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Hazard Model Analysis of Community College Outcomes

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Abstract

Community colleges serve a diverse set of students, from recent immigrants studying for citizenship tests to students looking to transfer to four-year institutions. Relative to continuous enrollment, the three most common outcomes for students are to graduate, transfer to a four-year institution, or drop out without either of the previous two outcomes. We use a competing-risks hazard model to jointly model the determinants of these three outcomes for Kentucky two-year college students. Our results highlight the importance of multiple factors such as working while enrolled, financial aid, demographics, and having a GED.

Keywords: Education, Hazard Models, Two-Year Colleges, Competing-Risks

JEL codes: I21, C41, J24

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1 Introduction

Higher education attracts significant state investments intended to reduce the financial barriers to completing college (Singell, 2004). However, only about 30% of full-time students at two-year colleges[1] graduate within 150% of "normal time," (Snyder and Dillow, 2010). Students who drop out or take longer to complete their degrees due to inconsistent enrollment place additional burdens on the government and the taxpayers who fund these investments. From a public policy standpoint, a better understanding of the obstacles to college completion is essential for improving retention rates, completion rates, and time to completion.

Using a competing risks hazard model, the present work seeks to provide a more comprehensive analysis of factors affecting two-year college student outcomes than previous research. Hazard (or survival) models[2] are ideally suited for studying educational outcomes because they explicitly model sequential decisions, fully utilizing detailed panel data. This paper analyzes, relative to continuous enrollment, three possible outcomes that two-year college students have each term: dropping out; graduating with a degree, diploma, or certificate; or transferring to a four-year institution.

Using administrative data from the Kentucky Community and Technical College System (KCTCS), the present research explores key determinants of these outcomes, relative to continuous enrollment. For example, earnings, employment, being nonwhite, and having a GED are positively associated with dropping out. Loans are positively related to transferring, but GED receipt is negatively associated with transfer or graduation. Financial aid is positively related to graduating, and women are much more likely to graduate.

2 Relation to Literature

The present work contributes to a sizable literature on the determinants of retention, graduation, and transfer in postsecondary education. A pioneering work on this topic is Tinto (1987), stressing the role of academic and social engagement. More recently, authors have

[1] Throughout the paper, we use the term "two-year colleges" to denote public two-year colleges, also known as community or junior colleges.
[2] As is common in the literature, the terms "hazard" and "survival" are interchangeable for these models.

tailored this model for community colleges (Halpin, 1990; Karp et al., 2010; Stuart et al., 2014). Melguizo (2011) reviews the models for student persistence from multiple fields including economics. The empirical studies on retention at community colleges are simply too numerous to mention, although recent papers such as Porchea et al. (2010) provide useful overviews. For brevity, our focus is on studies using hazard models to study community colleges. Within that narrow literature, few studies that look simultaneously at retention, graduation, and transfer among two-year college students.[3]

The papers most similar to our work are by Scott and Kennedy (2005), Park (2013), Mourad and Hong (2008), and Calcagno et al. (2007). Scott and Kennedy (2005) discuss a discrete-time, competing-risks hazard model by estimating a multinomial logit model of community college dropout, transfer, and associate's degree receipt in the High School and Beyond survey. The goal of the paper is to discuss concepts regarding the hazard model rather than to study the determinants of community college outcomes, as illustrated by their inclusion of only three covariates: a dummy variable for working during the semester, a dummy variable for starting community college at age 21 or higher, and a dummy variable identifying gaps in enrollment.

Park (2013) estimates single-risk hazard models as well as a competing-risks model for dropping out of two-year college versus going on to complete a bachelor's degree, relative to continuous enrollment. Estimating separate models for each of the first three enrollment spells, Park (2013) finds that pre-collegiate factors are significant predictors of initial enrollment spells but have little predictive power on later enrollment spells.

Mourad and Hong (2008) closely resemble our paper. Focusing on one cohort of entering students from one community college, they estimate a competing-risks model for a small set of independent variables as an exploratory analysis of the feasibility of using such models. We extend their analysis with a more comprehensive set of variables, such as earnings and employment, on a statewide sample of students from multiple entering cohorts.

Calcagno et al. (2007) use a single-risk hazard model to study the effect of age on two-year college completion and find that, conditional on mathematics aptitude, older students

[3] For brevity, we do not include the sizeable literature on four-year schools, including recent studies using competing risks models to study student outcomes outside the U.S. such as Clerici, Giraldo, and Meggiolaro (2015).

are no less likely to complete a degree or certificate than younger students. As a robustness test, they estimate a multinomial probit model, which is a more restricted type of competing risks model than the one we employ.

Most studies on community college outcomes use probit or logit models to study a single outcome, such as transferring (Surette, 2001; Dougherty and Kienzl, 2006) graduating from four-year institutions (Doyle, 2009), or continuing enrollment (Hawley and Harris, 2005; Wolfe and Williams, 2014; Windham et al., 2014).

This paper makes several contributions to the literature. It provides a competing-risks hazard model analysis of dropping out, transferring, or graduating (as compared to staying enrolled) that includes a more complete set of community college outcomes than most previous work. This model complements the work by Park (2013) using a subset of outcomes and work of DesJardins, Ahlburg, and McCall (2006), who use a competing-risks model to study multiple enrollment spells at a four-year college. Furthermore, we explore the relationship between working while enrolled and two-year college outcomes, using earnings in the previous semester to account for the potential simultaneity of work and dropout decisions.[4] The analysis benefits from a large administrative dataset and the use of a competing-risks hazard model that is ideally suited to study the longitudinal nature of postsecondary retention and the competing risks among the possible outcomes. One limitation of our analysis is that we have a limited number of control variables available, so we are unable to control for potentially important determinants, such as parental income.

3 Data

The data for this research are from a comprehensive administrative data set provided by KCTCS. KCTCS is the statewide community college system with 16 colleges and 67 campuses. Colleges are located in all parts of the state, with both urban and rural campuses. The Kentucky Postsecondary Education Improvement Act of 1997 created KCTCS. The majority of the consolidation in to the current set up of 16 colleges occurred between 2001-2003 with the last consolidation occurring in June 2005. The impact of the consolidation and time period of the data for this study makes it difficult to compare the student characteristics to colleges in other states. For the cohorts used, Kentucky is at the national average of

[4] Park (2013) also studies the effects of earnings while enrolled, generally finding a negative effect on graduation.

transfer rates to four-year colleges but differed when it came to retention and graduation. In other words, Kentucky may look similar to some states when it comes to graduation but looks different from those same states when it comes to retention. Overall, Kentucky cannot be easily generalized to the other states.[5]

This data set matches individual student records to administrative earnings data from the state's unemployment insurance department. The data set contains students who started at KCTCS between summer 2002 and spring 2004.[6] Students who are in correctional institutions, younger than 17 years of age, or more than 60 years of age at entry are excluded. Students are tracked for 12 semesters from their initial enrollment because transfer data are only available for the first 12 semesters. As a year has three semesters (fall, spring, and summer), students are tracked for four years. Although an appealing feature of the hazard model is that it explicitly accounts for this type of data censoring, we acknowledge that having a longer time period is preferable given that many students are still enrolled after 12 semesters.

The data include information on demographics, enrollment, courses, outcomes, transfers, financial aid, and earnings. Demographic data contain information such as age, race, gender, and type of high school attended. The enrollment-level data contain college of enrollment, enrollment semester, admittance type, and the academic plan the student intends to complete while at KCTCS. The course-level data include all the basic transcript information for all students who enrolled in KCTCS, including information by semester on grades, classes attempted, credits earned, and whether a student acquired credits for remedial classes.

Data on outcomes identify each type of graduation award (degree, certificate, and diploma) offered by KCTCS. Transfer data are obtained from the National Student Clearinghouse. These data provide information on whether the student transfers to a four-year college, a two-year college, a private college, a public college, a Kentucky college, or a non-Kentucky college. The date of transfer is also provided.

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[5] https://collegecompletion.chronicle.com/state/#state=ky&sector=public_two; http://www.higheredinfo.org/dbrowser/index.php?submeasure=24&year=2015&level=nation&mode=data&state=0

[6] Fall semester starts in September and ends in December; spring semester starts in January and ends in April; summer semester starts in May and ends in August. Thus, the data contain students who initially enroll in the summer of 2002, fall of 2002, summer of 2003, fall of 2003, or spring of 2004.

