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Abstract

Policy makers are becoming increasingly concerned about the high percentage of students who attend postsecondary education without completing a degree. Researchers have studied numerous potential determinants of retention behavior for postsecondary students, such as financial aid, socioeconomic status, academic preparedness, academic and social integration, and expected future wages. However, none of these studies considers students' earnings while in school as a potential determinant of retention. Using an administrative data from postsecondary institutions matched with administrative earnings data from the state's unemployment insurance department, our results indicate that student earnings are negatively correlated to student retention in Kentucky postsecondary institutions. Our preferred model, hazard, indicates that a percentage increase in earnings reduces time to stopout with a probability of 1.767%. Even after controlling for student intentions, students are more likely to stopout at the rate of 1.050%. Ability as measured by first-term GPA in KCTCS and credits earned in the first semester positively affects retention.

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I. Introduction

Policy makers are becoming increasingly concerned about the high percentage of students who attend postsecondary education without completing a degree. Fewer than 60 percent of full-time students at four-year institutions receive a bachelor's degree within six years of initial enrollment, and approximately 30 percent of full-time students at two-year institutions receive an award within 150% of "normal time" (Snyder and Dillow, 2010). To date, higher education has attracted significant state investments to reduce the financial barriers to completing college (Singell, 2004), and these costs are largely borne by taxpayers. The burden on government and hence taxpayers is ever increasing as students continue to stopout and take longer to complete schooling.[1] There is an absolute need to understand better the obstacles to college completion to help students achieve their education in a swift and efficient way. This paper explores one possible – but previously unexplored – explanation for low completion rates by investigating the relationship between earnings while in postsecondary education and student retention (i.e. the duration of attendance).

Moreover, the negative correlation between education and poverty status is well known. Individuals with postsecondary attendance without degree completion have higher earnings relative to individuals with no postsecondary experience and lower earnings relative to individuals with a postsecondary degree (Card, 1999). However, poverty is still a concern for individuals with some postsecondary attendance but no award, as illustrated for community-college students in Jepsen, Troske, and Coomes (2009). Therefore, a better understanding of the determinants of postsecondary retention will assist policy makers in designing education policies

[1] This study uses stopout to describe attrition. We use the definitions provided by Stratton et al. (2008) who describe stopouts to be a short term decision (usually less than a year) and dropouts to be a long term decision (usually longer than a year).

that help alleviate poverty by encouraging postsecondary completion rather than just postsecondary attendance.

We analyze students who have attended postsecondary schooling at two-year institutions.[2] Enrollment at the community colleges is rising at a tremendous rate. High four-year tuition rates, budget constraints on state governments, increases in the number of community-college campuses, and in the number of courses offered at these colleges are some of the reasons for the rising enrollment at two-year colleges. However, studies have indicated that community college dropout rate is around 50% (Goldrick-Rab and Berube, 2009). Recently, president Obama pledged two billion dollars to the development of community colleges to increase the number of graduates. With community colleges becoming an integral part of producing the future labor force, it is important to study the behavior of students who attend these colleges. This study benefits from a large and recent administrative dataset from Kentucky Technical and Community College System (KCTCS) to analyze the student retention behavior. Analysis is conducted using survival models that are considered more appropriate for education data (Calcagno et al., 2007, DesJardins et al., 1999, Doyle, 2009).[3]

Using an administrative data from postsecondary institutions matched with administrative earnings data from the state's unemployment insurance department, our results indicate that student earnings are negatively correlated to student retention in Kentucky community colleges. Our preferred model, hazard, indicates that a percentage increase in earnings reduces time to stopout with a probability of 1.050%, holding other covariates constant. Ability as measured by first term GPA in KCTCS and credits earned in the first semester positively affects retention.

[2] We use two-year colleges and community-colleges interchangeably.

[3] We use survival and hazard interchangeably.

II. Theoretical Motivation

Models of human capital assume that individuals are utility maximizers and analyze lifetime perception when making choices about education and training. Because the benefits are usually delayed, individuals weigh the net present value of benefits to the current costs of education. Individuals who put more weight on current events than the future discount the future with a relatively higher interest rate. Overall, investment is attractive if the present value of future benefits exceeds costs. Hence, individuals choose their path of investment where their net present value of that investment is the highest. In general, the labor literature shows positive return to investment in human capital (Card, 1999). Becker's (1993) Human Capital model assumes that students have some or all knowledge of their future costs and benefits of education with certainty such that individuals make all schooling decisions typically after completing high school.

