week of the school year. We also allow our model to contain random intercepts, in effect allowing each student to have a different starting level of absences. Lastly, our model includes a quadratic version of weekly time indicators to capture potential nonlinearity in disengagement, though we don't allow the coefficient on the quadratic term to vary by students because between-student variance on the term is essentially zero and statistically insignificant. We do not include any individual or school level covariates in the model, because our goal here is to describe the raw patterns of class-absences over time. Our model is specified below:

$$\begin{aligned}
Absent_{ij} &= \pi_{0j} + \pi_{1j} weekno_{ij} + \pi_2 weekno_{ij}^2 + e_{ij} \\
\pi_{0j} &= \beta_{00} + \gamma_{0j} \\
\pi_{1j} &= \beta_{10} + \gamma_{1j}
\end{aligned} \tag{1}$$

where we assume that

$$e_{ij} \sim N(0, \sigma^2) \text{ and } \gamma_{\mathbf{ij}} \sim MVN(\mathbf{0}, \tau) \tag{2}$$

We estimate this model separately for unexcused and excused absences and for three different samples–the full sample, the middle school cohort, and the high school cohort. For each model we fit to data, we allow for an unrestricted variance-covariance structure in order to estimate the correlation between the random intercepts and random slopes. We also fit a version of the model using schools as the third level. Given the results are substantively similar, we present results from the more parsimonious, two-level model.[8]

4.1 Estimating Different Disengagement Rates by Student Characteristics

Our second research question examines how disengagement rates differ by students' initial absenteeism, race/ethnicity, and neighborhood income. For students' initial absenteeism, we categorize students into quartiles depending on their total number of unexcused class absences in the first month of a school year. Then, we interact the quartile dummies with the time variable in our model. Essentially, this specifies π_{0j} and π_{1j} as functions of student first-month absences. Since students in different grade levels might have different initial absences, we apply GCM analyses by grade using our full sample. We visualize the results by plotting the growth curves by grade.

Similarly, to answer our second research question about racial- and income-disparities in disengagement rates, we specify π_{0j} and π_{1j} as functions of student race/ethnicity and income quartile of the student's residential tract to determine whether the level and rate of absenteeism vary by student sociodemographic background. We specify White students

[8]In the three level model, $\hat{\pi}_{1j} = 0.052, p < 0.001$; $\hat{\pi}_2 = -0.000, p < 0.001$. These estimates are near identical to those of our two-level model, for which we report the results in Table 2

and the highest neighborhood income quartile, respectively, as the reference groups for each analysis. We conduct postestimation tests to show whether group differences in the intercept (i.e., initial level of absences) and slope (i.e., rate of absence accrual) are statistically significant.

4.2 Linking Disengagement Rates with Students' Self-Reported School Climate and Culture

To demonstrate how students with different disengagement rates perceive school climate and culture, we first derive each individual student's disengagement rate from our main GCM analysis. We use the empirical Bayes method to predict each individual student's linear slope term, which effectively captures one's growth trajectory in unexcused absences.[9]

We then produce binned scatter plots for each construct in the survey to visualize the relationship between school culture and disengagement rates. One appealing feature of a binned scatter plot is that it can control for relevant covariates when plotting. In our case, we control for student characteristics including race/ethnicity, gender, grade level, neighborhood income quartiles. Additionally, we also include school fixed effects so as to compare students in the same school, which is more policy relevant in our context, and year fixed effects to account for district-level policies or other year-specific shocks that affect all schools in a given year. Another feature of a binned scatter plot is that it divides the sample into a prespecified number of groups: In our plot, we have 20 groups, with each capturing 5% of the overall observations. This allows us to easily gauge perceived school climate and culture among, for instance, a smaller group of students who have particularly high disengagement rates (e.g., the top 20% percent).

[9] As specified in Equation (1), we do not allow the quadratic term of the time variable to vary between students. Thus we only use the linear term to capture each individual student's different trajectory of accumulating unexcused and excused absences.

5 Main Results

Before estimating the GCM models, we first visually inspect temporal patterns of absences in our samples. As Figure 1 shows, there exist stark differences between unexcused and excused absences in the data. Specifically, we observe in the data that an average student starts the school year with slightly fewer than one unexcused absence in the first week of class, and half of that amount in excused absences. Second, unexcused absences occur at a much higher frequency than excused absences no matter the time of year. Excused absences stay relatively stable across the school year (although they accrue slightly more around late winter and early spring, which coincide with the flu season), whereas unexcused absences increase throughout the entire school year, with a seemingly slower growth rate in the spring. This visualization reveals the importance of timing and types of absences in understanding nuanced student absenteeism behavior prior to moving on to modeling strategies.

5.1 Quantifying Growth Patterns Using GCM

Motivated by the patterns shown in Figure 1, we turn to GCM to quantify the trends we observe in a more precise manner. The results of estimating Equation 1 are presented in Table 2. Our modelling results confirm that both the level and growth rate of unexcused absences are higher than those of excused absences in our full sample of students. The intercept for unexcused absences is 0.996, more than double the intercept for excused absences (0.406). The linear growth rate in unexcused absences is 0.051 and statistically significant: In other words, students accrue one unexcused class absence every two weeks of the school year. The quadratic term is small in magnitude, negative, and statistically significant, suggesting that the growth rate in unexcused absences slows down slightly as students progress over a school year, as initially suggested by Figure 1. While we also have a positive and statistically significant linear term for excused absences, the magnitude of this coefficient is much smaller than what is observed for unexcused absences. The bigger quadratic term confirms the presence of the inverse "U" shape of excused absences initially observed in Figure 1. Using these derived parameters, we plot the growth curves for unexcused and excused absences using our full sample in Figure 2. The patterns of Figure 2 almost mirror those of Figure 1 and the cohort-specific patterns visualized in Figure A3 are akin to modeling results shown in Figure A4, confirming the precision of GCM.[10]

Additionally, we observe that the middle and high school cohorts yield meaningfully different patterns in unexcused absences. Both the levels and growth rates of unexcused absenteeism are higher for older students (i.e., the high school cohort) compared to younger students (i.e., the middle school cohort). Per Table 2, middle school students start out the first two weeks of school with one unexcused absence (intercept=0.512, or one-half absence in the first week of school), while high school students start with 1.6 unexcused absences (intercept=0.803), an increase of over 50% in the older cohort. The growth rate of unexcused absences (linear slope=0.042) within the high school cohort is also much steeper, at more than four times that of the middle school cohort (linear slope=0.010). The level of unexcused absences increases as students in each cohort progress through more grade levels (see Figure 3). This shows a stark contrast to models estimating level and growth in excused absences, which are similar across the three analytic samples and maintain similar inverse-U patterns at consistent levels throughout each passing year. These patterns imply that students are absent for excused reasons throughout the school year at similar magnitudes, regardless of grade level, but that students skip school in varying degrees, and increasingly so as they advance in grade level. These results are also accurate to descriptive patterns seen in histograms of absences by cohort.[11]

Lastly, we observe several other characteristics with regards to unexcused absences that vary from those of excused absences. The GCM results in Table 2 show larger variances for

[10] To mitigate the potential issue that students enrolled in additional courses may accrue more absences, we also visualize the pattern observed in Figure 1 using absence ratios (i.e., ratio of class absences to class periods per week) for the full sample in Figure A1 and separately by cohorts in Figure A2. Furthermore, we replicate the main analysis with a restricted sample of students enrolled in exactly 35 periods per week and show the results in Table A2. All of these yield results similar to our main findings.

[11] See Figure A3.

individual intercepts and slopes of unexcused absences relative to that of excused absences, implying greater variation between students in the occurrence of unexcused absences. This finding is corroborated by the intra-class correlation (ICC) of the model estimating unexcused absence growth rates, which is two to four times bigger than those estimating excused absence rates regardless of the sample. Importantly, the covariances between the initial level and growth rate of unexcused absences are bigger by a degree of magnitude compared to those of excused absences, suggesting that students who skip school at the beginning of the year are more likely to skip more days of school throughout the school year. Together, these findings confirm anecdotal evidence of the increasing levels of disengagement across grade levels. In contrast to the near-universal consistency in excused absences, the phenomenon of unexcused absences in particular is striking and suggests varying rates of student disengagement in schools.

5.2 Results Disaggregated by Initial Absenteeism in A Given Year

When examining our first research question, findings suggest that initial unexcused absences in a given year predicts disengagement rates for the rest of that year. We address our second research question by formally modeling how students across the distribution of initial absences fare later into a school year.

Figure 4 presents a visualization of our analysis by each grade, where several important patterns emerge. First, across all grades, students who are in the top quartile (i.e., the most disengaged students as measured by the first month's worth of unexcused class absences) accrue far more absences relative to the remaining three quartiles. Students pertaining to the first three quartiles start off at similar and sometimes indistinguishable initial level of absences. In other words, we observe that the variation in initial absences at the onset of the school year is mainly driven by the upper tail of students with the most initial absences. These disparities are more evident in high school grades.

Second, consistent with findings addressing our first research question, the most disengaged students also accumulate unexcused absences faster than their less initially disengaged peers, and this rate of disengagement is steeper in the high school grades than in middle school grades. While students in the other three quartiles also accrue unexcused absences throughout the remainder of the school year, they end up with much fewer unexcused absences by the end of the school year. Together, these findings point to the importance of understanding how many classes students skip at the beginning of the school year, as they are strongly predictive of overall disengagement rates, or the number of absences a student would accrue later in the year.

5.3 Results Disaggregated by Demographic Background

Two additional extensions of our main model interact the time variable (i.e., variable indicating week of the school year) with race/ethnicity groups and neighborhood income quartiles, respectively, to show results by demographic background. Table 3 alongside an analog visualization in Figure 5 show both differences by race in the initial level as well as the growth in unexcused absences. Table 4 and Figure 6 demonstrate the same, except for income quartiles.

Figure 5 shows that Black and Hispanic students demonstrate a much higher initial level and faster growth of unexcused absences over time compared to White and Asian students. Black students (intercept=2.213, slope=0.093) start out missing four times as many unexcused classes as White students (intercept=0.536, slope=0.045) at the beginning of the year, and their unexcused absence growth rate is twice that of White students (Table 3). Meanwhile, Hispanic students (intercept=1.641) start out with roughly three times as many unexcused absences as White students and their growth rate (slope=0.069) is 50% faster than that of White students. These concerning disparities between race/ethnicity groups are statistically significant mostly at the 1% level and observed consistently in both the middle and high school cohorts. On the contrary, Asian students (intercept=0.228;

slope=0.040) start out with much fewer unexcused absences at the onset of the year relative to White students, with their growth rates similar to that of White students.

Additionally, we find that students who reside in neighborhoods with the highest median income miss the least amount of school for unexcused reasons and that their growth rates generally remain lower than that of others. This difference is driven by high school students (see Table 4)—in other words, there are small or insignificant differences by income in the initial level and growth rate among middle school students. Notably, students who are in Quartile 1 who live in the poorest neighborhoods in the district (intercept=1.291) miss more than twice as many classes in the first weeks of school compared to students who are in Quartile 4 (intercept=0.583). Disengagement among students in Quartile 1 (slope=0.072) also occurs nearly twice as fast as those in Quartile 4 (slope=0.048). [12]

Meanwhile, growth curve models estimating excused absence growth rates look remarkably similar across students of various sociodemographic backgrounds. Black students start with a similar initial number of excused absences as White students, and Hispanic and Asian students actually start with a significantly *lower* number of excused absences compared to White students (see Figure A9). By income, there are also no noticeable differences in students' accrual of excused absences (see Figure A10). Indeed, growth rates using excused absences are relatively similar in magnitude regardless of race/ethnicity or neighborhood income.[13]

To conclude, there exist stark disparities in the level and growth of academic disengagement rates (as measured by unexcused absences) amongst students of color, as well as students who reside in the poorest neighborhoods, relative to White and Asian students and less poor students. Black and Hispanic students are more disengaged and continue to miss more school for unexcused reasons compared to White students. Also, the biggest differences

[12]Cohort-specific visualizations of disengagement rates by race can also be seen in Figures A5 (middle school) and A6 (high school). Similar visualizations by cohort and income can be seen in Figures A7 (middle school) and A8 (high school).

[13]Full results are displayed in Table A3 for race, and Table A4 for income.

in disengagement rates can be observed amongst students living in the richest and poorest neighborhoods: Those at the top of the income spectrum are more engaged at the beginning of the year and remain so, compared to those at the bottom income quartile, while students in the middle two income quartiles perform similarly to students at the highest income quartile. In contrast, students yield relatively similar trends in excused absences regardless of income or race/ethnicity background.

5.4 Linking Disengagement Rates to School Climate and Culture

As an extrapolation of our main results, we extract student-level disengagement rates using empirical Bayes estimation and link them to student-reported perceptions of school climate and culture. In the literature review section, we previously discussed the positive links between attendance and school perceptions, including a student's sense of belonging and a supportive learning environment (Neel and Fuligni, 2013; Ladd et al., 2008). Again, while this analysis does not intend to draw any causal conclusion, which deserves a separate study, an understanding of the associations between absenteeism growth rates and school climate and culture can provide clues for plausible mechanisms that drive disengagement.

In Figure 7, which visualizes the association using a binned scatterplot, we observe that disengagement rates are negatively associated with all four constructs of school climate and culture, suggesting that students who become more disengaged throughout the school year consistently perceive every aspect of their school less favorably compared with their more consistently engaged peers. Second, the negative associations appear to be bigger in magnitude for two constructs (climate of support for academic learning and sense of belonging). Lastly, the most disengaged students, or those who are in the top 20% of disengagement rates, report the lowest perceptions of their school across all four constructs across all students.

In sum, consistent with prior literature on how school climate and culture might impact student engagement, we find that disengaged students perceive their schools less favorably, on average. In particular, they show a much lower sense of belonging to their learning environment and report a lower level of academic support compared with their peers. While we cannot draw any causal conclusions, it is plausible that compared to the other two constructs (i.e., knowledge of discipline and sense of safety), sense of belonging and academic support play a key role in ensuring that students continually show up for school.