KCTCS provides financial aid data by the type of aid for each student. There are two types of aid: (1) loans that need to be repaid and (2) grants and scholarships that do not need to be repaid.[7] For each type of aid, KCTCS provides information on semester of aid, year of aid, and the amount awarded. KCTCS did not provide information on whether a student applied for aid or not. DesJardins, Ahlburg, and McCall (1999) raise concerns about the potential endogeneity[8] of using financial aid awarded (i.e. actually received by the student) rather than the amount of financial aid offered. However, information is only available on aid awarded in this data set, and endogeneity concerns are somewhat mitigated as financial aid decisions are made before the semester starts rather than during the semester. Although selection may remain on who applies for and receives financial aid, we know so little about the relationship between financial aid and community college outcomes that even our descriptive analysis of this relationship is informative.

KCTCS provides employment and total wages for each student per quarter by combining student-level data with the unemployment insurance department data. For both cohorts, earnings data are provided from the first quarter of 2000 through the third quarter of 2008 and are gathered from the state's unemployment insurance program.[9] The quarterly earnings data are converted to earnings on an academic calendar with three semesters by averaging quarter 1 and quarter 2 to calculate earnings for the spring semester, quarter 2 and quarter 3 to calculate earnings for the summer semester, quarter 3 and quarter 4 to calculate earnings for the fall semester.[10] The data do not contain any additional information on employment such as hours worked, industry, or occupation.

[7] Because grant amounts are very small and because nearly all students who receive grants also receive scholarships, we cannot separately identify the effects of grants and scholarships. Instead, we combine these two types of aid into a single category of financial aid that does not need to be repaid.

[8] A simplified explanation of endogeneity is as follows. Desjardins, Ahlburg, and McCall (1999) are worried that the amount of financial aid actually awarded may be jointly determined with characteristics that are not observed such as financial hardship. If so, then the coefficient for financial aid awarded is actually a combination of the effects of financial aid and financial hardship. Economists refer to 'exogenous' variables as ones that do not suffer from these concerns about omitted variables. An example of such a variable is race / ethnicity, which is innate and cannot be changed or modified.

[9] A slight limitation of these data is that they ignore employment outside Kentucky, self-employment, illegal employment, and a few jobs that are not covered by the unemployment insurance.

[10] We also explore another conversion technique where we divide the total earnings for the year by three to provide earnings for each semester. The results are not sensitive to this conversion.

One concern with the earnings variable is the possibility that current earnings and student outcomes such as the decision to drop out are made jointly. To reduce this concern (often called endogeneity), we measure earnings in the previous semester using the timing algorithm discussed above. Sophisticated econometric techniques to deal with endogeneity, such as instrumental variables analysis or student fixed effects models as used in Dadgar (2012), are not feasible in a hazard model. Hazard models are well-suited for studying sequential decisions regarding education outcomes, but they are not well-suited for dealing with endogenous covariates.

Finally, data on county-level unemployment are collected from Bureau of Labor Statistics (BLS). The unemployment rate serves as a proxy for local labor-market conditions given the importance of local labor-market conditions on two-year college enrollment, as shown in Betts and McFarland (1995). The importance of local labor market conditions is tempered by the option of commuting to jobs outside the county of residence.

4 Model Specification

Many studies have modeled students' accumulation of human capital using Becker's human capital theory. Becker's (1964) human capital theory suggests that students will invest in postsecondary education as long as the marginal benefits are greater than the marginal costs. The theory suggests that students make their decisions typically right after they complete high school. For example, students with high abilities – which we proxy with first-semester GPA and a lower number of remedial classes – may have an easier time getting higher grades and therefore have lower psychic costs to college. If so, then human capital theory predicts that these students are more likely to graduate and to transfer to four-year schools than students with lower abilities.[11] Because the GED is often perceived as inferior to a high school diploma (Cameron and Heckman, 1993), an extension of this theory is the expectation that GED recipients are less likely to transfer to a four-year school or graduate than high school graduates. The theory is less clear on the expected direction of monetary variables such as earnings, employment, and financial aid. Students with jobs and / or

[11] To simplify the model, we assume that graduating and transferring are measures of more schooling relative to dropping out or continuous enrollment without looking specifically at the theoretical determinants of each specific schooling level.

financial aid may have fewer resources available, specifically time and money, and therefore may be more focused to complete their studies. On the other hand, the stress of having fewer time and / or money available may result in a lower likelihood of transferring or graduating.

Although some may assume that students have full information about the costs and benefits of postsecondary schooling, in reality, most if not all are uncertain about the future benefits and costs. These uncertainties are alleviated as students test both the schooling and labor markets to learn new information. Weisbrod's (1962) option value theory takes these uncertainties into account and by assuming that individuals lack perfect foresight. The theory models investment in education as a sequential choice problem. In other words, students can influence the timing of their investments and reevaluate their costs and benefits at the end of every stage to determine whether they want to drop out or continue schooling.

Uncertainties come in many forms. These include, but are not limited to, when students are uncertain of investing in additional education due to the uncertainty on future costs and benefits of the additional investment. These uncertainties are only resolved as students complete additional education. Upon completion of a semester, students learn new information about additional costs of education, current returns to the completed semester of education plus the value of exercising the option to acquire additional schooling, and any shock to these costs and benefits (Heckman et al., 2006). New information can be in the form of many unexpected shocks such as academic performance, falling ill, losing a job, acquiring a job, changes in marital or parental status, etc. or in the form of many expected shocks such as planning to marry, having children, buying a house, etc. Using this information, students recalculate their lifetime utility at the end of every semester to make their next investment choice.

Once students update their beliefs after completing a semester or academic year, they have two options: they can drop out and join the labor force or enroll for an additional semester. Students will drop out when they realize that their net present value is highest for the option to drop out. As noted earlier, students' investment decisions are largely influenced by unexpected positive (salary raise, promotion, etc.) or negative (job loss, failing a class, etc.) information while attending a postsecondary institution. Thus, apart from controlling for student background and ability factors, we are able to estimate the relationship between students' earnings while in school and the time to drop out. Earnings while enrolled is an important variable as it provides information either through an increase or decrease in earnings on the decision of a student to extend enrollment at a two-year college for an additional semester.

A novel feature of this study is that it uses a hazard model to estimate how student characteristics and institutional factors affect the time students take to graduate, transfer, or drop out. These models have been used in the community college literature (e.g., Calcagno et al., 2007; DesJardins, Ahlburg, and McCall, 1999; Doyle, 2009; Park 2013) due to their ability to take into account the longitudinal process involved in student education decision-making. Becker's (1964) human capital theory states that students will invest in postsecondary education as long as the net benefits exceed net costs of education. Students take into consideration their direct and opportunity costs of attending college and once enrolled, students remain enrolled until completion, or when net benefits of the labor market outweigh those of continuing school (Heckman et al., 2006; Mincer, 1974; Stratton et al., 2005). This process is not a one-time static-discrete choice problem – as modeled in probit or logit models – but rather a simultaneous process. Students update their utility maximizing decisions through new information gained at the end of every semester. More importantly, students take in to account changes in the local labor market over time. Since students can influence their timing of investments, it is more appropriate to use hazard functions than traditional models as the former explicitly account for time and the longitudinal process. Hazard models measure the likelihood of the event occurring over time.

The present work models student outcomes at two-year colleges by controlling for institutional, academic and economic factors. Dropping out is defined as missing two consecutive semesters (or more) without earning a degree or transferring. Two, rather than one, missed semesters are used to define dropping out because many students choose not to attend the summer semester(s). As shown in the results section containing analysis for dropping out defined as missing either three or four consecutive semesters, the results are not sensitive to alternate definitions of dropping out. Transferring is defined as transferring to a four-year program even if other outcomes are achieved. In other words, students who receive a degree, diploma, or certificate and transfer to a four-year school are defined as transferring, not graduating, because these students share the common goal of pursuing a four-year degree.[12] Transfers within the Kentucky community college system are treated as continuous enrollment; the very few students who transfer to community colleges outside the Kentucky community college system are excluded from the analysis. Graduating is defined as receiving a two-year college degree, diploma, or certificate but not transferring to a four-year college. Continuous enrollment is defined as not missing two or more consecutive semesters of schooling, not transferring, and not graduating.