However, in reality, most if not all individuals are uncertain about the future benefits and costs of schooling. Furthermore, college decisions are made by students on a term by term basis rather than with a onetime ex ante decision. Weisbrod's (1962) option value theory assumes that there is a lot of uncertainty about education in regards to the costs and benefits of schooling, and it indicates that investment in human capital is a sequential process rather than a simultaneous one. In other words, individuals have options to continue schooling or stopout and work after each term. These options are generated through uncertainties. There are three forms of uncertainty. One such uncertainty occurs when students are unsure of their future intentions. To improve career ambitions or choices, new information is collected through college performances such as grades earned that help alleviate some of these uncertainties. Costs are other uncertainties which arise in terms of increases in tuition rates, or short-term effects such as receiving a scholarship for a semester, parents stop paying for tuition due to job loss, etc. A large amount of uncertainty surrounds the benefits of schooling in terms of future earnings. As students successfully complete a stage, they realize their true return of education of the level of schooling completed and update their beliefs.

Students uncertain of their schooling abilities and /or the high costs of four-year schooling may choose not to acquire postsecondary education. A major barrier to postsecondary education for these individuals is the continuous rise of the cost of schooling. Average tuition rates at public universities have risen by 45% from 1998 to 2008 (Desrochers et al., 2010). Hence, the existence of community colleges provides students with a cheaper alternative to determine whether further education or work is the better option. Community colleges help alleviate the uncertainties surrounding postsecondary education by enabling students to experience postsecondary schooling at a relatively lower cost than enrolling at a four-year college. This affordability provides students with a chance to enroll and update their beliefs on their education goals. Thus, these colleges provide a sound and cost-effective education base to help students determine their career paths.

Two-year colleges affect the accumulation of human capital through education in three ways. First, because students are provided with options to continue or stopout after completion of every stage, it encourages more students to enroll, especially those students who are marginal students. Second, this option also provides those students who commit to graduating with a choice to stopout if their goals of commitments change. Third, at every stage, different education and labor opportunities are available for individuals to update their beliefs. Individuals only learn of these new, potentially better opportunities once an education stage (semester) is completed.

Students revise their expectations through new information after completing every semester or academic year at a two-year college. 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. Once students update their beliefs after completing a term or academic year, they have three options: they can stopout and join the labor force, transfer to a four-year college or receive an award (certificate, diploma, or degree). This study focuses on students' decisions to stopout. Past studies have indicated that financial aid, socioeconomic status, academic preparedness, academic and social integration, and expected future wages affect the decision to stopout. This research benefits from estimating the effect of students' earnings while in school on the probability of stopping out and/or on the time to stopout.

III. Literature Review

Researchers have studied numerous potential determinants of retention behavior for postsecondary students. These factors include financial aid (Singell, 2004; DesJardins, Ahlburg, and McCall, 2002), socioeconomic status (Vignoles and Powdthavee, 2009), academic preparedness (see Kerkvliet and Nowell (2005) for examples), academic and social integration (Tinto, 1993), and expected future wages (Kerkvliet and Nowell, 2005).

Tinto's (1993) model of retention is based on relationships between students and institutions. According to Tinto (1993), student retention depends on a commitment to get a degree at a specific institution. Hence, retention is affected by the academic, social and institutional culture of the universities. He finds that a student is less likely to transfer or dropout from a university where he/she is comfortable both academically and socially.

Wetzel et al. (1999) feel that Tinto's (1993) model requires some sort of financial variables. They therefore develop a model that considered three factors: degree of goal commitment-academic integration, institutional commitment (social integration) and financial status. Variables used to control for academic integration include proportion of credit hours completed to hours of credits attempted in each semester, cumulative GPA, at-risk status and enrollment status to proxy for an individual student's motivation and/or ability. Variables used to control for institutional commitment include marital status, part-time status, and evening enrollment status. Variables used to control for financial factors are real net cost (measures of out-of-pocket expenses), changes in real tuition to measure increment of costs on retention, student loans and work-study programs. Data are gathered from Virginia Commonwealth University for the entire set of freshmen and sophomore student records from 1989-1992. Results from a logit model indicate that readmitted students are less likely to return and that ability positively affects retention. Students with low level of institutional commitment are least likely to continue schooling and financial factors have weak effects on retention.

Desjardin et al. (2002) estimate the effect of changes in financial aid on student retention. Data are collected from the University of Minnesota for new students in the fall of 1986 and are followed for 22 trimesters. The authors employ the use of hazard models for their estimation to control factors that vary over time such as financial aid. After controlling for time-varying effects and unobserved heterogeneity, they find that grants and scholarship positively affect retention with scholarships having the largest impact on retention. They conclude that financial aid not only alleviates financial constraints but further improves student relationships with universities that could work to increase retention.

Singell (2004) improves on the past literature by estimating the effect of financial aid on the student's retention via controlling for observed covariates and self-selection. The richness of the data from the University of Oregon facilitates the estimation of the effects of different types of aid i.e. merit-based aid, grants, and need-based subsidized and unsubsidized loans. He utilizes a bivariate model to estimate the effect of observed covariates on retention conditioned on the effects of unobserved covariates that affect enrollment. Hence, the model provides less biased results by controlling for the correlation between enrollment and retention. He finds that family income and median household income have no effect on retention.

