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Grades and Graduation: A Longitudinal Risk Perspective to Identify Student Dropouts

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ABSTRACT. Studies of student risk of school dropout have shown that present predictors of at-risk status do not accurately identify a large percentage of students who eventually drop out. Through the analysis of the entire Grade 1–12 longitudinal cohort-based grading histories of the class of 2006 for two school districts in the United States, the author extends past longitudinal conceptions of dropout to a longitudinal risk perspective, using survival analysis, life tables, and discrete-time hazard modeling to appropriately account for student graduation, transfer, or dropout. The risk of dropout began in Grade 7, with the most hazardous years at Grades 8 and 11. A novel calculation of teacher-assigned grades, noncumulative GPA, is identified as a strong predictor of student dropout.

Keywords: at risk, discrete-time hazard modeling, dropout, dropout prediction, grades (scholastic), graduation, logistic regression, longitudinal studies, retention, survival analysis

Graduation from high school in the United States is known to lead to improved life outcomes for students, as opposed to dropping out of school or obtaining an alternative diploma (Berktold & Carroll, 1998; Greene & Caire, 2001; Kienzi & Kena, 2006; Tyler, 2003). However, reporting of student graduation rates has recently become a topic of much debate (Greene & Winters, 2005; Heckman & LaFontaine, 2007; National Center for Education Statistics [NCES], 2004; Sable, Gaviola, & Hoffman, 2007; Swanson, 2004a, 2004b; Viadero, 2006). Although the debate continues over estimations of national- and state-level graduation rates, school districts are in need of improved systems to help identify and assist students at risk of not graduating on time (Hammond, Linton, Smink, & Drew, 2007; Orfield, 2004) before the act of dropping out of school occurs.

The research to date examining student graduation and dropout rates has focused on large-scale estimation of national dropout rates as well as the issue of early prediction of dropouts. For the 2003–2004 school year, the U.S. Department of Education estimated a national graduation rate of 74.3% (Seastrom, Hoffman, Chapman, & Stillwell, 2006), and that data is supported by other studies that have also estimated national average graduation rates above 70% (Greene & Caire, 2001; Greene & Winters, 2005). However, other recent studies have begun to reexamine the methods of national graduation estimation and have reported national average graduation rates below 70% (Swanson, 2004a, 2004b). Although estimated averages for states are useful for reporting and policy purposes, examination of individual school district graduation rates and how best to predict failure to graduate has begun to come to the fore in the literature (Balfanz, Herzog, & MacIver, 2007; Balfanz & Legters, 2004; Hammond et al., 2007).

In the research that has attempted to examine which students drop out, there has been a focus on identifying early indicators of potential student dropouts to help schools focus resources for children that may be at risk of dropping out of school (Alexander, Entwisle, & Kabbani, 2001; Allensworth & Easton, 2005; Balfanz et al., 2007; Barrington & Hendricks, 1989; Dynarski & Gleason, 2002; Finn, 1989; Fitzsimmons, Cheever, Leonard, & Macunovich, 1969; Gleason & Dynarski, 2002; Jimerson, Egeland, Sroufe, & Carlson, 2000; Laird, DeBell, & Chapman, 2006; Lloyd, 1974, 1978; Rumberger, 1995). Recently, many of these studies have been situated in large, urban U.S. school districts. For instance, in Chicago, researchers found that the district graduation rate was 54% and that graduation rates differed by ethnic group, in that 39% of African American students graduated, in comparison with 51% of Hispanics, 71% of European Americans, and 85% of Asian students (Allensworth, 2005). Additionally, in Chicago, receiving a failing grade in one or more courses as well as having a low number of credits by the end of Grade 9 was predictive of a student not graduating, and this was especially problematic for male and Hispanic students (Allensworth & Easton, 2005; Roderick

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& Camburn, 1999). In a related study, representative samples of students in Baltimore were examined over their lifetime within the district's schools and many longitudinal factors were found that were useful in predicting risk of dropout, including grade retention, low academic achievement, and family socioeconomic status (SES; Alexander et al., 2001). Together, these studies have indicated that specific predictors of student graduation do exist for school districts and that these predictors can be identified by Grade 9 or earlier. However, although many longitudinal factors are known to influence the probability that a student becomes at risk for not graduating on time from high school (Rumberger, 2001, 2004b), most of these factors have been shown to be fairly inefficient and variable predictors of student risk (Gleason & Dynarski, 2002; Hammond et al., 2007). These issues with early dropout identification are especially problematic, given recent efforts to design and assess dropout prevention programs (for a review, see Hammond et al.). The purpose of the present study was to extend and improve on the present longitudinal perspective of dropout identification to a longitudinal risk perspective through the use of teacher-assigned grades to better understand and identify which students would dropout and when.

Identification of Students at Risk of Dropping Out of School

Retaining a student at any grade level is one of the highest predictors of dropping out (Abrams & Haney, 2004; Jimerson et al., 2005; Laird et al., 2006; Montes & Lehmann, 2004; Roderick, Nagaoka, Bacon, & Easton, 2000). Yet, other than retention, the literature on risk factors that predict student dropout also includes many other variables that have been tested for the ability to assign students as at risk with the purpose of predicting and ultimately preventing future student dropouts. For much of the early dropout literature, four main factors predicting student dropout were identified including academic achievement, as measured by teacher-assigned grades, absenteeism, retention and family SES (Barrington & Hendricks, 1989; Ensminger & Slusarcick, 1992; Finn, 1989; Fitzsimmons et al., 1969; Lloyd, 1974, 1978; Rumberger, 1995). These findings have recently been replicated (Alexander et al., 2001; Balfanz et al., 2007). However, across the literature to date, the predictive validity of these risk factors has been shown to be relatively low (Dynarski & Gleason, 2002; Gleason & Dynarski, 2002; Hammond et al., 2007).

Additional risk factors also explored have been a single-parent home, family on public assistance, sibling dropout, absenteeism, disciplinary problems, failing grades at the high school or middle school levels, and overage for grade level, among others (Allensworth, 2005; Balfanz et al., 2007; Bradley & Lenton, 2007; Eckstein & Wolpin, 1999; Gleason & Dynarski, 2002; Laird et al., 2006; Montes & Lehmann, 2004; Roderick, 1993; Rumberger, 2004b). Nevertheless, for many of these variables, individual dropout rates for students with each risk factor have been shown to be below 10% of the students with that risk factor at the middle school level, and below 30% at the high school level (Gleason & Dynarski; Hammond et al., 2007; Laird et al.; Montes & Lehmann; Weber, 1989). Additionally, Gleason and Dynarski have shown that when many of these factors are combined using multivariate statistics, the percentage of students identified with the multivariate prediction variable who ultimately drop out only rises to 23% at the middle school level and 42% at the high school level. Thus, many of these risk factors only accurately identify a subset of the students who ultimately dropout.

These studies were limited in that the vast majority of the research to date includes data only on students at the high school level and does not account for the longitudinal nature of the data or the dropout problem. This is problematic. If identification of potential dropouts does not occur until high school, the deleterious impact of these risk factors over the extended period of time before high school is not assessed or included when judging early risk factors. The literature on students' lack of motivation to stay in school suggests that the decision to drop out is not based on a single factor or moment, but rather is the cumulative effect of multiple risk factors, influencing the student over long periods of time within a district (Alexander et al., 2001; Jimerson et al., 2000; Randolph & Orthner, 2006). For many districts nationwide, early student dropout identification is critically important so that the district can potentially intervene early in a student's schooling career to help delay or prevent dropout. In the present study, I argue for an early preventative intervention approach, rather than focusing on students one or two years before they may drop out or after dropout has occurred.

Use of Teacher-Assigned Grades to Predict Dropout Risk

Although these multiple variables for predicting student dropout have been nominated and tested in the literature to date with varying results, teacher-assigned grades have consistently been identified as a useful variable in predicting student dropout (Barrington & Hendricks, 1989; Eckstein & Wolpin, 1999; Finn, 1989; Fitzsimmons et al., 1969; Lloyd, 1974, 1978; Rumberger, 1995). However, the definition of a grade has differed from study to study. Overall cumulative grade point average (GPA) has been incorporated into multiple different prediction statistics, and at the high school level, low grades are moderately predictive of student dropout (Gleason & Dynarski, 2002) with 27% of the students with low grades dropping out. Also with a focus on the high school years, receiving a failing grade in any course appears to be associated with a higher likelihood of a student dropping out of school (Allensworth & Easton, 2005). More recently, of students who dropped out, about 20% failed either mathematics or English at the Grade 6 level (Balfanz et al., 2007). Although these studies examining failing grades at either the high school or middle school levels are useful, the argument of the present study is that this past research has ignored the longitudinal nature of the data set available and has not used the entire grading scale of teacher-assigned grades across multiple courses.