6 Conclusion and Discussion

This study advances the literature on student absenteeism by taking a step toward unpacking the "black box" of the complex phenomenon of chronic absenteeism. Using detailed class-level attendance data from a large and diverse urban school district, we incorporate two aspects of absenteeism that were rarely studied in the previous literature–type and timing–in a comprehensive documentation of the dynamic phenomenon of absenteeism at the secondary school level. We define and operationalize growth rates in absenteeism to investigate beyond what common metrics, such as chronic absenteeism, can reveal about the distribution of learning opportunities both within a student over time and between student subgroups. The differentiation by type and timing also provides a more concrete interpretation of what we actually capture in student absenteeism, which is not possible with conventionally used aggregated absenteeism measures such as chronic absenteeism.

Overall, our findings suggest that students demonstrate drastically different patterns in their accrual of unexcused absences compared to that of excused absences. For an average secondary school student, unexcused absences increase steadily within a school year. As the student progresses over grades, both the initial level of unexcused absenteeism and the rate at which it accrues in a given school year see clear increases as well. In contrast, excused absences stay largely unchanged along these dimensions. Notably, this dynamic change found in unexcused absences are in line with findings from other longitudinal studies examining the nature of absence accrual over a multitude of school years (Connolly and Olson, 2012; Sanchez et al., 2015; Ansari et al., 2021). It also aligns with prior literature suggesting that unexcused absences, which proxies for disengagement in our study, are dynamic, malleable, and evolve over time as students interact with their school environment, while excused absences may not necessarily be the case (Gottfried, 2009; Liu and Loeb, 2021).

Our analysis also reveals important differences in the way disengagement evolves between student groups. Specifically, students who start the school year with a high number of unexcused absences, students of color, and those from low-income backgrounds have significantly higher growth rates of disengagement relative to each of their counterparts. These large disparities are troubling, as they suggest far fewer learning opportunities for students who are in greatest need of academic support. These patterns are also concerning in that disengagement in schooling can serve as a precursor to problematic outcomes later on, such as high school dropout (Rumberger, 1995).

Linking disengagement rates to data from student self-report school climate and culture, we find an overall negative correlation between disengagement rates and students-reported perceptions of school climate and culture. Importantly, students who are the most disengaged by the end of the year consistently report the lowest perceptions of all aspects of their school, including their sense of belonging to their schools, level of academic support, agreement with the fairness of discipline, rules, and norms, and sense of safety. This alignment between disengagement rates and perceived school climate and culture suggests that at least some of the evolving nature of disengagement can be largely driven by factors within the purview of schools.

There are several notable limitations with our work. First and foremost, our findings are not causal in nature: We use GCM to describe patterns in absenteeism for secondary school students, and how these patterns may vary across student subgroups. Likewise, associations between student disengagement and student perceptions of school climate and culture suggest a correlation between two measures of engagement rather than a causal relationship. Further work is needed to understand the driving forces behind varying disengagement rates across subgroups and whether there are causal links between individual or school-level factors and academic disengagement rates.

Additionally, while our analysis shows evidence that there exist differential patterns by excused and unexcused absences, we are not able to disentangle the potential mechanisms that drive patterns for each type of absence, nor can we comprehensively explain why disengagement rates increase over time. As such, unexcused absences are simply comprised of absences that are not communicated by the caregiver, even if they have occurred due to legitimate or unavoidable reasons. Therefore, it is possible that differential increases in disengagement (as measured by unexcused absences) is driven by similarly differential *decreases* in caregiver communication toward the end of the school year, for example. On the other hand, if we consider patterns of absenteeism to be driven by school- or community-level factors, it is feasible that the uptick in disengagement can be a result of time-varying patterns in the student's environment. Issues of implicit bias as well as disproportionately higher risk of court referrals for students of color due to unexcused absences are also potential contributors to our findings on disengagement gaps among minoritized and socioeconomically disadvantaged students in particular (McNeely et al., 2021; Holt and Gershenson, 2019). Additional research in this area, especially using longitudinal student data or those incorporating family- and community-level factors that can affect student attendance, can be useful in understanding why these different trends exist.

While our findings point to the prevalence of school disengagement, especially for minoritized and disadvantaged student populations, they also point to a few ways to potentially reduce absenteeism in more effective ways. Multiple targeted interventions have successfully decreased absences by leveraging various individual-level and environmental factors (Robinson et al., 2018; Rogers and Feller, 2018; Bergman and Chan, 2021). Our findings specifically around school climate and disengagement can be a good starting point, as school climate is positively associated with improved attendance according to our analysis. For example, if mentoring aspects of the Check and Connect program (Guryan et al., 2017) may boost students' perceptions of being supported by their schools and helps them build relationships with in-school adults, and these factors are associated with absenteeism, perhaps student attendance could potentially improve as a direct benefit of this intervention. Additionally, based on these results, pre-existing programs can be tailored to focus their resources on reducing absenteeism in targeted ways. Some examples include focusing on improving the driving factors behind unexcused absences in particular and timing interventions to help reduce unexcused absences specifically at the beginning of the year. In these ways, a nuanced understanding of patterns of attendance beyond chronic absenteeism can serve as a future gateway toward improving student engagement in more meaningful and effective ways.

References

Alexander, K. L., Entwisle, D. R., and Horsey, C. S. (1997). From first grade forward: Early foundations of high school dropout. *Sociology of education*, pages 87–107.

Allensworth, E. M. and Easton, J. Q. (2007). What matters for staying on-track and graduating in chicago public high schools: A close look at course grades, failures, and attendance in the freshman year. research report. *Consortium on Chicago School Research*.

Ansari, A., Pianta, R. C., Whittaker, J. E., Vitiello, V., and Ruzek, E. (2021). Enrollment in public-prekindergarten and school readiness skills at kindergarten entry: Differential associations by home language, income, and program characteristics. *Early Childhood Research Quarterly*, 54:60–71.

Attendance Works (2014). Why september matters. `https://awareness.attendanceworks.org/september-matters/`. Last accessed on 3/13/2022.

Attendance Works (2021). attendance works. `https://www.attendanceworks.org/wp-content/uploads/2019/06/Attendance-Works-Using-Chronic-Absence-to-Map_020221.pdf`. Last accessed on 3/13/2022.

Attwood, G. and Croll, P. (2006). Truancy in secondary school pupils: Prevalence, trajectories and pupil perspectives. *Research papers in education*, 21(4):467–484.

Balfanz, R. and Byrnes, V. (2006). Closing the mathematics achievement gap in high-poverty middle schools: Enablers and constraints. *Journal of Education for Students Placed at risk*, 11(2):143–159.

Balfanz, R. and Byrnes, V. (2012). The importance of being in school: A report on absenteeism in the nation's public schools. *The Education Digest*, 78(2):4.

Balfanz, R. and Byrnes, V. (2013). Meeting the challenge of combating chronic absenteeism. *Everyone Graduates Center at Johns Hopkins University School of Education*, pages 1–2.

Balfanz, R., Durham, R., Plank, S., et al. (2008). Lost days: Patterns and levels of chronic absenteeism among baltimore city public school students 1999-00 to 2005-06. *Baltimore, MD: Baltimore Education Research Consortium.*

Balfanz, R. and Legters, N. (2004). Locating the dropout crisis. which high schools produce the nation's dropouts? where are they located? who attends them? report 70. *Center for Research on the Education of Students Placed at Risk CRESPAR.*

Berabei, P. (2014). *Why Students Disengage in American Schools and What We Can Do About It.*

Bergman, P. and Chan, E. W. (2021). Leveraging parents through low-cost technology the impact of high-frequency information on student achievement. *Journal of Human Resources*, 56(1):125–158.

Cantor, P., Osher, D., Berg, J., Steyer, L., and Rose, T. (2019). Malleability, plasticity, and individuality: How children learn and develop in context1. *Applied Developmental Science*, 23(4):307–337.

Chang, H. N. and Romero, M. (2008). Present, engaged, and accounted for: The critical importance of addressing chronic absence in the early grades. report. *National Center for Children in Poverty.*

Childs, J. and Lofton, R. (2021). Masking attendance: How education policy distracts from the wicked problem (s) of chronic absenteeism. *Educational Policy*, 35(2):213–234.

Connell, J. P. and Wellborn, J. G. (1991). Competence, autonomy, and relatedness: A motivational analysis of self-system processes.

Connolly, F. and Olson, L. S. (2012). Early elementary performance and attendance in baltimore city schools' pre-kindergarten and kindergarten. *Baltimore Education Research Consortium.*

Corville-Smith, J., Ryan, B. A., Adams, G. R., and Dalicandro, T. (1998). Distinguishing absentee students from regular attenders: The combined influence of personal, family, and school factors. *Journal of Youth and Adolescence*, 27(5):629–640.

Crowder, K. and South, S. J. (2003). Neighborhood distress and school dropout: The variable significance of community context. *Social Science Research*, 32(4):659–698.

Darling-Hammond, L. (2015). *The flat world and education: How America's commitment to equity will determine our future*. Teachers College Press.

Ehrlich, S. B., Gwynne, J. A., Pareja, A. S., and Allensworth, E. M. (2013). Preschool attendance in chicago public schools. *Research Summary*.

Ehrlich, S. B., Gwynne, J. A., Stitziel Pareja, A., Allensworth, E. M., Moore, P., Jagesic, S., and Sorice, E. (2014). *Preschool Attendance in Chicago Public Schools: Relationships with Learning Outcomes and Reasons for Absences*. ERIC.

Fazlul, I., Koedel, C., and Parsons, E. (2021). Free and reduced-price meal eligibility does not measure student poverty: Evidence and policy significance.

Finn, J. D. (1989). Withdrawing from school. *Review of educational research*, 59(2):117–142.

Fraysier, K., Reschly, A., and Appleton, J. (2020). Predicting postsecondary enrollment with secondary student engagement data. *Journal of Psychoeducational Assessment*, 38(7):882–899.

Fredricks, J. A., Blumenfeld, P. C., and Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of educational research*, 74(1):59–109.

FutureEd (2017). Chronic absenteeism and the fifth indicator in state essa plans. `https://www.attendanceworks.org/wp-content/uploads/2017/10/Future-Ed-TABLE_Chronic_Absenteeism.pdf`. Last accessed on 3/13/2022.

Galloway, D. (1983). Research note: Truants and other absentees. *Journal of Child Psychology and Psychiatry*, 24(4):607–611.

Garrison, D. R., Cleveland-Innes, M., Koole, M., and Kappelman, J. (2006). Revisiting methodological issues in transcript analysis: Negotiated coding and reliability. *The internet and higher education*, 9(1):1–8.

Gershenson, S. (2016). Linking teacher quality, student attendance, and student achievement. *Education Finance and Policy*, 11(2):125–149.

Gershenson, S., Jacknowitz, A., and Brannegan, A. (2017). Are student absences worth the worry in us primary schools? *Education Finance and Policy*, 12(2):137–165.

Goodman, J. (2014). Flaking out: Student absences and snow days as disruptions of instructional time. Technical report, National Bureau of Economic Research.

Gottfried, M., Kirksey, J. J., and Fletcher, T. L. (2022). Do high school students with a same-race teacher attend class more often? *Educational Evaluation and Policy Analysis*, 44(1):149–169.

Gottfried, M. A. (2009). Excused versus unexcused: How student absences in elementary school affect academic achievement. *Educational Evaluation and Policy Analysis*, 31(4):392–415.

Gottfried, M. A. (2010). Evaluating the relationship between student attendance and achievement in urban elementary and middle schools: An instrumental variables approach. *American Educational Research Journal*, 47(2):434–465.

Gottfried, M. A. (2014). Chronic absenteeism and its effects on students' academic and socioemotional outcomes. *Journal of Education for Students Placed at Risk (JESPAR)*, 19(2):53–75.

Gottfried, M. A. (2017). Does truancy beget truancy? evidence from elementary school. *The Elementary School Journal*, 118(1):128–148.

Gottfried, M. A. and Hutt, E. L. (2019). Addressing absenteeism: Lessons for policy and practice. *Policy Analysis for California Education, PACE*.

Gottfried, M. A. and Kirksey, J. J. (2017). "when" students miss school: The role of timing of absenteeism on students' test performance. *Educational Researcher*, 46(3):119–130.

Guryan, J., Christenson, S., Claessens, A., Engel, M., Lai, I., Ludwig, J., Turner, A., and Turner, M. (2017). The effect of mentoring on school attendance and academic outcomes: a randomized evaluation of the check & connect program. northwestern university institute for policy research working paper series. Technical report, Working Paper-16-18. Retrieved from https://www. ipr. northwestern. edu/our ....

Hancock, K. J., Mitrou, F., Taylor, C. L., and Zubrick, S. R. (2018). The diverse risk profiles of persistently absent primary students: implications for attendance policies in australia. *Journal of Education for Students Placed at Risk (JESPAR)*, 23(1-2):53–69.

Henry, K. L. and Huizinga, D. H. (2007). School-related risk and protective factors associated with truancy among urban youth placed at risk. *The journal of primary prevention*, 28(6):505–519.

Henry, K. L., Knight, K. E., and Thornberry, T. P. (2012). School disengagement as a predictor of dropout, delinquency, and problem substance use during adolescence and early adulthood. *Journal of youth and adolescence*, 41(2):156–166.

Hess, G. A., Lyons, A., Corsino, L., and Wells, E. (1989). *Against the odds: The early identification of dropouts*. Chicago Panel on Public School Policy and Finance.

Hofkens, T. L. and Ruzek, E. (2019). Measuring student engagement to inform effective interventions in schools. In *Handbook of Student Engagement Interventions*, pages 309–324. Elsevier.

Holt, S. B. and Gershenson, S. (2019). The impact of demographic representation on absences and suspensions. *Policy Studies Journal*, 47(4):1069–1099.

Hough, H., Kalogrides, D., and Loeb, S. (2017). Using surveys of students' social-emotional learning and school climate for accountability and continuous improvement. *Policy Analysis for California Education, PACE.*

Jackson, C. K. (2018). What do test scores miss? the importance of teacher effects on non–test score outcomes. *Journal of Political Economy*, 126(5):2072–2107.