Kerkvliet et al. (2005) compare retention policies in two different universities. They control for covariates ignored in the past literature which include students' intentions to remain enrolled or not in the following year and wage-based opportunity costs. They control for background characteristics, academic and social integrations, opportunity cost of attending school and financial aid. Data are collected from Weber State University (WSU) and Oregon State University (OSU). Opportunity cost wage is determined by students indicating a self-reported wage rate earned if not attending school. Wage squared is controlled for to account for non-linearity. The percentage of tuition paid by student and family was included to control for direct costs and to control for financial aid they included a dummy variable for each type of aid. Using a negative binomial model for WSU, they found wage to be inversely related to retention. Veteran's aid and guaranteed student loans show weak support for retention, and academic variables have no significance. They do find positive significant effects for GED, parents' education and following year intentions. Using a Poisson model for the OSU dataset, they find a non-linear wage effect for this sample – higher retention during lower wages but lower retention during higher wages. Grants are negative and significant, whereas work-study is positive and significant. The self-reported wages in both universities provide conflicting results. At WSU, students substitute school for work when faced with higher wages, and in OSU higher wages encourage retention.

A more recent study by Powdthavee et al. (2009) focuses on the effect of socio-economic gap on students' retention. They compare dropout rates between students with lower socio economic background compared to their wealthy counterparts. Their main variable of focus is student's prior achievement. Data are collected from The English National Pupil Database (NPD), Pupil Level Annual School Census (PLASC) and individual student records maintained by the Higher Education Statistics Agency (HESA). The dependent variable of interest is simply whether or not the pupil continued in all universities in England from one year to the next. However, they are unable to differentiate between dropouts due to failure to pass exams versus students simply choosing to withdraw. Using a probit model and controlling for self selection by predicting the likelihood of higher education participation of each student and including that likelihood in the retention model, they find that pupils from a higher socio-economic background and pupils with parents with professional occupation have the least likelihood of dropping out. Overall, the significant gap in dropout falls drastically when controlling for prior education, and they recommend that polices should be directed in improving high school and remedial education rather than focusing on finance.

These studies have investigated multiple variables, but none of the studies have explored student earnings while in school. This paper improves on past papers by exploring one possible explanation for low completion rates by investigating the relationship between earnings while in postsecondary education and student retention (i.e. the duration of attendance).

IV. Data

We use administrative data from postsecondary institutions matched with administrative earnings data from Kentucky's unemployment insurance department. The administrative data are from the Kentucky Community and Technical College System (KCTCS). KCTCS, created by the Kentucky Postsecondary Education Improvement Act of 1997 (HB 1), is a statewide community college system with 16 colleges and 67 campuses all over the state of Kentucky. For both models, the cohorts of interest entered KCTCS in the 2002-2003 period or the 2003-2004 period. KCTCS data include student-level information on demographics such as age, race, gender, citizenship status, military status, student's state and county of origin, high school attended, high school graduation/GED date, and admittance type (freshmen, high school, visiting student and so on). In addition, we use enrollment level data on college of enrollment, enrollment term, and most importantly the academic plan the student intends to complete while at KCTCS.

KCTCS course data contain descriptive information on each course taken by the student. GPA and number of credits earned are calculated from the information on grades and credits provided in these data. This source also provides information on remedial classes.

We also utilize data on outcomes. These data identify each types of degree, certificate, and diploma awarded offered by KCTCS. The type of Associate's degree received is usually broken down into transfer degrees and career or professional degrees. Transfer degrees allow students to complete their basic or general education requirements before transferring or while at a university. To earn an associate's degree a student must complete 60 to 76 credit hours depending on the program. Certificates are specialized programs where students can demonstrate a specific set of skills to potential employers. It is offered in technical programs and can be completed in as little as one semester, depending on the program. Schools offer Certificates in several program areas. Diplomas prepare students for employment in specific technical fields. Diplomas tend to target broader areas than certificates and usually require more credits (often one year or more of full-time studies).

Transfer data are obtained from the National Student Clearinghouse. These data provide information on whether the student transferred 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. The National Student Clearinghouse has gathered educational records on a majority of students in Kentucky. KCTCS collects quarterly earnings data for each student from the state's unemployment insurance program. KCTCS provides employment and total wages for each student per quarter. Total wages are reported for each person and job. For both cohorts, earnings data are provided from the first quarter of 2000 through the third quarter of 2008. Because student-level data are in the form of semesters (Fall, Spring and Summer), we convert the earnings data from quarterly date to term data by taking an average of quarter 1 and quarter 2 to calculate earnings for the spring term, an average of quarter 2 and quarter 3 to calculate earnings for the summer term and an average of quarter 3 and quarter 4 to calculate earnings for the fall term. Finally, data on county-level unemployment are collected from Bureau of Labor Statistics.