To date, the most systematic examination of dropout prediction and the utility of teacher-assigned grades was conducted by Eckstein and Wolpin (1999). They defined grades as cumulative GPA in five core courses (mathematics, English, social studies, science, and foreign language) from Grades 8–12. They showed that grades were highly predictive of dropout, in that, in their sample, four types of students existed: students who received, on average, high grades (*A*–) throughout high school and graduated on time; students who received, on average, medium grades (*C*+) throughout high school and graduated on time; students who received, on average, lower grades (*C*–) and dropped out throughout high school; and students who received, on average, low grades (*D*+) and dropped out mostly before Grade 9. This showed that rather than examine failing grades only, intervals of GPA should be considered in which low grades (*D*+ or lower) may be predictive of students dropping out of school. Additionally, these results indicated that two high-risk time-periods exist for students who may drop out of school, at Grade 8 and midway through high school. However, these results are problematic for three main reasons. First, the data was from a 1979 survey of students and has not been repeated with a more recent data set. Second, the initial research questions posed by Eckstein and Wolpin focused on the potential link between number of hours worked outside of school by students and dropout, which they found marginal evidence for, rather than a specific focus to identify potential early variables that could identify students at risk of dropping out of school. Third, their model, a structured logistic regression model, was overparameterized, incorporating 92 parameters, making it difficult to identify individual parameters, such as teacher-assigned grades, that, on their own, may be useful for school districts in identifying present students at risk of dropping out of school.

Thus, these issues in the dropout identification literature underscore the need for more research in this area for five reasons. First, there is a need for analysis of recent data sets, analyzing these same issues with dropout prediction for recently graduated or dropped-out students. Second, acknowledging the longitudinal nature of a student's decision to drop out of school as well as the ability to use the longitudinal data that exists for students in schools, recent innovations in longitudinal data analysis, such as the use in this study of risk analysis and discrete time hazard modeling, can be used to help test which variables are most predictive of a student's risk of dropping out of school. Third, building on the work of Eckstein and Wolpin (1999), there is a need to analyze teacher-assigned grades in a systematic fashion, rather than as single course failures or GPA in selected courses only at the high school level, to replicate and extend the findings in a more parsimonious model to identify how predictive teacher-assigned grades can be in identifying students who may drop out of school. Overall, the aim of the present study was to detail an analysis of the usefulness of teacher-assigned grades, from Grade 1 to Grade 12, in predicting the likelihood of students dropping out of school as a way to provide a single useful variable for school districts to identify not only the students who are most likely to drop out of school but also at which grade levels those students are most likely to drop out.

Method

For the present study, the entire teacher-assigned, subject-specific grade histories of a sample of students were collected. The sample of students comprised all of the students of the entire cohort of the class of 2006 (whether they graduated or not) for two districts, West Oak and South Pine (pseudonyms). Although the overall sample size of students for this study was small ($N = 193$), the two districts that agreed to participate in the study were selected based on their willingness to participate and the availability of the data for students who either graduated or dropped out of school.[1] Both districts were located in the midwestern United States within 10 miles of each other, had contiguous borders with each other, and were first-ring suburbs of a large metropolitan area. Due to the requirements imposed by both districts to allow access to the student data and for issues of confidentiality, throughout this study district specifics, including the number of subgroups, have been intentionally left vague. In addition, as recommended for determining the minimum sample size required for the method used here, survival analysis (Lakatos, 1988), a priori power-analysis calculations assuming a power of 0.8 ($\alpha = .05$) and an overall predicted rate from the literature of survival to graduation of 75% indicated a required sample size of 183, which was exceeded.

District Context

West Oak was defined as a midsized central city by the U.S. census, with fewer than 3,000 students attending two elementary schools, a middle school, and a high school. In 2006, the district served an overall student population that was about 70% economically disadvantaged, 50% Hispanic, 30% European American, and 15% African American. The district has historically lagged behind the state averages on state standardized tests in reading and mathematics at all grade levels (NCES, 2006; Standard & Poor's, 2006).

South Pine was defined as an urban fringe of a midsized city by the U.S. census, with fewer than 3,000 students attending three elementary schools, a middle school, and a high school. In 2006, the district served a student population that was about 50% economically disadvantaged, 50% European American, 20% Hispanic, and 15% African American. The district has historically scored near the state averages on state standardized tests in reading and mathematics at all grade levels (NCES, 2006; Standard & Poor's, 2006).

Data Collection

Data collected included the entire longitudinal grading histories from Grade 1 to Grade 12 for all subjects for each student who had ever been on track to graduate from high school in June of 2006. Students were included in the sample if they started Grade 1 on track to graduate in 2006, regardless of if they actually graduated. For both districts, the Grade 1 school year was 1994–1995. This resulted in an total sample of 193 students, 103 from West Oak and 90 from South Pine.

Each student's permanent record in paper form was accessed from the district's long-term paper file storage (i.e., report cards). Student data was entered into SPSS (Version 15). For each student, grades for every subject for every year (Grades 1–12) were recorded. Because it was outside of the scope of the present study, attendance was not recorded. Letter grades for each subject at each grade level were converted into the following numeric grading scale: $A = 4.0$, $A– = 3.666$, $B+ = 3.333$, $B = 3.0$, $B– = 2.666$, $C+ = 2.333$, $C = 2.0$, $C– = 1.666$, $D+ = 1.333$, $D = 1.0$, $D– = 0.666$, E or $F = 0$. Mean noncumulative GPAs for each grade level were then calculated by calculating the mean GPA for all subjects within each grade level.

Additional variables were also recorded for each student, including gender, ethnicity, if the student had ever been retained, and if the student had graduated on time with their cohort or had dropped out. The issue of the designation of dropout is highly contested in the literature (Greene & Winters, 2005; NCES, 2004; Swanson, 2004a, 2004b; Viadero, 2006) and official definitions differ by state and by region. Nevertheless, many students who were on track to graduate on time with their cohort in this sample did not. Because the term *dropout* is presently under contention in the literature and policy domains, in the present study, as has been previously recommended (Bowers, 2007; Ensminger & Slusarcick, 1992; Marrow, 1986), I handled dropout designation by categorizing students into three mutually exclusive groups: on-time graduation, censored, or dropped out. Students were designated as graduating on time if there was a record of a diploma awarded in June of 2006. Students were censored from the data set if there was a record of transfer to another school district or if the student was still enrolled in either district at the end of Grade 12 but did not graduate (indicating that the student was behind their cohort in credits, but was on track to graduate from high school in 5 years, rather than 4).[2] The remaining students were designated as having dropped out of school. Thus, the focus of the present study and the designation of students as dropouts were aimed at students who stopped attending school with their cohort in either district and thus were unable to graduate on time with a regular high school diploma.

Although these three designations may seem fairly straightforward, the options presented to students in the U.S. system who do not wish to graduate on time are many, and exact categorization of dropout or not is difficult due to these multiple options (Swanson, 2004a). For the present study, I handled these issues in the following manner: A *valid student transfer* was defined as any student's record which contained a request for student transcripts for student transfer to another school district or school which was not an alternative school. A *record of a transcript request* from an alternative school was defined as a nonvalid indicator of student transfer for on-time high school graduation, and thus was an indicator of the educational challenges faced by the student with a high probability that the student would not graduate on time with their cohort in June of 2006. Lacking confirming graduation or alternative degree-completion data from the alternative education schools, it could not be determined if the students who transferred to alternative education programs graduated on time with their cohort with a full high school diploma, rather than a GED. It is the case that many students who transferred to alternative high schools had low or failing grades in multiple subjects at the time of the transfer. Past research on the GED option has shown that it is not equivalent to a regular high school diploma (Cameron & Heckman, 1993; Tyler, 2003) and thus was not considered for the present study as on-time graduation with a standard high school diploma. Even if these students did graduate from an alternative high school with a diploma or an alternative high school degree (GED), I focused on the on-time graduation of the cohort of students in a traditional high school program, and so thus considered students who transferred to an alternative education program as having dropped out of the regular high school program.

