ANNENBERG
BROWN UNIVERSITY

EdWorkingPaper No. 24-960

Empowering Educational Leaders: On-Track Indicators for College Enrollment

Brian Holzman
Texas A&M University

Horace Duffy
Keecha Harris and Associates

As states incorporate measures of college readiness into their accountability systems, school and district leaders need effective strategies to identify and support students at risk of not enrolling in college. Although there is an abundant literature on early warning indicators for high school dropout, fewer studies focus on indicators for college enrollment, especially those that are simple to calculate and easy for practitioners to use. This study explores three potential indicators of college readiness that educational leaders may consider using as part of an early warning system for college enrollment. Using district administrative data, our analysis shows that an indicator based on attendance, grades, and advanced course-taking is slightly more effective at predicting college enrollment than indicators based on course failures or standardized test scores. However, the performance of these indicators varies across different student demographic and socioeconomic subgroups, highlighting the limitations of these measures and pointing to areas where they may need to be supplemented with contextual information. Through event history analysis, we demonstrate that the ninth grade is a particularly challenging year for students, especially those who are male, Black, Hispanic, or economically disadvantaged. These results suggest that educational leaders ought to consider identifying and targeting students at risk of not attending college with additional resources and support during the freshman year of high school.

VERSION: May 2024

Suggested citation: Holzman, Brian | Duffy, Horace. (2024). Empowering Educational Leaders: On-Track Indicators for College Enrollment. (EdWorkingPaper: 24-960). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/styt-2294

Empowering Educational Leaders: On-Track Indicators for College Enrollment

Brian Holzman, Ph.D., Texas A&M University
Horace Duffy, Ph.D., Keecha Harris and Associates

May 7, 2024

Abstract
As states incorporate measures of college readiness into their accountability systems, school and district leaders need effective strategies to identify and support students at risk of not enrolling in college. Although there is an abundant literature on early warning indicators for high school dropout, fewer studies focus on indicators for college enrollment, especially those that are simple to calculate and easy for practitioners to use. This study explores three potential indicators of college readiness that educational leaders may consider using as part of an early warning system for college enrollment. Using district administrative data, our analysis shows that an indicator based on attendance, grades, and advanced course-taking is slightly more effective at predicting college enrollment than indicators based on course failures or standardized test scores. However, the performance of these indicators varies across different student demographic and socioeconomic subgroups, highlighting the limitations of these measures and pointing to areas where they may need to be supplemented with contextual information. Through event history analysis, we demonstrate that the ninth grade is a particularly challenging year for students, especially those who are male, Black, Hispanic, or economically disadvantaged. These results suggest that educational leaders ought to consider identifying and targeting students at risk of not attending college with additional resources and support during the freshman year of high school.

Keywords
college enrollment, college readiness, early warning indicators, predictive modeling, discrete-time event history analysis

Type of Article
Empirical paper

Acknowledgments
We thank leaders and staff at our school district partner for their feedback and collaboration on this research project, as well as Rice University's Houston Education Research Consortium for providing access to the data. We are grateful for comments from staff and workshop participants at Rice University (Houston Education Research Consortium), as well as discussant and participant feedback at academic conferences and a National Network of Education Research-Practice Partnerships webinar. Correspondence should be directed to Brian Holzman at bholzman@tamu.edu. This material is based upon work supported by Houston Endowment Inc. Opinions reflect those of the authors and do not necessarily reflect those of the Houston Independent School District. The results, conclusions, and errors are our own.

Introduction

An essential function of public education systems is to prepare students to lead productive lives and contribute to society (Labaree, 1997). Implicit in this goal is the expectation that high school graduates master content knowledge and develop skills that enable their transition into college and the workforce. In an era of increasing globalization, a quality education is critical not only for the individual but also for the nation (Hanushek et al., 2017). Beyond education’s role in economic growth, there is a growing demand for advanced skill sets in the labor market (Goldin & Katz, 2008), and by 2031, it is estimated that 72 percent of American jobs will require some level of postsecondary training (Carnevale et al., 2023).

Federal and state policymakers have recognized the importance of preparing the next generation by developing curricular standards that ensure high school graduates are ready for college. Malin et al. (2017) observe that the 2015 Every Student Succeeds Act (ESSA) marked a significant shift from previous reauthorizations of the Elementary and Secondary Education Act, not only by returning autonomy to state education agencies but also by emphasizing college readiness as a central policy goal. This legislation encouraged states to prioritize college readiness in their ESSA plans. Hackmann et al. (2019) report that three-quarters of states have referenced college readiness in their state standards and incorporated college readiness measures as indicators of high school quality.

With the increasing demand for states, districts, and schools to enroll students in college, understanding when students are college-ready becomes crucial. If teachers, counselors, and other staff can identify early on when a student is not making adequate progress toward college enrollment, they can intervene to help that student get back on track. Developing a reliable predictor of college enrollment may enhance the efficiency of educational systems (Gleason &

Dynarski, 2002). Since schools and districts do not have unlimited personnel, it is not feasible to provide individualized support to each student. Many students may not require targeted assistance; they might already perform well and be on track for a successful transition to higher education. Therefore, expending resources on students who are already college-ready could be seen as a waste. With limited time, educational leaders should focus on students most at risk of not enrolling in college without intervention. Identifying indicators that can guide practitioners to these students will help avoid wasteful allocations of resources while still achieving school and district college readiness goals.

There is an abundance of research on indicators and predictors of high school dropout that can be used to identify students for dropout prevention programs (Bowers et al., 2013). However, there is less literature on analogous measures focused on college enrollment (see Soland, 2013, 2017, as exceptions). Given the push for states to integrate measures of college readiness into school and district accountability systems, it becomes important to develop and assess potential indicators and predictors of college enrollment that may be used in an early warning system. A reliable measure could help schools and districts identify which students to target for intervention, allowing for an efficient allocation of personnel and time as they work toward their goals.

Our investigation consists of two studies. First, we test three potential indicators of college readiness that a district may choose to use in an early warning system. We explore how well these indicators predict college enrollment and non-enrollment for all students, as well as for sociodemographic subgroups. In the second study, we examine when students fall off the college path, specifically identifying when they are at the greatest risk of not meeting these indicators. This analysis also examines which student characteristics are most predictive of not meeting the indicators. The findings offer insights into when practitioners ought to consider intervening, as well as which students are more likely to fall off track from college. Both studies aim to provide schools and districts with information to develop tools that can guide students through the high school-to-college transition more efficiently — not only to meet state-defined college readiness benchmarks, but also to increase college access, particularly for those from historically marginalized backgrounds.

College Readiness

College readiness encompasses a range of skills beyond those required for high school completion. Conley (2010) offers a framework with four dimensions for understanding college readiness: (1) *Key Cognition Strategies* — critical thinking skills; (2) *Key Content Knowledge* — proficiency in core academic areas, including research and writing; (3) *Academic Behaviors* — time management and the ability to delay gratification to achieve goals; (4) *Contextual Skills and Awareness* — understanding the college admission process and developing the skills to navigate college life. Similarly, the College Readiness Indicator System (CRIS) Framework identifies three dimensions akin to Conley's: (1) *Academic Preparedness* — content knowledge and readiness for college-level coursework; (2) *Academic Tenacity* — motivation and effort in school; and (3) *College Knowledge* — understanding the college application and enrollment process (Borsato et al., 2013). Although the dimensions outlined in the Conley and CRIS frameworks are vital in the postsecondary pathway, they do not magically appear when students start applying to college. College readiness grows over time (Conley, 2010), enabling schools that aim to improve postsecondary outcomes to monitor and target students who need assistance.

Few studies have focused on early warning indicators for college access, possibly because college readiness is a difficult concept to measure. Schools and districts may struggle to create and collect measures related to all the dimensions of the Conley (2010) and CRIS (Borsato et al., 2013) frameworks. For example, to assess the academic tenacity and college knowledge dimensions, the CRIS framework recommends administering surveys to gather information on students' attitudes about school, their study skills, and their familiarity with the college application process (Stanford University John W. Gardner Center for Youth and Their Communities, 2014). In contrast, schools and districts already collect numerous measures of academic performance. While these measures reflect a narrower interpretation of the Conley and CRIS frameworks, covering just one or two dimensions, they are arguably more actionable for practitioners; that is, a teacher or principal can use this data to develop interventions to prevent students from falling off track.

There is limited research focused on developing indicators for early warning systems that can predict college enrollment or non-enrollment. Using the National Education Longitudinal Study of 1988 (NELS), Soland (2013) compared the effectiveness of measures typically found in early warning systems with a measure of teacher intuition to predict high school graduation and college enrollment. He found that the early warning system measures were more accurate at predicting college-going than teacher intuition and improved the balance between false positive and negative predictions. However, the early warning system model was more accurate at predicting high school graduation than college enrollment, suggesting that high school graduation and college enrollment are different processes that require distinct inputs. Although Soland restricted his analysis to characteristics available in administrative data systems, it still included 20 variables, which could be challenging for in-school practitioners to work with, especially if lack experience conducting or interpreting regression analysis. Another Soland study (2017) found that a machine learning model using 40 NELS variables correctly predicted about 90 percent of student enrollment decisions. Despite this high level of accuracy, the techniques employed to achieve these results may be beyond the capacity of many school districts, and many of the variables used are not collected in administrative data systems (e.g., educational expectations, importance of financial aid).

There is a thorough body of literature on predictors of high school dropout (Bowers et al., 2013; Zheng et al., 2023). The primary goal of this research is to offer school and district leaders measures to identify students at risk of dropping out of high school. If a student is deemed at risk, then educational leaders and staff may target them for intervention or provide resources to help them get back on track to graduation. Allensworth and Easton (2005) developed the on-track indicator, which is calculated at the end of the freshman year of high school and satisfied if 1) students completed five course credits and 2) they had at most one semester F in a core subject course. In Chicago Public Schools (CPS), 81 percent of students who met these conditions graduated high school within four years, while 78 percent of students who failed to meet either condition did not graduate. In a detailed analysis of high school dropout predictors, Bowers et al. (2013) showed that the Chicago on-track indicator was the most accurate measure examined. Moreover, they noted its simplicity and usability, as it relied on data schools already collected (course failures and credits) and did not require sophisticated software or training to generate. Allensworth (2013) reported that the adoption of the on-track indicator in CPS reshaped staff conversations on how to address high school dropout and assisted the district in identifying students for prevention (before ninth grade), intervention (during ninth grade), and recovery (after ninth grade) programs. She also noted that the release of on-track indicator research reports coincided with an increase in student performance in CPS.

While the Chicago on-track indicator is simple to calculate and easy for a school practitioner to use, it is geared toward high school graduation and may not capture the additional skills and knowledge needed for college enrollment (Allensworth & Easton, 2005). Although Soland's analyses (2013, 2017) are valuable for focusing on college enrollment, they used survey data that may not be readily available in school district data systems and require resources and training in complex modeling that many practitioners do not have. Project Unicorn, an initiative aimed at improving data operations in school districts, surveyed 208 district leaders, and concluded that "[t]here is a disconnect between the desire to prioritize data to support decision-making and the capacity to do so" (2023, p. 21). Similarly, in a large-scale survey of thousands of district administrators, principals, and teachers, Moore and Croft (2018) revealed that time and technical skills were major barriers to data-driven decision-making. Thus, educators and leaders may prefer simpler measures like the on-track indicator which requires little effort to compute.

Early Intervention

In addition to identifying appropriate measures of college readiness, practitioners must understand the best time to assess students' readiness and when to intervene. Klasik (2012) examines the various steps to four-year college enrollment, including aspiring to earn a four-year degree in 10th grade, maintaining that aspiration in 12th grade, taking the SAT or ACT, achieving a strong academic record (based on grades, test scores, and course-taking), and applying to a four-year college. He shows that decreasing numbers of students complete each step as time progresses. For example, fewer students held four-year college aspirations in 12th grade than in 10th grade, and even fewer took the SAT or ACT. The drop in step completion was more pronounced among racial and ethnic minorities and low-income individuals. As one might expect, a major finding from this research was that early steps strongly predicted later steps:

"there was a certain momentum students gained as they moved closer to college enrollment" (Klasik, 2012, p. 542). Additionally, for some groups, particularly Black and Hispanic students, this momentum was more pronounced — the correlation between early and late steps was stronger.

Using data from Jefferson County Public Schools, Royster et al. (2015) examined the timing of college readiness, as defined by benchmarks on the EXPLORE, PLAN, and ACT tests, and found that most students met the college-ready benchmark in eighth grade. In a review of the literature, Hein et al. (2013) noted that although elementary and middle school measures did not directly predict college access and success, they did influence high school performance, which was linked to college outcomes. These studies suggest that indicators measured years before students enter college or even high school can directly or indirectly predict long-term outcomes. Taken together, intervening early in the pathway to college may be an effective way for practitioners to improve college outcomes. Early interventions can set students on track to enroll in college and may more efficient than late interventions (Carneiro & Heckman, 2003; Holzman et al., 2020; Klasik, 2012; Knudsen et al., 2006), especially if they can close gaps in intermediate steps like taking the SAT or ACT and applying to college. However, if schools and districts plan to intervene early, they identify which students require intervention and determine the best time to intervene. Addressing these two questions not only helps practitioners and policymakers strategize and reduce their burden, but it may also enable them to maximize the impact of their interventions on college outcomes.