i) <u>Dependent and Independent Variables</u>

Students are followed up to 19 trimesters (Fall, Spring and Summer). The dependent variable used in this study is a dummy variable that is coded 1 if a student attends KCTCS during the period of sample and 0 otherwise for the logit model. In the hazard model, the dependent variable is time till first stopout. This paper focuses more on stopout behavior rather than dropout behavior. These behaviors are differentiated by Stratton et al. (2008) who describe stopouts to be a short-term decision (students miss consecutive terms for less than a year) and dropouts to be a long-term decision (students miss consecutive terms for more than a year). Students who stop attending school may or may not reenroll at a later date. Because we face a right-censoring issue with our data (we have no way of determining if students do reenroll out of our sample period), we believe the term stopout is a more appropriate term for this research.

A student is continuously enrolled if he/she is registered in every semester. This paper uses a two-semester rule where if a student misses two consecutive semesters (including summers), he/she is considered to have stopped out from the institution.[4] Students usually choose not to enroll over summer due to work or vacation; therefore we feel that a two-semester rule is a valid rule to follow. Hence, if a student is not enrolled for one semester and re-enrolls, he/she is still considered as continuous enrollment. Our sample includes students who stop enrolling in KCTCS after transferring or acquiring a degree. There is an indicator that identifies this outcome, and these students are not assumed to have stopped out. Because we are particularly interested in the determinants of stopping out without achieving an award/transferring, this analysis uses a narrower definition of stopout that does not include students who leave after receiving an award.

The independent variables of interest are listed in Table 1. Explanatory variables include demographic variables such as age, age squared, race and gender. Younger students are expected

[4] An analysis with a larger semester gap is conducted i.e. a student who misses three consecutive semesters is considered to have stopped out. The magnitude of the results decreased by a small amount but overall the signs remained unchanged. Results are available upon request.

to have fewer responsibilities than older students as older students are more likely to be working, married or have children and therefore the younger group is less likely to stopout. The sample consists of 80% white, 7% black, 1% Hispanic, 1% other race and the rest is accounted by missing race. I therefore entered race in the models by including two dummy variables (non-white and missing race). Non-white represents blacks, Hispanic and other race. The reference group is white students. Gender is controlled for by including a dummy variable indicating whether the student is a female or not. Over time, the gender attendance and graduation gap has diminished, and some studies indicate that women have higher attendance or retention rates than that of men (Surette, 2001).

Students' intentions are measured by the number of courses taken in the first KCTCS term and a set of dichotomous variables for each student's area of study (non-award is the omitted category). The set of dichotomous variables for each student's area of study include whether or not student pursues an award, and what field of study in which to pursue an award. All these variables are measured in the first semester. By including controls for student intentions, we are able to compare retention outcomes for students with very similar intentions upon entry at KCTCS. Therefore, we can address the different motivations and intentions of students who choose to acquire a degree, diploma, certificate or no degree.

The data contain several controls for student ability. The number of credits earned in the first semester and first semester GPA are used to control for ability upon arrival at KCTCS. We also control for remedial credits earned in the first term. Students who attempt these credits vie to improve their knowledge in certain subjects so as to improve ability for advanced level subjects. Calcagno et al. (2007) find enrolling in a remediation class reduces the odds of graduating. Many students register for these courses and hence it was appropriate to include this variable to determine its effect on stopping out. Whether a student earned a high school degree or GED is included in the model through two dummy variables (GED and missing high school information). A dummy variable representing graduation from high school is used as a reference group.

Economic factors may also affect student retention. Many students choose to attend two-year colleges or skip college altogether due to financial constraint. Students who are employed have to also balance time between school and work. Students who work full time have difficulties attending school full time and are more likely to be in financial difficulties. Therefore, we control for earnings while at KCTCS. To control for the macroeconomic factors, we included the county unemployment rate. Finally, a dummy variable to separate the two cohorts is also incorporated.

The data clearly have some omitted explanatory variables compared to a survey dataset. The KCTCS data do not contain family socioeconomic status (SES) and parents' education. Students from higher-income families are more likely to complete college and parents with college education increase children's graduation probabilities. Other variables that are unavailable for this proposal include attributes while in high school (such as GPA, etc.) and availability of financial aid.

For future analysis, we plan to incorporate additional data made available from KCTCS. These variables include student's ACT scores, whether a student received a GED, High School Diploma or not, and information on financial aid and family socioeconomic status from financial aid forms.

ii) <u>Descriptive Statistics</u>

Students are observed term by term until the event date (stopout) or end of sample. Therefore the number of observations represents one observation per student per semester attended. Therefore, if a student attended college for three semesters and then stopped out, the number of observations for that student will be three.