Johnson, S. M. (2006). The workplace matters: Teacher quality, retention, and effectiveness. working paper. *National Education Association Research Department.*

Johnson, S. M., Kraft, M. A., and Papay, J. P. (2012). How context matters in high-need schools: The effects of teachers' working conditions on their professional satisfaction and their students' achievement. *Teachers college record*, 114(10):1–39.

Jordan, P. and Chang, H. (2015). Mapping the early attendance gap: Charting a course for school success. *Attendance Works.*

Kearney, C. A. (2008). School absenteeism and school refusal behavior in youth: A contemporary review. *Clinical psychology review*, 28(3):451–471.

Ladd, G. W., Herald-Brown, S. L., and Reiser, M. (2008). Does chronic classroom peer rejection predict the development of children's classroom participation during the grade school years? *Child development*, 79(4):1001–1015.

Lamdin, D. J. (1996). Evidence of student attendance as an independent variable in education production functions. *The Journal of educational research*, 89(3):155–162.

Liu, J., Lee, M., and Gershenson, S. (2021). The short-and long-run impacts of secondary school absences. *Journal of Public Economics*, 199:104441.

Liu, J. and Loeb, S. (2021). Engaging teachers measuring the impact of teachers on student attendance in secondary school. *Journal of Human Resources*, 56(2):343–379.

London, R. A., Sanchez, M., and Castrechini, S. (2016). The dynamics of chronic absence and student achievement. *Education Policy Analysis Archives*, 24:112–112.

Marsh, J. A., Bush-Mecenas, S., Hough, H. J., Park, V., Allbright, T., Hall, M., and Glover, H. (2016). At the forefront of the new accountability era: Early implementation findings from the core waiver districts. *Policy Analysis for California Education, PACE.*

McNeely, C. A., Alemu, B., Lee, W. F., and West, I. (2021). Exploring an unexamined source of racial disparities in juvenile court involvement: Unexcused absenteeism policies in us schools. *AERA Open*, 7:23328584211003132.

Neel, C. G.-O. and Fuligni, A. (2013). A longitudinal study of school belonging and academic motivation across high school. *Child development*, 84(2):678–692.

Neild, R. C. and Balfanz, R. (2006). An extreme degree of difficulty: The educational demographics of urban neighborhood high schools. *Journal of education for students placed at risk*, 11(2):123–141.

Nichols, M. (2003). A theory for elearning. *Journal of Educational Technology & Society*, 6(2):1–10.

Osher, D., Cantor, P., Berg, J., Steyer, L., and Rose, T. (2020). Drivers of human development: How relationships and context shape learning and development1. *Applied Developmental Science*, 24(1):6–36.

Osher, D. and Kendziora, K. (2010). Building conditions for learning and healthy adolescent development: Strategic approaches. *Handbook of youth prevention science*, pages 121–140.

Pyne, J., Grodsky, E., Vaade, E., McCready, B., Camburn, E., and Bradley, D. (2021). The signaling power of unexcused absence from school. *Educational Policy*, page 08959048211049428.

Resnick, M. D., Bearman, P. S., Blum, R. W., Bauman, K. E., Harris, K. M., Jones, J., Tabor, J., Beuhring, T., Sieving, R. E., Shew, M., et al. (1997). Protecting adolescents from harm: findings from the national longitudinal study on adolescent health. *Jama*, 278(10):823–832.

Robinson, C. D., Lee, M. G., Dearing, E., and Rogers, T. (2018). Reducing student absenteeism in the early grades by targeting parental beliefs. *American Educational Research Journal*, 55(6):1163–1192.

Rogers, T. and Feller, A. (2018). Reducing student absences at scale by targeting parents' misbeliefs. *Nature Human Behaviour*, 2(5):335–342.

Rumberger, R. W. (1995). Dropping out of middle school: A multilevel analysis of students and schools. *American educational Research journal*, 32(3):583–625.

Rumberger, R. W. and Larson, K. A. (1998). Student mobility and the increased risk of high school dropout. *American journal of Education*, 107(1):1–35.

Rumberger, R. W. and Rotermund, S. (2012). The relationship between engagement and high school dropout. In *Handbook of research on student engagement*, pages 491–513. Springer.

Rumberger, R. W. and Thomas, S. L. (2000). The distribution of dropout and turnover rates among urban and suburban high schools. *Sociology of education*, pages 39–67.

Ryan, A. M. and Patrick, H. (2001). The classroom social environment and changes in adolescents' motivation and engagement during middle school. *American educational research journal*, 38(2):437–460.

Sanchez, M., London, R., and Castrechini, S. (2015). The dynamics of chronic absence and student achievement. *Available at SSRN 2743041*.

Schanzenbach, D. W., Bauer, L., and Mumford, M. (2016a). Lessons for broadening school accountability under the every student succeeds act. *The Hamilton Project: the Brookings Institute*, pages 1–27.

Schanzenbach, D. W., Nunn, R., Bauer, L., Mumford, M., and Breitwieser, A. (2016b). Seven facts on noncognitive skills from education to the labor market. *Washington: The Hamilton Project*.

Sheldon, S. B. and Epstein, J. L. (2004). Getting students to school: Using family and community involvement to reduce chronic absenteeism. *School Community Journal*, 14(2):39–56.

Simon, O., Nylund-Gibson, K., Gottfried, M., and Mireles-Rios, R. (2020). Elementary absenteeism over time: A latent class growth analysis predicting fifth and eighth grade outcomes. *Learning and Individual Differences*, 78:101822.

Singer, J. D., Willett, J. B., Willett, J. B., et al. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. Oxford university press.

Skinner, E., Furrer, C., Marchand, G., and Kindermann, T. (2008). Engagement and disaffection in the classroom: Part of a larger motivational dynamic? *Journal of educational psychology*, 100(4):765.

Smerillo, N. E., Reynolds, A. J., Temple, J. A., and Ou, S.-R. (2018). Chronic absence, eighth-grade achievement, and high school attainment in the chicago longitudinal study. *Journal of school psychology*, 67:163–178.

Spencer, A. M. (2009). School attendance patterns, unmet educational needs, and truancy: A chronological perspective. *Remedial and Special Education*, 30(5):309–319.

Tran, L. and Gershenson, S. (2021). Experimental estimates of the student attendance production function. *Educational Evaluation and Policy Analysis*, 43(2):183–199.

U.S. Department of Education (2019). Chronic absenteeism in the nation's schools. `https://www2.ed.gov/datastory/chronicabsenteeism.html`. Last accessed on 3/13/2022.

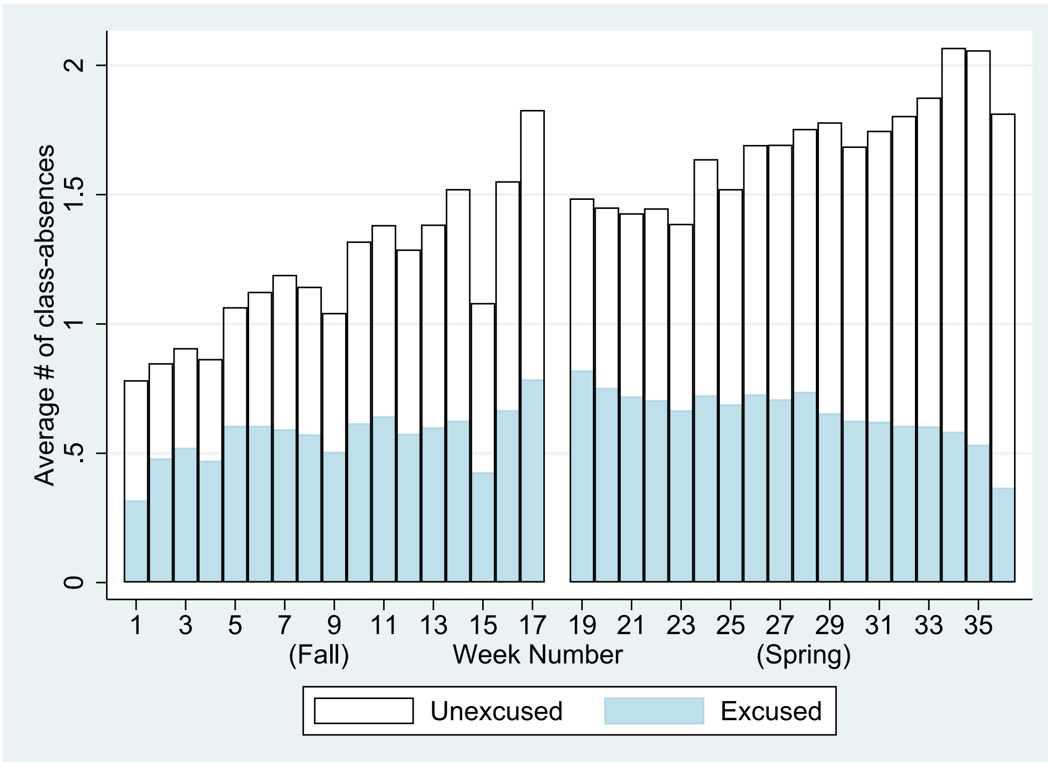
Whitney, C. R. and Liu, J. (2017). What we're missing: A descriptive analysis of part-day absenteeism in secondary school. *AERA Open*, 3(2):2332858417703660.

Woodward, H. and Munns, G. (2003). Insiders' voices: Self-assessment and student engagement. In *New Zeeland Association for research in Education (NZARE) and Australian Association for Research in Education (AARE) Joint Conference*. Citeseer.

Youth Justice Board (2013). From absent to present: Reducing teen chronic absenteeism in new york city. *Center for Court Innovation*.