The Present Study

As states integrate college readiness and enrollment metrics into accountability systems, schools and districts may seek innovative approaches to ensure students are prepared for college.

While existing research offers insights into early warning systems and indicators predicting high school graduation and dropout (see Bowers et al., 2013, for a review), college enrollment is a distinct concept that may require different benchmarks. Consequently, our aim is to explore potential indicators that practitioners can use to identify students at risk of not going to college and to determine when schools and districts should consider providing extra support and resources. Given concerns with educational equity, we also test for differences by gender, race and ethnicity, and socioeconomic status. If the indicators do not perform well for specific student groups, or if the timing of when students are most at risk of deviating from the college path varies, then practitioners need this information before adopting the indicators or implementing an intervention.

In the first study, we examine how college readiness indicators measured in grades seven, nine, and 11 predict college outcomes. We assess how well each indicator predicts college enrollment and non-enrollment, with and without control variables, and how these indicators perform among different sociodemographic subgroups. This analysis may be useful to school and district leaders interested in adopting college readiness indicators as part of an early warning system. The second study focuses on the timing of college readiness. Specifically, we seek to determine during which grade levels students are most at risk of falling off the college path. Identifying when students fall off track is critical for practitioners considering implementing interventions to ensure that students at risk of non-enrollment remain college ready.

Study 1: Exploring On-Track Indicators for College Enrollment

In this first study, we assess potential on-track indicators that may be used to predict college enrollment. Our goal is to identify measures that are both associated with college enrollment and available in annual administrative data; the latter goal is useful to teachers, counselors, and school staff interested in monitoring students' college readiness and implementing early interventions to help students stay or get back on track to enrollment. We also seek indicators that accurately predict college enrollment across sociodemographic subgroups. For example, if a measure is more accurate at predicting college enrollment for female students than male students, it is crucial for practitioners and policymakers to understand the measure's limitations before deciding to use it to identify students for intervention.

Data

We used data from the Houston Education Research Consortium (HERC), a research-practice partnership between Rice University and the Houston Independent School District (HISD), the nation's ninth-largest school district (National Center for Education Statistics, 2022). Our analysis focused on students who were in seventh grade during the 2007-2008 and 2008-2009 school years, and we tracked them through fall 2013 and 2014, which was they might be expected to first attend college if they graduated high school on time and matriculated immediately. The data included measures of demographic and socioeconomic background, behavioral characteristics (e.g., attendance, suspensions), and academic characteristics (e.g., standardized test scores, grades earned, courses passed). (Please refer to Appendix Table 1 for a detailed description of the variables used in studies 1 and 2.) College enrollment measures came from the National Student Clearinghouse, a nonprofit that collects information on postsecondary attendance and graduation from U.S. institutions. The analysis was limited to students who were enrolled in HISD from seventh through 12th grade and who had non-missing data on the on-track indicators tested, the control variables, and college enrollment. We excluded Native American students due to small sample size. Of course, restricting the analysis to continually enrolled students might induce biased estimates of college outcomes and skew inequalities between groups, but college enrollment data were unavailable for high school dropouts. Our sample consisted of 11,912 students, with nearly three-fifths enrolling in college in the fall after graduation. Summary statistics for study 1 are available in Appendix Table 2.

The outcome in this analysis was binary and measured whether a student enrolled in a college or university at any level (e.g., four-year, two-year, less-than-two-year) the fall following their expected high school graduation. Students who did not high school graduate with their class were coded as not enrolled. The primary independent variables were the potential indicators of college readiness, which are described in Table 1. While college readiness is a multidimensional concept (Borsato et al., 2013; Conley, 2010), we strived to develop indicators that were based on data readily available in district administrative data systems and that a practitioner could easily understand and generate as part of an early warning system.

[Insert Table 1 Here]

First, we examined the Chicago indicator, which was based on the freshman on-track indicator developed by the University of Chicago Consortium on School Research (Allensworth & Easton, 2005). The on-track indicator, which combines measures of credits earned and courses failed, is typically measured in ninth grade, and is known to be a strong predictor of high school dropout (Bowers et al., 2013). With a slight modification for the HISD data, we developed a similar on-track measure. Specifically, to meet the indicator, students had to have no more than two semester Fs in any subject and no more than one semester F in a core subject (English, math, science, or social studies). Although the on-track indicator was originally designed to address high school dropout, we study it here to determine whether a high school dropout indicator can also identify students at risk of not attending college.

We developed the second indicator, the HERC indicator, as an attempt to create an on-track measure tailored specifically for college enrollment. We examined a host of measures, ranging from attendance rates to college preparatory coursework, and experimented with different cutpoints for coding. A detailed description of our data-driven process is provided in the appendix. To meet the indicator, a student had to satisfy three conditions: 1) maintain an attendance rate of at least 90 percent or above (non-chronic absence), 2) earn an average grade of 80 percent or above (a B-average), and 3) take and pass at least one semester-long advanced course.[1]

The third indicator we examined was derived from the College-Ready Graduates measure used in the Texas state accountability system through spring 2013 (Texas Education Agency, 2007). This measure was based on student test scores: 11th-grade students had to earn English language arts (ELA) and mathematics scores on the Texas Assessment of Knowledge and Skills (TAKS) at or above 2200. For each subject and year, we identified the *z* score corresponding to a scale score of 2200, then applied these *z* score cutoffs to all grade levels tested. For example, in 2007-2008, an 11th-grade ELA score of 2200 corresponded to a *z* score of -0.57 standard deviations (SD), while an 11th-grade mathematics score of 2200 corresponded to a *z* score of -0.24 SD. A *z* score of -0.57 SD corresponded to a scale score of 2153.45 on the seventh-grade ELA test, while a *z* score of -0.24 SD corresponded to a scale score of 2175.68 on the seventh-grade mathematics test. To code the seventh-grade indicator, we set these values as the cutoffs: a student had to score at or above 2153.45 on the ELA test and at or above 2175.68 on the mathematics test to meet this indicator.

[1] Advanced courses were defined as any Advanced Placement (AP), International Baccalaureate (IB), pre-AP, pre-IB, or academic dual credit course.

We generated the Chicago, HERC, and state indicators for students in grades seven, nine, and 11. This allowed us to compare the effectiveness of the three indicators and assess their ability to predict college enrollment over time. We chose seventh grade because many students are sorted into advanced coursework based on their measured and perceived academic abilities during middle school (Dauber et al., 1996; Gamoran, 1992). Ninth grade was selected because it marks the beginning of high school, while 11th grade is when many students take college entrance exams like the SAT and intensify their search for college options (Hossler et al., 1989). During our study period, 11th grade was also the last time students took state accountability tests.

Methods

Using binary logistic regression models, we predicted college enrollment. Our primary independent variable was the Chicago, HERC, or state indicator measured during the seventh, ninth, or 11th grade. We also estimated models that controlled for student sociodemographic characteristics, including age, gender, race and ethnicity, English learner status, special education status, and economic disadvantage, along with cohort and school fixed effects. After each model, we generated predicted probabilities to determine whether the model accurately predicted each student's college enrollment. A prediction was considered correct if 1) a student's likelihood of college enrollment was greater than or equal to 0.50 and they eventually enrolled, or 2) a student's likelihood of college enrollment was less than 0.50 and they did not enroll.

Main Results

Table 2 displays the results from our tests of the Chicago, HERC, and state indicators in the seventh, ninth, and 11th grades. The first three rows of each panel in the table show how well each indicator predicted college enrollment without controlling for student background characteristics, cohort, or school fixed effects. In Panel A, which corresponds to indicators measured in seventh grade, we see that all three indicators were positively associated with college enrollment. Nevertheless, the HERC indicator demonstrated the highest tetrachoric correlation (r = 0.45), while the HERC and state indicators explained more of the variance in college enrollment (pseudo-R^2 = 0.06) compared to the Chicago indicator. The last three columns of the table show correct predictions — the percentage of students whose college enrollment outcome was correctly predicted by the seventh-grade Chicago, HERC, or state indicator. In the absence of student background, cohort, or school controls, the indicators correctly predicted enrollment outcomes for nearly two-thirds of students. Nonetheless, the HERC and state indicators performed slightly better than the Chicago indicator, possibly because the Chicago indicator was originally designed to predict high school graduation, whereas the HERC and state indicators were developed with college enrollment in mind.

[Insert Table 2 Here]

Discrepancies between the seventh-grade indicators grew when comparing correct positive predictions (for college enrollment) and correct negative predictions (for non-college enrollment). While the Chicago indicator correctly predicted college enrollment 92 percent of the time, it was quite inaccurate at predicting non-enrollment. It correctly predicted non-enrollment just 21 percent of the time, which means that it incorrectly assumed that 79 percent of non-enrollees would attend college. Given that states are incorporating college readiness measures into school accountability systems (Hackmann et al., 2019), practitioners may consider targeting students at risk of not enrolling in college for intervention. If an indicator suggests a student will enroll in college when they actually will not, then that error represents a missed opportunity for intervention. The Chicago indicator's inaccurate predictions of non-enrollment may be due to its greater leniency in academic performance compared to the HERC indicator. For example, while the HERC and state indicators had slightly lower rates of correct positive predictions (79% and 69%, respectively) than the Chicago indicator, they had higher rates of correct negative predictions (49% and 60%).[2] The HERC and state indicators accurately identified half or more of non-college enrollees, which could be crucial information for practitioners before implementing early interventions.

The next two sections of Panel A add controls for students' sociodemographic background, as well as school and cohort fixed effects. We see that the explained variances, as measured by the pseudo-R^2, more than double for all three indicators, and the percentage of correct overall predictions increases slightly. The correct positive and negative prediction rates also change significantly, with the three indicators showing more consistent rates when controls and fixed effects are added.

Using seventh-grade data, we observe that all three indicators had similar rates of correct overall predictions. However, in terms of non-enrollment, the Chicago indicator performed quite poorly when omitting sociodemographic characteristics and cohort and school fixed effects. To achieve correct negative prediction rates like the HERC and state indicators, these controls must be included. The HERC and state indicators appeared more stable before and after statistical adjustments. Due to these patterns, practitioners may prefer the HERC and state indicators over the Chicago indicator to predict college enrollment. Since practitioners may lack the training or

[2] In a robustness check, we tested potential indicators from eighth grade and found patterns similar to those from seventh grade. Specifically, the state indicator performed slightly better than the HERC indicator in terms of correct negative predictions. It is possible that attendance, grades, and advanced courses passed in middle school are less predictive of college enrollment than they are in high school. Therefore, practitioners may consider relying more on test score indicators in earlier grades and indicators like the HERC indicator in later grades.

software to develop complex prediction models, they may seek indicators that can identify potential non-enrollees with reasonable accuracy without extensive covariate adjustment.

The next two panels of Table 2 display the same set of statistics using the Chicago, HERC, and state indicators generated from ninth- and 11th-grade data. In later grades, the tetrachoric correlations and explained variances between the indicators and college enrollment were a little bit higher, potentially because these indicators were timed closer to when students typically enrolled in college. The rates of correct overall predictions in grades nine and 11 were quite similar to those observed in grade seven. However, without adjusting for student sociodemographic characteristics and cohort and school fixed effects, the HERC indicator showed lower rates of correct positive predictions, while the state indicator showed higher rates. In contrast, the HERC indicator had higher rates of correct negative predictions, whereas the state indicator had lower rates. A potential explanation for this trend is that low test scores during high school may be less influential on college enrollment than chronic absenteeism, poor grades, and failing to take and pass advanced courses. These measures, which combine to form the HERC indicator, may capture unobservable socioemotional characteristics like self-regulation (Galla et al., 2019) and school engagement (Willingham et al., 2002) that an indicator based solely on test scores may miss. Practitioners seeking to intervene with students at risk of not enrolling in college may gravitate toward the HERC indicator, which had higher rates of correct negative predictions without statistical adjustments in grades nine and 11, rather than the state indicator, whose performance weakened over time.

Results by Subgroup

School and district practitioners may wonder if the college readiness indicators accurately predict enrollment across different student populations. Appendix Figure 1 illustrates how well each indicator performed for gender, race and ethnicity, and economic disadvantage subgroups. Unfortunately, the graphs show considerable variation in accuracy. Correct overall prediction rates were slightly higher for female, White, Asian, and non-economically disadvantaged students than for male, Black, Hispanic, and economically disadvantaged students. Despite the higher correct overall prediction rates for White, Asian, and non-economically disadvantaged students, these groups had very low correct negative prediction rates for non-enrollment. To clarify, the model seemed to assume that advantaged students who did not meet the Chicago, HERC, or state indicator would not go to college. However, many of these students *did* end up in college. This is an important lesson for practitioners interested in using these college readiness indicators: these measures are unable to capture external factors like cultural and social capital, which can support advantaged students as they transition to college (McDonough, 1997; Sandefur et al., 2006), even if they did not perform well or meet key benchmarks during high school. If the models could adjust for these factors, their predictions might have been more accurate. Practitioners should be mindful of this limitation when using the indicators and may consider collecting contextual information from students before identifying them for early intervention.