Hazard models estimate the conditional probability of an event (hazard function) at time t given that the student has not experienced the event before time t. In this study, we consider the timing of three events of interest: dropout, graduation, and transfer. The comparison for all these outcomes is continuous enrollment. The data is right censored where t>12; for some students, there was no recorded event because they did not have an outcome of interest in the 12 semesters of data we have. A linear regression model would ignore the censoring, and a logistic or probit model ignores the time aspect of the data. Hazard models account for censored observations as well as time to event.

The basic hazard model used is:

$$h(t_{ij}) = \Pr[y_i = j | y_i \geq j-1, i \in A_j, X_1, \ldots\ldots, X_J], \qquad (1),$$

where $y_i = j$ indicates student i's outcome in semester j. The probability is conditional on the event of interest not occurring in period j – 1 or earlier, and time $j \leq 12$ because, as mentioned above, we only have 12 semesters of data for each student.

The proportional hazards regression model is given by:

$$h_1(t, X) = h_0(\mathrm{t}) \exp\ (\beta X) \qquad (2),$$

$$h_1\ (t, X) = h_0\ (\mathrm{t}) \exp\ (\beta_1 X_1 + \cdots\cdots\cdots + \beta_m X_m), \qquad (3),$$

where t is the time of event, X_i are the set of covariates, $h_1(t)$ is the hazard for the outcome of interest (transfer, graduation, drop out), and $h_0(t)$ is the hazard for the reference outcome (continuous enrollment). The covariates, X_i, are assumed to act additively on log h (t, X), which changes linearly with the βs. Typically, in a parametric survival model such as Weibull,

[12] Because only two percent of our sample transfer and receive an award, our results are not affected by this assumption.

an assumption is made about the distribution of the underlying hazard, $h(t)$. The benefit of estimating a Cox proportional-hazards model is that it leaves the baseline hazard function unspecified, so the baseline can take any form. Most situations involve stronger interest in the parameter estimates than the shape of the hazards. This preference for the parameter estimates makes the Cox model more appropriate for this study. In addition, Cox models allow controlling for time-varying coefficients.

Hazard ratios are estimated for each covariate, which provide the likelihood of the event occurring with respect to the reference outcome:

$$\frac{h_1 t}{h_0 t} = \exp(\beta), \qquad (4),$$

which is independent of time. Consequently, the Cox model is a proportional-hazards model.

The outcome of interest (dropout, transfer, or graduate) is affected by a vector of both time-varying and time-invariant explanatory variables X_j, which controls for all the observed student characteristics. Although each outcome of interest can be estimated individually, results from single-risk Cox proportional models should be treated with caution because single-risk models assume that all outcomes are independent of each other. It seems unlikely in our context that this assumption would hold.

A general concern in hazard models is that bias can be introduced through unmeasured factors (disturbances) which affect several outcomes, or through outcomes that have direct causal impact on each other.[13] These factors are difficult to measure. For example, it is difficult to measure the motivation to study acquired from parents or how dropping out disrupts the acquisition and maintenance of study skills. Our detailed set of explanatory variables helps reduce this problem, but it is a potential limitation of hazard models in general.

To study the multiple outcomes of continuous enrollment, dropout, transfer, and graduation, we estimate a competing risks model introduced by Fine and Gray (1999). This

[13] In single-risk hazard models, researchers include control variables to account for unmeasured heterogeneity (such as the frailty option in Stata). A frailty model attempts to measure this overdispersion by modeling it as resulting from a latent multiplicative effect on the hazard function. Unfortunately, such controls are not possible in competing risks models using Stata. The results for single-risk hazard models were not sensitive to the inclusion or exclusion of controls for unmeasured heterogeneity.

model is a modified version of the Cox proportional hazards model (also known as subdistribution hazard) where the hazard corresponds to the cumulative incidence function (CIF). The cumulative incidence function gives the proportion of students at time t who have exited the college from one outcome (e.g., dropout) accounting for the fact that the student can exit the college due to other outcomes (e.g., graduate or transfer to a four-year college). The CIF is a more descriptive approach that focuses on the probability of each type of event. The model takes the form of:

$$\bar{\lambda}_1(t|X) = \bar{\lambda}_{1,0}(t) \exp \ (\beta^t X) \qquad (5),$$

where t is the time of event, X_i are the set of covariates, $\bar{\lambda}_{1,0}$ is the baseline distribution hazard for the event of interest. Solving for the CIF gives:

$$I_1(t|X) = \ 1 - \exp(-\exp \ (\beta^t X) \cdot \int_0^t \bar{\lambda}_{1,0} \ (s) ds) \qquad (6),$$

where $exp \ (\beta^t X) \cdot \int_0^t \bar{\lambda}_{1,0} \ (s) ds$ is the cumulative subdistribution baseline hazard function.

The model is similar to the Cox model in that covariates act to multiply the baseline subdistribution hazard in a time-independent manner. Therefore, we can interpret the subdistribution hazard ratio in a similar fashion as the ratio for a single-risk Cox model, but we do not have to make the assumption as in the single-risk Cox model that the events of interest are independent. Positive coefficients (subdistribtuion hazard ratio > 1.0) increase the CIF, whereas negative coefficients decrease the CIF. This model is most widely used and allows for a proportional hazards interpretation. Similar to the Cox proportional model, the Fine and Gray (1999) model allow for time-varying coefficients.

The hazard model used in this paper is summarized as follows. We estimate how the observable time-varying covariates such as earnings, financial aid and county unemployment rate and several time-constant covariates affect the likelihood and timing of dropout, graduation, or transfer. For each outcome, the dependent variable is a dummy variable coded 1 if a student achieved the outcome (such as dropping out from KCTCS) at the end (or during) the semester, and 0 otherwise. The independent variables included in this model are listed in Table 1, as well as dummy variables for each semester (such as spring 2007). Our administrative data set does not contain all of the variables included in previous studies. For example, we have limited data on family background.

5 Descriptive Statistics and Timing of Outcomes

Table 1 contains student-level descriptive statistics. The final sample used for the analysis contains 65,523 unique individuals: 29,914 men and 35,609 women. The average age at initial enrollment is 27.9 years. The sample is 78% white, 9% non-white, and 13% not reported. Approximately 80% are high school graduates, 12% hold GEDs, and 8% have missing education variables. On average, students take 0.54 remedial credits their first semester. The average earnings of the sample (measured in the previous semester to reduce endogeneity concerns) are $3,045 per semester. Nearly 40% of students are employed in the previous semester. The average amount of financial aid awarded is $446 for grants and scholarships combined and $91 in loans. The low amounts for loans are due to the relatively small percentages of students who receive this type of financial aid.[14] On average, students attempt almost two and a half classes per semester, and the average GPA after the first semester is 2.34.

Over one-third (37.4%) of students do not intend to pursue a degree, diploma, or certificate. The most popular degree as determined by student intentions is health (17.0%), followed by vocational (9.9%) and humanities (8.6%); 12.8% of the sample is undecided with respect to field of study. Fall is the most common semester of entry, followed by spring. Few students start during the summer.

Table 1 also provides descriptive statistics by outcome. The table shows that 62% of the sample drop out. Students who drop out are, on average, older, more likely to have a GED, and more likely to be nonwhite than other students. They have higher earnings and lower GPAs. Transfer students are considerably younger, are more likely to be female, have lower earnings, and take fewer classes per semester than other students. Graduates are more likely to be female, white, and have higher GPAs than other students. Students who are continually enrolled throughout the sample periods are more likely to be female and take more remedial classes in the first semester than other students.

[14] Less than 0.1 percent of students receive other types of financial aid.

Timing differs for dropping out, transferring, or graduating (receiving a certificate, diploma, or associate's degree without transferring to a four-year institution). Graduating typically occurs at the end of each semester. Transferring typically occurs at the end of a semester but is possible at any time. Dropping out is measured as the semester of last attendance even though it is defined as not returning for two semesters. For example, a student who attends the first semester and misses the next two (or more) semesters is defined as dropping out at the end of the first semester.