The focus is on two cohorts of students who started at KCTCS from summer 2002 to spring 2003 and from summer 2003 to spring 2004. All individuals for whom no wages are reported are assumed to be not working. Students, who are in correctional institutions, fewer than 17 years old or more than 60 years old as of June 1, 2002 for the 2002-03 cohort, are excluded.[5] Similar exclusions are applied to the 2003-04 cohorts i.e. age of students in this sample is determined as of June 1, 2003. Students are followed until the Summer of 2008. Therefore, students who enrolled in the Fall of 2002 are followed for up to 19 terms. The final sample used for this analysis is 71,133 students out of which there are 32,519 men and 38,614 women.

Table 1 provides the descriptive statisitcs for the sample. The average age of the sample is 29, and 9% of the sample is nonwhite. Students, on average, attempted around 3 classes in the first semester, earned around 6 credits in the first semester and averaged a GPA of 2.3. The average earnings of the sample are $6000 per semester and the county unemployment rate is 6.3. The majority of the sample plan on acquiring some kind of degree and 32.11% do not plan on acquiring a degree at KCTCS. Students planning on acquiring a Health degree account for 19.44%, 9.37% plan on acquiring a Vocational degree, 9.51% choose to acquire a degree in

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[5] 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. The first cohort is made up of students who enroll in the Fall of 2002, Spring of 2003 or Summer of 2003 whereas the second cohort is a sample of students who enrolled in the Fall of 2003, Spring of 2004 or Summer of 2004.

Humanities and 14.28% are undecided. The remaining 15% represent students intending to acquire a Business, Services, Social Works or Sciences degree.

Descriptive statistics by gender are also provided. In general, women did better than men in terms of GPA. Women have a GPA of 2.64 compared to men who have GPA of 1.89. More women earned a high school degree than men. There is a large difference in earnings between men and women. Men earned approximately $3,000 more in a semester than women.

iii) Kaplan Meier Estimates by gender, race and age.

Kaplan Meier survival analysis is a method of generating tables and/or plots of the risk/probability of stopping out over time without controlling for any covariates. We plotted the survival functions – these estimate the probability of not stopping out. Survival graphs are downward sloping as the probability of surviving (not stopping out) decreases over time. The estimates are recalculated at the end of every term for students who have not stopped out in the previous term. Therefore, the Kaplan Meier estimates illustrate when (timing) the greatest and the least hazard (risk) of stopping out occurs.

Figure 1 shows the empirical survival analysis for retention by gender. The vertical axis indicates the likelihood of stopping out. Therefore, estimated survival probability of 1 indicates that student is 100% not likely to stopout. The downward sloping curves (survival estimates) hence indicate that students' likelihood of stopping out increases over time. The curves for gender indicate that for both men and women, there is a high likelihood of stopping out around the fourth semester with men being more likely to stopout than women. The likelihood of stopping out is very similar for both men and women up to the fourth semester after which the probability of continuous enrollment is higher for women than men for the rest of the sample time period.

Figure 2 shows the empirical survival for stopout by race. The curves for race also indicate that there is a low probability of stopping out at the initial enrollment up to the fourth semester, and the probability of stopping out increases over time as indicated by the downward-sloping survival estimates. The closeness of the curves indicates that there are no race differences in terms of enrollment.

Figure 3 shows the empirical survival by different age groups. Six different age groups are used for the analysis: ages 17 to 20, ages 21 to 25, ages 26 to 30, ages 31 to 40, ages 41 to 50, and ages 51 to 60. The top panel of Figure 3 shows the survival probabilities for the first three age groups. All three age groups have very similar curves, but the 17-20 age groups have the lowest likelihood of stopping out compared to the other age groups. The estimates are converging around the 0.50 mark indicating students' are 50% likely to stopout around the 19th term.

The bottom panel of Figure 3 shows similar patterns with students aged 51-60 have a high likelihood of stopping out rates from fourth term onwards. The other two age groups (31-50 and 41-50) have very similar curves. Overall, the oldest group is at the highest risk of stopping out. This is indicated when comparing the two panels of the figure.

Overall, the gender descriptive hazards indicate that female students have lower conditional probability in all time periods of stopping out. The probabilities are very close for race. However, in both cases the largest stopouts occur around the fourth semester, indicating institutions need to pay more attention to students in the first two years to ensure continuous enrollment. As for the different age groups, the younger group is more likely to continue schooling, whereas the older group is more likely to stopout early.

V. **Model Specification**

We use the KCTCS data to estimate the likelihood of students returning the following semester on condition that they have maintained continuous attendance in the previous semesters. We analyze the probability of retention by controlling for institutional, academic and economic factors. We break down the analysis for gender, race and age groups. The analysis is conducted using both logistic and survival models. We discuss each model in more detail below.

i) Logistic Model

In the logit model, student retention is assumed to be discrete and time constant. In other words, events are not limited to certain points in time. Each student is observed for every semester he/she attends school. The dependent variable is a dummy variable equal to 0 during a term when a student does not register for any credits, and it is equal to 1 for all other terms of attendance. We estimated a logit regression as noted below:

$$Prob(Retention = 1) = logit\ (X\beta i) = \frac{e^{Xi\beta i}}{1+ e^{Xi\beta i}}, \tag{1}$$

where the X is a vector of independent variables described in Table 1.