Supplementary Analyses

Our assessment of college readiness indicators shows that meeting the Chicago, HERC, and state indicators in specific grade levels positively predicts college enrollment. Additionally, Appendix Figure 2 illustrates a positive relationship between meeting these indicators in multiple grade levels and college attendance. For example, while only 30 percent of students who never met the HERC indicator later enrolled in college, 82 percent of those who met it every year from seventh to 12th grade went on to enroll in college. Although the HERC and state trend lines follow similar patterns, the trend line for the Chicago indicator lies below, suggesting that meeting the Chicago indicator multiple times is less predictive of college enrollment. This discrepancy may be because the Chicago indicator was originally designed to predict high school graduation. A student could meet the Chicago indicator several times but have little interest in or preparation for college attendance.

Study 2: Determining When Students Fall Off Track the College Path

Study 1 focused on three indicators a district practitioner might use to identify students at risk of not going to college and assessed how well they predicted enrollment. Overall, we found that indicators developed with college readiness in mind (the HERC and state indicators) performed as well as or slightly better than an indicator designed to address high school dropout (the Chicago indicator). However, we observed more pronounced differences when examining correct positive predictions of enrollment and correct negative predictions of non-enrollment. Specifically, while the Chicago indicator was accurate at predicting enrollment for students for students who did enroll in college, it poorly predicted non-enrollment among students who did not enroll. We may expect this pattern because the Chicago indicator was designed to predict high school graduation, not college enrollment. Regardless of which indicator is used in a school or district's early warning system, practitioners may want to understand when students are at greatest risk of falling off the college path and the best time to intervene. In study 2, we aim to address these questions by focusing on the timing of college readiness. Using the college readiness indicators described earlier, we estimate 1) between which grades, from seven through 12, do students first fail to achieve each benchmark (i.e., when they fall off track) and 2) which subgroups are most at risk of not achieving each benchmark.

Data

The analysis used the HERC data described in study 1, focusing on students who were in the seventh grade in fall 2007 and 2008, and tracking them through the end of 12th grade. Unlike the college readiness indicators analysis, we did not exclude students who left HISD because they dropped out of school or moved. The final analytic sample consisted of 17,879 students. Summary statistics are available in Appendix Table 3.

Methods

We structured our data into a longitudinal, person-period format in which each observation represented a student-grade (e.g., student A in grade 7, student A in grade 8, student A in grade 9).[3] After constructing a student-by-grade dataset, we predicted the first time a student fell off track (i.e., failed to meet the Chicago, HERC, or state indicator) using discrete-time event history analyses, a class of models used to understand whether and when events occur. Specifically, we estimated the following logistic regression:

$$\text{logit}\left(h_{isg}\right) = \Gamma_g + \boldsymbol{X}_{is}\Phi + \boldsymbol{Z}_{isg}\Psi + \Delta_c + \Lambda_s$$

where h_{isg} was the hazard of falling off track for student *i* in school *s* in grade *g* (conditional on being on track). The logit of the hazard was modeled as a function of grade fixed effects Γ_g, time-invariant student characteristics $\boldsymbol{X}_{is}$, time-variant student characteristics $\boldsymbol{Z}_{isg}$, cohort fixed effects Δ_c, and seventh-grade school fixed effects Λ_s. Standard errors were clustered at the initial school, and we estimated separate models for each college enrollment indicator. The key independent variable was the grade level during which a student first fell off track (ref. = 7th grade), meaning that they failed to meet the Chicago, HERC, or state indicator. The coefficients

[3] Through the person-period data structure, we retained all students with non-missing baseline data until they failed to meet an indicator. Students who left the district before they had a chance to fall off track were censored. Please contact the authors for additional details on the statistical modeling.

on the grade dummies indicated when students were at the greatest risk of falling off the college path, potentially suggesting the best time for practitioners to intervene. In addition to the grade dummies, the models controlled for baseline academic performance measures from sixth grade: total number of courses passed[4], number of core courses failed, attendance rate, average course grade, number of advanced courses passed, reading test scores, and math test scores. Other controls included age, gender, race and ethnicity, English learner status, special education status, economic disadvantage, and the number of in-school and out-of-school suspensions. Most covariates remained constant over time, while the suspension controls varied by grade level. Finally, we accounted for school context with seventh-grade school fixed effects and school year differences through a cohort dummy (ref. = 2007-2008).

Main Results

Figure 1 presents graphs generated from the event history analyses of the Chicago, HERC, and state indicators (full regression tables are in the Appendix). Each graph includes two plots. First, the hazard curve shows the percentage of students who failed to meet an indicator in each grade. A higher hazard curve in a given grade level means that more students are falling off track, suggesting a potential point for intervention by a practitioner. The second plot in each graph shows the survival curve, a cumulative measure showing the share of students still on track at the end of each grade. For instance, if the survival curve in 12th grade is at 40 percent, it indicates that only two-fifths of students met the indicator each year from seventh to 12th grade. Each plot has two lines: the dotted line represents the hazard or survival curve unadjusted for

[4] We controlled for the total number of courses passed instead of the total number of courses failed (as used in the Chicago indicator) to avoid multicollinearity in statistical modeling. The correlation between the sixth-grade total and core course failure variables was 0.93.

covariates, while the solid line shows the curve adjusted for covariates (includes the full set of controls and fixed effects).

[Insert Figure 1 Here]

In Figure 1A, we show hazard and survival curves from models predicting failure to meet the Chicago indicator by grade level. Adjusting for covariates, the plot of the hazard curve shows that in ninth grade, a higher share of students failed to meet the Chicago indicator (19%). In comparison, 14 percent of students failed to meet the indicator in seventh grade, 16 percent failed to meet it in 10th grade, and 15 percent failed to meet it in 11th grade. These results are consistent with prior research that demonstrates that the freshman year of high school is key to predicting graduation (Allensworth & Easton, 2005). Turning to the survival curve, by high school graduation, about 46 percent of students did not meet the Chicago indicator at least once, while 54 percent met it each year from seventh to 12th grade.

Figure 1B plots hazard and survival curves from models predicting failure to meet the HERC indicator. With and without controls, it is clear that ninth grade is the most hazardous year for falling off track, with about 45 percent of students failing to meet the indicator that year. The hazard rate sharply attenuates after ninth grade, likely because the remaining students are increasingly high achieving. However, analyzing the hazard rate without controls may be misleading, as many seventh graders should not be considered on track at the start of the analysis — they may be lower-achieving students with little chance of college enrollment.[5] Once we control for covariates, including academic performance in sixth grade, the hazard curve changes. The adjusted hazard rate in seventh grade significantly reduces, confirming that ninth grade is the most hazardous year. The survival curve between eighth and ninth grade shows a steep

[5] In robustness checks, we limited the sample to students on-track in sixth grade. Results were substantively similar to those discussed.

decline, indicating that a significant share of students did not meet the HERC indicator in ninth grade. By the end of the eighth grade, most students (58%) were still on track, having met the indicator in both seventh and eighth grades. However, by the end of the ninth grade, only 32 percent of students were still on track. By the end of high school, that number dropped further: only 10 percent of students met the HERC indicator each year from grade seven to 12, while 90 percent failed to meet it at least once.

Figure 1C plots unadjusted and adjusted curves for the test score outcome — failure to score above the cutoffs in reading and math. This outcome includes only four years of data because state tests were not administered in 12th grade. With controls, the grade with the highest percentage of students falling off track was seventh grade (24%); afterward, the hazard curve flattened and remained stable. This pattern contrasts with the Chicago and HERC indicator results. By the end of the final test administration in 11th grade, 55 percent of students met the state indicator every year from grade seven to 11, while 45 failed to meet it at least once.

Overall, the event history analyses show that according to the HERC and Chicago indicators, students were at greater risk of falling off track in ninth grade. They are less likely to achieve key benchmarks like earning high grades and passing advanced courses that year. Practitioners concerned with low college enrollment rates may consider monitoring college readiness indicators during the freshman year and possibly implement an intervention for students who appear to be off track. Interestingly, the test score-based indicator did not show a similar ninth-grade spike. A higher share of students failed to meet the state indicator in seventh grade, the first year examined in this study, while the trend remained flat afterward.

This pattern may reflect the strong correlation in test scores year-to-year (Gibbs et al., 2023). In an additional analysis, we found that state indicators from non-sequential and distant years still had moderate and statistically significant tetrachoric correlations.[6] Furthermore, test scores may not capture changes in student effort or external shocks impacting student performance (Galla et al., 2019; Wentzel, 1989; Willingham et al., 2002). The increased hazard rate in ninth grade for the HERC indicator may partially reflect the transition to high school, where the structural move and increased expectations can challenge students and affect their performance (Cohen & Smerdon, 2009; Neild, 2009). These changes, however, may not affect students' ability to take a standardized test.

Results by Subgroup

Aside from the main results, we examined patterns across sociodemographic subgroups by incorporating interaction terms to test for heterogeneous effects by gender, race and ethnicity, and economic disadvantage. These models allowed us to determine whether the grade level during which students fell off track, as measured by the Chicago, HERC, and state indicators, varied by student background. Generally, patterns by grade were similar across groups: regardless of demographic or socioeconomic background, ninth grade was a challenging year in terms of the HERC indicator and, to an extent, the Chicago indicator. For the state indicator, seventh grade (the first year of our analyses) was when a plurality of students fell off track.

Although the grade-level patterns were somewhat similar, we found that the ninth-grade hazard rate varied by subgroup. Appendix Figures 3-5 reveal that male, Black, Hispanic, and economically disadvantaged students were less likely to meet the Chicago, HERC, and state indicators compared to female, White, Asian, and non-economically disadvantaged students. This is evident in the hazard curves, which are higher and steeper for these groups. For example, 15 percent of White students and 12 percent of Asian students failed to meet the HERC indicator

[6] These results are available from the authors upon request.

in ninth grade. In contrast, Black and Hispanic students were much more likely to not meet the indicator, with hazard rates of 64 and 53 percent, respectively. Similarly, we observed large differences by economic disadvantage: while one-quarter of non-disadvantaged students failed to meet the HERC indicator in ninth grade, the rate for disadvantaged students was more than twice as high, at 58 percent. The transition from middle school to high school appeared particularly challenging for students from historically marginalized backgrounds. If we assume the HERC indicator is a reliable predictor of college outcomes, these findings suggest that school and district practitioners should consider targeting male, Black, Hispanic, and economically disadvantaged students with extra support in ninth grade to help keep them on track for college.

To test the robustness of our findings, we controlled for time-varying characteristics that proxy each school's opportunity structure. Specifically, we accounted for the share of students taking advanced coursework, the share of economically disadvantaged students, the student-teacher ratio, and the average level of teacher experience. Adding these covariates did not alter the results. In another check, we limited the sample to students who followed a traditional pathway to college by excluding those who transferred schools or districts, dropped out, were retained, or graduated early (i.e., students who continuously attended HISD schools for six years). We also estimated models with a sample limited to students who were on track in sixth grade. Again, our findings remained consistent with these restrictions: ninth grade was the most hazardous year using the Chicago and HERC indicators, while seventh grade was the most hazardous year for the state indicator.

Supplementary Analyses

Our analyses indicate that ninth grade is a challenging time for adolescent students, with many at a higher risk of falling off track from the pathway to college enrollment. But is ninth grade the best time to intervene? If a practitioner finds that a student is not meeting college readiness benchmarks early on, should they wait until ninth grade to help the student get back on track? Since academic performance in ninth grade is tied to performance in earlier grade levels (Gibbs et al., 2023), a student's on- or off-track status is likely tied to their on- or off-track status in the seventh and eighth grades. Therefore, teachers and counselors who notice a student is struggling and not meeting benchmarks early on may consider intervening sooner than later to help the student get back on track before the transition to high school.

Using structural equation modeling, we examined how each grade-level indicator predicted college enrollment, considering both the direct and indirect effects of each grade-level indicator on enrollment. For example, there may be a direct effect of the seventh-grade indicator on college enrollment, but there may be indirect effects as well. Specifically, a student's on- or off-track status in seventh grade may affect their status in eighth, ninth, and subsequent grade levels. Appendix Figure 6 plots the total effects from our structural equation model — how the grade-specific Chicago, HERC, and state indicators predicted college enrollment, considering that indicators in earlier grades predicted indicators in later grades. Across all three indicators, the seventh-grade measures (orange lines) show the strongest associations with college enrollment. This relationship is most pronounced for the state indicator, where the 95 percent confidence interval of the seventh-grade measure does not overlap with the confidence interval of any other grade-level measure. The associations between the grade-level measures and college enrollment vary the most for the HERC indicator, possibly capturing the importance of the ninth-grade transition as well as the year in which many students begin their college search. Regardless, the patterns suggest that, when considering the cumulative nature of these indicators, the seventh-grade measure has the strongest association with college enrollment.