Figure 1 and Appendix Table 1 show the timing of outcomes by semester after initial enrollment. The outcomes are cumulative. For example, the number 48.9% for dropout in semester 3 means nearly half of students have dropped out of two-year colleges by the end of semester 3. The figure illustrates that, after the first semester, dropping out is the most likely outcome. Approximately 20% of the sample transfer, with most students transferring by the end of semester 9. After the first year, the percentage of students graduating increases steadily. By the end of the 12-semester sample, 13% of students have graduated.

Appendix Table 1 also displays the male-female gap in outcomes. The table illustrates that gender gaps in outcomes are driven largely by higher dropout rates among men, with a gap 12% to 15%. Women have higher transfer rates and lower graduation rates.

6 Hazard Results

Table 2 shows the hazard ratios from competing-risk models of independent variables on the three outcomes of interest: dropping out, transferring, and graduating. In other words, one competing-risks model provides results for all three outcomes relative to continuous enrollment. For each outcome, the first column represents the combined sample of men and women, the middle column represents men, and the third column represents women. Thus, the table contains results from three competing-risks models based on gender.

For all hazard models, the reported results are hazard ratios, e^{β}. A hazard ratio above 1 implies an increased likelihood of an outcome associated with a positive change in the independent variables. A value less than 1 reflects a smaller hazard rate of the outcome of interest at each unit of change in the predictor variable. Deducting 1 from the hazard ratio yields the percentage change in the hazard for a 1-unit increase in the independent variable.

For example, in the first column, the coefficient of 1.06 for employment shows that employment is associated with a 6% increase in the likelihood of dropping out.

6.1 Dropout

Holding other factors constant, employment is associated with a 6% increase in the hazard of dropping out. Although earnings are statistically significant for the combined sample of men and women, the result is not economically significant. Increasing earnings by $1,000 per semester corresponds with an increased likelihood of dropping out of 0.3%. Park (2013) finds a larger, negative relationship between log wages and stopping out. Employment and earnings are lagged one semester to reduce the possibility that employment and earnings are jointly determined with dropping out.

Both measures of financial aid are negatively related to dropping out. However, the association of a $1,000 increase in financial aid is much larger for loans (22%) than for grants/scholarships (5%). Thus, there is a negative relationship between financial aid and the likelihood of dropping out.

Student demographics are also significantly related to dropping out in ways that are similar to previous work on student retention in community colleges (Porchea et al., 2010). Being a woman corresponds with a decreased probability of dropping out of 11%, holding other factors constant. Nonwhites have slightly higher dropout probabilities of 7%. Age is positively associated with dropping out; each year of age is associated with an increased dropout probability of 1%. Holding a GED rather than a high-school diploma is associated with an increase in the likelihood of dropping out of 32%.

Ability as measured by first semester GPA has a negative relationship with dropping out. A one-point increase in GPA corresponds with a decreased likelihood of dropping out by 23%. First-term remedial credits also provide a measure of student preparation before arriving at a community college. An increase of three remedial credits – an amount typical for one class – is associated with an increase in the hazard of dropping out by 6%, similar to the relationship found in Hawley and Harris (2005). Taking an additional class in the current semester is related to a 13% decrease in the hazard of dropping out. In other words, students with more courses are more likely to stay enrolled than students with fewer courses, all else equal.

The hazard ratios for the separate samples of men and women are broadly similar to the hazard ratios for the combined sample. The main exception is that the county unemployment rate estimate is not statistically significant for men. In most cases, women's hazard ratios are larger in magnitude compared to men's. For instance, the relationship between employment and dropping out is an increased likelihood of 5% for men and 8% for women, although this difference is not statistically different (Appendix Table 2). Having a GED is associated with an increased dropout hazard of 28% for men and 35% for women (Appendix Table 2).

6.2 Transfer

Unlike dropping out, the relationship between student earnings while in school and transferring to a four-year school is negative and significant. A $1,000 increase in earnings is associated with a decrease in the likelihood of transferring by 3%. This result is more pronounced for men. Although the association between being employed and transferring is positive, the hazard ratio is not statistically significant at p = .10.[15]

The hazard ratio for financial aid varies by type. Grants/scholarships have an insignificant association on transfers, but loans promote transfers to four-year colleges. A $1,000 loan is associated with a 31% increased likelihood of transferring. A student with a firm plan to transfer to a four-year college and obtain a bachelor's degree is more likely to be willing to take on debt that a student simply taking one or two courses for enrichment. This scenario produces a positive correlation between taking on a loan and transferring to a four-year college and a negative correlation between financial aid and dropping out.

Gender and race have insignificant hazard ratios on the probability of transfer, consistent with findings in Dougherty and Kienzl (2006) but not with the lower transfer rates for women found in Surette (2001). Age is negatively associated with transferring, with the likelihood of transferring decreasing by 4% per year of age. Dougherty and Kienzl (2006) also find negative hazard ratios for age. Having a GED is related to a decreased likelihood of transferring of 50%.

A one-point increase in first semester GPA has a large, positive association (41%) on the likelihood of transferring. An increase of three remedial credits corresponds with a

[15] Dougherty and Kienzl (2006) also find generally insignificant effects of working on transferring.

decrease in probability of transferring by 7%. Taking an additional class in the current semester is associated with a 9% increase in the hazard of transfer, analogous to the positive relationship between full-time enrollment and transferring in Dougherty and Kienzl (2006).

The results for men and women are largely similar, although the pattern in results by gender is less consistent for transferring than for dropping out. For example, loans have a larger positive association for men (37%) than women (29%), but the number of classes attempted has a larger positive association for women (11%) than men (8%). However, neither of these differences is statistically significant (Appendix Table 2).

6.3 Graduate

The hazard ratios for earnings and employment on the probability of graduating for the combined sample of men and women are insignificant, but the hazard ratios differ by gender. A $1,000 increase in earnings correlated with an increased likelihood that men graduate by 2% and a decreased likelihood than women graduate by 5%. Park (2013) finds a positive effect of log wages on the likelihood of graduating with a bachelor's degree for a combined sample of men and women. Employment has an imprecise relationship with graduation. The employment hazard ratio is insignificant for men and the 15% increase in graduation for women is only statistically significant at p = .10 for women.

Both financial aid variables correspond with increased likelihoods of graduation. The associations of $1,000 increases in financial aid are 25% for grants/scholarships and 32% for loans. Grants/scholarships have larger hazard ratios for women, whereas the hazard ratios for loans are greater for men than women.

For graduation, student demographics are generally statistically significant. Being a woman corresponds with an increased likelihood of graduation of 34%, but there are no discernable differences by race. A one-year age increase is associated with a 1% increase in the probability of graduating. Having a GED correlates with a decreased likelihood of graduating by 16%, although the relationship differs dramatically by gender. For men, the correlation between GED and graduation is positive but insignificant, but the correlation for women is large (24%) and negative.

First semester GPA has a large, positive association on graduating (31%). First-term remedial credits are negatively associated with graduation. Each three-credit class of remedial education corresponds with a reduced graduation probability of 12%. The number of classes attempted has no discernable relationship with graduation for the combined sample of men and women. For men, an additional class is associated with an increase in graduation probability of 10%; for women, an additional class is associated with a decrease in graduation probability of 5%. A 1% increase in the county unemployment rate relates to a decrease in the likelihood of graduating of 6%, suggesting that students, when faced with poor economic conditions prefer continuous enrollment. This result is consistent with the findings in Betts and McFarland (1995).

6.4 Sensitivity Analysis

Several models are estimated to test the sensitivity of our results to alternative definitions of variables and estimation techniques. The most important sensitivity test is the comparison of the competing-risks model to the single-risks models that are more common in the literature. A major contribution of the paper is a more comprehensive analysis of the three most common outcomes in two-year college – dropping out, transferring to a four-year school, or graduating relative to continuing enrollment. The previous literature is dominated by single-risk models, although Calcagno et al. (2007) include a multinomial probit model, a restricted type of competing-risks model, as a robustness check.[16]

For the combined sample of men and women, Table 3 presents the results from the competing-risks hazard model alongside single-risk models. For each outcome, the first column is the competing-risks model (identical to Table 2), and the second column is the Cox single-risk model for that outcome. In both cases, the comparison outcome is continuous enrollment. The table shows that the competing-risk and the single-risk model are quite similar for studying dropout decisions, but some differences in magnitude and statistical significance exist for transferring and for graduating. For example, grants and scholarships are associated with a lower likelihood of transferring in the single-risk model compared to an insignificant hazard ratio for the competing-risks model.[17] Thus, some of the results from single-risk hazard models in Calcagno et al. (2007) and Park (2013) may be sensitive to the

[16] Scott and Kennedy (2005) and Patel (2011) also use multinomial logit and probit models, which can be interpreted as discrete-time competing risks models, although such models are constrained in their treatment of time-varying characteristics. Park (2013) includes a competing-risks model of bachelor's degree completion.