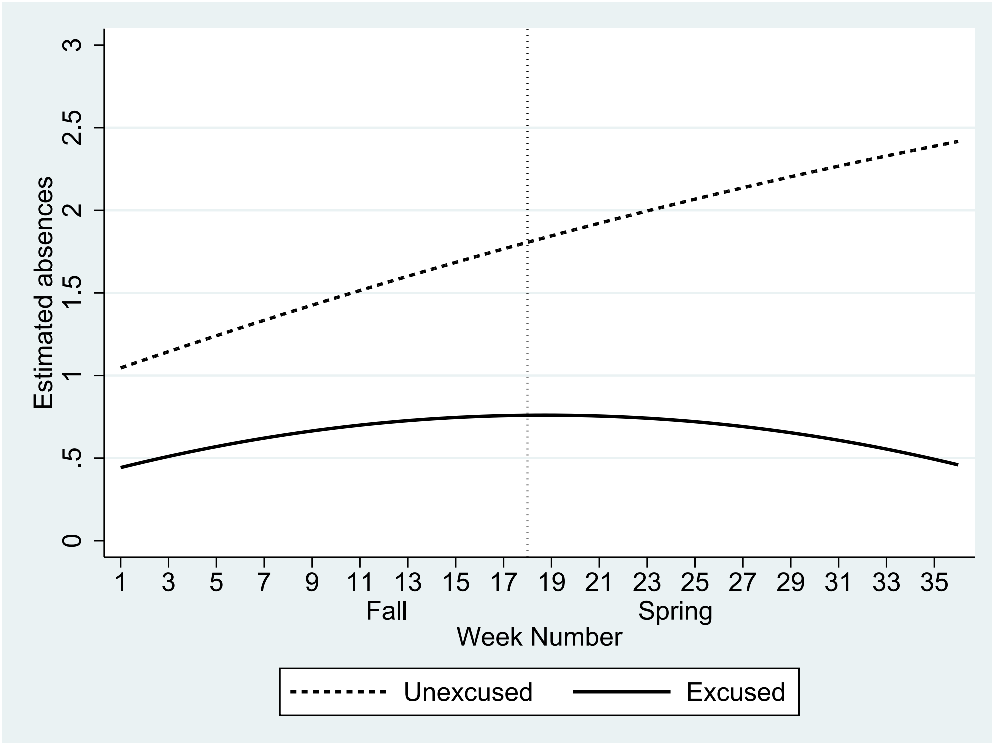
Figures and Tables

Figure 1: Weekly Average Number of Class Absences, by Absence Type



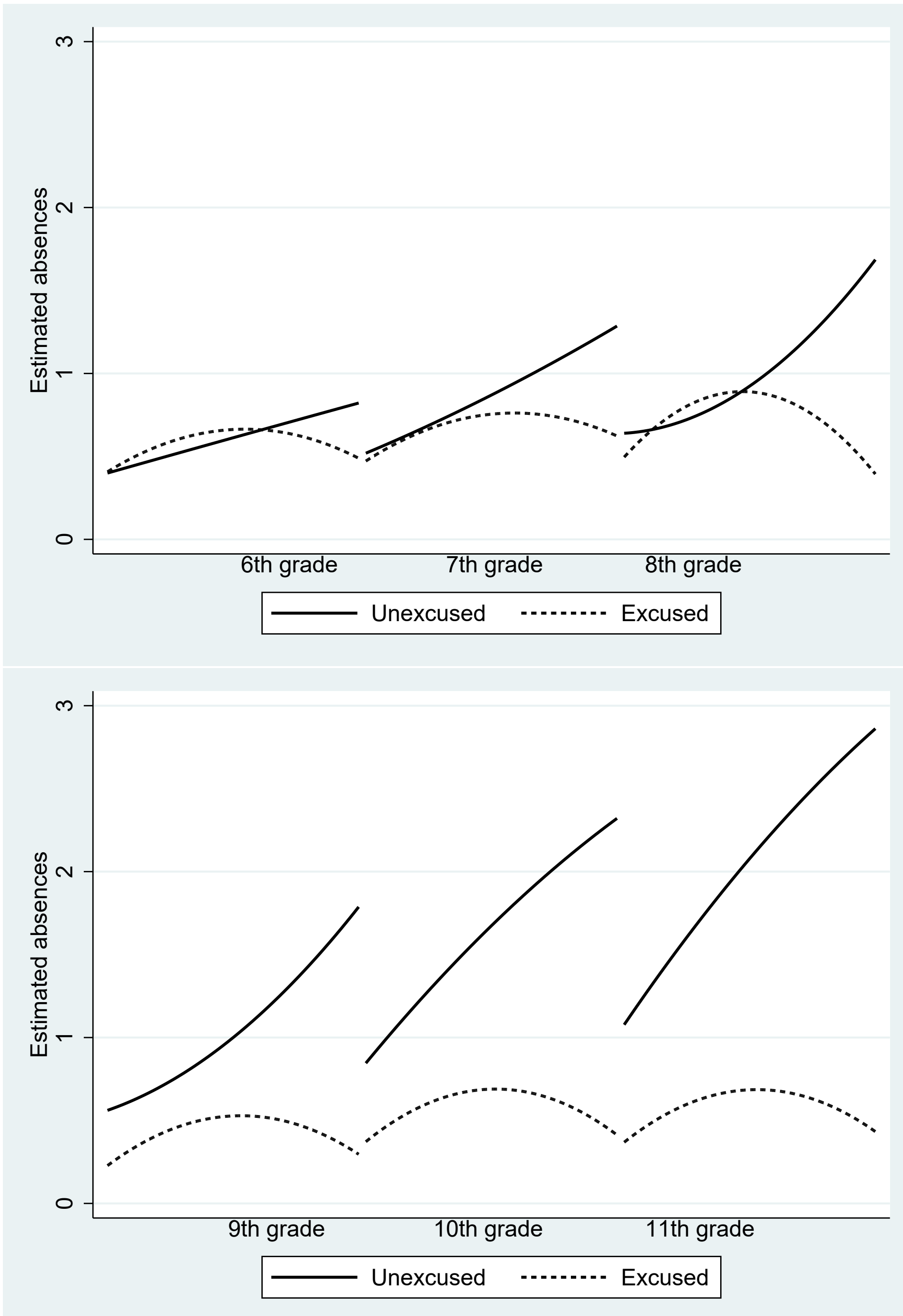
Note: Observations are average counts of class-level absences per week for all students in the data across three academic years (2015-16 SY through 2017-18 SY). Absence type differentiated by bar colors, which are overlaid: Transparent bars signify average unexcused absences and blue bars signify excused absences. Week 18 and weeks 37-39 (i.e., end of fall and spring semester) omitted due to start of winter and summer breaks.

Figure 2: Growth Curve Model Results of Absence Growth Rates by Absence Type



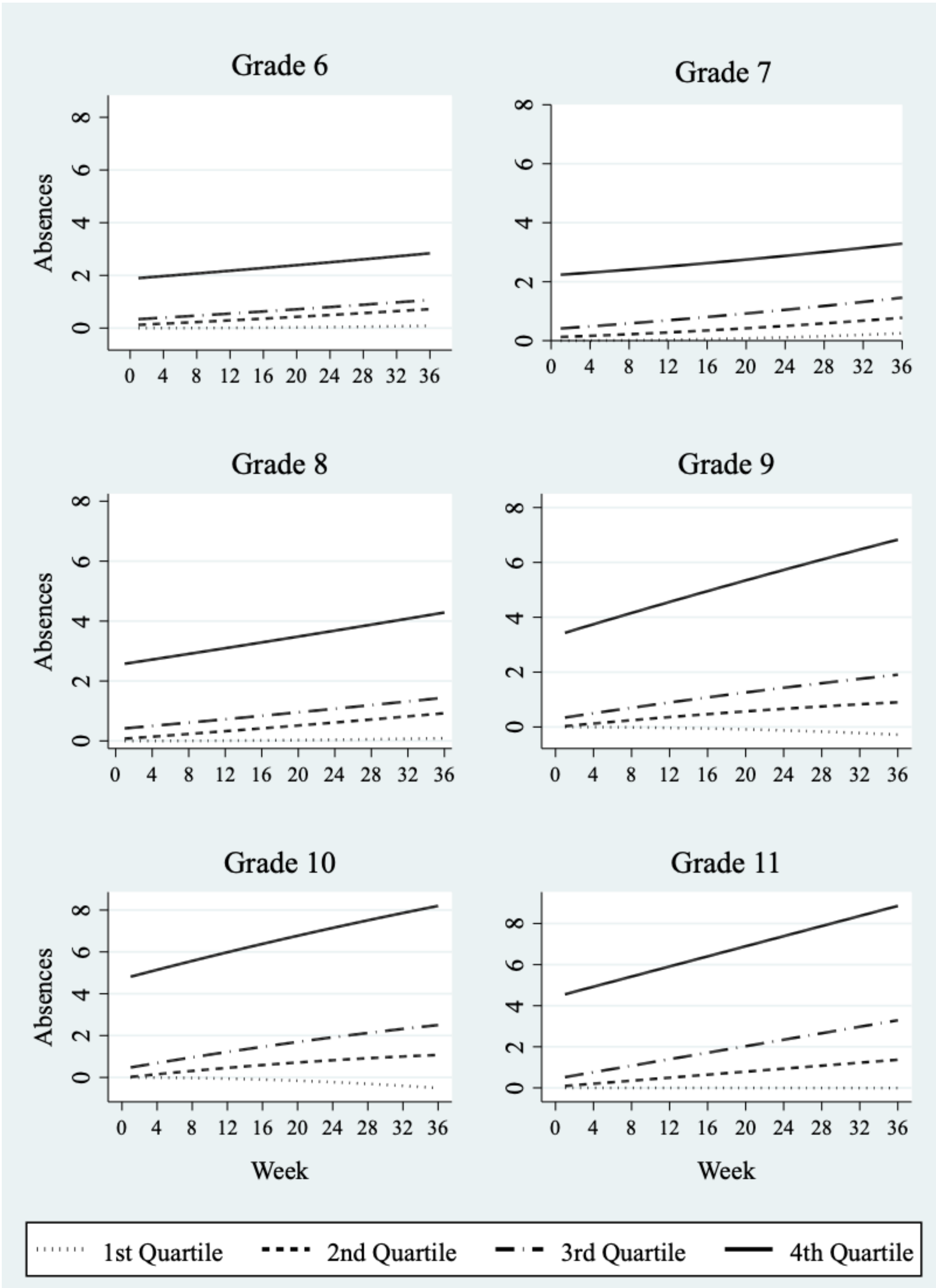
Note: Graph shows results from non-linear growth curve models estimating growth rate in absences by absence type (unexcused and excused absences) for all students in the sample across three academic years (2015-16 SY through 2017-18 SY). Levels and slopes calculated separately by absence type.

Figure 3: Growth Curve Model Results of Absence Growth Rates Across Years for Middle School (top) and High School (bottom) Cohorts



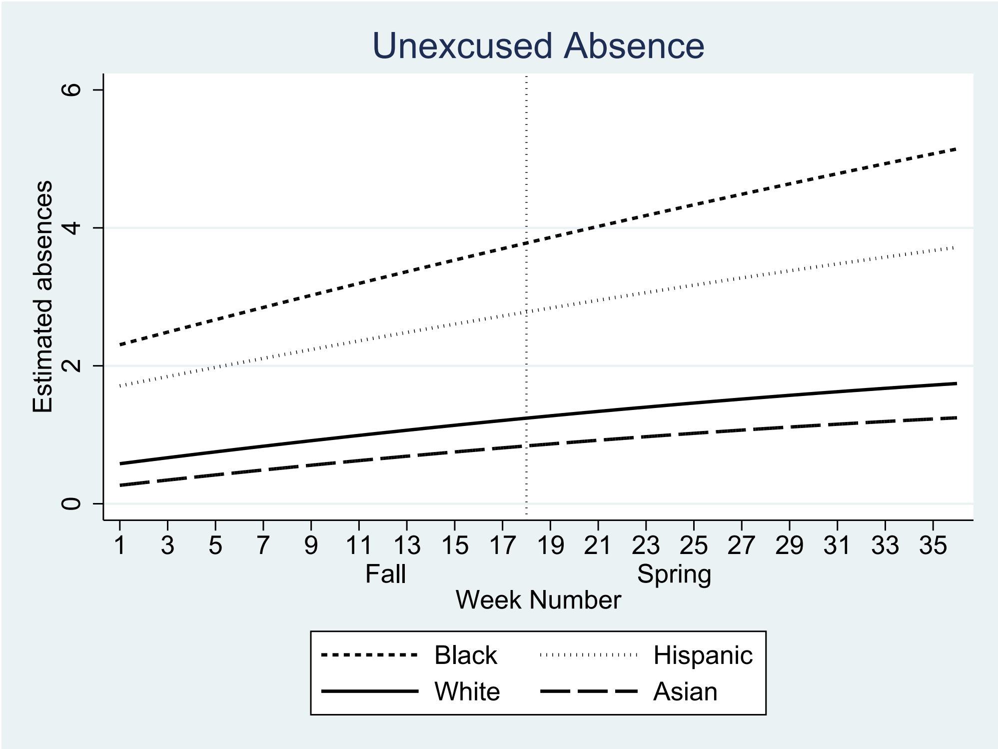
Note: Graph shows results from non-linear growth curve models estimating growth rate in absences by absence type (unexcused and excused absences) separately for the Middle School Cohort (6th graders in the 2015-16 SY enrolled continuously through 2017-18 SY) and the High School Cohort (9th graders in the 2015-16 SY enrolled continuously through 2017-18 SY). Levels and slopes calculated separately by absence type, grade level, and cohort.

Figure 4: Growth Curve Model Results of Unexcused Absence Growth Rates by Grade and Initial Absences



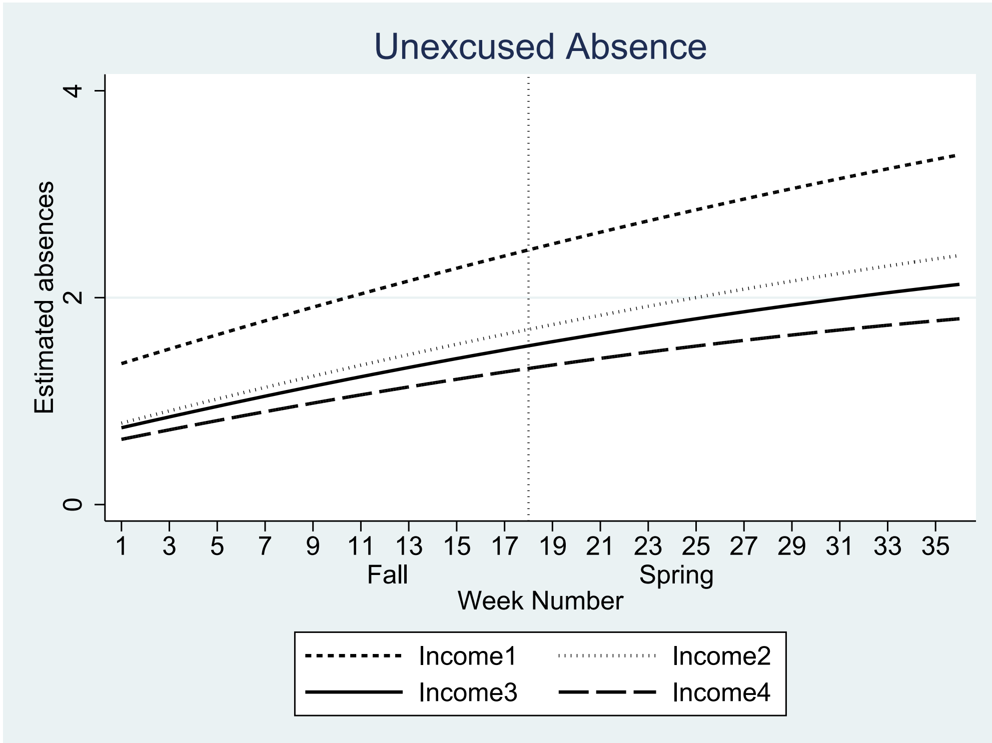
Note: Graph shows weekly average absence growth rates across three academic years (2015-16 SY through 2017-18 SY) from 6th grade to 11th grade, separately by quartiles. Quartiles are generated using students' initial class absences within the grade, with the fourth quartile being students with the highest number of unexcused absences in the first week of school.

Figure 5: Growth Curve Model Results of Unexcused Absence Growth Rates by Race/Ethnicity



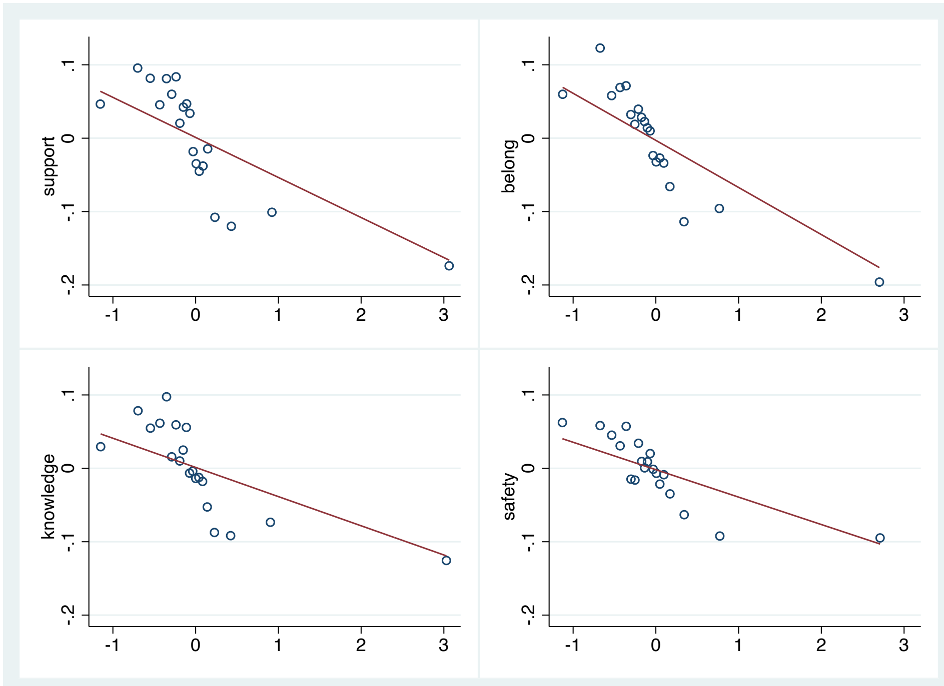
Note: Graph shows results from non-linear growth curve models estimating growth rate using unexcused absences, separately by race for all students in the sample across three academic years (2015-16 SY through 2017-18 SY). Levels and slopes calculated separately by race using interaction terms.