We must clarify that we do not imply that seventh grade is more important than other grade levels. The strong association we find may be due to it being the earliest grade in our analysis, which mechanically has the greatest potential to influence subsequent grade levels. Nonetheless, the analysis may suggest that practitioners ought to identify at-risk students for earlier intervention, which could yield more benefits than intervening in later grades. Indeed, the event history analyses indicated that ninth grade is a challenging year for students, as reflected by the Chicago and HERC indicators. While intervening in earlier grades may have a greater impact, providing additional support to ninth-grade students may also be essential, especially since this transition seems to be when students are most likely to fall off track from college.

Discussion

Using data readily available in school districts, we explored potential college readiness indicators that practitioners might use to identify and target students at risk of not attending college. Our goal was to determine when students might be at risk of not meeting these indicators in order to provide guidance on when practitioners might decide to intervene. We discovered that the HERC indicator was the strongest predictor of college enrollment. In addition to demonstrating high rates of correct overall predictions, it reliably predicted outcomes for the majority of students who did not enroll in college, particularly when using the indicator from later grades. Predicting non-enrollment for non-college enrollees is crucial for practitioners. Accurate information can assist them in targeting their early intervention efforts toward students who are unlikely to enroll in college. It is also important to precisely predict outcomes for those who are likely to enroll. Practitioners may prefer not to allocate their time to students who are already on track to attend college without additional support. Overall, accurate enrollment forecasting can guide educational decision-makers in distributing resources more effectively.

Our event history analyses revealed that the ninth-grade transition poses significant challenges in terms of meeting the Chicago and HERC indicators, with more students falling off track that year. We observed a dissimilar pattern with the state indicator, which was based on test score cutoffs. There are two potential reasons for this finding. First, test score measures are strongly associated year-to-year (Gibbs et al., 2023). Indicators from adjacent grade levels should be expected to correlate with each other since academic performance may not change significantly within a single year. In contrast, indicators from non-sequential and distant years should have muted correlations (Gibbs et al., 2023). If test scores measures like the state indicator are more stable over time compared to measures like course-taking and grades earned, which make up the Chicago and HERC indicators, that may explain why the state indicator's hazard curve changes little after the seventh grade.

A second reason why the Chicago and HERC indicators may show different patterns from the state indicator is that the Chicago and HERC indicators could capture factors beyond academic ability (Galla et al., 2019; Wentzel, 1989; Willingham et al., 2002). A student must be academically skilled to receive an A or B in a course, but they also need to be engaged in their schoolwork by attending and participating in class, completing assignments, and studying for quizzes and tests. Naturally, levels of interest and effort can fluctuate, especially if students face issues like bullying, conflicts with teachers, school transfers, or family problems (Cohen & Smerdon, 2009; Neild, 2009). Test score-based measures, which tend to be consistent year-to-year (Gibbs et al., 2023), may be less susceptible to such changes in motivation, effort, or confounding events (Willingham et al., 2002), since they represent snapshots of student performance (i.e., state tests are typically administered near the end of the schoolyear). Of course, we must acknowledge that a primary reason why the Chicago and HERC indicators show higher hazard rates in ninth grade is likely due to the transition from middle to high school transition. This transition often involves a structural move (i.e., attending school in a new building), meeting new classmates and teachers, and an increase in the rigor of coursework (Cohen & Smerdon, 2009; Neild, 2009). All these factors can affect students' motivation and effort, along with their attendance, grades, and course choices.

In addition to the ninth-grade results, it is noteworthy that the HERC indicator's survival curve is steeper than the Chicago indicator's. This means that over time, more students failed to meet the HERC indicator than the Chicago indicator. Since the Chicago indicator was designed to predict high school graduation, we might consider it a more lenient benchmark for college enrollment. To be sure, the middle-to-high school transition is difficult, and many students may struggle to pass their classes. However, this transition can also be difficult for middle- and higher-performing students (i.e., those unlikely to drop out of high school). Although they may pass their classes and advance to the next grade, students may find it hard to meet the increased academic expectations, leading to lower grades or a decision to take easier coursework. The HERC indicator may represent a higher benchmark that affects all students who find the demands of high school challenging, not just those at greater risk of dropping out.

Implications

School and district leaders are uniquely positioned to bring stakeholders together to consider, plan, and implement strategies to improve college readiness. Based on our analyses, we recommend that these leaders focus on the ninth-grade transition, as it appears essential to keeping students on track to college. The potential college readiness indicators tested could be part of those efforts and assist school staff in identifying students for resources and support as part of an early warning system. Many school districts dedicate staff to identifying potential dropouts and providing these students with small-group instruction and counseling (Dynarski & Gleason, 2002). Building on these dropout prevention efforts, districts could develop systems to target and intervene with students at risk of not attending college. Students at risk of not attending college may share characteristics with students at risk of dropping out of high school. Early intervention may help practitioners and policymakers achieve their postsecondary goals and, in doing so, they may also curb high school dropout. Therefore, integrating college readiness indicators into existing early warning systems may satisfy two benchmarks, college enrollment and high school graduation, commonly used in school accountability systems.

Schools and districts may consider structural solutions, such as ninth-grade academies, which can address the fact that many students are changing schools between the eighth and ninth grades. Dedicated spaces for freshmen may allow teachers and staff to better orient students to the rigors and emotions of high school, facilitate advising around grades, coursework, and other college enrollment predictors, and monitor students to see if they are at risk of falling off track. The research on ninth-grade academies is either descriptive (Cook et al., 2008; Styron & Peasant, 2010) or finds null effects (Somers & Garcia, 2016). While dedicated structures and services that can support high school freshmen may be a strategy, additional investigation is warranted.

Although ninth grade is crucial, it is important to remember that the pathway to college starts early and is a continuum (Klasik, 2012; Roderick et al., 2011). Our findings showed that students who met the college readiness indicators for multiple years were more likely to enroll in college. Given this relationship, schools may consider adopting a college-ready curriculum spanning middle school through high school. Middle and high school educators should connect with each other, participate in professional development activities together, and engage in long-term planning to ensure a seamless transition from middle school to high school. This collaboration may offer students early opportunities to learn about college and take advanced coursework.

We must caution that the college readiness indicators tested may not perform equally well for all sociodemographic groups, potentially underestimating college enrollment rates among more advantaged populations like White and non-economically disadvantaged students. These students might have additional support outside the classroom, which was not considered in our analyses, and which could encourage college enrollment despite lower academic performance. Furthermore, our indicators focused solely on any college enrollment and did not distinguish between two- and four-year institutions or between broad access and selective four-year institutions. If schools and districts aim to improve more selective college choice, they may need to develop indicators tailored to the requirements of those institutions (e.g., increasing the number of advanced courses passed in the HERC indicator).

As college enrollment increasingly becomes a part of accountability systems, school and district leaders may seek new strategies to achieve their postsecondary goals. This study shows how educational leaders can develop and use simple indicators to identify students at risk of not attending college and examines when students are most likely to fall off track. The HERC indicator, which was based on attendance rates, grades, and advanced course-taking, appeared to be more effective at predicting college enrollment than an indicator geared toward high school graduation and an indicator solely based on test scores. We also found that ninth grade was when students were at the greatest risk of falling off track. Based on these findings, we recommend that practitioners incorporate this information into existing early warning systems and focus on identifying and supporting students, especially during the ninth-grade transition.

References

Adelman, C. (2006). *The Toolbox Revisited: Paths to Degree Completion from High School through College*. Washington, DC: U.S. Department of Education. https://eric.ed.gov/?id=ED490195

Allensworth, E. (2013). The Use of Ninth-Grade Early Warning Indicators to Improve Chicago Schools. *Journal of Education for Students Placed at Risk, 18*(1), 68–83.

Allensworth, E. M., & Clark, K. (2020). High School GPAs and ACT Scores as Predictors of College Completion: Examining Assumptions About Consistency Across High Schools. *Educational Researcher, 49*(3), 191–211.

Allensworth, E. M., & Easton, J. Q. (2005). *The On-Track Indicator as a Predictor of High School Graduation*. Chicago, IL: The University of Chicago Consortium on Chicago School Research. https://consortium.uchicago.edu/publications/track-indicator-predictor-high-school-graduation

Allensworth, E. M., & 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*. Chicago, IL: Consortium on Chicago School Research at the University of Chicago. https://eric.ed.gov/?id=ED498350

Allensworth, E. M., Gwynne, J. A., Moore, P., & de la Torre, M. (2014). *Looking Forward to High School and College: Middle Grade Indicators of Readiness in Chicago Public Schools*. Chicago, IL: The University of Chicago Consortium on Chicago School Research. https://eric.ed.gov/?id=ED553149

Attewell, P. A., & Domina, T. (2008). Raising the Bar: Curricular Intensity and Academic Performance. *Educational Evaluation and Policy Analysis, 30*(1), 51–71.

Balfanz, R., & Byrnes, V. (2012). *The Importance of Being There: A Report on Absenteeism in the Nation's Public Schools*. Baltimore, MD: Johns Hopkins University Center for Social Organization of Schools. https://eric.ed.gov/?id=EJ1002822

Borsato, G. N., Nagaoka, J., & Foley, E. (2013). College Readiness Indicator Systems Framework. *Voices in Urban Education, 38*, 28–35.

Bowen, W. G., Chingos, M. M., & McPherson, M. S. (2009). Test Scores and High School Grades as Predictors. In *Crossing the Finish Line: Completing College at America's Public Universities* (pp. 112–133). Princeton, NJ: Princeton University Press.

Bowers, A. J., Sprott, R., & Taff, S. A. (2013). Do We Know Who Will Drop Out?: A Review of the Predictors of Dropping out of High School: Precision, Sensitivity, and Specificity. *The High School Journal, 96*(2), 77–100.

Carneiro, P., & Heckman, J. J. (2003). Human Capital Policy. In J. J. Heckman & A. B. Krueger (Eds.), *Inequality in America: What Role for Human Capital Policies?* (pp. 77–239). Cambridge, MA: MIT Press.

Carnevale, A. P., Smith, N., Van Der Werf, M., & Quinn, M. C. (2023). *After Everything: Projections of Jobs, Education, and Training Requirements through 2031*. Washington, DC: Georgetown University Center on Education and the Workforce. https://cew.georgetown.edu/cew-reports/projections2031/

Cohen, J. S., & Smerdon, B. A. (2009). Tightening the Dropout Tourniquet: Easing the Transition From Middle to High School. *Preventing School Failure: Alternative Education for Children and Youth, 53*(3), 177–184.

Conley, D. T. (2010). *College and Career Ready: Helping All Students Succeed Beyond High School*. San Francisco, CA: Jossey-Bass.

Cook, C., Fowler, H., & Harris, T. (2008). *Ninth Grade Academies: Easing the Transition to High School*. Raleigh, NC: North Carolina Department of Public Instruction. https://web.archive.org/web/20190924142411/www.ncpublicschools.org/docs/intern-research/reports/9thgradeacademies.pdf

Dauber, S. L., Alexander, K. L., & Entwisle, D. R. (1996). Tracking and Transitions through the Middle Grades: Channeling Educational Trajectories. *Sociology of Education, 69*(4), 290–307.

Dynarski, M., & Gleason, P. (2002). How Can We Help? What We Have Learned From Recent Federal Dropout Prevention Evaluations. *Journal of Education for Students Placed at Risk, 7*(1), 43–69.

Fox, J. H., & Balfanz, R. (2020). Keeping Students on Track to Postsecondary Success: Learnings from the Pathways to Adult Success (PAS) Initiative. *Teachers College Record*, *122*(14), 1–24.

Galla, B. M., Shulman, E. P., Plummer, B. D., Gardner, M., Hutt, S. J., Goyer, J. P., D'Mello, S. K., Finn, A. S., & Duckworth, A. L. (2019). Why High School Grades Are Better Predictors of On-Time College Graduation Than Are Admissions Test Scores: The Roles of Self-Regulation and Cognitive Ability. *American Educational Research Journal*, *56*(6), 2077–2115.

Gamoran, A. (1992). Access to Excellence: Assignment to Honors English Classes in the Transition from Middle to High School. *Educational Evaluation and Policy Analysis, 14*(3), 185–204.

Geiser, S., & Santelices, M. V. (2007). *Validity of High School Grades in Predicting Student Success Beyond the Freshman Year: High School Record vs. Standardized Tests as*

Indicators of Four-Year College Outcomes (Research & Occasional Paper Series No. CSHE.6.07). Berkeley, CA: Center for Studies in Higher Education, University of California, Berkeley. https://eric.ed.gov/?id=ED502858

Gibbs, N. P., Pivovarova, M., & Berliner, D. C. (2023). Same Tests, Same Results: Multi-Year Correlations of ESSA-Mandated Standardized Tests in Texas and Nebraska. *Education Policy Analysis Archives, 31*(10).

Gleason, P., & Dynarski, M. (2002). Do We Know Whom to Serve? Issues in Using Risk Factors to Identify Dropouts. *Journal of Education for Students Placed at Risk*, *7*(1), 25–41.