If a student's file did not contain a record of a diploma award, a request for student records from another district, or the record ended prematurely, that student was designated as a student dropout. Thus, this categorization of students dropping out of school may contain some unknown degree of false positives (e.g., students who were categorized as dropouts but did graduate on time in some other district that had not requested that student's transcripts from the two districts in this study). Although the false-positive issue was a threat to the internal validity of the conclusions of the present study because the number of false positives could not be estimated, *dropout*, as defined in the present study, was a reasonable designation, given that the majority of the students coded as dropouts did have records of either nonattendance, refusing to attend school, incarceration, or expulsion. In this way, dropout, although not a pure indication of students who opted to stop attending school, should be considered a reasonable proxy.

Statistical Analyses

Following the methods recommended for longitudinal data analysis (Singer & Willet, 2003), the person-level data set was converted into a person-period data set, with *event* defined as student dropout at the time when the student's academic record ended with either school district. Students who graduated on time were censored at Grade 12, whereas students who had a record of a valid transfer to another school district were censored at the end of the last academic year they were present in either school district. Students who transferred into the district at any time between Grades 1 and 12 were considered late entrants, and were included into the study with missing data for all variables other than grade-level and dropout-event variables up to the late-entry time point. Students who were retained at any grade level and whose records ended before June 2006 without requests for transcripts from a different school district were considered dropouts, whereas students who did not graduate on time but were still enrolled in the districts due to retention or future planned graduation after summer school or a fifth year of high school were censored at the end of their present grade in June 2006.

As suggested previously, to most effectively study time-dependent effects on a student's risk of dropping out of school (Bradley & Lenton, 2007; Willett & Singer, 1991), the effects of multiple variables on a student's probability of dropout were estimated employing survival and discrete-time hazard analysis using logistic regression with the person-period data set (Bradley & Lenton, 2007; Singer & Willet, 1993, 2003; Willett & Singer, 1991, 1995). Time-invariant dichotomous variables included in the analysis were the following: gender (girls = 0, boys = 1), not European American or ethnicity (European Americans = 0, all other ethnic groups = 0), and district (South Pine = 0, West Oak = 1). Three time-variant variables were included. First, for the variable *retained*, students retained at any grade level (Grades 1–12) were coded as 1 in the time period in which they were retained and then, at all other periods thereafter, all other students were coded as 0. The continuous variable *DEtotal* recorded the total number of letter grades *D* or lower in all subjects for each time period. The variable *noncumulative GPA* contained the mean student GPAs for each time period for all subjects. Logit discrete-time hazard models were estimated and fit to the dropout grade-level data as well as the calculation of life tables, estimated hazard and survival functions, and median lifetimes using the methods detailed by Singer & Willet (2003).

Results

Descriptive Statistics

The entire grading and enrollment histories from Grades 1 to 12 were recorded for two cohorts of students. These two cohorts were the graduating classes of 2006 from two school districts in the industrial Midwest, West Oak and South Pine (pseudonyms). For the overall sample, the total sample included 193 students, which included all of the students who were ever enrolled in either district who could have graduated with their cohort in 2006 (see Method section), with 103 having attended West Oak and 90 having attended South Pine (Table 1). The percentages of female and male students differed somewhat between the two cohorts, as did student ethnicity, with the majority of students in the West Oak cohort of Hispanic ethnicity, whereas the majority of students in the South Pine cohort were of European American ethnicity (Table 1). Due to the vagaries of district data collection and data retention, although many student records included data such as ethnicity, for both districts multiple students did not have any ethnicity recorded. This issue with missing ethnicity data was most prevalent for the West Oak cohort, with 31.1% of the student records containing no information on ethnicity.

TABLE 1. Descriptive Variables and Frequencies, by District

	West Oak		South Pine	
Variable	*n*	%	*n*	%
Students sampled	103	—	90	—
Gender				
Female	42	40.8	54	60.0
Male	61	59.2	36	40.0
Ethnicity				
European American	30	29.1	56	62.2
Hispanic	31	30.1	8	8.9
African American	10	9.7	9	10.0
Asian	0	0.0	4	4.4
No Ethnicity Data	32	31.1	13	14.4

Student Dropout

As described in the Method section, *student dropout* was mainly defined as students whose academic records ended prematurely in either district before June 2006 graduation from high school without a valid record of transfer. For the entire sample, 75.6% of the students graduated on time with a full high school diploma, whereas 24.4% of the students dropped out. By district, the on-time graduation rate for West Oak was 65.0% and for 87.8% for South Pine. The data correspond to previous research that has shown that graduation rates are highly variable district to district and fall above and below the 74.3% graduation rate reported for the United States as a whole (Greene & Caire, 2001; Greene & Winters, 2005; Rumberger, 1995; Seastrom et al., 2006; Swanson, 2004a, 2004b).

Data on multiple variables were recorded for each student in the sample. Table 2 presents descriptive data for the dichotomous variables gender, not European American, district, and retained. Data are presented for the overall data set and disaggregated by dropout status. For the overall data set, nearly half of the students were female and half were male. While both districts had ethnically diverse student cohorts (see Table 1), due to the need for dichotomous non-

TABLE 2. Dichotomous Variables and Percentages of Students Who Graduated on Time or Were Dropouts, by Variable

	Overall		On-time graduation		Dropped out	
Variable	*n*	%	*n*	%	*n*	%
Gender						
Female	96	49.7	78	81.3	18	18.8
Male	97	50.3	68	70.1	29	29.9
Ethnicity						
European American	86	44.6	76	88.4	10	11.6
Not European American	62	32.1	49	79.0	19	30.6
District						
West Oak	103	53.4	67	65.0	36	35.0
South Pine	90	46.6	79	87.8	11	12.2
Retained						
Never retained	171	88.6	144	84.2	27	15.8
Retained in any grade	22	11.4	2	9.1	20	90.9

multicateogrical variables in the discrete-time hazard model described below, ethnicity was dichotomized for the overall data set as either European American or all other ethnic groups. For the data set, 11.4% of the students were retained at some time during their time in either district (Table 2).

Disaggregating the data by on-time graduation or dropout reveals striking differences within each of the categorical variables in Table 2. While female and male students were nearly evenly split in the sample, 29.9% of males dropped out of school in comparison to only 18.8% of females. Similarly, non-European American students disproportionally dropped out in comparison with European American students. District rates of dropout also varied, with West Oak having higher rates of student dropouts than South Pine (Table 2). These findings replicate previous studies and extend the past national and large urban district findings to the context of small first-ring suburbs.

The literature to date on dropouts and on-time graduation has indicated that student grade retention is a strong predictor of a student not graduating on time (Jimerson, Anderson, & Whipple, 2002; Jimerson et al., 2005; Laird et al., 2006; Montes & Lehmann, 2004; Roderick, 1993; Roderick & Camburn, 1999; Roderick et al., 2000). For the present study, 90.9% of the students who were retained in any grade level dropped out (Table 2, bottom right). This result confirms and extends the previously reported negative impact of repeating a grade level on graduation rates to small urban and first-ring suburban districts (Alexander et al., 2001; Jimerson et al., 2002; Jimerson et al., 2005; Roderick; Roderick et al.), demonstrating that retention at any level in districts of the size included in the sample may not be serving students in a way that promotes increased achievement and eventual graduation.

Although the data presented replicates and extends the results of past studies that have shown similar patterns of student dropout in large urban contexts, dropout data presented as aggregated overall rates of dropping out does not acknowledge the time-sensitive nature of the schooling and dropout process. Rather, although past standard practice has been to calculate overall dropout rates as percentages of students who have remained in school versus those who have not over an entire period, such as aggregating Grades 9–12 as was done in Table 2, better methods have been nominated to deal with dropout data. These methods are able to account for the conditional nature of dropout rates over each year of schooling as well as more appropriately handle data of students who leave the data set with unknown outcomes, such as transfers to other school districts. It is this issue and the uses of survival analysis and discrete-time hazard analysis that I subsequently discuss.

Survival Analysis of Student On-Time Graduation or Dropout

To investigate the event occurrence of students leaving school early through dropout, survival analysis using a discrete-time hazard model was utilized as has been suggested in the longitudinal data analysis literature (Singer & Willet, 1993, 2003; Willett & Singer, 1991), and more recently in the emerging dropout literature (Bradley & Lenton, 2007). Such analyses have been shown to be superior to simple means and weighted means when analyzing the risk of a terminal event (Singer & Willet, 2003; Willett & Singer), such as dropping out of school, in which a student, once having dropped out, cannot reverse the dropout status and become a student who has never dropped out. Survival analysis allows researchers to examine the students in each grade level still at risk of leaving school and not graduating on time, rather than aggregating all years in the data set. This requires the removal of two types of students from calculations at each grade level, such as those who have already left the school before that grade level, because they can no longer be at initial risk of an event that has already happened to them.