Figure 6: Growth Curve Model Results of Unexcused Absence Growth Rates by Income



Note: Graph shows results from non-linear growth curve models estimating growth rate using unexcused absences, separately by income quartile for all students in the sample across three academic years (2015-16 SY through 2017-18 SY). Income quartiles are derived from census tract-level data of median household income, with the first quartile being students with the lowest neighborhood income and the fourth quartile consisting of students with the highest neighborhood income. Levels and slopes calculated separately by income quartile using interaction terms.

Figure 7: Binned Scatterplot of School Climate-Culture and Unexcused Absence Growth Rate



Note: Graph shows relationship between the four constructs measured by the SCC (School Climate and Culture) survey and unexcused absence growth rate at the student level. Each scatter point bins 5 percent of the full sample by their absence growth rate. SCC measures are raw averages across all items under each construct and then standardized at the year-grade level. All models control for student race/ethnicity, gender, neighborhood income, school fixed effects, and year fixed effects.

Table 1: Descriptive Statistics by Sample

	All Students	Middle School Cohort	High School Cohort
A. Demographic Indicators:			
Female (%)	47.96	47.96	49.63
Asian (%)	44.48	44.78	49.63
Black (%)	7.82	7.66	6.42
Hispanic (%)	25.34	24.34	23.45
Other(%)	5.44	5.45	4.96
White (%)	11.02	12.75	9.79
Special Education(%)	7.58	7.98	7.25
High School Graduation(%)			88.41
B. Socioeconomic Indicators:			
Median Household Income ($)	69,912.30	70,432.49	70,436.23
	(27,076.99)	(27,200.18)	(26,655.77)
% Below Poverty	14.92	14.77	14.28
C. Weekly Absence Indicators:			
Full-Day Absences	0.01	0.01	0.01
	(0.11)	(0.07)	(0.30)
Total Class Absences	2.16	1.45	1.94
	(4.79)	(3.98)	(4.29)
Unexcused Class Absences	1.54	0.79	1.42
	(4.10)	(2.90)	(3.67)
Excused Class Absences	0.62	0.66	0.52
	(2.55)	(2.71)	(2.27)
Unexcused Ratio of Absences	0.06	0.03	0.06
	(0.03)	(0.01)	(0.04)
Excused Ratio of Absences	0.02	0.02	0.02
	(0.007)	(0.00)	(0.01)
Number of Students	39,145	3,517	3,416
Number of Schools	49	26	23
Average Number of Classes	28.09	31.31	26.56
	(8.35)	(8.37)	(7.12)

Note: Each column presents descriptive statistics for a distinct sample. Demographic indicators are time-invariant, socioeconomic indicators are student-year specific, and absence indicators are student-week-year specific. Standard deviations shown in parentheses for non-binary measures. Absence ratios are calculated by dividing the total number of each type of absence per week by the total number of class periods a student attends per week.

Table 2: Growth Curve Model Results, by Absence Type and Sample

	Unexcused Absences			Excused Absences		
	Full Sample	Middle School Cohort	High School Cohort	Full Sample	Middle School Cohort	High School Cohort
Week (Linear)	0.051***	0.010***	0.042***	0.038***	0.036***	0.036***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Week (Quadratic)	-0.000***	0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.996***	0.512***	0.803***	0.406***	0.424***	0.288***
	(0.014)	(0.024)	(0.034)	(0.006)	(0.019)	(0.017)
L-1 Var(Residual)	8.778***	5.934***	7.654***	5.834***	6.706***	4.592***
L-2 Var(Intercept)	6.549***	1.516***	3.347***	0.829***	0.765***	0.631***
L-2 Var(Slope)	0.007***	0.002***	0.004***	0.001***	0.000***	0.000***
Cov(Int,Slope)	0.033***	0.011***	0.035***	-0.009***	-0.007***	-0.007***
ICC	0.427***	0.204***	0.304***	0.124***	0.102***	0.121***
N	2,922,125	380,609	368,595	2,922,125	380,609	368,595

Note: Each column represents separate model estimates by absence type (i.e., unexcused or excused) and sample (i.e., full sample, middle school cohort and high school cohort). Coefficients on both linear and quadratic terms of Week (i.e., count variable indicating week number in the school year) indicate weekly growth rate of absences and the rate of change in absences. We define the intercept as the grand mean of absences in the first week of school across all three academic years in the data (2015-16 SY through 2017-18 SY). The random effect components are as follows: the variance within students across time (i.e., variance of residuals); the variance of the average number of week 1 absences between students (i.e., variance of the intercepts); the variance of absence growth rate between students (i.e., variance of the slope), and the correlation between random intercepts and slopes (i.e., covariance). The ICC, or intraclass correlation coefficient, represents the percentage of clustering in the data. Standard errors in parentheses. + $p<0.10$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Table 3: Growth Curve Model Results for Unexcused Absences, by Race and Cohort

	Full Sample	Middle School Cohort	High School Cohort
A. Intercept			
White	0.536***	0.300***	0.555***
	(0.011)	(0.024)	(0.031)
Black	2.213***	1.494***	1.904***
	(0.013)	(0.030)	(0.038)
Hispanic	1.641***	0.916***	1.588***
	(0.008)	(0.018)	(0.021)
Asian	0.228***	0.143***	0.231***
	(0.007)	(0.014)	(0.016)
Other	0.974***	0.531***	1.229***
	(0.016)	(0.035)	(0.043)
B. Slope			
White	0.045***	0.004	0.035***
	(0.002)	(0.003)	(0.006)
Black	0.093***	0.046***	0.083***
	(0.003)	(0.004)	(0.007)
Hispanic	0.069***	0.025***	0.060***
	(0.002)	(0.003)	(0.004)
Asian	0.040***	0.002	0.034***
	(0.001)	(0.002)	(0.003)
Other	0.062***	0.013**	0.055***
	(0.003)	(0.005)	(0.008)
L-1 Var(Residual)	9.974	6.266	8.376
L-2 Var(Slope)	0.022	0.004	0.011
Number of Observations	2,922,125	380,609	368,595
p-value of postestimation test: Different from White?			
Intercept			
Black	0.000	0.000	0.000
Hispanic	0.000	0.000	0.000
Asian	0.000	0.000	0.000
Other Race	0.000	0.000	0.000
Slope			
Black	0.000	0.000	0.000
Hispanic	0.000	0.000	0.000
Asian	0.044	0.515	0.851
Other Race	0.000	0.121	0.054

Note: Each column represents separate model estimates using week by race interactions, suppressing the intercept. Quadratic week term omitted from display. The random effect components are as follows: the variance in absences within students across time (i.e., variance of residuals); and the variance of absence growth rate between students (i.e., variance of the slope). P-values at bottom of table are derived from postestimation tests testing the difference in intercepts (or slopes) between White students and each non-White student category. Standard errors in parentheses. + p<0.10 * p<0.05 ** p<0.01 *** p<0.001.

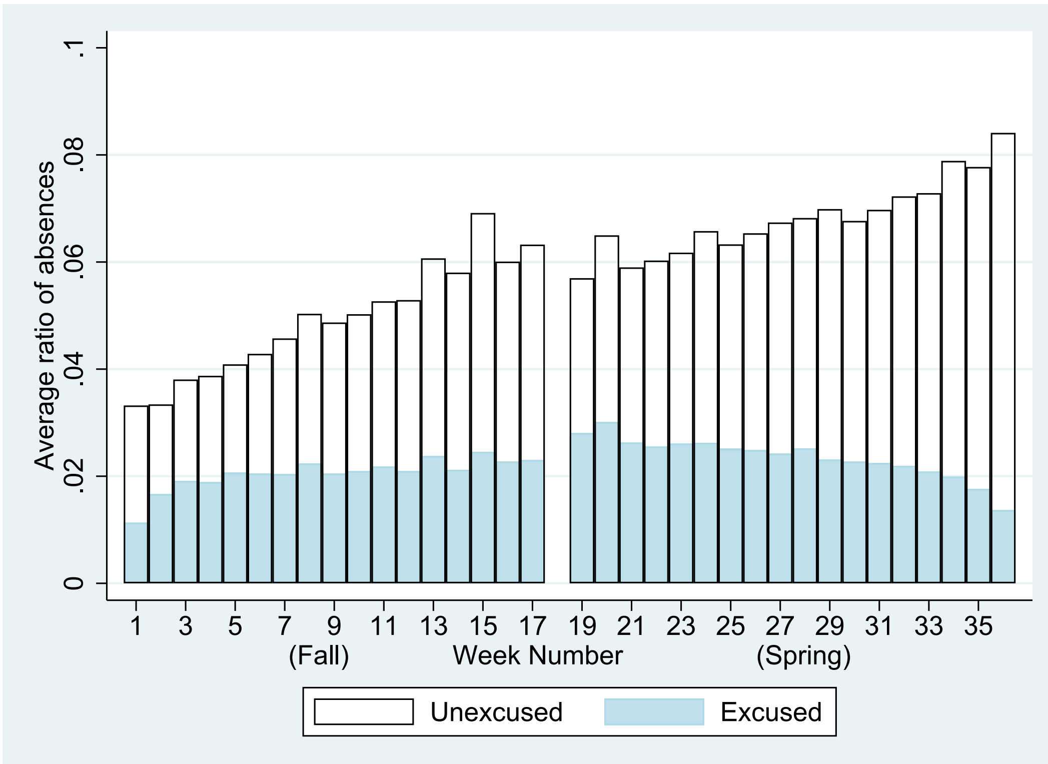
Table 4: Growth Curve Model Results for Unexcused Absences, by Income and Cohort

	Full Sample	Middle School Cohort	High School Cohort
A. Intercept			
Quartile 1	1.291***	0.697***	1.058***
	(0.008)	(0.018)	(0.021)
Quartile 2	0.727***	0.346***	0.638***
	(0.008)	(0.018)	(0.022)
Quartile 3	0.689***	0.439***	0.692***
	(0.008)	(0.018)	(0.021)
Quartile 4	0.583***	0.379***	0.561***
	(0.008)	(0.018)	(0.022)
B. Slope			
Quartile 1	0.072***	0.025***	0.059***
	(0.002)	(0.003)	(0.004)
Quartile 2	0.061***	0.010***	0.047***
	(0.001)	(0.003)	(0.004)
Quartile 3	0.054***	0.012***	0.040***
	(0.001)	(0.003)	(0.004)
Quartile 4	0.048***	0.008**	0.044***
	(0.002)	(0.003)	(0.004)
L-1 Var(Residual)	10.088	6.312	8.478
L-2 Var(Slope)	0.024	0.005	0.013
Number of Observations	2,922,125	380,609	368,595
p-values of postestimation test: Different from Quartile 4?			
Intercept			
Quartile 1	0.000	0.000	0.000
Quartile 2	0.000	0.165	0.006
Quartile 3	0.000	0.010	0.000
Slope			
Quartile 1	0.000	0.000	0.005
Quartile 2	0.000	0.487	0.504
Quartile 3	0.000	0.267	0.404

Note: Each column represents separate model estimates using week by income interactions, suppressing the intercept. Income quartiles are derived from a student's median household income based on Census tract data of their residence. Quartile 1 contains students with lowest income and Quartile 4 contains students with the highest income. Quadratic week term omitted from display. The random effect components are as follows: the variance in absences within students across time (i.e., variance of residuals); and the variance of absence growth rate between students (i.e., variance of the slope)). P-values at bottom of table are derived from postestimation tests testing the difference in intercepts (or slopes) between the top income quartile and another quartile. Standard errors in parentheses. + p<0.10 * p<0.05 ** p<0.01 *** p<0.001.