Goldin, C., & Katz, L. F. (2008). *The Race between Education and Technolog*y. Cambridge, MA: The Belknap Press of Harvard University Press.

Hackmann, D. G., Malin, J. R., & Bragg, D. D. (2019). An Analysis of College and Career Readiness Emphasis in ESSA State Accountability Plans. *Education Policy Analysis Archives, 27*(160).

Hanushek, E. A., Ruhose, J., & Woessmann, L. (2017). Economic Gains from Educational Reform by US States. *Journal of Human Capital, 11*(4), 447–486.

Hein, V., Smerdon, B., & Sambolt, M. (2013). *Predictors of Postsecondary Success*. Washington, DC: College and Career Readiness and Success Center, American Institutes for Research. https://eric.ed.gov/?id=ED555671

Holzman, B., Klasik, D., & Baker, R. (2020). Gaps in the College Application Gauntlet. *Research in Higher Education, 61*(7), 795–822.

Hossler, D., Braxton, J., Coopersmith, G., & Smart, J. C. (1989). Understanding Student College Choice. In *Higher Education: Handbook of Theory and Research* (Vol. V, pp. 231–288). New York City, NY: Agathon Press.

Kemple, J. J., Segeritz, M. D., & Stephenson, N. (2013). Building On-Track Indicators for High School Graduation and College Readiness: Evidence from New York City. *Journal of Education for Students Placed at Risk, 18*(1), 7–28.

Klasik, D. (2012). The College Application Gauntlet: A Systematic Analysis of the Steps to Four-Year College Enrollment. *Research in Higher Education, 53*(5), 506–539.

Knudsen, E. I., Heckman, J. J., Cameron, J. L., & Shonkoff, J. P. (2006). Economic, neurobiological, and behavioral perspectives on building America's future workforce. *Proceedings of the National Academy of Sciences, 103*(27), 10155–10162.

Labaree, D. F. (1997). Public Goods, Private Goods: The American Struggle over Educational Goals. *American Educational Research Journal, 34*(1), 39–81.

Long, M. C., Conger, D., & Iatarola, P. (2012). Effects of High School Course-Taking on Secondary and Postsecondary Success. *American Educational Research Journal, 49*(2), 285–322.

Mac Iver, M. A., & Messel, M. (2013). The ABCs of Keeping On Track to Graduation: Research Findings from Baltimore. *Journal of Education for Students Placed at Risk, 18*(1), 50–67.

Malin, J. R., Bragg, D. D., & Hackmann, D. G. (2017). College and Career Readiness and the Every Student Succeeds Act. *Educational Administration Quarterly, 53*(5), 809–838.

McDonough, P. M. (1997). *Choosing Colleges: How Social Class and Schools Structure Opportunity*. Albany, NY: State University of New York Press.

Moore, R., & Croft, M. (2018). *Reducing Barriers to Educator Data Use*. Iowa City, IA: ACT Inc. https://www.act.org/content/act/en/research/pdfs/R1662-data-use-barriers-2018-01.html

National Center for Education Statistics. (2022). Enrollment, poverty, and federal funds for the 120 largest school districts, by enrollment size in 2021: School year 2019-20 and fiscal year 2022 (Table 215.30). In *Digest of Education Statistics*. https://nces.ed.gov/programs/digest/d22/tables/dt22_215.30.asp

Neild, R. C. (2009). Falling Off Track during the Transition to High School: What We Know and What Can Be Done. *The Future of Children*, *19*(1), 53–76.

Project Unicorn. (2023). *The State of the Sector 2023*. New York City, NY: InnovateEDU. https://drive.google.com/file/d/1ari0N2Il_kG30jmithdb3J_jGJGh4Vjc/view

Roderick, M., Coca, V., & Nagaoka, J. (2011). Potholes on the Road to College: High School Effects in Shaping Urban Students' Participation in College Application, Four-year College Enrollment, and College Match. *Sociology of Education*, *84*(3), 178–211.

Royster, P., Gross, J., & Hochbein, C. (2015). Timing is Everything: Getting Students Back on Track to College Readiness in High School. *The High School Journal*, *98*(3), 208–225.

Sandefur, G. D., Meier, A. M., & Campbell, M. E. (2006). Family resources, social capital, and college attendance. *Social Science Research*, *35*(2), 525–553.

Soland, J. (2013). Predicting High School Graduation and College Enrollment: Comparing Early Warning Indicator Data and Teacher Intuition. *Journal of Education for Students Placed at Risk*, *18*(3-4), 233–262.

Soland, J. (2017). Combining Academic, Noncognitive, and College Knowledge Measures to Identify Students Not on Track For College: A Data-Driven Approach. *Research & Practice in Assessment*, *12*(Summer), 5–19.

Somers, M.-A., & Garcia, I. (2016). *Helping Students Make the Transition into High School: The Effect of Ninth Grade Academies on Students' Academic and Behavioral Outcomes*. New York City, NY: MDRC. https://eric.ed.gov/?id=ED566404

Stanford University John W. Gardner Center for Youth and Their Communities. (2014). *Menu of College Readiness Indicators and Supports* (College Readiness Indicator Systems Resource Series). Seattle, WA: Bill & Melinda Gates Foundation. https://eric.ed.gov/?id=ED565475

Styron, R. A., & Peasant, E. J. (2010). Improving Student Achievement: Can Ninth Grade Academies Make A Difference? *International Journal of Education Policy and Leadership*, *5*(3).

Texas Education Agency. (2007). *Glossary for the Academic Excellence Indicator System, 2006-07 Report*. Austin, TX: Author. https://rptsvr1.tea.texas.gov/perfreport/aeis/2007/glossary.html

Texas Education Agency. (2018). *2018 Accountability Manual for Texas Public School Districts and Campuses*. Austin, TX: Author. https://tea.texas.gov/2018accountabilitymanual.aspx

Torres, D. D., Bancroft, A., & Stroub, K. (2015*). Evaluating High School Dropout Indicators and Assessing Their Strength*. Houston, TX: Houston Education Research Consortium, Kinder Institute for Urban Research, Rice University. https://kinder.rice.edu/research/evaluating-high-school-dropout-indicators-and-assessing-their-strength

Wentzel, K. R. (1989). Adolescent Classroom Goals, Standards for Performance, and Academic Achievement: An Interactionist Perspective: Journal of Educational Psychology. *Journal of Educational Psychology*, *81*(2), 131–142.

Willingham, W. W., Pollack, J. M., & Lewis, C. (2002). Grades and Test Scores: Accounting for Observed Differences. *Journal of Educational Measurement, 39*(1), 1–37.

Zheng, Y., Gao, X., Shen, J., Johnson, M. R., & Krenn, H. Y. (2023). A Meta-Analysis of the Predictors of On-time High School Graduation in the United States. *NASSP Bulletin, 107*(2), 130–155.

Figures

Figure 1. Falling Off Track Based on the Chicago, HERC, and State Indicators

Figure 1A. Chicago Indicator

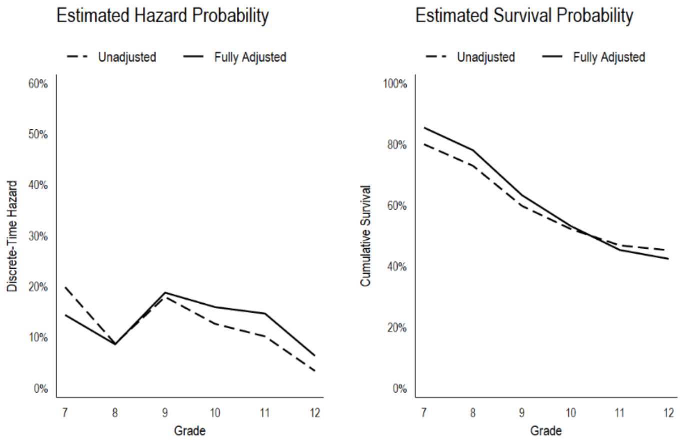


Figure 1B. HERC Indicator

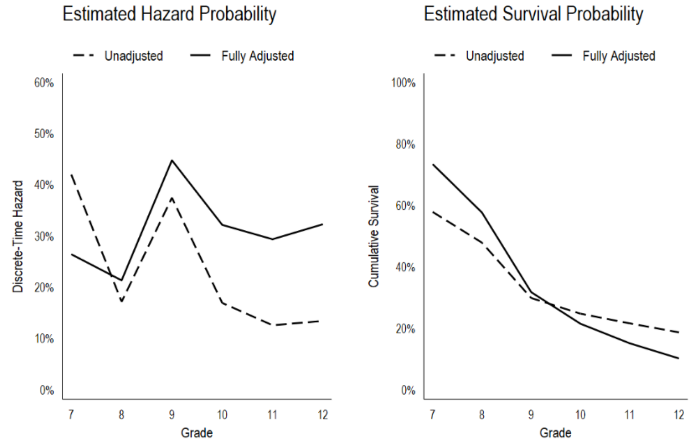
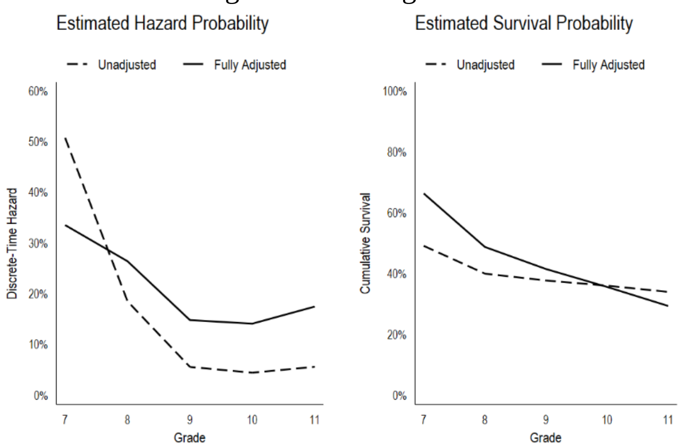


Figure 1C. Chicago Indicator



Note. Sample is limited to 17,879 non-Native American students with non-missing data. Results come from discrete-time hazard models. The unadjusted model includes grade fixed effects, while the fully adjusted model adds control variables, cohort fixed effects, and initial school fixed effects.

Tables

Table 1. College Readiness Indicators Used in the Analyses			
Indicator	*Developer*	*Origin*	*Definition Used in Study*
Chicago	University of Chicago Consortium on School Research	This indicator was developed to predict high school graduation (Allensworth & Easton, 2005). At the end of ninth grade, students were classified as on track if they earned five course credits — the minimum number to advance to 10th grade in Chicago Public Schools — and had at most one semester grade of F in a core subject (English, math, science, or social studies). Despite its simplicity, the indicator was considered an accurate predictor of high school graduation (Bowers et al., 2013).	Had at most two semester Fs in any subject and had at most one semester F in a core subject (English, math, science, or social studies)[7]
HERC	Rice University Houston Education Research Consortium	By reviewing relevant literature and analyzing HERC data, our goal was to develop an indicator that was relatively easy for a school or district practitioner to calculate and assess (like Chicago's) and was more tied to college enrollment; additional details are available in Appendix A. Three components were considered — attendance rates, grades earned in courses taken, and advanced courses passed. Advanced courses referred to pre-Advanced Placement (AP), pre-International Baccalaureate (IB), AP, IB, or academic dual credit[8] courses.	Had an attendance rate of 90% or higher, had a B-average (80% or higher), and passed any semester-long advanced course
State	Texas Education Agency Academic Excellence Indicator System	During the 2006-2007 school year, the state of Texas incorporated a measure called College-Ready Graduates into its annual school performance reports (Texas Education Agency, 2007). This measure identified students who met benchmarks on the state English/language arts test, state mathematics test, SAT test, or ACT test.	Met the benchmark on the English/language arts and mathematics tests[9,10]

[7] This definition represents a slight alteration from the Chicago on-track indicator. The course credits variable in the HISD data did not appear reliable: there was missing data, the student credits data did not always align with the course catalog records, and the student credits data did not always align with the term or grades data. In Chicago, high school students typically complete 6 credits each year. Therefore, earning 5 of 6 credits is equivalent to failing 1 full-year course or 2 semester-long courses. Therefore, we substituted the 5 credits component of the Chicago indicator with having at most 2 semester Fs in HISD. A semester-long course with a grade below 69.5 percent counted as a semester F.

[8] Academic dual credit courses were dual credit courses that were not classified as Career & Technical Education.

[9] Although the College-Ready Graduates measure incorporated multiple tests, the study focused on the state English/language arts and mathematics tests since the goal was to generate annual measures.

[10] English/language arts and mathematics cutoffs were based on the 11th-grade tests — 2200 for English/language arts and 2200 for mathematics. The numerical cutoffs were identical for the two subjects and did not change over time. Cutoffs identified in the test score distribution were applied to tests in other grades. For example, the mathematics cutoff for the 11th-grade test in 2007-2008 corresponded to a standardized score of -0.24. In the same year, a standardized score of -0.24 corresponded to a raw score of 2175.68 on the seventh-grade mathematics test. This raw score was the cutoff used to determine whether a student met the mathematics standard in seventh grade.