TABLE 3. Life Table for the Event Histories for Student Dropout of the Sample of 193 Students

	n			Proportion	
Grade	Enrolled at the end of the school year	Who dropped out during the school year	Censored at the end of the school year	Students at the beginning of the school year who dropped out before the start of the next school year (Hazard estimate)	All students still enrolled at the end of the school year (Survival estimate)
1	193	0	0	0.0000	1.0000
2	193	0	0	0.0000	1.0000
3	193	0	0	0.0000	1.0000
4	193	0	0	0.0000	1.0000
5	193	0	0	0.0000	1.0000
6	193	0	0	0.0000	1.0000
7	186	5	2	0.0262	0.9738
8	176	8	9	0.0435	0.9315
9	167	7	19	0.0402	0.8940
10	160	6	27	0.0361	0.8617
11	144	15	34	0.0943	0.7804
12	135	5	53	0.0357	0.7525

One type is students who dropped out. The other type is students who left the school but had a valid transfer to another school district. These students' risk of dropping out once they left West Oak or South Pine could no longer be determined, and thus they were censored (removed from the data set) from the calculations at those grade levels and beyond.

As suggested by Singer and Willett (2003), Table 3 presents a life table detailing these dropout event histories for Grades 1–12 of the sample of 193 students in the data set. A life table with hazard and survival estimates, as is presented in Table 3, is superior to past statistical techniques used to describe the dropout event. This is due to the way in which dropouts and transferred students are described in the life table, as either experiencing the event and then being removed from subsequent time points or becoming unknown for the event and being censored, which provides a more realistic and complete numerical description over time than previous methods. For Grades 1–6, no student in the data set left school. After Grade 6, a number of students in each grade level left school and were categorized as dropouts (Table 3, column 3). Additionally, beginning in Grade 7, students began to transfer to other school districts, and thus their dropout status became unknown and they were censored from the data set (Table 3, column 4). Table 3 also presents the estimated hazard and survival probabilities (Table 3, columns 5 and 6). As suggested for longitudinal data of this type (Singer & Willet), graphing the estimated hazard and survival probabilities allows for greater ease in examining and interpreting each of these functions (Figure 1).

The estimated hazard probability shows the proportion of students in the sample at each grade level still at risk of dropping out (i.e., all students who were still enrolled at the beginning of that academic school year) who left school within that grade level and were thus categorized as student dropouts (Table 3, column 5; Figure 1A). This type of analysis is read as the percentage risk of experiencing the event at each specific time point for the data set. Additionally, plotting the hazard function allows for the visual identification and interpretation of the trend of students experiencing the dropout event across the time periods, visually identifying peak time points while controlling for the conditional nature of the event (i.e., students who dropped out in Grade 8 were no longer present in the data set for Grade 9). For example, a hazard probability of .0361 in column 5 of Table 3 for Grade 10, and graphed in Figure 1A at the Grade 10 time point, indicated that for the students still in the data set at Grade 10, 3.61% experienced the event of dropping out.

Using these life table calculations, estimating the hazard function for dropping out, the probability of dropping out for this data set was 0 until Grade 7, at which point it rose to 2.6%. The percentage of students at risk of dropping out continued to increase over the subsequent years, appearing to level off somewhat across Grades 8–10 at about 4%, peaking dramatically at 9.4% in Grade 11 and then falling to 3.6% in Grade 12. These data replicate past research indicating that the middle school years are important to consider when examining dropout rates (Balfanz et al., 2007; Rumberger, 1995). This analysis, for the first time in the U.S. context, also quantifies the hazard and survival estimates as calculations of the percentage of students at risk of experiencing the event while controlling for students who have left the data set through already experiencing the event (already dropping out) or leaving the data set (censored due to transfer to another district). Risk of dropping out began in middle school at Grade 7, with 2.6% of the students dropping out.

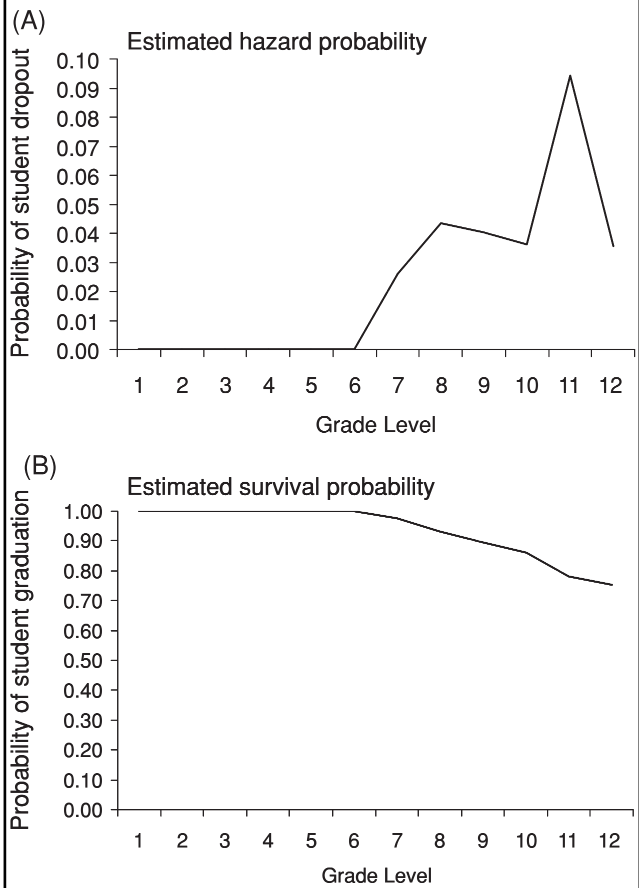

FIGURE 1. Estimated hazard and survival functions for the overall data set. For the overall data set, the estimated hazard function showed that the probability of dropout is 0% until Grade 7, and then rises thereafter, with the most hazardous year at Grade 11, at which almost 10% of students are at risk of dropping out (A). The estimated survival function shows that for this data set, a cumulative decline in the probability of graduating on time began at Grade 7, dropped steadily over the subsequent grades, and showed that in Grade 12 over 70% of the students did not experience the dropout event, and thus graduated on time (B).

The percentage then rose over time, with the most hazardous years being Grades 8 and 11, with 4.4% and 9.4% of students dropping out, respectively. However, if students in this data set remained in school into Grade 12, their risk of dropping out fell to 3.6% (Table 3, column 5; Figure 1A).

The final far-right column of Table 3, the survival function, presents the data in a cumulative manner, displaying the data points as the percentage of the full sample who survived (i.e., those who did not leave school and did eventually graduate on time), appropriately controlling for students who already dropped out of the data set (Table 3, column 6; Figure 1B). At Grade 7, 97.4% of the sample was still enrolled in the two districts. This number decreased over time and by the end of Grade 9, 89.4% of the students were still enrolled. By the end of Grade 12, 75.3% of the students were still enrolled and subsequently graduated on time with their cohort. This number can be considered the graduation rate of these two districts together. As previously suggested (Willett & Singer, 1991), I have argued in the present study that this method of estimating a survival function, from Grades 1 to 12 as a graduation rate, is superior to previously articulated methods of calculating graduation rates as end-product statistics (Greene & Winters, 2005; Laird et al., 2006; Seastrom et al., 2006; Swanson, 2004a, 2004b). This is due to the use in survival analysis of student-level data from Grades 1–12, the ability to easily handle transfer students through censoring, and the more accurate estimates provided by survival analysis over standard descriptive statistical techniques.

Although the calculation of overall graduation and dropout rates using survival analysis and life tables with this sample are of interest, these numbers do not give an indication of which students are most at risk of dropping out, only when. The main focus of the present study was to combine the previous techniques of examining the timing of dropout with a quantification of the usefulness of teacher-assigned grades, as a previously identified variable in the dropout literature, in helping to predict which students identified in the previous analysis at each time point were most at risk of dropping out. In this way, the aim of the present study was to improve on past dropout-identification research and use an appropriate longitudinal analysis technique to analyze if teacher-assigned grades are useful to school districts as predictors of students at risk of dropping out as well as helpful in identifying the times when students are most at risk of dropping out.