[17] Conversely, loans have a positive relationship with graduating in the competing-risks model, but the hazard ratio is not statistically significant in the single-risk model.

exclusion of competing two-year college outcomes. These differences are most notable for time-variant determinants such as financial aid and for the outcomes of transferring or graduating.

As mentioned previously, the dropout decision is defined as students missing two consecutive semesters without subsequently receiving a graduation award (certificate, diploma, or associate's degree) or transferring to a four-year institution. In Appendix Table 3, we explore the sensitivity of the results to alternate definitions of the dropout outcome. Specifically, hazard ratios from the two-missed-semester definition (column 1) of dropouts are compared with the hazard ratios where dropouts are defined as missing three (column 2) or four consecutive semesters (column 3). The table only contains the results for the dropout outcome because the hazard ratios for the transfer and graduation outcomes do not change. The dropout definition only affects whether an observation is defined as a dropout or as continual enrollment. The table contains results for the combined sample of men and women. Although not shown, the results for the three definitions of dropout are also nearly identical for the separate samples of men and women.

Results illustrate that the determinants are not sensitive to the definition of dropout. Any changes in hazard ratios among different dropout definitions are quite small in magnitude and have no effect on the statistical significance of the ratios. This similarity is notable because a non-trivial number of students take breaks of two or three semesters, so they are affected by the definition of dropout.

Figure 1 shows that many students drop out after the first semester, so the finding that first-semester GPA is negatively associated with dropping out may be endogenous if people drop out because they have low GPAs. Therefore, we also estimate hazard models that exclude first-semester GPA. In general, the results are robust to the exclusion of GPA. The only notable difference is that nonwhites are less likely to transfer or graduate in the models excluding GPA, compared to insignificant differences in the model including GPA. This pattern of results suggests that nonwhites may be less likely to transfer or graduate in part due to low GPAs in the first semester.[18]

[18] Another difference is that, for men, the hazard ratio of dropping out for first-term remedial credits changes from being slightly above one (1.01) to slightly below one (0.99). However, the hazard ratio is so close to one that it is not economically meaningful in either model.

The sensitivity of the financial aid variables is also investigated. Specifically, the existence of financial aid's relationship with two-year college outcomes is examined by replacing the two variables measuring the dollar amount of financial aid for grants/scholarships and loans with one dichotomous variable equal to one for students who received any type of financial aid. The receipt of financial aid (i.e. the dummy variable) is negatively associated with dropping out, has a statistically insignificant association on transferring, and is positively associated with graduating. These results are broadly similar with the findings when financial aid amounts were measured, suggesting that the results for financial aid may largely be driven by the receipt of financial aid – going from no aid to aid – rather than by changes in the amount of financial aid for students receiving aid.

6.5 Heterogeneity by Age and Initial Intentions

Two-year colleges serve many different student types, such as recent high-school graduates seeking to transfer to four-year universities and mature students returning to formal education for the first time in a decade or more. This section investigates whether the determinants of two-year college outcomes vary across two student types.

First, Table 4 contains the results of separate competing-risks hazards models by age at initial enrollment, dividing the sample into traditional aged students (under age 23) and non-traditional-aged students (age 23 and over) based on age at initial enrollment. For each outcome, the first column is for traditional-aged students, and the second column is for non-traditional-aged students. Findings reveal several differences between age groups. For traditional-aged students, employment is associated with increases in the likelihood of transferring and graduating, although the latter result is not statistically significant at p = .10. For non-traditional-aged students, employment is associated with increases in the likelihood of dropping out and decreases the likelihood of transferring or graduating, but the transfer result is insignificant at p = .10.

Financial aid corresponds with decreases in the likelihood of dropping out and increases the likelihood of graduating for both age groups, although the magnitude of the hazard ratio varies across the type of financial aid and the age range of the student. Grants/scholarships correspond with slightly reductions in the likelihood of transferring for both age groups, although the hazard ratio is statistically insignificant at p = .10 for non-traditional-aged students. Loans have a much larger positive relationship with the likelihood of graduating for non-traditional-aged students compared with traditional-aged students.

The differences in demographic and educational characteristics are less pronounced. Differences by gender and race are more noticeable in traditional-aged students than non-traditional-aged students. Holding a GED corresponds with an increased likelihood of dropping out and decreased likelihood of transferring much more for traditional-aged students than for non-traditional-aged students. The positive relationships of first-term GPA on transferring or graduating are larger for non-traditional-aged students than for traditional-aged students. Attempting more classes is associated with an 8% increase in the likelihood of graduating for traditional-aged students, but more classes are associated with a 6% decline in the likelihood of graduating for non-traditional-aged students.

The final analysis explores the determinants of two-year college outcomes for the most academically-minded students. Specifically, the sample is limited to students who, when initially enrolling, state an intention to transfer to a four-year institution or to graduate. Outcomes such as transferring and graduating are less pertinent for students who have no intention of seeking these outcomes. Many students enter community college to take one or two courses with no intention of obtaining an Associate's degree or of transferring to a four-year college. Table 5 contains the hazard ratios for the competing-risks model estimated on this subset of the sample. The hazard ratios for the transfer/graduate intent sample are quite similar to the ratios for the full sample even though only 63% intend to transfer or graduate. An exception is the negative association between being female and transferring in the transfer/graduate intent sample, whereas women are equally likely to transfer in the overall sample.

7 Conclusion

Using administrative data on postsecondary education and earnings, the determinants of retention, transfer, and graduation in Kentucky two-year colleges are analyzed using competing-risks hazard models. The availability of such detailed, administrative data has allowed researchers to estimate sophisticated models such as hazard models that explicitly account for time. Although the determinants of student outcomes have been studied extensively in the education literature, most of the research has focused on a single outcome such as retention, usually with models such as logit or probit that cannot include time-varying determinants. Even the papers using hazard models typically focus on one outcome. Only Calcagno et al. (2007) consider a competing-risks model, and that model is a multinomial probit model.

We find that employment and earnings while enrolled have modest associations with two-year college outcomes. Both are positively associated with dropping out, suggesting that students may favor present increases in earnings to potential future increases due to increased human capital. Financial aid generally corresponds with reductions in dropping out and increases in transferring or graduating.

With respect to the demographics, women are associated with lower likelihoods of dropout and higher likelihoods of graduation. Nonwhites are associated with higher likelihoods of dropout but are no less or more likely to transfer or graduate. Non-traditional-aged students have higher likelihoods of drop out or graduation and have lower likelihoods of transfer. Even though the methods differ, these results are consistent with previous work on community college student retention (Porchea et al., 2010; Hawley and Harris, 2005).

With respect to educational variables, having a GED rather than a high school diploma is associated with increases the likelihood of dropping out by one-third, decreases in the likelihood of transferring by half, and decreases in the likelihood of graduation by 16%. First-semester GPA is negatively associated with dropping out and positively associated with transferring and graduating. Taking remedial credits in the first semester has the opposite result.

There are limitations to the present analysis. The administrative data have detailed measures of enrollment, financial aid, and earnings, but they do not contain information on other likely determinants such as prior education level, marital status, children, hours worked, and cognitive ability. Furthermore, it is assumed that the included covariates are exogenous, given the inability to control for endogeneity through techniques like instrumental variables in hazard models. Lastly, only the initial enrollment spell in two-year college is examined, not the enrollment outcomes that may occur when students re-enroll after dropping out. Thus, the present findings may not extend to re-enrollment.