Table 2. Correct Predictions of Potential College Readiness Indicators, by Grade

Panel A. 7th Grade Indicators					
Indicator	Tetrachoric Corr.	Pseudo-R^2	Correct Overall	Correct Positive	Correct Negative
Base Model					
Chicago	0.36	0.03	62%	93%	20%
HERC	0.45	0.06	66%	78%	49%
State	0.43	0.06	65%	69%	59%
Add Sociodemographic Characteristics					
Chicago		0.11	66%	78%	49%
HERC		0.12	67%	80%	50%
State		0.12	68%	76%	56%
Add Cohort and Initial School Fixed Effects					
Chicago		0.13	69%	80%	53%
HERC		0.14	69%	79%	54%
State		0.14	68%	77%	55%
Panel B. 9th Grade Indicators					
Indicator	Tetrachoric Corr.	Pseudo-R^2	Correct Overall	Correct Positive	Correct Negative
Base Model					
Chicago	0.40	0.04	64%	89%	29%
HERC	0.50	0.08	66%	61%	72%
State	0.42	0.05	65%	81%	43%
Add Sociodemographic Characteristics					
Chicago		0.12	67%	82%	47%
HERC		0.14	69%	73%	62%
State		0.12	67%	81%	49%
Add Cohort and Initial School Fixed Effects					
Chicago		0.16	69%	78%	57%
HERC		0.17	71%	78%	61%
State		0.15	69%	78%	55%
Panel C. 11th Grade Indicators					
Indicator	Tetrachoric Corr.	Pseudo-R^2	Correct Overall	Correct Positive	Correct Negative
Base Model					
Chicago	0.51	0.07	67%	89%	36%
HERC	0.57	0.11	69%	65%	73%
State	0.46	0.06	66%	79%	49%
Add Sociodemographic Characteristics					
Chicago		0.13	69%	84%	49%
HERC		0.16	71%	76%	63%
State		0.12	68%	80%	52%
Add Cohort and Initial School Fixed Effects					
Chicago		0.17	71%	81%	57%
HERC		0.19	72%	78%	63%
State		0.16	70%	79%	57%

Note. Sample is limited to 11,912 non-Native American students who attended HISD schools for 6 years and had non-missing data. Correct positive predictions refer to situations in which a student who enrolled in college had a predicted probability of enrollment greater than or equal to 0.50 based on the logistic regression model. Correct negative predictions refer to situations in which a student who did not in college had a predicted probability of enrollment less than 0.50 based on the model. Correct overall predictions combined correct positive and negative predictions.

Appendix

Development of the HERC Indicator

The Chicago indicator used in this study was based on research by Allensworth and Easton (2005) but adapted for the HISD context and data. The state indicator was based on a college readiness metric used in the Texas Education Agency's school accountability system (2007). We developed the HERC indicator given the absence of simple early warning indicators for college enrollment and consulted research briefs and peer-reviewed journal articles for guidance (Allensworth & Easton, 2007; Allensworth et al., 2014; Hein et al., 2013; Kemple, et al., 2013; Mac Iver & Messel, 2013; Torres et al., 2015). Informed by research, we explored the HISD data in an iterative, data-driven way.

Inspired by the Chicago indicator, we sought to create an intuitive indicator that a practitioner might be able to generate on their own. The Chicago indicator was based on students' course-taking and grades in the freshman year of high school. Research shows that grades are better predictors of success in higher education than test scores (Allensworth & Clark, 2020; Bowen et al., 2009; Galla et al., 2019; Geiser & Santelices, 2007). Grades reflect not only academic performance but also a student's motivation and effort in school (Galla et al., 2019; Willingham et al., 2002), which aligns with the non-cognitive factors outlined in the Conley (2010) and CRIS (Borsato et al., 2013) college readiness frameworks. Passing classes and accumulating credits are necessary steps toward enrolling in college, but they may be considered a low bar for entry, especially since research shows that advanced course-taking is associated with college enrollment (Adelman, 2006; Attewell & Domina, 2008; Long, et al., 2012). In addition, our emphasis on advanced, rather than total, courses passed is in line with the state accountability system's new College, Career, and Military Readiness component, which students can meet by completed a predetermined number of dual credit courses or earning high scores on Advanced Placement and International Baccalaureate tests (Texas Education Agency, 2018).

Using the HISD data, we estimated logistic regression models to predict college enrollment, including controls for student background characteristics, as well as school and cohort effects. We incorporated measures that aligned with what Fox & Balfanz (2020, p. 12) refer to as "[t]he ABCs of K-12 high school graduation and postsecondary success indicators": attendance, behavior, and course-taking/grades. From these models, we identified three key predictors of enrollment: attendance rates, grades earned, and advanced courses completed; suspensions showed weaker associations with college enrollment. To find the appropriate thresholds for these predictors, we examined analyzed descriptive statistics and kernel density plots, looking for natural breaking points — areas in the distributions that corresponded to a change in college enrollment. The tipping point for attendance was around 90 percent, which aligns with a common definition of chronic absenteeism (Balfanz & Byrnes, 2012), while for grades, it was approximately 80 percent, or a B-average.[11] Unfortunately, no clear natural breaking point emerged for the number of advanced courses completed. We tested various configurations through regression analysis, ranging from any to 18 advanced courses completed between the seventh and 12th grades. Examining the models' explained variances, we found that completing three year-long advanced courses had the lowest pseudo-R^2 (0.11), while the pseudo-R^2 for the other configurations ranged from 0.14-0.15. We ultimately chose the three-course definition, which corresponds to a student passing, on average, at least one semester-long

[11] According to the University of Chicago Consortium on School Research, "[s]tudents who earn Cs or Ds in high school are unlikely to graduate from college, while those with a B average (a 3.0 GPA) have about a 50/50 chance of earning a four-year college degree" (Allensworth et al., 2014, p. 55).

advanced course each year between grades seven and 12. Therefore, to meet the HERC indicator in a given grade, students had to satisfy these three conditions:

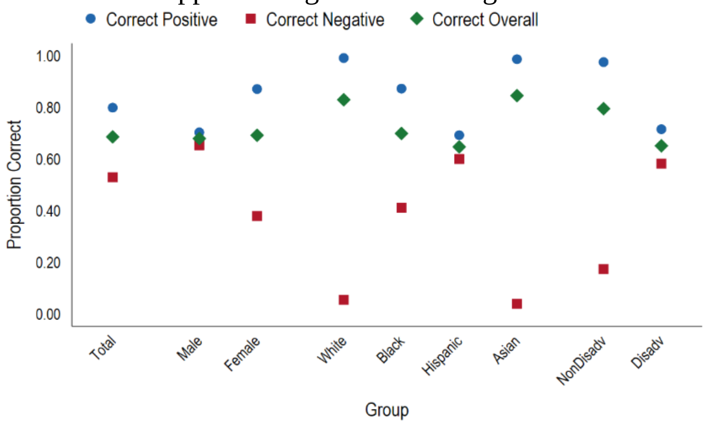
1. Not be classified as chronically absent (i.e., have an attendance rate at or above 90%)
2. Maintain a B-average among all classes taken (i.e., have a grade percentage at or above 80%)
3. Successfully pass at least one semester-long advanced course

Broadly, our goal was to develop an indicator that could shift the focus of early warning systems from high school to college and provide practitioners with an additional tool to achieve their objectives. It is important to note that the current definition of the HERC indicator is based on enrollment in any college or university. The indicator may not be appropriate if a school or district's objective is to promote four-year or more selective college enrollment. In that case, a practitioner may consider intensifying the components comprising the indicator, such as raising the grades and advanced courses thresholds (e.g., earning an A-average across all courses, passing at least two advanced courses). Furthermore, the HERC indicator may not be applicable in certain contexts. For example, if a school does not offer any advanced coursework, then the advanced course component may not be relevant and could be omitted. In sum, practitioners should carefully evaluate their school and district policies and practices before deciding to adopt the HERC indicator or any other indicator, aligning them with their specific college enrollment goals.

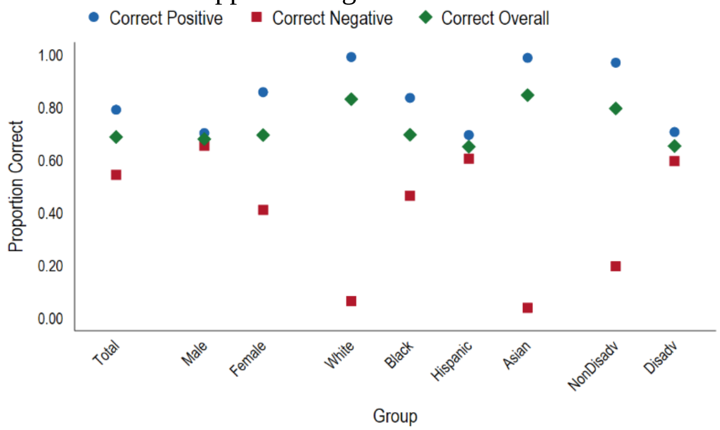
Appendix Figures

Appendix Figure 1. Correct Predictions of College Enrollment by Gender, Race, and SES Based on the Chicago, HERC, and State Indicators from Seventh Grade

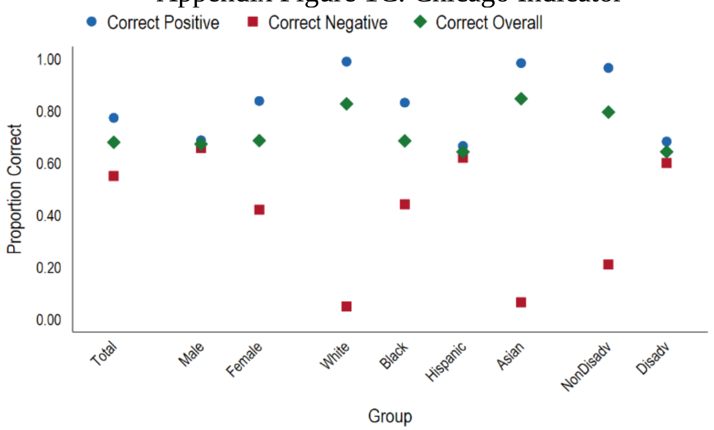
Appendix Figure 1A. Chicago Indicator



Appendix Figure 1B. HERC Indicator

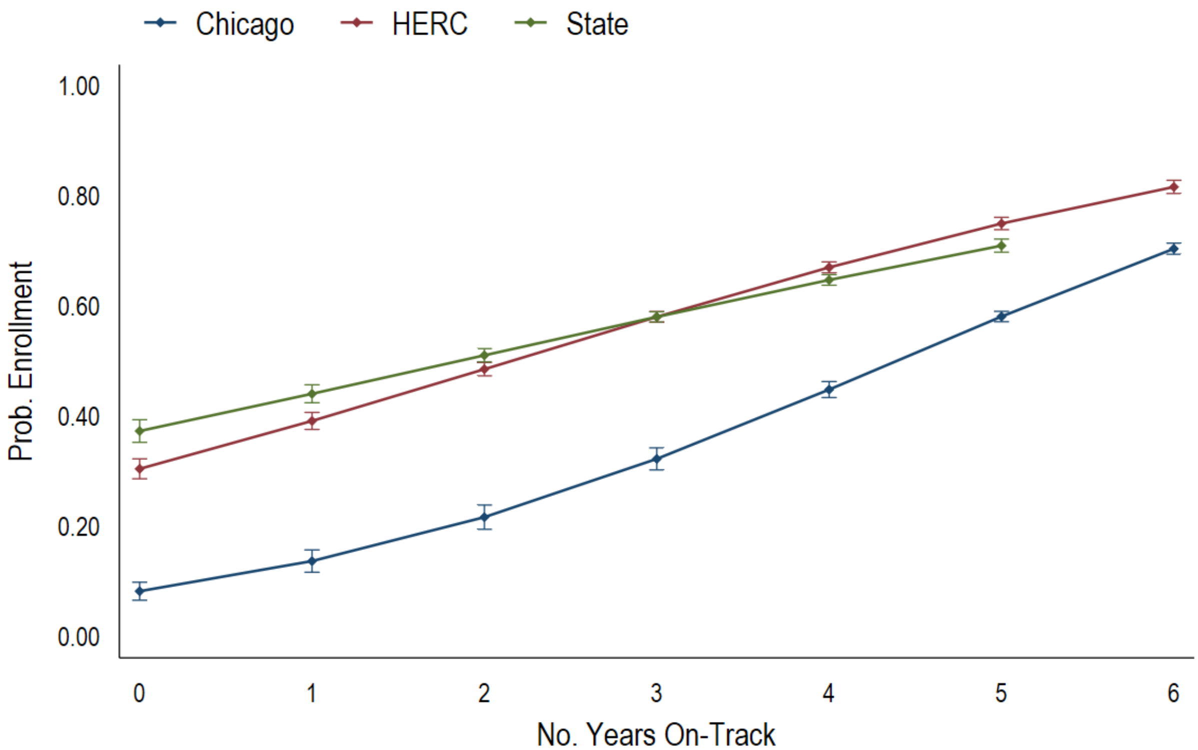


Appendix Figure 1C. Chicago Indicator



Note. Sample is limited to 11,912 non-Native American students who attended HISD schools for 6 years and had non-missing data. Results come from logistic regression models that predicted college enrollment and controlled for the Chicago, HERC, or state indicator in grade seven, as well as student background characteristics (age, gender, race/ethnicity, English learner, special education, economic disadvantage), cohort fixed effects, and initial school fixed effects.