Teacher-Assigned Grades and the Prediction of Dropout

As discussed previously, previous research has indicated that low and failing teacher-assigned grades may be a useful predictor of student dropout (Alexander et al., 2001; Allensworth, 2005; Allensworth & Easton, 2005; Balfanz et al., 2007; Eckstein & Wolpin, 1999; Roderick, 1993; Roderick & Camburn, 1999). However, much of this literature has been focused on general descriptive characteristics of the data, the high school level, grades in specific core subjects, the number of failing grades per grade level, or subsamples of students from large urban districts. I addressed these issues in four ways. First, rather than a small sample of students from a much larger district-wide population, such as previous research, which sampled approximately 12% of a student cohort from a large urban district (Alexander et al.), for the present study, I analyzed 100% of the students in a cohort from two different school districts. Second, previous dropout studies have focused on specific grade levels, middle school or high school, or created different statistical models for each of the different levels (Alexander et al.; Balfanz et al.; Gleason & Dynarski, 2002). As I subsequently discuss, I analyzed the risk of dropping out using a discrete-time hazard model that appropriately handled student dropout and transfer data, as presented previously, and modeled and tested the effect of time at each grade level on the risk of dropping out. Third, the literature that has explored teacher-assigned grades as predictors of student dropout has overly focused on specific subjects, such as English and mathematics (Balfanz et al.; Eckstein & Wolpin), rather than considering grades in all courses for each grade level.

Fourth, and of greatest interest, much of the literature on grades and dropouts has overly focused on overall counts of the number of course failures (Allensworth & Easton, 2005; Balfanz et al., 2007), rather than on using the entire traditional 4.0 grading-scale data available. Additionally, of the few studies that have examined dropout risk statistically using the 4.0 grading scale, the variable used has been cumulative GPA (Eckstein & Wolpin, 1999; Gleason & Dynarski, 2002; Roderick, 1993). This is problematic due to the discrete time nature of the act of dropping out. Using a cumulative variable for grades over time, such as GPA, masks the inherent ups and downs in the data that could occur within any one year that could indicate that a student is challenged with school. In addition, acknowledging the work that has shown that the middle school years are exceptionally problematic for students (Balfanz et al.; Rumberger, 1995), the use of GPA, traditionally calculated cumulatively for only the high school Grades 9–12, does not provide any information on grades in middle school. Thus, I argue that GPA, considered as a cumulative variable to date, should rather be calculated noncumulatively, creating a noncumulative GPA variable that reflects a student's grades across all subjects, one grade level at a time. Consequently, there is a need for a study on the usefulness of teacher-assigned grades for predicting student dropout that addresses each of these four issues together. I addressed these issues by examining all students within cohorts (i.e., all potential dropouts, rather than a sample), testing the effect of time on the risk of dropping out, and analyzing teacher-assigned grades as effective predictors of student dropout, using all subjects, the full grading scale, and noncumulative GPA.

Discrete-Time Hazard Modeling of Student Dropout as a Time-Varying Event

To address the question of the extent to which different variables, including teacher-assigned grades, may correspond to a student's increased risk of dropout, I used discrete-time hazard models using logit regression. As has been argued previously, a discrete-time hazard model using logit regression is more appropriate for predicting a student's risk of dropout from some set of variables, while controlling for demographic variables (Bradley & Lenton, 2007; Singer & Willet, 2003; Willett & Singer, 1991). This is because of the dichotomous outcome variable, dropout or not, the appropriate handling of transfer students through censoring, and the ability to include the effect of time within the equation—modeling the discrete nature of time due to grade-level changes within the equation. Rather than experiencing a continuous change over time, students experience school in discrete sections, one grade level at a time, with open time periods in the summer between each discrete period. Thus, a discrete-time hazard model is appropriate for modeling dropout risk and testing different variables for the ability to predict which students may dropout, specifically testing the extent to which teacher-assigned grades are predictive of student dropout.

As noted previously, to calculate student risk of dropout, many variables have been nominated in the literature and shown to be marginally effective (Allensworth, 2005; Gleason & Dynarski, 2002; Hammond et al., 2007; Laird et al., 2006; Montes & Lehmann, 2004). For the present study, multiple variables were analyzed for their ability to estimate student risk of dropout over time, including time, as modeled by the effect of each grade level from Grade 7–12, gender, ethnicity, district, DEtotal, retained, and noncumulative GPA (see Method section). For the latter three variables, DEtotal was a simple count of the total number of *D*, or *E–F* letter grades for each student in each school year to replicate past research that has nominated the number of student failures or low grades as a predictor of student dropout (Alexander et al., 2001; Allensworth & Easton; Balfanz et al., 2007). Acknowledging the previous research that has shown that one of the most powerful predictors of student dropout is retention (Jimerson et al., 2002; Jimerson et al., 2005; Roderick, 1994; Rumberger, 1995), the variable *retained* included all students who were ever retained at any grade level. As discussed previously, noncumulative GPA was used, rather than overall GPA, as the average of a student's grades across all subjects within each grade level.

A discrete-time hazard model was fit to the data by estimating parameters for each time period and for each of these variables using logistic regression. However, because no students dropped out before Grade 7, intercept parameters for Grades 1–6 were not determinable and thus not included in the model. Hence, the beginning of time for the model is Grade 7. In contrast to ordinal least squares (OLS) regression techniques, to include the conditional effect of time in estimating the risk of experiencing an event of interest at any one time-point,[3] discrete-time hazard models usually begin with a test for the significance of multiple pseudointercepts for each time point, modeling the effect of time in the analysis of a participant's risk of the event. Additional parameters that estimate the effects of variables collected on a sample are then fit to the model as β estimates, similar to OLS regression, and then model fit is assessed. Seven discrete-time hazard models are presented in Table 4, listing parameter estimates and significance levels, standard errors for each estimate (in parentheses), the overall *N* of the person-period data set at each time point, and tests of model goodness of fit, including –2 log likelihood, chi square, and Cox & Snell pseudo R^2.

The first model fitted to the data included only time-point intercepts for Grades 7–12 (Table 4, Model A). Each

TABLE 4. Discrete-Time Hazard Model Fitting by Logistic Regression for Students at Risk of Dropout

	Model A	Model B	Model C	Model D	Model E	Model F	Model G
Parameter estimates and asymptotic standard errors							
Grade 7	−3.616***	−2.620***	−2.854***	1.150			
	(0.453)	(0.595)	(0.607)	(1.004)			
Grade 8	−3.091***	−2.299***	−2.769***	1.426			
	(0.361)	(0.521)	(0.538)	(0.961)			
Grade 9	−3.172***	−1.843***	−2.954***	2.538*	0.066		
	(0.386)	(0.435)	(0.578)	(1.028)	(0.665)		
Grade 10	−3.283***	−2.034***	−3.675***	1.759	−0.362		
	(0.416)	(0.472)	(0.653)	(1.051)	(0.668)		
Grade 11	−2.252***	−1.494***	−2.385***	2.390**	1.304**	1.287**	
	(0.271)	(0.385)	(0.462)	(0.919)	(0.494)	(0.393)	
Grade 12	−3.296***	−2.215***	−2.831***	2.309*	0.690		
	(0.455)	(0.523)	(0.571)	(0.943)	(0.618)		
Gender		−2.182***	−2.339***	−0.552			
		(0.238)	(0.259)	(0.457)			
Ethnicity		−1.812***	−1.327***	0.277			
		(0.245)	(0.262)	(0.507)			
District		−1.467***	−1.774***	0.825			
		(0.239)	(0.274)	(0.521)			
DEtotal			0.356***	−0.346*	0.004		
			(0.090)	(0.138)	(0.075)		
Retained			3.297***	3.160***	2.262***	2.205***	2.325***
			(0.517)	(0.545)	(0.433)	(0.398)	(0.385)
Non Cumulative GPA				−2.615***	−1.970***	−1.943***	−1.826***
				(0.307)	(0.145)	(0.123)	(0.107)
N	2172	1768	1493	1493	1655	1655	1655
n parameters	6	9	11	12	7	3	2
−2 log-likelihood	1970.267	794.584	684.323	158.199	250.143	252.173	261.814
χ^2	1040.764	1653.385	1385.415	1911.539	2044.174	2042.144	2032.503
Cox & Snell R^2	0.381	0.608	0.605	0.722	0.709	0.709	0.707

Note. * $p < .05$. ** $p < .01$. *** $p < .001$.

time-point parameter was significant, and the model appears to moderately fit the data according to the goodness of fit statistics. This indicated that for the base model including only time as a predictor, as would be expected from the trends plotted in Figure 1, each grade level, beginning at Grade 7, was significant when considering a student's risk of dropping out. Model B built on Model A in an attempt to hold known categorical predictors of dropout constant in the equations and included significant parameter estimates for the time invariant variables gender, ethnicity and district (Table 4, Model B). Because retention and the number of low and failing grades are known to be associated with students not graduating on time, Model C included the main effects of retained as a dichotomous time-varying variable (repeated a grade level = 1, never retained = 0) and DEtotal (total number of *D*s or lower per grade level). In Model C, all of the parameter estimates were significant, and the –2 log-likelihood decreased from Models A and B, indicating less remaining variance left unexplained, while the chi square increased, indicating that Model C fit the data better than did Models A and B.