Despite these limitations, the findings presented in this paper are relevant for education policy. Two-year colleges provide different outcomes that must be considered jointly in order to understand their determinants. The dropout decisions of some students may be influenced by short-run gains in earnings while enrolled in postsecondary education. Financial aid helps alleviate some costs of schooling, but this aid likely represents a small portion of a family's overall budget, particularly for non-traditional-aged students who do not live with their parents. Of particular policy concern are high dropout likelihoods and low transfer probabilities of GED recipients – these students deserve special attention from policy makers and researchers. Hopefully, future research in this area will have access to detailed enrollment and demographic data in order to identify plausibly causal determinants of community college outcomes, building on the descriptive analysis that has been conducted to date.

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Table 1: Descriptive Statistics

Variable	All Mean	All Std. Dev	Dropouts Mean	Dropouts Std. Dev	Transfers Mean	Transfers Std. Dev	Graduates Mean	Graduates Std. Dev	Still Enrolled Mean	Still Enrolled Std. Dev
Time-invariant characteristics										
Female	0.543	0.498	0.494	0.500	0.602	0.490	0.639	0.480	0.697	0.459
White	0.784	0.412	0.763	0.425	0.796	0.403	0.854	0.353	0.813	0.390
Nonwhite	0.085	0.279	0.090	0.286	0.081	0.273	0.069	0.253	0.094	0.291
Missing race	0.131	0.337	0.147	0.354	0.123	0.328	0.077	0.267	0.094	0.291
Age at first term	27.9	10.8	29.6	11.3	23.0	7.8	28.5	10.2	26.0	9.1
High school graduate	0.805	0.396	0.752	0.432	0.923	0.267	0.853	0.354	0.857	0.350
GED	0.118	0.323	0.140	0.347	0.047	0.213	0.125	0.331	0.120	0.325
Missing education	0.077	0.266	0.108	0.310	0.030	0.170	0.022	0.146	0.023	0.149
First-semester remedial credits	0.54	1.61	0.56	1.63	0.34	1.25	0.69	1.76	0.99	2.09
First-semester GPA	2.34	1.55	1.90	1.61	2.98	1.21	3.28	0.85	2.89	1.16
Time-varying characteristics										
Lagged earnings	3,045	4,521	3,757	5,347	2,490	3,911	2,417	3,727	3,206	3,959
Lagged employment	0.384	0.486	0.355	0.479	0.387	0.487	0.445	0.497	0.337	0.473
Loans (1,000s)	0.091	0.359	0.066	0.293	0.058	0.287	0.131	0.431	0.148	0.467
Grants and scholarships (1,000s)	0.446	0.748	0.400	0.727	0.331	0.636	0.592	0.833	0.489	0.762
Classes attempted	2.41	2.15	2.53	1.88	1.99	2.18	2.73	2.39	2.14	2.15
Unemployment rate	6.39	1.36	6.41	1.39	6.37	1.32	6.42	1.41	6.30	1.25
Students	65,523		40,701		13,703		8,597		2,522	
Observations	245,312		94,002		56,527		64,519		30,264	
Percent of students	100%		62%		21%		13%		4%	

Table 1: Descriptive Statistics (Continued)

	All		Dropouts		Transfers		Graduates		Still Enrolled	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Intended degree subject										
Business	0.061	0.239	0.057	0.231	0.048	0.213	0.101	0.301	0.065	0.247
Health	0.170	0.376	0.150	0.357	0.111	0.314	0.331	0.471	0.282	0.450
Humanities	0.086	0.281	0.080	0.271	0.122	0.328	0.053	0.225	0.110	0.313
Science	0.006	0.076	0.005	0.067	0.011	0.104	0.002	0.048	0.008	0.091
Services	0.069	0.253	0.062	0.242	0.076	0.265	0.083	0.276	0.084	0.278
Social Studies	0.007	0.082	0.006	0.075	0.006	0.076	0.013	0.114	0.009	0.093
Vocational	0.099	0.299	0.091	0.288	0.049	0.216	0.224	0.417	0.080	0.272
Undecided	0.128	0.334	0.120	0.325	0.160	0.366	0.104	0.305	0.160	0.366
Non-degree	0.374	0.484	0.431	0.495	0.417	0.493	0.089	0.285	0.201	0.401
Semester of initial enrollment										
Summer 2002	0.056	0.230	0.040	0.195	0.106	0.307	0.052	0.222	0.061	0.239
Fall 2002	0.278	0.448	0.268	0.443	0.279	0.448	0.315	0.465	0.314	0.464
Spring 2003	0.153	0.360	0.159	0.366	0.126	0.332	0.153	0.360	0.194	0.396
Summer 2003	0.060	0.237	0.048	0.214	0.109	0.312	0.042	0.200	0.046	0.210
Fall 2003	0.300	0.458	0.314	0.464	0.270	0.444	0.298	0.458	0.241	0.428
Spring 2004	0.153	0.360	0.171	0.377	0.109	0.312	0.140	0.347	0.144	0.351
Students	65,523		40,701		13,703		8,597		2,522	
Observations	245,312		94,002		56,527		64,519		30,264	
Percent of students	100%		62%		21%		13%		4%	

Table 2: Competing Risks Hazard Model Results, Hazard Ratios

	Dropout			Transfer			Graduate		
	All	Men	Women	All	Men	Women	All	Men	Women
Explanatory Variables									
Earnings (1,000s)	1.003 ***	1.004 ***	1.003	0.97 ***	0.95 ***	0.999	0.99	1.02 ***	0.95 ***
	(0.001)	(0.001)	(0.002)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Employment	1.06 ***	1.05 ***	1.08 ***	1.04	1.07	0.97	1.00	0.90	1.15 *
	(0.01)	(0.01)	(0.02)	(0.03)	(0.06)	(0.04)	(0.06)	(0.08)	(0.09)
Grants and Scholarships	0.95 ***	0.94 ***	0.96 ***	0.96	0.98	0.96	1.25 ***	1.13 **	1.29 ***
(1,000s)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.03)	(0.04)	(0.07)	(0.05)
Loans (1,000s)	0.78 ***	0.81 ***	0.76 ***	1.31 ***	1.37 ***	1.29 ***	1.32 ***	1.36 ***	1.28 ***
	(0.02)	(0.03)	(0.02)	(0.06)	(0.12)	(0.08)	(0.07)	(0.14)	(0.08)
Female	0.89 ***			1.01			1.34 ***		
	(0.01)			(0.03)			(0.08)		
Non White	1.07 ***	1.05 **	1.08 ***	1.02	1.05	0.99	0.99	0.84	1.05
	(0.02)	(0.02)	(0.02)	(0.05)	(0.08)	(0.06)	(0.08)	(0.15)	(0.10)
Age	1.01 ***	1.01 ***	1.01 ***	0.96 ***	0.96 ***	0.96 ***	1.01 ***	1.001	1.01 ***
	(0.0004)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
GED	1.32 ***	1.28 ***	1.35 ***	0.49 ***	0.36 ***	0.57 ***	0.84 ***	1.06	0.76 ***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.06)	(0.13)	(0.07)
First Term GPA	0.77 ***	0.80 ***	0.75 ***	1.41 ***	1.42 ***	1.38 ***	1.31 ***	1.44 ***	1.24 ***
	(0.002)	(0.003)	(0.003)	(0.02)	(0.03)	(0.02)	(0.03)	(0.06)	(0.03)
First Term Remedial	1.02 ***	1.01 *	1.02 ***	0.93 ***	0.97 *	0.91 ***	0.96 ***	0.93 ***	0.98
Credits	(0.003)	(0.004)	(0.003)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)
Classes Attempted	0.87 ***	0.87 ***	0.86 ***	1.09 ***	1.08 ***	1.11 ***	1.01	1.10 ***	0.95 **
	(0.003)	(0.004)	(0.004)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)
County Unemployment	0.99 *	1.002	0.98 ***	0.93 ***	0.91 ***	0.95 ***	0.94 ***	0.94	0.94 **
Rate	(0.004)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)
Number of Students	65,523	29,914	35,609	65,523	29,914	35,609	65,523	29,914	35,609

Notes: Standard errors are in parentheses. All models also contain controls for, missing race, missing high school, semester of entry dummy variables, and dummy variables for each semester. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 3: Single and Competing Risks Hazard Model Ratios