There are several disadvantages of using the logit model. First, logit models cannot exploit the timing of stopout. Specifically, they assume that a student who stops out after the 1st semester has a higher propensity to stopping out than a student who stops out at a later semester. Moreover, the initial conditions are assumed to be fixed over time and that each year/semester the overall probability of stopout is assumed to be the same. In addition, traditional models are not designed to handle time-varying coefficients and cannot accommodate unmeasured student heterogeneity. Last, traditional models cannot handle right-censoring (when the outcome is unobserved during the spell due to end of sample). All of these limitations can lead to biased estimates.

Hazard models have several advantages over logit or probit models. First, hazard models work on the conditional probability without regard to the specific periods found in the data. These models, hence, provide an opportunity to use more information compared to the discrete models by explicitly accounting for time. Second, these models can incorporate both time-invariant and time-variant variables. Third, hazard models can adjust for periods at risk automatically. Last, hazard models can be generalized to control for unmeasured heterogeneity. Recently, many education studies have adopted hazard models for their research due to the models' ability to handle limitations of traditional models (Calcagno et al., 2007, DesJardins et al., 1999, Doyle, 2009).

ii) Survival Model

Survival models are statistical models of a person over a period of time until the event of interest occurs, another event occurs, or the sample period ends. Specifically, we look at the conditional probability of a stopout at time *t* given that the student has not stopped-out before time *t*. The variable of interest is the time to first stopout. The hazard estimates the likelihood and the timing of stopping out from two-year colleges. Our data are collected term by term for all students up to the point where the student stops out, transfers, graduates or the sample period ends. For those students who stopout, students will be followed up to the point of stopout. Those who do not stopout will be followed up to the end of sample which include transfer, end of time period in the sample or students' award completion and school exit**.** Hence, the observations for students who have not transferred or graduated are right censored. Survival models utilize all available information to compute the baseline hazard, whereas static models such as logits treat censored cases the same as those for whom the event occurred in the final time period or as missing data, either of which leads to biased coefficients.

There is an indicator that identifies students who graduate or transfer, thus enabling the hazard to be estimated without dropping these observations.

We do not observe the exact length of the duration of stopout but rather observe when a student stops out at discrete moments in time. In other words, we observe whether a student stops out or not at the end of every semester. Because this study looks at the risk of one outcome (stopout) we estimate a single-risk discrete-time hazard model. All observations are observed in continuous time. However, we do not observe the instantaneous time at which a person stops out. Finally, estimates are based on Maximum Likelihood Estimation. The hazard model used is:

$$h(t_{ij}) = \Pr[y_i = j \mid y_i \geq j - 1, i \in A_j, X_1, \ldots\ldots, X_j], \quad (2)$$

where $y_i = j$ indicates student *i's* outcome in term *j*. The condition $y_i \geq j - 1, i \in A_j$ states that the student *i* has not yet transferred, graduated or stopped out from school before time period *j* and the student is still observed at time *j*. The probability is conditional on an event's not occurring in period *j-1* or earlier. We assume that the event of interest, stopout, is affected by a vector of both time-varying and time-invariant explanatory variables X_j, which controls for all the observed student characteristics. This model assumes all the determinants of the event are explained by the explanatory variables (X_j) and these effects are constant over time. The estimates of this preliminary analysis will be biased if these assumptions fail. The first assumption may be violated as we have no way of determining whether unobserved characteristics prompted students to attend KCTCS. Hence, future work will include generalizing the model to include a control for unmeasured heterogeneity.

There is also a possibility of correlated outcomes while estimating single-risk models. Other outcomes include: transfer and graduation. Student's who transfer or graduate can be misspecified as stopouts and this can cause interdependence among the outcomes. DesJardin et al. (1999) estimated a competing-risk model to test the sensitivity of their single-risk model that studied student departure. They were concerned because their single-risk model did not differentiate graduation from stopout/dropout behavior. In other words, a student was categorized as stopout when he/she has graduated which makes the two outcomes correlated. However, as mentioned in the data section, we do not consider observations of students after transfer or graduate as stopouts because we are particular interested in determinants of stopping out without achieving an award. But, due to these concerns, we also estimate a competing risk hazard model with three possible outcomes: dropout, transfer and graduate which controls for the interdependence between the three outcomes.[6]

For both models, the cohorts of interest first enrolled in KCTCS in the 2002-2003 period or the 2003-2004 period. We observe all students from the start date and have observations of students over time up to a point in time when they transfer, graduate or stopout. Thus, we assume that there is no left censoring. The variables of interest are listed in Table 1.