Having thus tested and replicated previously identified predictors of student dropout, I turn to the main question of the present study. The question of interest concerned the main effect of teacher-assigned grades on a student's risk of not graduating on time. To test grades in the model, the variable noncumulative GPA (within-year noncumulative GPA for all subjects taken that year) was added (Table 4, Model D). The addition of noncumulative GPA radically shifted the estimates and significance levels of the majority of the parameters in the model, reducing or eliminating the significance of each time point as well as the time invariant variables gender, ethnicity, and district. As the main significant finding of this study, in support of the idea that teacher-assigned grades are a significant predictor of student dropout, this finding suggests that the variable noncumulative GPA accounted for much of the variance in the estimated probability of a student dropping out of school, more so than grade level, gender, ethnicity, district, or DEtotal.

To explore the fit of more parsimonious models, Models E, F, and G were estimated. Model E fit to the data only those variables that had significant parameters in Model D or those that represented a continuous stretch of time from Grades 9 to 12. Model F fit only the most significant parameters: Grade 11, retained, and noncumulative GPA. Model G, as a subset of Model F, fit only retained and noncumulative GPA. Although the difference between Models F and G was statistically significant, Δ –2 log-likelihood (1) = 9.64, $p < .01$, the magnitude of the effect of the Grade 11 time point on the model was weak, as evidenced by the relatively small 0.2% difference in the pseudo R^2 results between the two models, and thus contribution to the variance explained (Table 4). Hence, to simplify analysis and interpretation while using the most parsimonious model, the remaining results and discussion focus on Model G.

As the final model, Model G is interesting in four ways. First, it was acknowledged that all logistic regression pseudo R^2 calculations are notoriously inaccurate as they approach 1.0, due the issue that no true R^2 calculations exist for logistic regression analysis (Aldrich & Nelson, 1984). Hence, for all of the models presented, once the R^2 calculation, as an indicator of the amount of variance explained by the equation, surpasses 0.5, the interpretation of the accuracy of that calculation must be taken with caution. However, Model G appeared to explain well over 50% of the variance in the probability of a student dropping out of school (Cox & Snell $R^2 = .707$), which was an improvement over past logistic regression dropout estimations (Alexander et al., 2001; Balfanz et al., 2007). In addition, Model G was reasonable, given past research that nominated retention and grades as useful in identifying dropouts. Second, Model G did not contain any time-point parameters, suggesting that at any grade level a student's risk of dropout in this sample was explained well by that student's retention status and noncumulative GPA. Stated another way, for this data set, a student's risk of dropping out was mainly time invariant and based more on a student's noncumulative GPA and retention status. This is a significant finding when considering that past at-risk prediction and prevention measures have considered time to be significant and grades to be only one of many possible variables to assess risk (Alexander et al.; Balfanz et al.; Bradley & Lenton, 2007; Eckstein & Wolpin, 1999; Jimerson et al., 2000).

Third, it is interesting that none of the three time invariant parameters were significant in the final model. Time-invariant variables are usually included in discrete-time hazard models to help control for factors that lead to sample bias, in this study postulated to be gender, ethnicity, and which district a student had attended. The inclusion of noncumulative GPA shifted the parameters for these variables to nonsignificant levels in Model D, suggesting that noncumulative GPA explained more of the variance in a student's risk of dropping out than did a student's gender, ethnicity, or which of the two districts the student attended. Fourth, transforming the logit parameter estimates in Model G into odds denoted that for this sample, when controlling for a student's noncumulative GPA, at any grade level after Grade 6, students who were retained at any time in a school district were 10.2 times more likely to dropout than were students who are not retained.[4] Transforming the same retained logit parameter estimate into hazard probabilities[5] indicated that retained students were 91.1% more likely to dropout than were nonretained students, replicating past research and extending it to more precise estimates for the risk of dropping out using survival analysis. When controlling for retention, transforming the logit parameter estimate for noncumulative GPA to odds signified that for every one-unit increase in noncumulative GPA, students were 0.161 times less likely to dropout. More intuitive is to invert this calculation, which indicates that at any grade level after Grade 6, for every one unit increase in noncumulative GPA, one whole letter grade, students were 6.02 times more likely to graduate. Odds ratios such as these are difficult to interpret (Aldrich & Nelson, 1984; Davies, Crombie, & Tavakoli, 1998), and thus it is more intuitive to transform the logit parameter for noncumulative GPA into a hazard probability. This indicated that when controlling for if a student had ever been retained in any one grade level after Grade 6, a one-unit increase in noncumulative GPA, one whole letter grade, corresponded to a 13.9% decrease in a student's risk of dropping out. Together, these results confirmed the negative impact of retention found in previous studies, and, more importantly, provided new evidence suggesting that teacher-assigned grades, as recorded as noncumulative GPA, are a significant and important predictor of a student's longitudinal risk of dropping out of school. In addition, it appears that this risk, rather than being restricted to the high school levels, begins in middle school.

The final model, Model G, was tested for assumption violations of linear additivity and proportional hazard. The first assumption was of linear additivity, that the effect of predictors is linear. For this study, it is possible to imagine a difference in the behavior of low- versus high-GPA students that may not necessarily be linear. To test this assumption, noncumulative GPA was categorized at four levels—0–1.5, 1.5–2.5, 2.5–3.5, 3.5–4[6] —and parameters were tested in the model with retention. Overall, when retention was controlled for, noncumulative GPA appeared to generally behave in a linear manner when predicting student dropout, with increasing levels of noncumulative GPA rising multiplicatively and with a leveling off only between the top two categories (data not shown). The assumption of proportionality was assessed with the assumption that each predictor had an identical effect in every time period under study. This was assessed by evaluating interaction terms between each grade level (Grades 7–12), with noncumulative GPA in the logit regression model predicting dropout. Although it was found that each interaction term was significant, it also appeared that Grades 9 and 10 might have had a slightly larger interaction with noncumulative GPA than did the other grade levels. The overall model was less parsimonious and a much poorer fit than was Model G (data not shown), and thus proportionality over time is assumed. In addition, the deviance residuals were analyzed to explore how well the model performed for individual cases. Few cases had extremely high outlier deviance residuals (data not shown). Thus, overall, Model G appeared to be well specified, fit the data well, and did not appear to violate any major assumptions of discrete-time hazard modeling.

In reference to a final issue of unobserved heterogeneity, which may pose a problem for a discrete-time hazard model such as this, due to the possibility that one or more important predictors had been omitted from the equation that could explain the risk profile identified, Singer and Willet's (2003) recommendations have been followed. Because unobserved heterogeneity asserts a consistent effect over time that leads to hazard functions that decline, because the hazard functions for the present study all rose substantially over time, unobserved heterogeneity was not considered problematic. Additionally, the aim of the present study was to identify if teacher-assigned grades, as represented by noncumulative GPA, are a significant and useful predictor of dropout that should be considered as useful by school districts in identifying students at risk of dropping out. The aim was not to identify a single predictor equation that is generalizable to a larger population, such as attempting to infer that Model G may represent a population-level estimation equation of student dropout, the sample size was insufficient to make this claim. Thus, even if unobserved heterogeneity was an issue, which most likely was not due to the increasing risk profile over time, that would not negate the point that Model G suggests that noncumulative GPA is a significant and important variable to consider when predicting student dropout (the main focus of this study).

Interpreting the Results of the Discrete-Time Hazard Model

Because the hazard model in Model G was mainly time invariant, predicting a student's risk of dropping out after Grade 6 solely on retention status and noncumulative GPA, it was not possible to plot the fitted model over time. However, the model was striking in the specification of the role that noncumulative GPA plays in the risk of student dropout. Thus, to provide an intuitive graphical display for results interpretation, the estimated sample hazard and survival functions were disaggregated for noncumulative GPA and plotted (Figure 2A and 2B).