	Dropout		Transfer		Graduate	
	Competing	**Single**	**Competing**	**Single**	**Competing**	**Single**
Explanatory Variables						
Earnings (1,000s)	1.003 ***	1.002 ***	0.97 ***	0.96 ***	0.99	0.97 ***
	(0.001)	(0.001)	(0.01)	(0.01)	(0.01)	(0.01)
Employment	1.06 ***	1.05 ***	1.04	1.02	1.00	1.04
	(0.01)	(0.01)	(0.03)	(0.03)	(0.06)	(0.07)
Grants and Scholarships	0.95 ***	0.93 ***	0.96	0.83 ***	1.25 ***	1.15 ***
(1,000s)	(0.01)	(0.01)	(0.03)	(0.02)	(0.04)	(0.03)
Loans (1,000s)	0.78 ***	0.75 ***	1.31 ***	1.10 **	1.32 ***	1.03
	(0.02)	(0.02)	(0.06)	(0.05)	(0.07)	(0.05)
Female	0.89 ***	0.90 ***	1.01	0.99	1.34 ***	1.22 ***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.08)	(0.07)
Non White	1.07 ***	1.09 ***	1.02	1.06	0.99	1.04
	(0.02)	(0.02)	(0.05)	(0.05)	(0.08)	(0.08)
Age	1.01 ***	1.01 ***	0.96 ***	0.97 ***	1.01 ***	1.01 ***
	(0.0004)	(0.0004)	(0.002)	(0.002)	(0.003)	(0.002)
GED	1.32 ***	1.31 ***	0.49 ***	0.56 ***	0.84 ***	0.98
	(0.02)	(0.02)	(0.03)	(0.03)	(0.06)	(0.07)
First Term GPA	0.77 ***	0.78 ***	1.41 ***	1.30 ***	1.31 ***	1.18 ***
	(0.002)	(0.00)	(0.02)	(0.01)	(0.03)	(0.03)
First Term Remedial	1.02 ***	1.01 ***	0.93 ***	0.92 ***	0.96 ***	0.94 ***
Credits	(0.003)	(0.003)	(0.01)	(0.01)	(0.01)	(0.01)
Classes Attempted	0.87 ***	0.86 ***	1.09 ***	1.01	1.01	0.94 ***
	(0.003)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)
County Unemployment	0.99 *	0.997 *	0.93 ***	0.97 **	0.94 ***	0.99
Rate	(0.004)	(0.004)	(0.01)	(0.01)	(0.02)	(0.02)
Number of Students	65,523	65,523	65,523	65,523	65,523	65,523

Notes: Standard errors are in parentheses. All models also contain the set of control variables listed in Table 2 and its notes. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 4: Competing Risks Hazard Model for Traditional-Aged (Age<23) and Non-Traditional-Aged (Age>=23) Students, Hazard Ratios

	Dropout		Transfer		Graduate	
	Age<23	Age>=23	Age<23	Age>=23	Age<23	Age>=23
Explanatory Variables						
Earnings (1,000s)	1.02 ***	0.999 ***	0.92 ***	0.99	1.04 *	0.997
	(0.004)	(0.001)	(0.01)	(0.01)	(0.02)	(0.01)
Employment	0.99 ***	1.04 ***	1.16 ***	0.92	1.08	0.83 **
	(0.02)	(0.01)	(0.05)	(0.06)	(0.10)	(0.07)
Grants and Scholarships	0.89 ***	0.99 ***	0.93 **	0.95	1.36 ***	1.21 ***
(1,000s)	(0.01)	(0.01)	(0.03)	(0.04)	(0.08)	(0.05)
Loans (1,000s)	0.81 ***	0.75 ***	1.06	1.42 ***	1.26 ***	1.34 ***
	(0.03)	(0.02)	(0.09)	(0.08)	(0.12)	(0.09)
Female	0.86 ***	0.93 ***	0.95	1.07	1.43 ***	1.23 ***
	(0.01)	(0.01)	(0.03)	(0.06)	(0.12)	(0.10)
Non White	1.13 ***	1.05 ***	0.96	1.11	0.85	1.05
	(0.03)	(0.02)	(0.05)	(0.09)	(0.13)	(0.11)
Age	1.02 ***	1.002 ***	1.02 **	0.97 ***	1.000	1.01 ***
	(0.005)	(0.001)	(0.01)	(0.003)	(0.03)	(0.004)
GED	1.58 ***	1.21 ***	0.34 ***	0.60 ***	0.87	0.84 **
	(0.04)	(0.02)	(0.04)	(0.05)	(0.13)	(0.07)
First Term GPA	0.76 ***	0.81 ***	1.27 ***	1.57 ***	1.26 ***	1.32 ***
	(0.004)	(0.003)	(0.02)	(0.03)	(0.05)	(0.04)
First Term Remedial	1.02 ***	1.002 ***	0.95 ***	0.89 ***	0.94 ***	0.99
Credits	(0.004)	(0.004)	(0.01)	(0.02)	(0.02)	(0.02)
Classes Attempted	0.87 ***	0.86 ***	1.15 ***	1.08 ***	1.08 ***	0.94 ***
	(0.004)	(0.004)	(0.01)	(0.02)	(0.03)	(0.02)
County Unemployment	1.01 *	0.98 *	0.96 ***	0.90 ***	0.91 **	0.96
Rate	(0.007)	(0.005)	(0.02)	(0.02)	(0.04)	(0.03)
Number of Students	30,769	34,754	30,769	34,754	30,769	34,754

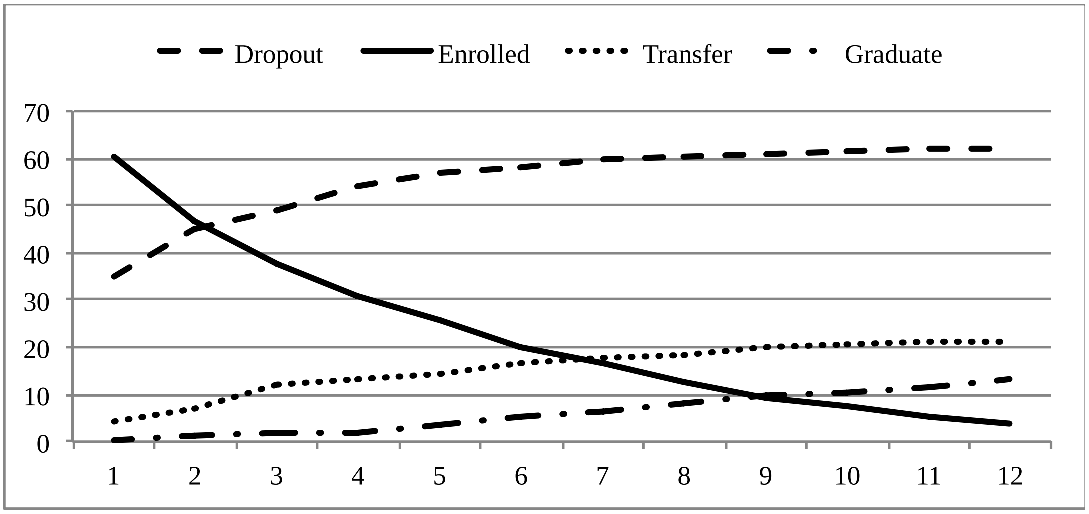
Notes: Standard errors are in parentheses. All models also contain the set of control variables listed in Table 2 and its notes. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 5: Competing Risks Hazard Model by Initial Intent, Hazard Ratios