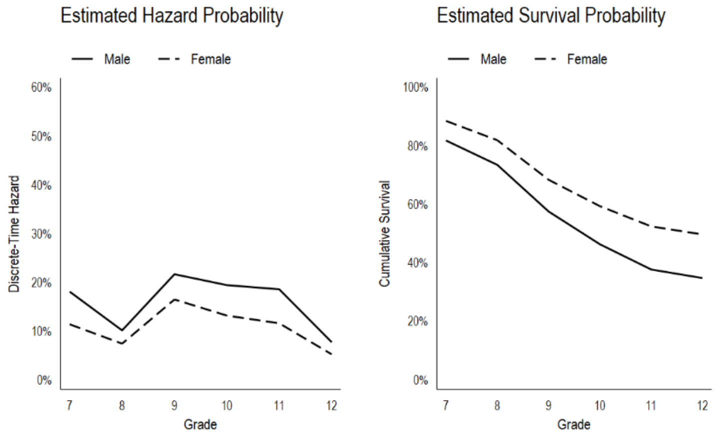
Appendix Figure 2. College Enrollment by the Number of Years On Track



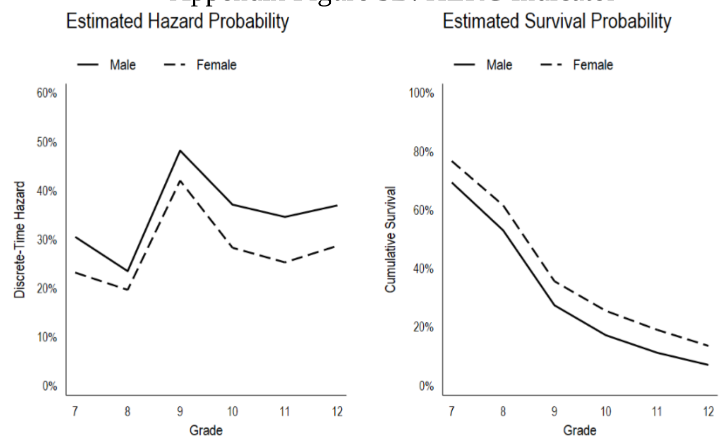
Note. Sample is limited to 11,318 non-Native American students who attended HISD schools for 6 years and had complete indicator data. Results come from logistic regression models that predicted college enrollment and controlled for the number of years a student met the Chicago, HERC, or state indicator, as well as student background characteristics (age, gender, race/ethnicity, English learner, special education, economic disadvantage), cohort fixed effects, and initial school fixed effects.

Appendix Figure 3. Falling Off Track Based on the Chicago, HERC, and State Indicators by Gender

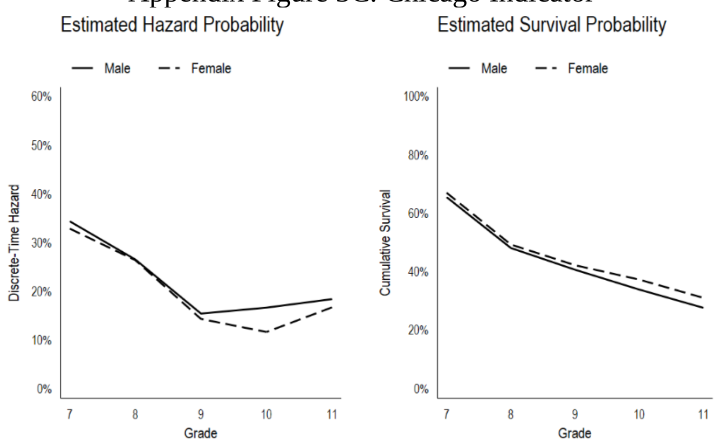
Appendix Figure 3A. Chicago Indicator



Appendix Figure 3B. HERC Indicator



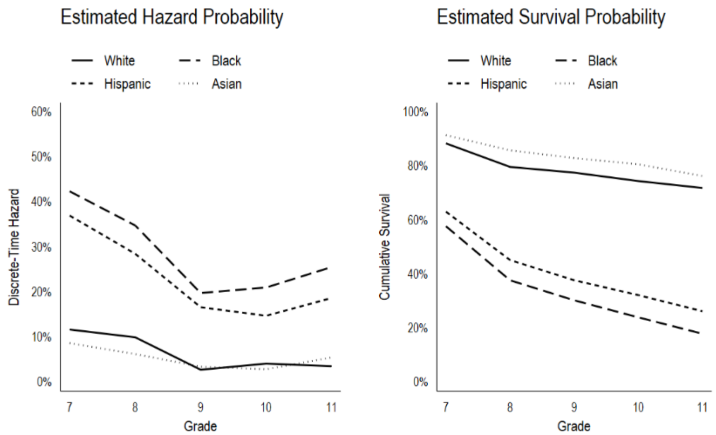
Appendix Figure 3C. Chicago Indicator



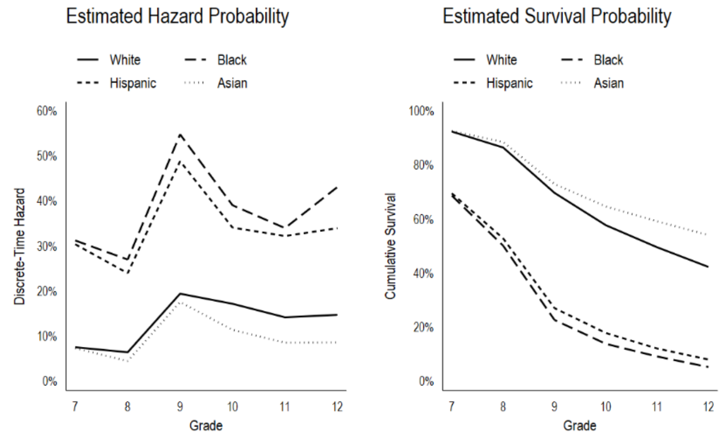
Note. Sample is limited to 17,879 non-Native American students with non-missing data. Results come from discrete-time hazard models with control variables, cohort fixed effects, and initial school fixed effects.

Appendix Figure 4. Falling Off Track Based on the Chicago, HERC, and State Indicators by Race

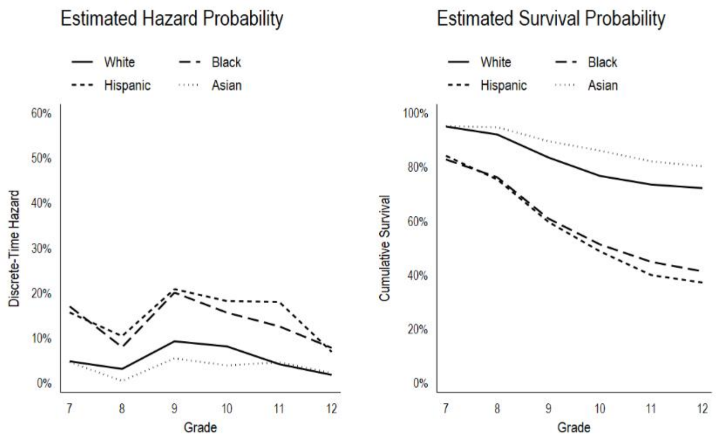
Appendix Figure 4A. Chicago Indicator



Appendix Figure 4B. HERC Indicator



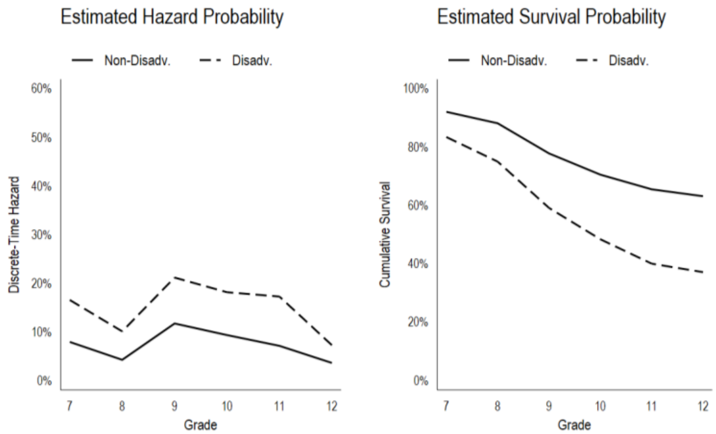
Appendix Figure 4C. Chicago Indicator



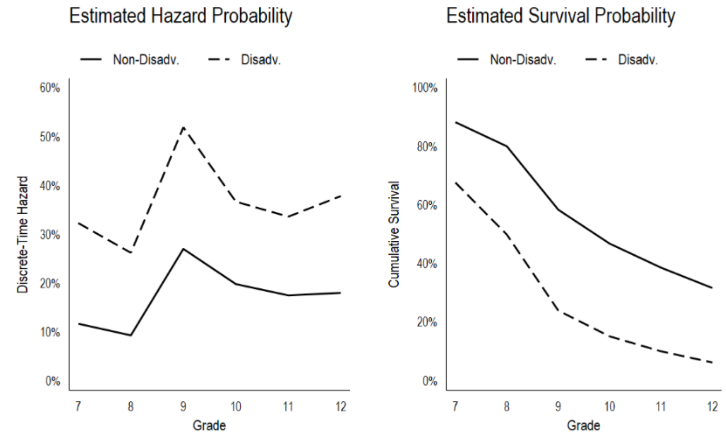
Note. Sample is limited to 17,879 non-Native American students with non-missing data. Results come from discrete-time hazard models with control variables, cohort fixed effects, and initial school fixed effects.

Appendix Figure 5. Falling Off Track Based on the Chicago, HERC, and State Indicators by SES

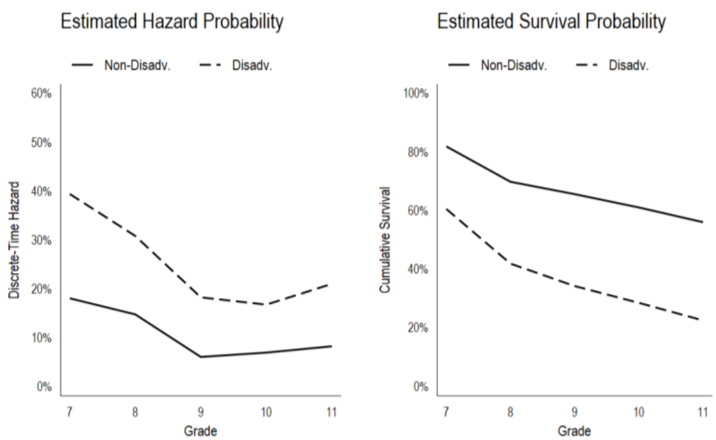
Appendix Figure 5A. Chicago Indicator



Appendix Figure 5B. HERC Indicator

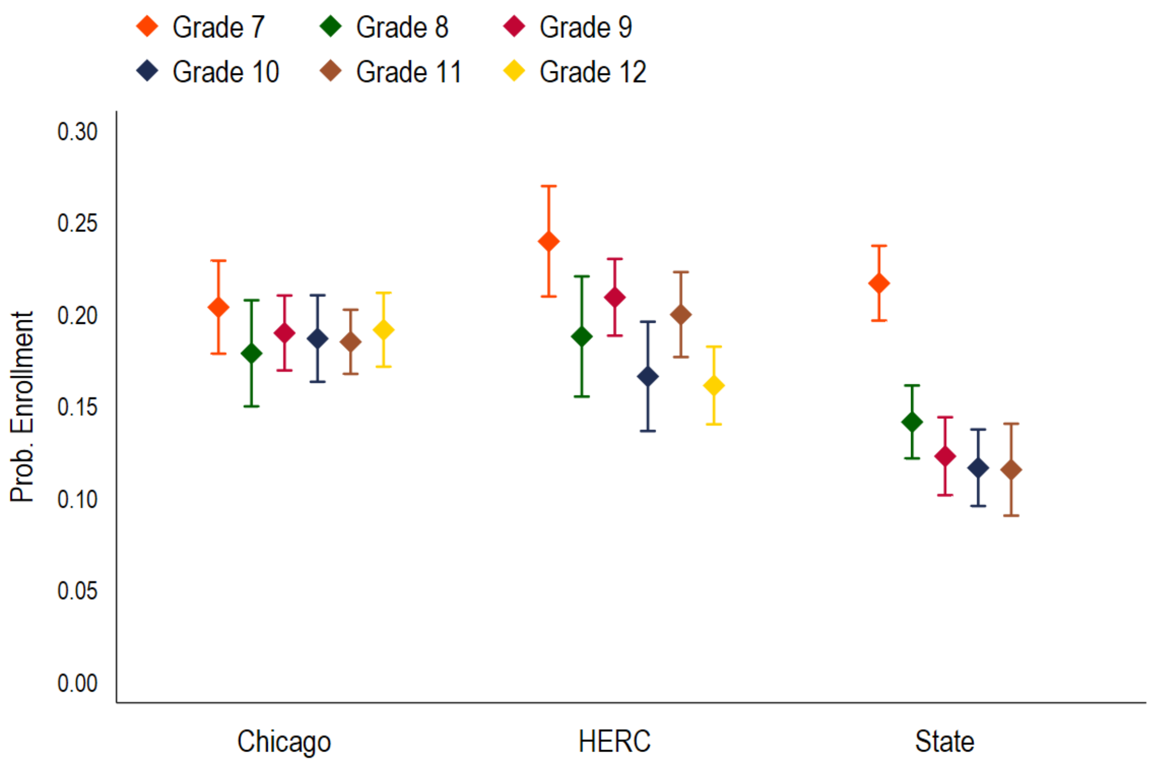


Appendix Figure 5C. Chicago Indicator



Note. Sample is limited to 17,879 non-Native American students with non-missing data. Results come from discrete-time hazard models with control variables, cohort fixed effects, and initial school fixed effects.