Plotting the estimated hazard and survival functions by noncumulative GPA category showed that students who received the lowest grades were most at risk of dropping out. Noncumulative GPA was divided into four categories corresponding to the four major letter grades of *E* or *F* through *D*, *C*, *B*, and *A*; 0–1.5, 1.5–2.5, 2.5–3.5, and 3.5–4, respectively. Hazard and survival functions for dropout were estimated and plotted for students in these four categories (Figure 2). The hazard function indicated that students in the lowest noncumulative GPA category were at the highest risk of dropout in every grade level after Grade 6 (Figure 2A). Periods of highest risk for this group were in Grade 8 (30% of students with low grades dropped out) and Grade 11 (45% of students with low grades dropped out). Additionally, the survival function showed that students who received the lowest grades had the lowest rates of on-time graduation (Figure 2B). The median lifetime indicated that the average student who received grades in the lowest category stayed in school for 8.47 academic years, suggesting that the average student in the lowest noncumulative GPA category drops out of school before the start of the second semester of Grade 8. Additionally, the survival analysis showed that only 14% of the students in the lowest noncumulative GPA category graduated on time by Grade 12 (Figure 2B). Moreover, these graphical results compared well with the results

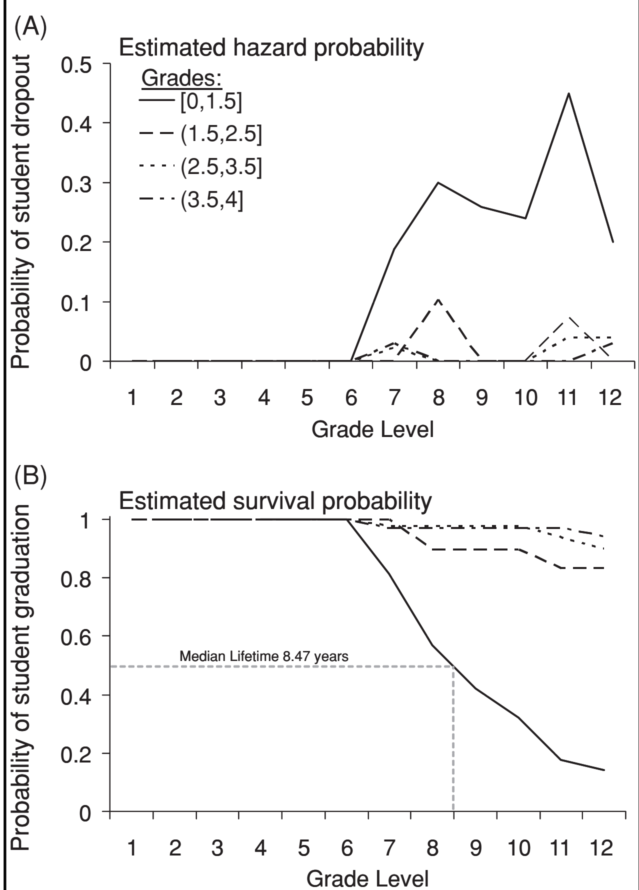

FIGURE 2. Estimated hazard and survival functions, disaggregated by noncumulative GPA categories. Noncumulative GPA was divided into four categories and hazard and survival functions were estimated and plotted. The subset of students most at risk of dropout was students who received noncumulative GPAs from 0 to 1.5 (A). Student risk began in Grade 7. Risk at each grade level was highest for students with low grades, peaking in Grade 11, with almost 45% of students with low grades at risk of dropout. The estimated survival function shows that students in the lowest noncumulative GPA category had the lowest rates of survival, with a median lifetime of 8.47 years, and only 14% surviving in school to graduation in Grade 12 (B).

of Model G and the overall hazard estimates (Table 4). Together, they provided further evidence that noncumulative GPA explains much of the variance in the probability of a student dropping out of school because the overall hazard trend for the data set was highly similar to the hazard trend for student dropout from the low noncumulative GPA category (compare Figures 1 and 2). These results are novel and significant, calculating risk of dropout based on teacher-assigned grades, utilizing the entire grading scale, encompassing all subjects for each grade level, producing a novel calculation of grades with noncumulative GPA, sampling all grade levels rather than just middle school or just high school, and handling the data appropriately using a life table and discrete-time hazard modeling. It appears that teacher-assigned grades were highly predictive of a student's risk of dropping out, suggesting that grades are useful and should play a much larger role in the prediction of student at-risk status. Additionally, in comparison with previous methods of predicting student risk of dropping out, Gleason and Dynarski (2002) showed that a regression composite of multiple risk-factor variables only accurately predicted 42% of the students who would have dropped out. More recently, Balfanz et al. (2007) were able to identify up to 60% of the students who drop out, using information from the end of Grade 6 and including a failing grade in English or mathematics. The results presented in Figure 2B indicate that 86% of the students who received low grades, as measured by noncumulative GPA, did not graduate on time. This appears to be a significant improvement over past at-risk prediction methods.

Discussion

In the longitudinal Grade 1–12 analysis for the event of dropping out of school, this study produced six main conclusions. First, the use of survival analysis and life tables in studying dropout appears to be useful and informative. At the minimum, this study affirms that life tables and survival analysis that utilize student-level data from Grades 1–12 may be an improvement over past graduation and dropout calculation methods. Second, it appears that risk of dropout in the present data set began in Grade 7 in middle school, two years earlier than the majority of present district at-risk prediction and prevention programs begin. Third, the most hazardous years for dropout in this data set appeared to be Grades 8 and 11, the transition before entering high school in Grade 9, and the year when students are old enough to drop out of school legally. Fourth, replicating past research, retention of students at any grade level was shown to have a highly negative impact on a student's probability of graduating on time. Fifth, teacher-assigned grades, as measured by noncumulative GPA, appeared to be a significant and useful predictor of student dropout, with students who received grades in the lowest category also experiencing a drastically increased risk of dropping out. Last, in comparison to past research on grades and dropout, the methods detailed in the present study appropriately controlled for the longitudinal and conditional discrete-time nature of Grades 1–12 student data when examining the utility of teacher-assigned grades for predicting student dropout.

These results appear to be novel and significant; however, issues of validity and generalizability must be addressed. The sample size for this study was small, consisting of only two cohorts of students from two school districts. This may have led to sample bias, district effects, or cohort effects due to the intact nature of the sample. However, this issue was attenuated somewhat by the inclusion of two school districts as well as the power analysis that indicated that the sample size was sufficient. Additionally, the longitudinal nature of the study increased its internal validity for these two districts. Overall, although this issue of an intact sample must be addressed, the study findings correspond to the findings of similar studies in different locations and extend those findings to a quantification of low grades as a significant and useful predictor of student dropout, through an initial test of the use of discrete-time hazard modeling using noncumulative GPA. Future research should include many more cohorts of students in many more districts to help control for this issue as well as further explore the utility of survival analysis in predicting the risk of student dropout.

The main purpose of the present study was to investigate teacher-assigned grades as a predictive indicator for students at risk of dropout through an initial use of life tables, survival analysis, and discrete-time hazard modeling. The results showed that grades as measured by noncumulative GPA were predictive of students at risk of dropping out, and that this risk was greatest for students who received the lowest grades. Grades were a major contributor to the fit of the discrete-time hazard model, outperforming previously known predictive categorical variables, such as gender, ethnicity, and even district effects. The predictive power of grades is made more evident when comparing the similarity in the shapes of the estimated hazard functions between Figures 1A and 2A. For this data set, grades appeared to account for much of the variance in the risk of student dropout. Additionally, the use of grades to predict if a student becomes at risk appeared to be an improvement over past methods, indicating that 86% of the students who received grades in the lowest category did not graduate on time. This suggests that for districts and schools wishing to assess if a student is at risk of dropping out, that student's longitudinal grade history should be considered as a predictor of risk.