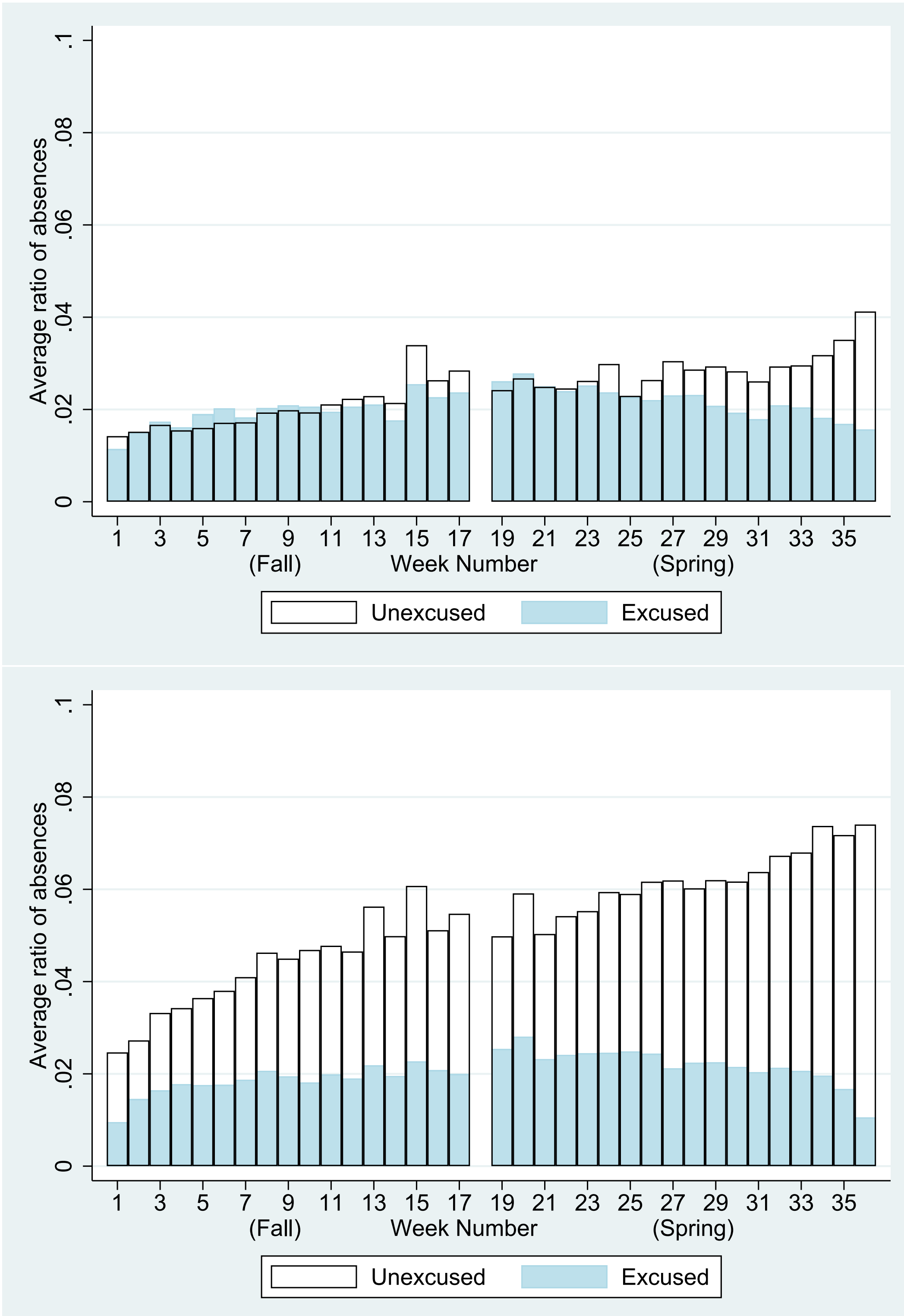
Online Appendix

Figure A1: Weekly Average Ratio of Absences, Full Sample



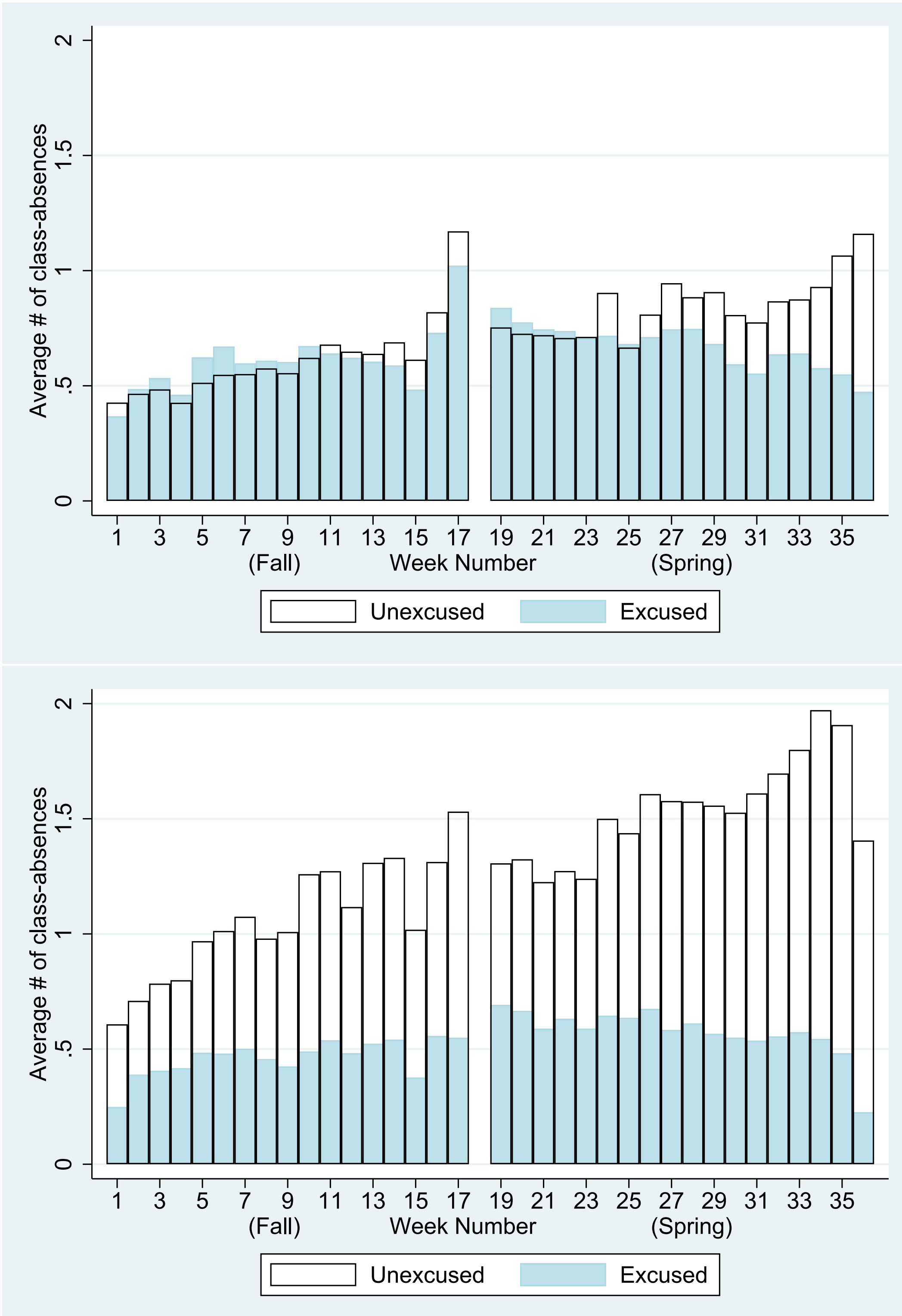
Note: Observations are average ratios of class-level absences per week for all students in the data across three academic years (2015-16 SY through 2017-18 SY). Absence type differentiated by bar colors, which are overlaid: Transparent bars signify average unexcused absences and blue bars signify excused absences. Week 18 and weeks 37-39 (i.e., end of fall and spring semester) omitted due to start of winter and summer breaks.

Figure A2: Weekly Average Ratio of Absences for the Middle School (Top) and High School (Bottom) Cohorts



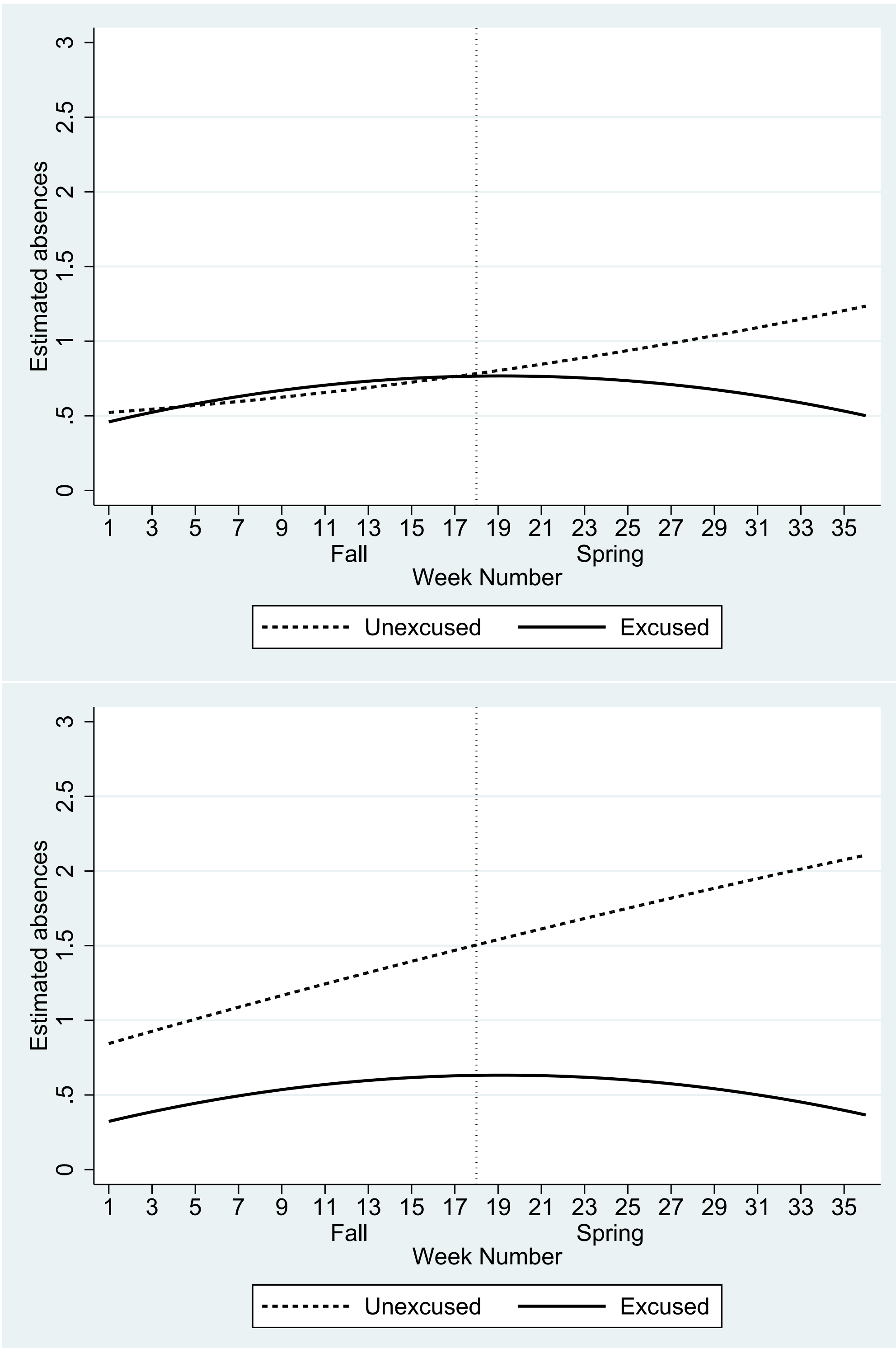
Note: Observations are average ratios of class-level absences per week separately for the middle and high school cohorts. Absence type differentiated by bar colors, which are overlaid: Transparent bars signify average unexcused absences and blue bars signify excused absences. Week 18 and weeks 37-39 (i.e., end of fall and spring semester) omitted due to start of winter and summer breaks.

Figure A3: Weekly Average Number of Absence for the Middle School (Top) and High School (Bottom) Cohorts



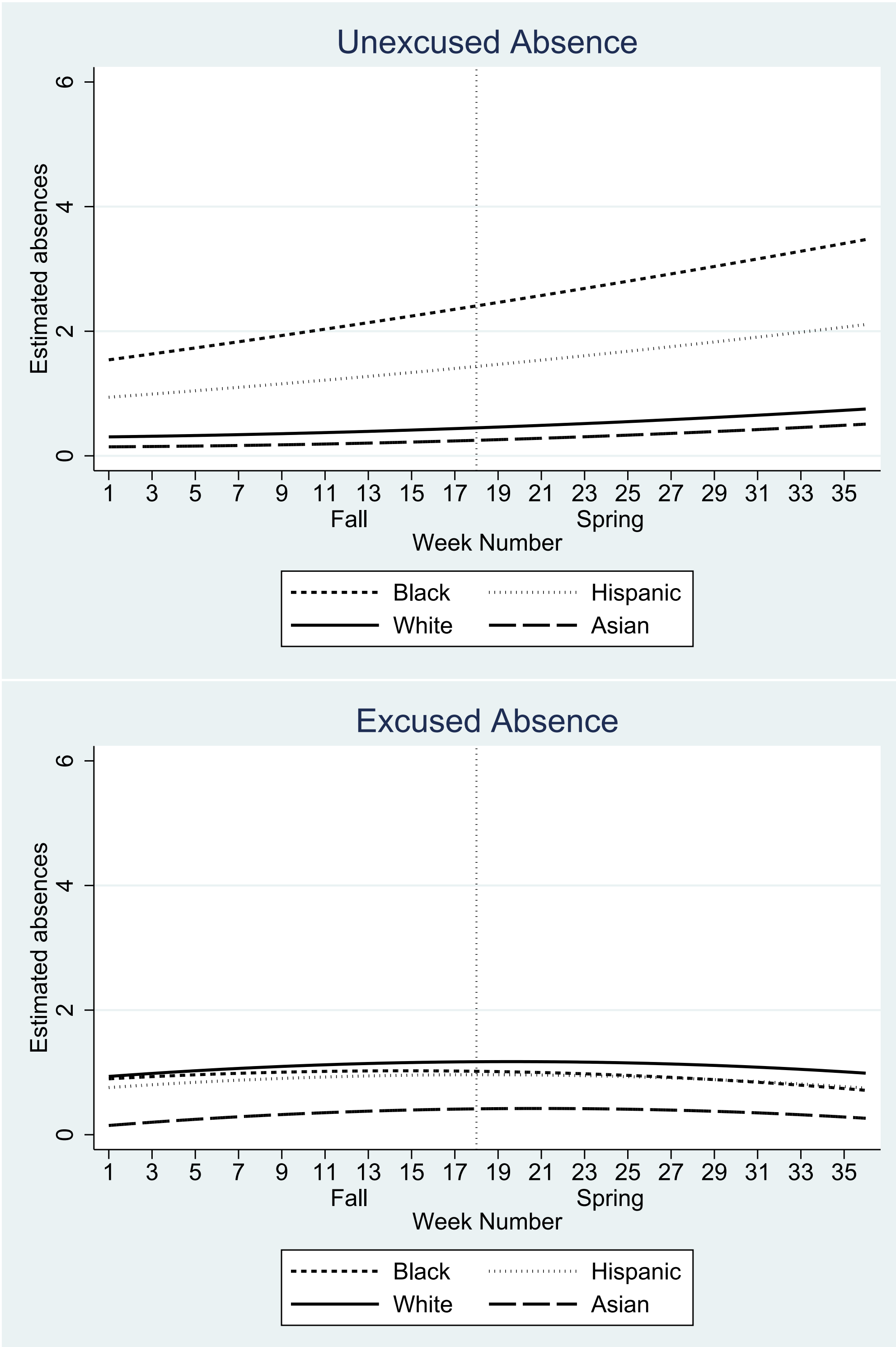
Note: Observations are average counts of class-level absences per week separately for the middle and high school cohorts. Absence type differentiated by bar colors, which are overlaid: Transparent bars signify average unexcused absences and blue bars signify excused absences. Week 18 and weeks 37-39 (i.e., end of fall and spring semester) omitted due to start of winter and summer breaks.