Appendix Figure 6. Total Effect of Potential Grade-Level Indicators on College Enrollment



Note. Sample is limited to 25,331 non-Native American students. Results come from full-information maximum likelihood structural equation models that predicted college enrollment and controlled for the Chicago, HERC, or state indicator in each grade, as well as student background characteristics (age, gender, race/ethnicity, English learner, special education, economic disadvantage) and cohort fixed effects.

Appendix Tables

Appendix Table 1. Control Variables Used in the Analyses

Variable	Description
Grade Level	Categorical: 7th (ref.), 8th, 9th, 10th, 11th, and 12th.
Number of Total Courses Passed in 6th Grade	Continuous: Courses failed (percentage grade below 69.5) are not counted. Semester-long courses count as 0.50 courses, while year-long courses count as 1.00 courses.
Number of Core Courses Failed in 6th Grade	Continuous.
Attendance Rate in 6th Grade	Continuous: Percentage of school days attended (reported in 10s).
Average Grade Percentage in 6th Grade	Continuous: Average percentage grade among all courses taken (reported in 10s).
Number of Advanced Courses Passed in 6th Grade	Continuous: Advanced courses include Pre-Advanced Placement (Pre-AP), Pre-International Baccalaureate (Pre-IB), AP, IB, and academic dual credit courses (i.e., dual credit courses that are not Career & Technical Education).
English/Language Arts Test Score in 6th Grade	Continuous: English/Language Arts test score from the Texas Assessment of Knowledge and Skills (TAKS; reported in standard deviation units).
Mathematics Test Score in 6th Grade	Continuous: Mathematics test score from the Texas Assessment of Knowledge and Skills (TAKS; reported in standard deviation units).
Age	Continuous.
Female	Binary.
Race/Ethnicity	Categorical: White (ref.), Black, Hispanic, and Asian.
English Learner	Binary.
Special Education	Binary.
Economically Disadvantaged	Binary: Eligible for the free and reduced-price lunch program or other federal poverty programs or living below the federal poverty line.
Number of In-School Suspensions	Continuous.
Number of Out-of-School Suspensions	Continuous.

Source. Houston Education Research Center (HERC) Longitudinal Database, 2007-2014.

Appendix Table 2. Study 1 Summary Statistics

Variable	Mean	SD
Age	12.29	(0.54)
Female	0.52	(0.50)
Black	0.24	(0.43)
Hispanic	0.62	(0.49)
Asian	0.04	(0.20)
English Learner	0.12	(0.32)
Special Education	0.05	(0.21)
Economically Disadvantaged	0.76	(0.43)

Note. Sample is limited to 11,912 non-Native American students who attended HISD schools for 6 years and had non-missing data.

Appendix Table 3. Study 2 Summary Statistics

Variable	Mean	SD
Ever Failed to Meet Chicago Indicator	0.49	(0.50)
Ever Failed to Meet HERC Indicator	0.77	(0.42)
Ever Failed to Meet State Indicator	0.64	(0.48)
No. Total Courses Passed in 6th Grade	7.07	(1.49)
No. Core Courses Failed in 6th Grade	0.27	(0.67)
Attendance Rate in 6th Grade (in 10s)	9.68	(0.39)
Average Grade Percentage in 6th Grade (in 10s)	8.43	(0.65)
No. Advanced Courses Passed in 6th Grade	1.77	(1.62)
Reading Test Score in 6th Grade (std.)	-0.19	(0.98)
Mathematics Test Score in 6th Grade (std.)	-0.20	(0.94)
Age	12.42	(0.66)
Female	0.52	(0.50)
Black	0.26	(0.44)
Hispanic	0.62	(0.48)
Asian	0.03	(0.17)
English Learner	0.13	(0.34)
Special Education	0.04	(0.19)
Economically Disadvantaged	0.79	(0.41)
No. In-School Suspensions	0.49	(1.28)
No. Out-of-School Suspensions	0.40	(1.05)
N (students)	17,816	

Note. Sample is limited to 17,879 non-Native American students with non-missing data.

Appendix Table 4. Log-Odds from a Discrete-Time Hazard Model of Failing to Meet the Chicago On-Track Indicator

Variable	Model 1			Model 2			Model 3		
	β	S.E.		β	S.E.		β	S.E.	
Grade (ref. = 7th)									
8th	-0.95	(0.04)	***	-0.72	(0.04)	***	-0.69	(0.04)	***
9th	-0.12	(0.03)	***	0.34	(0.03)	***	0.39	(0.03)	***
10th	-0.54	(0.04)	***	0.09	(0.04)	*	0.15	(0.04)	***
11th	-0.78	(0.04)	***	-0.02	(0.05)		0.03	(0.05)	
12th	-1.95	(0.07)	***	-1.12	(0.08)	***	-1.07	(0.08)	***
No. Total Courses Passed in 6th Grade				0.09	(0.01)	***	0.09	(0.02)	***
No. Core Courses Failed in 6th Grade				0.20	(0.03)	***	0.15	(0.03)	***
Attendance Rate in 6th Grade (in 10s)				-0.22	(0.04)	***	-0.21	(0.04)	***
Average Grade Percentage in 6th Grade (in 10s)				-1.21	(0.04)	***	-1.36	(0.04)	***
No. Advanced Courses Passed in 6th Grade				0.02	(0.01)	+	0.00	(0.01)	
Reading Test Score in 6th Grade (std.)				-0.03	(0.02)	+	-0.04	(0.02)	*
Mathematics Test Score in 6th Grade (std.)				-0.27	(0.02)	***	-0.24	(0.02)	***
Age				0.06	(0.02)	**	0.06	(0.02)	**
Female				-0.19	(0.03)	***	-0.17	(0.03)	***
Race/Ethnicity (ref. = White)									
Black				-0.08	(0.07)		-0.12	(0.07)	
Hispanic				0.23	(0.06)	***	0.33	(0.07)	***
Asian				-0.31	(0.12)	*	-0.26	(0.12)	*
English Learner				-0.11	(0.04)	**	-0.11	(0.04)	**
Special Education				-0.26	(0.07)	***	-0.27	(0.07)	***
Economically Disadvantaged				0.11	(0.04)	**	0.16	(0.04)	***
No. In-School Suspensions				0.23	(0.01)	***	0.23	(0.01)	***
No. Out-of-School Suspensions				0.14	(0.02)	***	0.14	(0.02)	***
Initial School Fixed Effects								✓	
Observations (student-grade)		64,254			64,254			64,254	
Log-likelihood		-24,663			-20,748			-20,525	
Pseudo R^2		0.04			0.19			0.20	

Note. Sample is limited to 17,879 non-Native American students with non-missing data. All models include cohort fixed effects and use robust standard errors.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Appendix Table 5. Log-Odds from a Discrete-Time Hazard Model of Failing to Meet the HERC On-Track Indicator

Variable	Model 1			Model 2			Model 3		
	β	S.E.		β	S.E.		β	S.E.	
Grade (ref. = 7th)									
8th	-1.25	(0.03)	***	-0.58	(0.04)	***	-0.46	(0.04)	***
9th	-0.19	(0.03)	***	1.14	(0.04)	***	1.31	(0.04)	***
10th	-1.26	(0.04)	***	0.28	(0.05)	***	0.45	(0.05)	***
11th	-1.61	(0.05)	***	0.06	(0.06)		0.24	(0.06)	***
12th	-1.54	(0.05)	***	0.28	(0.06)	***	0.46	(0.07)	***
No. Total Courses Passed in 6th Grade				0.06	(0.01)	***	0.10	(0.02)	***
No. Core Courses Failed in 6th Grade				0.03	(0.03)		0.06	(0.04)	
Attendance Rate in 6th Grade (in 10s)				-0.75	(0.05)	***	-0.79	(0.05)	***
Average Grade Percentage in 6th Grade (in 10s)				-1.28	(0.04)	***	-1.37	(0.04)	***
No. Advanced Courses Passed in 6th Grade				-0.21	(0.01)	***	-0.22	(0.01)	***
Reading Test Score in 6th Grade (std.)				-0.19	(0.02)	***	-0.22	(0.02)	***
Mathematics Test Score in 6th Grade (std.)				-0.33	(0.02)	***	-0.38	(0.02)	***
Age				0.22	(0.02)	***	0.21	(0.02)	***
Female				0.01	(0.03)		0.02	(0.03)	
Race/Ethnicity (ref. = White)									
Black				0.03	(0.06)		-0.15	(0.06)	*
Hispanic				0.01	(0.05)		0.06	(0.06)	
Asian				-0.12	(0.10)		-0.20	(0.10)	*
English Learner				0.74	(0.05)	***	0.75	(0.05)	***
Special Education				0.22	(0.08)	**	0.18	(0.08)	*
Economically Disadvantaged				0.09	(0.04)	*	0.06	(0.04)	
No. In-School Suspensions				0.27	(0.02)	***	0.28	(0.02)	***
No. Out-of-School Suspensions				0.39	(0.03)	***	0.41	(0.03)	***
Initial School Fixed Effects								✓	
Observations (student-grade)	46,627			46,627			46,627		
Log-likelihood	-26,362			-19,432			-18,867		
Pseudo R^2	0.07			0.31			0.33		

Note. Sample is limited to 17,879 non-Native American students with non-missing data. All models include cohort fixed effects and use robust standard errors.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)

Appendix Table 6. Log-Odds from a Discrete-Time Hazard Model of Failing to Meet the State On-Track Indicator

Variable	Model 1			Model 2			Model 3		
	β	S.E.		β	S.E.		β	S.E.	
Grade (ref. = 7th)									
8th	-1.51	(0.03)	***	-0.64	(0.04)	***	-0.60	(0.04)	***
9th	-2.85	(0.06)	***	-1.89	(0.07)	***	-1.83	(0.07)	***
10th	-3.09	(0.07)	***	-1.98	(0.08)	***	-1.92	(0.08)	***
11th	-2.85	(0.06)	***	-1.57	(0.07)	***	-1.50	(0.07)	***
No. Total Courses Passed in 6th Grade				0.09	(0.05)	+	0.15	(0.05)	**
No. Core Courses Failed in 6th Grade				-0.11	(0.04)	**	-0.15	(0.04)	***
Attendance Rate in 6th Grade (in 10s)				-0.17	(0.01)	***	-0.17	(0.01)	***
Average Grade Percentage in 6th Grade (in 10s)				-0.61	(0.03)	***	-0.60	(0.03)	***
No. Advanced Courses Passed in 6th Grade				0.08	(0.01)	***	0.08	(0.02)	***
Reading Test Score in 6th Grade (std.)				0.27	(0.03)	***	0.27	(0.03)	***
Mathematics Test Score in 6th Grade (std.)				-1.31	(0.03)	***	-1.29	(0.03)	***
Age				-0.64	(0.04)	***	-0.81	(0.05)	***
Female				0.21	(0.03)	***	0.25	(0.03)	***
Race/Ethnicity (ref. = White)									
Black				0.35	(0.07)	***	0.39	(0.08)	***
Hispanic				0.09	(0.07)		0.12	(0.08)	
Asian				-0.20	(0.13)		-0.15	(0.13)	
English Learner				0.46	(0.06)	***	0.48	(0.06)	***
Special Education				0.46	(0.12)	***	0.45	(0.12)	***
Economically Disadvantaged				0.01	(0.05)		0.04	(0.05)	
No. In-School Suspensions				0.06	(0.02)	***	0.05	(0.02)	**
No. Out-of-School Suspensions				0.15	(0.02)	***	0.15	(0.02)	***
Initial School Fixed Effects								✓	
Observations (student-grade)	42,125			42,125			42,125		
Log-likelihood	-19,599			-13,031			-12,837		
Pseudo R^2	0.20			0.47			0.48		

Note. Sample is limited to 17,879 non-Native American students with non-missing data. All models include cohort fixed effects and use robust standard errors.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (two-tailed tests)