Nevertheless, the point that grades are important in predicting graduation may seem intuitive, if not trivial or banal. Shouldn't higher grades predict graduation? The argument therein is that grades do predict graduation, but this point is important because according to the literature schools presently do not use grades as data for decision making in the manner suggested in this study. Grades are seen as hodgepodge (Cizek, 2000; Cross & Frary, 1999), incorporating an assessment of not only academic knowledge but also attendance, behavior, and participation. Also, grades are perceived in the literature as needing to be reported only to parents and students (Shepard et al., 2005). However, in the studies that have examined grades and student dropout, although methodological issues have somewhat clouded the point (as discussed previously), with some studies concentrating on certain subjects (Eckstein & Wolpin, 1999), grade levels (Balfanz et al., 2007), or overall counts of failing grades (Allensworth & Easton, 2005), the overall conclusion that was also supported strongly by the study findings is that teacher-assigned grades are a significant predictor of student dropout. This is especially important given that schools already assign grades to students, rather than needing to add yet another new test to the school routine, and that grades have a high level of face validity with students, parents, and teachers (Farr, 2000; Hargis, 1990; Kirschenbaum, Napier, & Simon, 1971; Shepard, 2006).

If grades are hodgepodge and thus not a pure indicator of a student's academic knowledge, then how is it that low grades appear to predict a student's risk of dropout? If low grades are predictive of students dropping out, one argument would be to give all students higher grades to prevent them from dropping out. However, this would be confusing correlation with causation and most likely would not lead to any reduction in student risk based on grades. However, an alternative argument is that although grades may not be a pure assessment of student's academic knowledge because grades incorporate all of the factors indicated by the hodgepodge grading literature, grades may be an accurate assessment of a student's ability to negotiate the intricacies of the schooling process (Bowers, 2009). Teachers may be assessing a student's ability at this process through the grades they assign. Because teachers incorporate into grades whether or not a student attends class, participates, and hands in homework, as indicated by the hodgepodge grading literature, I hypothesize that teachers, through grades, may be accurately assessing a student's ability to perform well in the school process, as indicated by noncumulative GPA, and thus graduate on time. Future research should look more closely at this issue.

The discrete-time hazard model indicated that retention and noncumulative GPA were more significant in predicting a student's risk than were time-invariant categorical variables such as gender, ethnicity, and district attended. As has been postulated in previous studies (Catterall, 1998), this shows that the use of a student's performance to date in the system provided to that student to predict at-risk status, rather than strictly relying on categorical factors outside of the school context, such as family SES, is important and worthwhile. Much of the present practice in schools that attempts to determine a student's risk of dropout (Gleason & Dynarski, 2002; Hammond et al., 2007) may be overly biased towards such categorical variables, ignoring the rich set of data that exists for each student at every grade level to date, assessing that student's performance in the system that's been provided to the student. To this end, future research should analyze the effects on risk of dropout of multiple assessments throughout a student's career in a school district, including grades and standardized assessments.

As suggested previously, but to date rarely utilized (Bradley & Lenton, 2007; Willett & Singer, 1991), survival analysis and discrete-time hazard modeling appear to be novel and interesting methods for assessing the magnitude of the probability of the risk of student dropout at every grade level in which students leave school, and in the present study beginning after Grade 6. However, for studies of this type, there is the question of using a single-risk model over a competing-risks model. In a single-risk model, only one dichotomous event outcome is assumed (e.g., student dropout vs. graduation; Singer & Willet, 2003). It could be argued that a competing-risks model could be used for this data set, modeling three events, a student's probability of dropout, graduation, or transfer into or out of a school district. However, the focus of the present study was to understand the effect of grades on the prediction of student dropout, so extending the analysis to a competing-risks model, although interesting, would overcomplicate the analysis as well as address a different research focus, modeling student transfer as an alternative to dropping out, and thus must be left to future studies. Moreover, I argue that a competing-risks model is inappropriate in that the event under consideration is the termination of a student's school career. Thus, as a student transferring to another school cannot be considered a competing risk for such an event because the student is still enrolled in a school somewhere, a single-risk model is more appropriate with student transfer handled through censoring, as was done in the present study.

For student dropout overall, the results of the survival analysis indicated that the most hazardous grade levels were Grades 8 and 11. This replicated past research that has shown that the transition from middle school to high school is an especially hazardous time (Catterall, 1998; Eckstein & Wolpin, 1999; Roderick, 1993; Roderick & Camburn, 1999; Rumberger, 1995; Zvoch, 2006). It also shows that for the state in which these districts reside, student risk of school dropout increased in Grade 11 after students reached the age to legally dropout of school for the state, age 16 years. This point that a large percentage of students drop out during the middle school grades is significant for three reasons. First, because these results show that the median grade level for dropout for students with low grades is at the Grade 8 level, national and state-level graduation rate estimates that do not include the middle school grades (Swanson, 2004a) are missing an important segment of each district's student population that may have dropped out of school before Grade 9. Second, these results further stress the need for longitudinal data on each student that spans at least the middle and high school grades, rather than concentrating only on the high school level or relying entirely on cross-sectional data, to better track and understand when and how students are at the greatest risk for dropping out of school. Third, as discussed previously, the literature indicates that most at-risk prevention and intervention measures take place at the high school level (Dynarski & Gleason, 2002). The literature further indicates that a student's decision to drop out is not based on a single event, but rather builds from a long history of events (Alexander et al., 2001; Jimerson et al., 2000), eventually convincing the student to leave school early. The present study results showed that students begin to experience a risk of leaving school at the middle school level, which generally rises over subsequent years. Together, these issues point to the conclusion that at-risk identification and prevention measures must begin to be utilized much earlier than in high school, starting at least at the middle school level.

Thus, this discussion leads to the question that if grades are predictive of student risk of dropout, starting in middle school, what is to be done about it? The results of this study do not speak to this issue. Although outside the scope of this study, it is important to take up this question because accurate identification is only the first step of many in helping to address the needs of students who may be experiencing difficulties with school. However, to date, little work has been done to systematically evaluate at-risk prevention programs.

For most of the evidence on at-risk students and dropout prevention, methodological problems persist that inhibit a robust evaluation of what works, such as biased groupings and estimates of effects, because randomized controlled trials are rarely performed in this area (Agodini & Dynarksi, 2004; Lehr, Hansen, Sinclair, & Christenson, 2003; Rumberger, 2004a). Nevertheless, what the literature indicates is that historically, most dropout prevention programs appear to not reduce student dropouts (Dynarksi, 2004; Dynarski & Gleason, 2002). As reviewed by Dynarski and Gleason (2002) and Lehr et al. (2003), these programs mostly occur at the high school level and consist of helping students build self-esteem, overcome personal and family issues, and increase attendance through periodic counseling; consist of the creation of smaller school settings; or provide tutoring or mentoring services. Similar programs at the middle school level have had somewhat more of an impact, but, as discussed previously, the accuracy of identification of students at risk of dropping out using middle school level data to date has been low and problematic. Hence, any program that appears to work using middle school level data may have worked only to the extent that the majority of the students identified for at-risk interventions were misidentified originally as being students at risk of dropping out.

Acknowledging that much more high-quality work is needed in the evaluation of dropout prevention programs before any one individual program can be recommended over another (Dynarski & Gleason, 2002; Hammond et al., 2007; Lehr et al., 2003), recent literature has begun to urge for a shift from a deficit model of attempting to prevent dropouts to a more positive model of promoting and encouraging successful school completion (Christenson & Thurlow, 2004). Although definitive data on such programs is presently lacking, it should be interesting to combine increasingly accurate dropout prediction methods, such as the results presented in the present study, with controlled studies evaluating the effects of providing resources to students to help them complete high school on time.

In the end, as discussed previously, this study replicated and extended previous findings that have nominated teacher-assigned grades as useful in predicting student dropout. For the first time, this study has shown with life tables, survival analysis and discrete-time hazard modeling that a novel calculation of grades, noncumulative GPA, examined from Grades 7–12 is a significant and useful predictor of student dropout. Based on these findings, I recommend that school districts begin to immediately investigate the utility of noncumulative GPA as a very easy and cost-effective number to calculate, in comparison to additional tests or surveys, as a primary means to identify students at risk of dropping out of school, starting at Grade 7.

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NOTES

1. Multiple school districts and student cohorts were considered for this study; however, some districts were not willing to participate and some districts did not retain data on students who dropped out of school, thus limiting the overall size of the study sample.
2. As recommended for data of this type, censoring indicates that data for a specific student includes all of the variables up until the time of the student's exit from the data set, but with 0 recorded for the variable dropout rather than 1. For a review of censoring, see Singer & Willet (2003).
3. Each time point is conditional due to the fact that any student who experiences the event in one time point is removed from the calculations for all future time points.
4. Odds ratio $= e^{\beta} = e^{(2.325)} = 10.2$
5. Probability $= 1/(1 + e^{-\beta})$
6. A bracket indicates inclusive in a series of numbers and an open parenthesis indicates noninclusive.

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