	Dropout		Transfer		Graduate	
	All Students	Academic Students	All Students	Academic Students	All Students	Academic Students
Explanatory Variables						
Earnings (1,000s)	1.003 ***	1.003 ***	0.97 ***	0.97 ***	0.99	0.996
	(0.001)	(0.001)	(0.01)	(0.01)	(0.01)	(0.01)
Employment	1.06 ***	1.06 ***	1.04	1.02	1.002	0.95
	(0.01)	(0.01)	(0.03)	(0.05)	(0.06)	(0.06)
Grants and Scholarships	0.95 ***	0.95 ***	0.96	0.92 ***	1.25 ***	1.22 ***
(1,000s)	(0.01)	(0.01)	(0.03)	(0.03)	(0.04)	(0.04)
Loans (1,000s)	0.78 ***	0.78 ***	1.31 ***	1.29 ***	1.32 ***	1.32 ***
	(0.02)	(0.02)	(0.06)	(0.06)	(0.07)	(0.07)
Female	0.89 ***	0.89 ***	1.01	0.86 ***	1.34 ***	1.30 ***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.08)	(0.08)
Non White	1.07 ***	1.07 ***	1.02	0.94	0.99	1.01
	(0.02)	(0.02)	(0.05)	(0.06)	(0.08)	(0.09)
Age	1.01 ***	1.01 ***	0.96 ***	0.96 ***	1.01 ***	1.01 ***
	(0.0004)	(0.0004)	(0.002)	(0.003)	(0.003)	(0.003)
GED	1.32 ***	1.32 ***	0.49 ***	0.50 ***	0.84 ***	0.82 ***
	(0.02)	(0.02)	(0.03)	(0.04)	(0.06)	(0.06)
First Term GPA	0.77 ***	0.77 ***	1.41 ***	1.41 ***	1.31 ***	1.26 ***
	(0.002)	(0.002)	(0.02)	(0.03)	(0.03)	(0.03)
First Term Remedial	1.02 ***	1.02 ***	0.93 ***	0.92 ***	0.96 ***	0.97 **
Credits	(0.003)	(0.003)	(0.01)	(0.01)	(0.01)	(0.01)
Classes Attempted	0.87 ***	0.87 ***	1.09 ***	1.05 ***	1.01	0.97
	(0.003)	(0.003)	(0.01)	(0.01)	(0.02)	(0.02)
County Unemployment	0.99 *	0.99 *	0.93 ***	0.95 ***	0.94 ***	0.94 ***
Rate	(0.004)	(0.004)	(0.01)	(0.02)	(0.02)	(0.02)
Number of Students	65,523	41,012	65,523	41,012	65,523	41,012

Notes: Standard errors are in parentheses. All models also contain the set of control variables listed in Table 2 and its notes. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Figure 1: Cumulative Outcomes by Semesters after Initial Enrollment, Percent



Appendix Table 1: Cumulative Percentages of Community College Outcomes after Each Semester, by Gender

	Semesters after Initial Enrollment											
	1	2	3	4	5	6	7	8	9	10	11	12
Men and Women												
Dropout	60.4%	47.0%	37.4%	30.8%	25.6%	20.2%	16.4%	12.8%	9.3%	7.5%	5.4%	3.8%
Enrolled	35.0%	44.9%	48.9%	54.0%	56.8%	57.9%	59.6%	60.5%	60.9%	61.5%	62.0%	62.1%
Transfer	4.3%	6.9%	11.9%	13.1%	14.2%	16.5%	17.6%	18.5%	20.1%	20.8%	20.9%	20.9%
Graduate	0.3%	1.2%	1.8%	2.1%	3.3%	5.4%	6.4%	8.2%	9.7%	10.2%	11.7%	13.1%
Men												
Dropout	42.2%	52.4%	56.5%	61.5%	64.3%	65.3%	66.7%	67.5%	67.8%	68.4%	68.7%	68.8%
Enrolled	54.2%	41.3%	31.9%	25.6%	20.7%	15.5%	12.1%	9.2%	6.5%	5.0%	3.5%	2.6%
Transfer	3.5%	5.5%	10.2%	11.3%	12.2%	14.5%	15.4%	16.1%	17.5%	18.1%	18.2%	18.2%
Graduate	0.2%	0.8%	1.4%	1.7%	2.7%	4.8%	5.8%	7.2%	8.2%	8.6%	9.6%	10.4%
Women												
Dropout	28.9%	38.7%	42.4%	47.7%	50.5%	51.8%	53.6%	54.7%	55.1%	55.8%	56.3%	56.5%
Enrolled	65.7%	51.8%	42.0%	35.2%	29.8%	24.2%	20.0%	15.9%	11.7%	9.6%	7.1%	4.9%
Transfer	4.9%	8.0%	13.3%	14.7%	15.9%	18.2%	19.5%	20.4%	22.2%	23.0%	23.2%	23.2%
Graduate	0.5%	1.5%	2.2%	2.5%	3.8%	5.8%	6.9%	9.0%	11.0%	11.6%	13.5%	15.4%
Male-female gap												
Dropout	13.3%	13.7%	14.1%	13.8%	13.8%	13.5%	13.2%	12.8%	12.7%	12.6%	12.5%	12.4%
Enrolled	-11.5%	-10.5%	-10.2%	-9.6%	-9.0%	-8.7%	-7.9%	-6.7%	-5.2%	-4.6%	-3.6%	-2.4%
Transfer	-1.5%	-2.5%	-3.2%	-3.4%	-3.6%	-3.7%	-4.1%	-4.3%	-4.8%	-4.9%	-4.9%	-4.9%
Graduate	0.2%	0.4%	0.4%	0.5%	0.6%	0.6%	0.6%	1.0%	1.5%	1.6%	2.1%	2.8%

Appendix Table 2: Competing Risks Hazard Model Result Differences by Gender, Hazard Ratios for Interactions Terms with Female

	Dropout	Transfer	Graduate
Explanatory Variables			
Female*Earnings	1.00	1.05 ***	0.94 ***
	(0.00)	(0.01)	(0.01)
Female*Employment	1.03	0.91	1.30 **
	(0.02)	(0.06)	(0.16)
Female*Grants and Scholar-	1.02	0.97	1.13 *
ships (1,000s)	(0.02)	(0.06)	(0.08)
Female*Loan (1,000s)	0.95	0.93	0.96
	(0.04)	(0.10)	(0.12)
Female*Non White	1.03	0.94	1.26
	(0.03)	(0.09)	(0.25)
Missing Race	1.05 *	1.30 ***	1.00
	(0.03)	(0.11)	(0.18)
Female*Age	1.00 ***	1.00	1.01 *
	(0.00)	(0.00)	(0.01)
Female*GED	1.06 **	1.60 ***	0.72 **
	(0.03)	(0.22)	(0.11)
Female*First Term GPA	0.94 ***	0.97	0.85 ***
	(0.01)	(0.02)	(0.04)
Female*First Term Remedial	1.01 **	0.95 ***	1.05
Credits	(0.01)	(0.02)	(0.04)
Female*Classes Attempted	0.98 ***	1.03	0.86 ***
	(0.01)	(0.02)	(0.03)
Female*County Unemployment	0.98 **	1.05	0.99
Rate	(0.01)	(0.03)	(0.05)
Number of Students	71,604	32,837	38,767

Notes: Standard errors are in parentheses. All models also contain the set of control variables listed in Table 2 and its notes. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Appendix Table 3: Competing Risks Hazard Model Results for Alternate Dropout Definitions, Dropping Out Hazard Ratios

	Dropout Length		
	2 Semesters	**3 Semesters**	**4 Semesters**
Explanatory Variables			
Earnings (1,000s)	1.003 ***	1.001 ***	1.001 ***
	(0.001)	(0.001)	(0.001)
Employment	1.06 ***	1.06 ***	1.05 ***
	(0.01)	(0.01)	(0.01)
Grants and Scholarships	0.95 ***	0.96 ***	0.95 ***
(1,000s)	(0.01)	(0.01)	(0.01)
Loans (1,000s)	0.78 ***	0.76 ***	0.76 ***
	(0.02)	(0.02)	(0.02)
Female	0.89 ***	0.91 ***	0.92 ***
	(0.01)	(0.01)	(0.01)
Non White	1.07 ***	1.08 ***	1.08 ***
	(0.02)	(0.02)	(0.02)
Age	1.01 ***	1.01 ***	1.01 ***
	(0.0004)	(0.0004)	(0.0004)
GED	1.32 ***	1.34 ***	1.34 ***
	(0.02)	(0.02)	(0.02)
First Term GPA	0.77 ***	0.77 ***	0.77 ***
	(0.002)	(0.003)	(0.003)
First Term Remedial	1.02 ***	1.01 ***	1.01 ***
Credits	(0.003)	(0.003)	(0.003)
Classes Attempted	0.87 ***	0.86 ***	0.86 ***
	(0.003)	(0.003)	(0.003)
County Unemployment	0.99 *	0.99 *	0.99 *
Rate	(0.004)	(0.004)	(0.004)
Number of Students	65,523	65,523	65,523

Notes: Standard errors are in parentheses. All models also contain the set of control variables for model specification 3 (listed in Table 2 and its notes). *, **, and *** denote significance at 10%, 5%, and 1%, respectively.