VI. Results

For both models, we estimated three different specifications. The first specification controls for the earnings, demographics variables, county unemployment rate and the cohort dummy variable. The second specification adds KCTCS first-term experiences. Finally, the third specification further controls for intentions for attending community colleges. Results for both models are reported in the form of marginal elasticity effects. Marginal elasticity effects are calculated in the form of in the form of d(lny)/d(lnx). Hence, the elasticity effects calculate the percentage change in the dependent variable due to a percentage change in the independent variable, holding other covariates constant. Note the marginal elasticity effects

[6] The results from the competing-risk model did not deviate much from the single-risk model. Therefore, we only discuss the single-risk results. Future versions of this paper will include a discussion on the competing-risk results.

from the hazard model are interpreted differently compared to a logistic model. A positive (negative) marginal elasticity implies an increase (decrease) in time to stopout (or decrease (increase) in the likelihood of stopping out in a given semester). A positive (negative) marginal elasticity in the logistic model indicates lower (higher) likelihood of attendance.

i) Logistic Results

Table 3 provides marginal elasticity effects from logit estimation for all three specifications. All three specifications indicate strong, negative significance between student earnings while in school and attendance. The first specification indicates a percentage increase in earnings leads to 0.662% decrease in retention, holding other factors constant. Even after controlling for student intentions and college characteristics, a percentage increase in earnings reduces attendance by 0.528%. Due to the time constraint, hours worked and hours spent on studying act as substitutes. Hence, working students are assumed to spend more hours working and are more likely to stopout.

The first specification indicates that females are less likely to stopout. Being a woman increases attendance rates by 0.023%, holding other factors constant. The magnitude decreases in specification 2, and the third specification notes that there are no attendance differences between men and women. There are no race differences in attendance across between whites and non-whites in the first two specifications. After controlling for all covariates, being non-white decreases the probability of continuous enrollment in the following semester by 0.001%. Age is inversely correlated to attendance. A percentage increase in age decreases the likelihood of attendance by 0.159%, holding other covariates constant.

Specification 1 indicates that an increase in the county unemployment rate by 1% increases the probability of continuous enrollment by 0.036%, holding other variables constant.

After controlling for other variables, this probability increases to 0.053%. Betts and McFarland (1995) have shown attendance to be counter-cyclical - more people enroll during economic downturns. Increasing unemployment rate due to economic downturn increases enrollment as poor labor-market prospects lower the opportunity cost of enrollment.

College characteristics are strongly correlated to enrollment. A percentage increase in GPA increases the probability of enrolment by 0.059%, and a percentage increase in the number of credits earned in the first semester increases the probability of enrolment by 0.085%. A remedial credit earned in the first semester has a small negative effect on attendance. Registering for remedial credits might be an indicator of low ability students.

We conduct separate analysis for men and women because studies have shown that men and women make different human capital decisions (Surrette, 2001). Table 4 and Table 5 show analysis of men and women respectively. Earnings have a larger negative effect on stopping out for men than for women. A percentage increase in income increases the likelihood of stopping out by 0.599% and 0.451% for men and women, respectively. Older women stopout at a higher rate than older men as noted in specification 3 in both tables. However, ability factors and student intentions have larger positive effects on retention for women than for men.

ii) <u>Survival Model</u>

We then estimate a survival model using the same three specifications. Table 6 shows the marginal elasticity effects of independent variables on retention.

As noted before, this model is more appropriate for the education data and is our preferred model for this analysis. As with the logit, all three specifications indicate strong, negative relationships between student earnings while in school and attendance. The first specification indicates a percentage increase in earnings decreases time to stopout by 1.767%, holding other factors constant. Even after controlling for student intentions and college characteristics, a percentage increase in earnings decreases time to stopout by 1.050%. Hence, in a given semester, students are more likely to stopout with increases in earnings.

The effects of gender are similar to that of the logit model. However, all three specifications are significant here unlike the logit model. The first specification indicates that females are less likely to stopout in a given semester. Being a woman increases time to stopout by 0.163%, holding other factors constant. The second and third specification provide similar intuition but with smaller probabilities. We find no differences in attendance probabilities between nonwhites and whites in all three specifications. The logit model finds small evidence of nonwhites having a negative relationship with attendance in the third specification. Attendance and age are positively correlated. The results indicate that the older students have a lower probability of stopping out. A percentage increase in age increases time to stopout by 0.625%. The models differ in their analysis on age. Logit models indicate students are more likely to stopout with age increases whereas the hazard model indicates that students are less likely to stopout with age increases. Older students who enroll/reenroll in postsecondary institution take schooling more seriously.

The two models agree on the sign for the unemployment variable. In the hazard model, specification 1 indicates that an increase in the county unemployment rate by 1% increases the time to stopout by 0.060%, holding other variables constant. However, the second specification indicates a positive but insignificant correlation with attendance. After controlling for other variables, unemployment rate has a positive and significant effect on attendance. These results agree with the theoretical prediction that attendance is counter-cyclical.