Figure A4: Main Growth Curve Model Results for Middle School (Top) and High School (Bottom) Cohorts



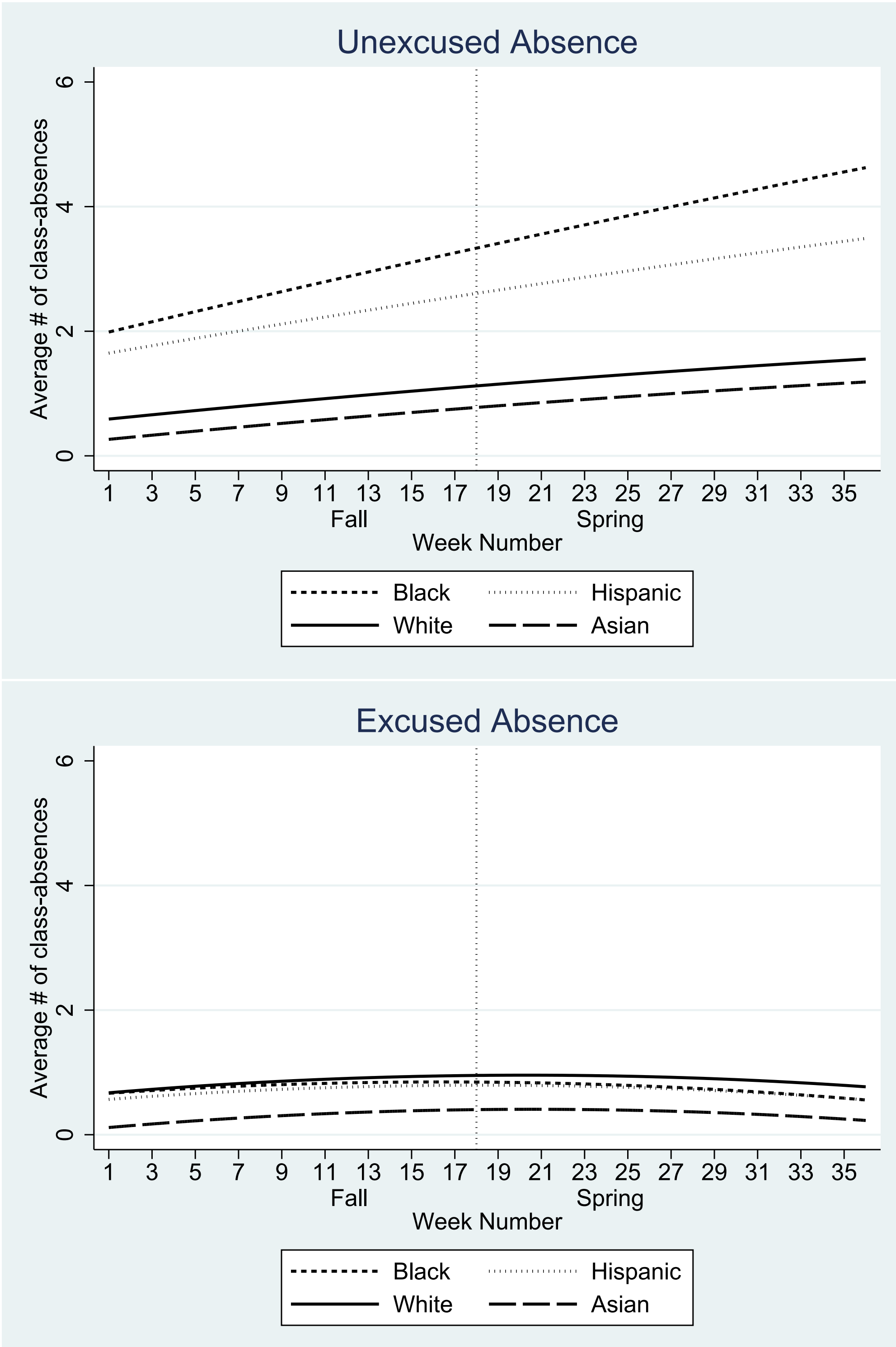
Note: Graph shows results from non-linear growth curve models estimating growth rate in absences by absence type (excused and unexcused absences) separately for middle school and high school cohorts. Levels and slopes calculated separately by absence type.

Figure A5: Growth Curve Model Results for Middle School Cohort by Race



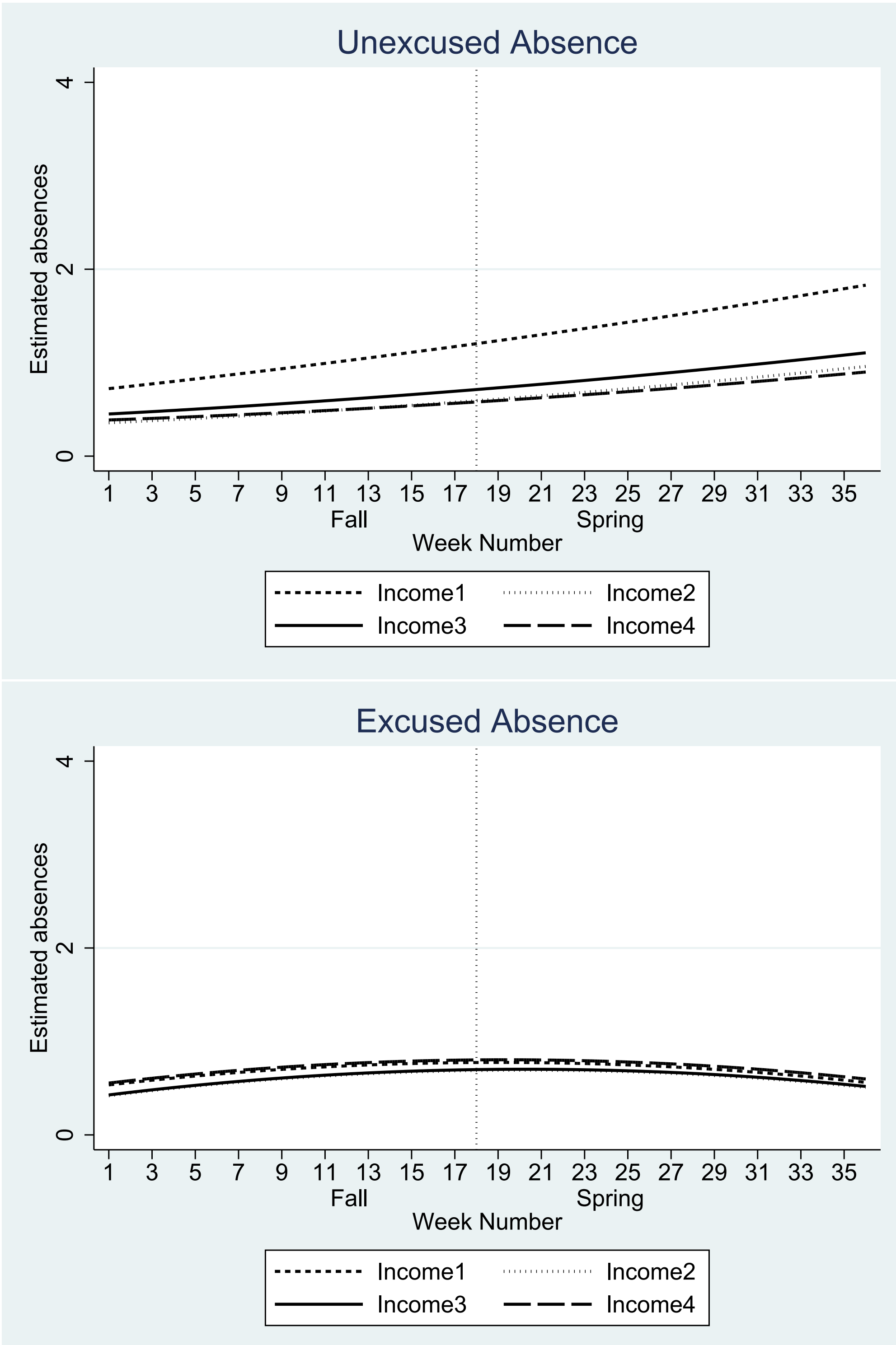
Note: Graph shows results from non-linear growth curve models estimating growth rate, separately by race for the middle school cohort. Levels and slopes calculated separately by race using interaction terms. Separate models for excused and unexcused absences.

Figure A6: Growth Curve Model Results for High School Cohort by Race



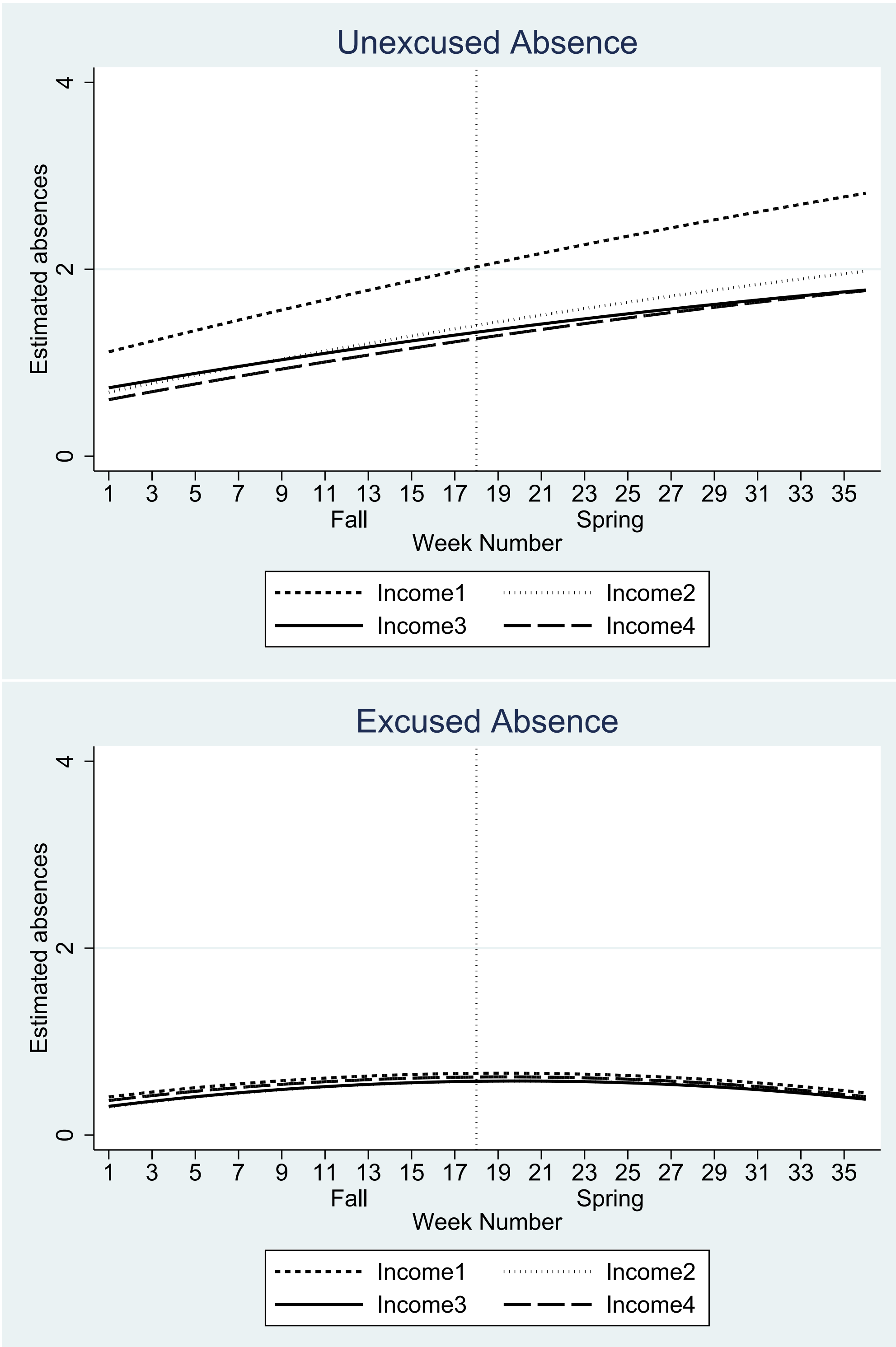
Note: Graph shows results from non-linear growth curve models estimating growth rate, separately by race for the high school cohort. Levels and slopes calculated separately by race using interaction terms. Separate models for excused and unexcused absences.

Figure A7: Growth Curve Model Results for Middle School Cohort by Income



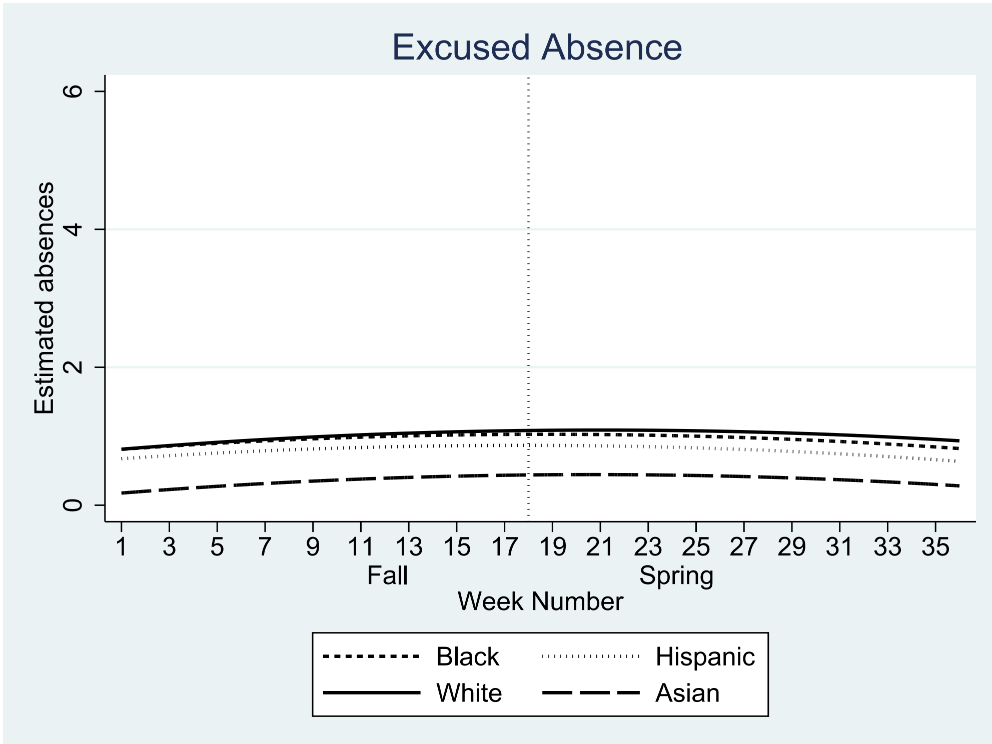
Note: Graph shows results from non-linear growth curve models estimating growth rate, separately by income for the middle school cohort. Levels and slopes calculated separately by income using interaction terms. Income quartiles are derived from census tract-level data of median household income. Separate models for excused and unexcused absences.

Figure A8: Growth Curve Model Results for High School Cohort by Income



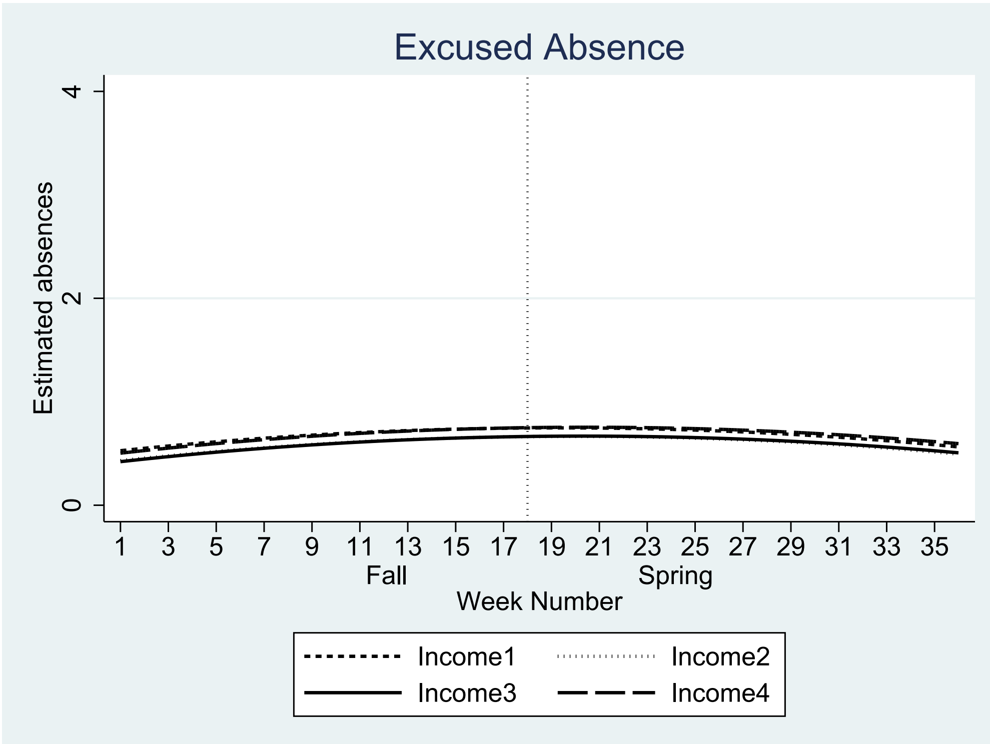
Note: Graph shows results from non-linear growth curve models estimating growth rate, separately by income for the high school cohort. Levels and slopes calculated separately by income using interaction terms. Income quartiles are derived from census tract-level data of median household income. Separate models for excused and unexcused absences.

Figure A9: Growth Curve Model Results for Full Sample by Race for Excused Absences Only



Note: Graph shows results from non-linear growth curve models estimating growth rate using excused absences, separately by race for all students in the sample across three academic years (2015-16 SY through 2017-18 SY). Levels and slopes calculated separately by race using interaction terms.

Figure A10: Growth Curve Model Results for Full Sample by Income for Excused Absences Only



Note: Graph shows results from non-linear growth curve models estimating growth rate using excused absences, separately by income quartile for all students in the sample across three academic years (2015-16 SY through 2017-18 SY). Income quartiles are derived from census tract-level data of median household income, with the first quartile being students with the lowest neighborhood income and the fourth quartile consisting of students with the highest neighborhood income. Levels and slopes calculated separately by income quartile using interaction terms.

Table A1: School Culture Climate Survey Construct Definitions and Corresponding Items

<table>
<tr><th>Construct Definition</th><th>Student Items</th></tr>
<tr><td>Climate of Support for Academic Learning

Students and teachers feel that there is a climate conducive to learning and that teachers use supportive practices, such as:
encouragement and constructive varied opportunities to demonstrate knowledge and skills; support for risk-taking and independent thinking; feedback; atmosphere conducive to dialog and questioning; academic challenge; and individual attention to support differentiated learning</td><td>How strongly do you agree or disagree with the following statements about your school?
[Strongly Disagree, Disagree, Neither Disagree Nor Agree, Agree, Strongly Agree]
• Adults at school encourage me to work hard so I can be successful in college or at the job I choose.
• My teachers work hard to help me with my schoolwork when I need it.
• Teachers give students a chance to take part in classroom discussions or activities.
• Teachers go out of their way to help students.</td></tr>
<tr><td>Sense of Belonging – School Connectedness
A positive sense of being accepted, valued, and included, by others (teacher and peers) in all school settings. Students and parents report feeling welcome at the school.</td><td>How strongly do you agree or disagree with the following statements?
[Strongly Disagree, Disagree, Neither Disagree Nor Agree, Agree, Strongly Agree]

• I feel close to people at this school
• I am happy to be at this school
• I feel like I am part of this school
• The teachers at this school treat students fairly</td></tr>
<tr><td>Knowledge and Fairness of Discipline, Rules and Norms
Clearly communicated rules and expectations about student and adult behavior, especially regarding physical violence, verbal abuse or harassment, and teasing; clear and consistent enforcement and norms for adult intervention</td><td>How strongly do you agree or disagree with the following statements?
[Strongly Disagree, Disagree, Neither Disagree Nor Agree, Agree, Strongly Agree]

5 Item Scale (Rule Clarity)
• This school clearly informs students what would happen if they break school rules.
• Rules in this school are made clear to students.
• Students know how they are expected to act.
• Students know what the rules are.
4 Item Scale (Respectful and Fair)
• Adults at this school treat all students with respect.
• Students treat teachers with respect.
• The school rules are fair.
• All students are treated fairly when they break school rules.</td></tr>
<tr><td>Sense of Safety
Students and adults report feeling safe from verbal abuse, teasing, or exclusion by others in the school.</td><td>How safe do you feel when you are at school?
[Very Safe, Safe, Neither Safe nor Unsafe, Unsafe, Very Unsafe]

During the past 12 months, how many times on school property have you . . .
[0 Times, 1 Time, 2 or 3 Times, 4 or More Times]

• been pushed, shoved, slapped, hit or kicked by someone who wasn't just kidding around?
• had mean rumors or lies spread about you?
• had sexual jokes, comments, or gestures made to you?
• been made fun of because of your looks or the way you talk?</td></tr>
</table>

Table A2: Replication of Main Results Using an Alternative Sample

	Excused Absences			Unexcused Absences		
	Full Sample	Middle School Cohort	High School Cohort	Full Sample	Middle School Cohort	High School Cohort
Week Linear	0.039***	0.038***	0.018***	0.031***	0.016***	0.040***
	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)	(0.004)
Week Quadratic	-0.001***	-0.001***	-0.000***	-0.000***	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.489***	0.438***	0.273***	0.808***	0.421***	0.724***
	(0.014)	(0.031)	(0.029)	(0.021)	(0.032)	(0.067)
L-1 Var(Residual)	7.371	6.893	3.312	5.45	4.407	6.231
L-2 Var(Intercept)	1.229	1.092	0.425	5.549	1.739	4.949
L-2 Var(Slope)	0.000	0.000	0.000	0.009	0.002	0.005
Cov(Int,Slope)	-0.008	-0.014	-0.005	0.073	0.005	0.059
ICC	0.143	0.137	0.113	0.505	0.283	0.442
N	502486	117289	70134	502486	117289	70134

Note: This sample consists of students who have 35 class periods a week. Each column represents separate model estimates by absence type (i.e., excused or unexcused) and sample (i.e., full sample, middle school cohort and high school cohort). Coefficients on both linear and quadratic terms of Week (i.e., count variable indicating week number in the school year) indicate weekly growth rate of absences and the rate of change in absences. We define the intercept as the grand mean of absences in the first week of school across all three academic years in the data (2015-16 SY through 2017-18 SY). The random effect components are as follows: the variance within students across time (i.e., variance of residuals); the variance of the average number of week 1 absences between students (i.e., variance of the intercepts); the variance of absence growth rate between students (i.e., variance of the slope), and the correlation between random intercepts and slopes (i.e., covariance). The ICC, or intraclass correlation coefficient, represents the percentage of clustering in the data. Standard errors in parentheses. + $p<0.10$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Table A3: Growth Curve Model Results for Excused Absences, by Race and Cohort

	Full Sample	Middle School Cohort	High School Cohort
A. Intercept			
White	0.784***	0.909***	0.643***
	(0.009)	(0.025)	(0.023)
Black	0.785***	0.878***	0.641***
	(0.010)	(0.031)	(0.028)
Hispanic	0.650***	0.732***	0.540***
	(0.006)	(0.019)	(0.016)
Asian	0.148***	0.120***	0.085***
	(0.005)	(0.015)	(0.012)
Other	0.605***	0.595***	0.520***
	(0.012)	(0.036)	(0.032)
B. Slope			
White	0.029***	0.027***	0.031***
	(0.001)	(0.002)	(0.002)
Black	0.026***	0.020***	0.025***
	(0.001)	(0.003)	(0.003)
Hispanic	0.025***	0.025***	0.028***
	(0.001)	(0.002)	(0.002)
Asian	0.029***	0.029***	0.031***
	(0.001)	(0.002)	(0.001)
Other	0.025***	0.027***	0.026***
	(0.001)	(0.003)	(0.003)
L-1 Var(Residual)	6.016	6.880	4.742
L-2 Var(Slope)	0.001	0.001	0.001
Number of Observations	2,922,125	380,609	368,595
p-value of postestimation test: Different from White?			
Intercept			
Black	0.915	0.413	0.960
Hispanic	0.000	0.000	0.000
Asian	0.000	0.000	0.000
Other Race	0.000	0.000	0.002
Slope			
Black	0.003	0.024	0.066
Hispanic	0.000	0.441	0.209
Asian	0.526	0.390	0.825
Other Race	0.001	0.881	0.145

Note: Each column represents separate model estimates using week by race interactions, suppressing the intercept for ease of interpretation. Quadratic Week term omitted from display. Initial level and growth rate of absences (i.e., slope) shown separately by race via interaction term. The random effect components are as follows: the variance in absences within students across time (i.e., variance of residuals); and the variance of absence growth rate between students (i.e., variance of the slope). P-values at bottom of table are derived from postestimation tests testing the difference in intercepts (or slopes) between White and each non-White student category. Standard errors in parentheses. + $p<0.10$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Table A4: Growth Curve Model Results for Excused Absences, by Income and Cohort

	Full Sample	Middle School Cohort	High School Cohort
A. Intercept			
Quartile 1	0.502***	0.508***	0.379***
	(0.006)	(0.018)	(0.016)
Quartile 2	0.405***	0.390***	0.272***
	(0.006)	(0.019)	(0.016)
Quartile 3	0.395***	0.399***	0.278***
	(0.006)	(0.019)	(0.016)
Quartile 4	0.477***	0.527***	0.341***
	(0.006)	(0.019)	(0.016)
B. Slope			
Quartile 1	0.025***	0.028***	0.029***
	(0.001)	(0.002)	(0.002)
Quartile 2	0.026***	0.030***	0.030***
	(0.001)	(0.002)	(0.002)
Quartile 3	0.027***	0.030***	0.030***
	(0.001)	(0.002)	(0.002)
Quartile 4	0.027***	0.029***	0.029***
	(0.001)	(0.002)	(0.002)
L-1 Var(Residual)	6.035	6.908	4.756
L-2 Var(Slope)	0.001	0.001	0.001
Number of Observations	2,922,125	380,609	368,595
p-values of postestimation test: Different from Quartile 4?			
Intercept			
Quartile 1	0.002	0.426	0.063
Quartile 2	0.000	0.000	0.001
Quartile 3	0.000	0.000	0.002
Slope			
Quartile 1	0.023	0.807	0.980
Quartile 2	0.228	0.526	0.493
Quartile 3	0.776	0.501	0.586

Note: Each column represents separate model estimates using week by income interactions, suppressing the intercept for ease of interpretation. Income quartiles are derived from a student's median household income based on Census tract data of their residence. Quartile 1 contains students with lowest income and Quartile 4 contains students with the highest income. Quadratic Week term omitted from display. The random effect components are as follows: the variance in absences within students across time (i.e., variance of residuals); and the variance of absence growth rate between students (i.e., variance of the slope)). P-values at bottom of table are derived from postestimation tests testing the difference in intercepts (or slopes) between the top income quartile and another quartile. Standard errors in parentheses. + p<0.10 * p<0.05 ** p<0.01 *** p<0.001.