Ability as measured by performance in KCTCS in the first semester has strong direct correlation with attendance. A percentage increase in GPA increases continuous enrolment by 0.348%, and a percentage increase in the number of credits earned in the first semester increases the time to stopout by 0.340%. However, students taking remedial credits are less likely to remain enrolled. In a given semester, a percentage increase in acquiring a remedial credit in the first term increases the likelihood of stopping out by 0.012%. Students who acquired a GED are more likely to stopout compared to students with a high school certificate.

Table 7 and Table 8 show analysis of men and women respectively. Earnings have a negative impact on attendance for both men and women. The first specification indicates that earnings have a larger impact for men than women. However, after controlling for all the other variables, the magnitude is higher for women. For men, an increase in earnings by 1% decreases time to stopout by 0.856%, holding other covariates constant. However, for women, an increase in earnings by 1% decreases time to stopout by 1.077%, holding other covariates constant. There are also gender differences for the effect of age on retention. Older women are more likely to have continuous enrollment compared to older women. Ability factors have large positive effect on retention for both genders with women having larger effects than for men.

For the pooled model combining men and women, the logit and survival model agree entirely on the effect of student earnings while at school on retention. Earnings have large negative impact on attendance at postsecondary institutions. Both models indicated there are gender differences with women less likely to stopout (hazard model indicated significant coefficient in the third specification). However, the hazard model found no race effects but the third specification in the logit model indicates that nonwhites are more likely to stopout compared to whites. Both models provide contradictory results in the effects of age on stopping out. The logit model indicates negative correlation between age and attendance, and the hazard model indicates otherwise. There are no differences in the analysis of county unemployment rate. KCTCS ability variables had the same effects in both models. Intentions in both models had very similar effects in both size and magnitude.

VII. Conclusion and Implications

Using administrative data from postsecondary institutions matched with administrative earnings data from the state's unemployment insurance department, our results indicate that student earnings are negatively correlated to student retention in Kentucky community colleges. In our preferred model, hazard, a percentage increase in earnings is associated with over a 1.767% increase in stopout. Even after controlling for student intentions, the elasticity is 1.050%. Ability as measured by first-term GPA in KCTCS and credits earned in the first semester positively affected retention.

Overall, this paper contributes by studying an important but not previously used variable on retention – earnings while in school. It employs a hazard model, a robust model that is becoming popular in the education literature and that is suited for the education data.

The paper has implications for education policy because future earnings are highly correlated with years of completed schooling. Therefore, it is important to understand the extent to which postsecondary students sacrifice potential long-term increases in earnings for short-run gains in earnings while enrolled in postsecondary education. Past studies have shown financial aid work to reduce stopout probabilities with grants and scholarships having the largest impact (DesJardins et al, 2002). However, these different types of aid do not consider expenses other than schooling expenses. Living expenses represent large portion of family budgets and therefore students are more likely to make schooling decisions based on earnings. Hence, this study provides a better understanding of the determinants of postsecondary retention that will assist policy makers in designing education policies that help alleviate poverty by encouraging postsecondary completion rather than just postsecondary attendance.

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Table 1: List of Independent Variables

Female	Dummy variable coded 1 for females and 0 for males
Non-White	Dummy variable coded 1 for non-white and 0 otherwise
Missing Race	Dummy variable coded 1 for missing race and 0 otherwise
Age	Age in number of year
First term GPA	First Term GPA per student
GED	Dummy variable coded 1 for GED and 0 otherwise
Missing High School	Dummy variable coded 1 for no information on high school graduation and 0 otherwise
Number of Credits in First Term	Total Number of Credits Earned in the First Semester/Quarter
Number of classes in First Term	Total Classes attempted in First Semester
First Term Remedial Credits	Number of Remediation Credits earned while attending KCTCS
Student's Aspiration	Whether or not to pursue an award, and what field of study in which to pursue an award
Earnings	Log of Total Earnings
Employed	Dummy Variable coded 1 if student has positive earnings and 0 otherwise
County Unemployment	Unemployment rates per county per quarter
Cohort0203	Dummy variable coded 1 if sample is from 02-03 cohort and 0 for 03-04 cohort

Table 2: Descriptive Statistics of the Sample

Variable	Full Sample Mean	Full Sample S.E	Men Mean	Men S.E	Women Mean	Women S.E
Age	29.05	10.35	29.87	11.07	28.39	9.67
Female	0.55	0.50				
White	0.80	0.40	0.79	0.41	0.81	0.39
Nonwhite	0.09	0.40	0.07	0.41	0.11	0.39
Missing Race	0.11	0.31	0.14	0.35	0.08	0.27
Number of classes attempted in first term	2.93	1.82	2.83	1.96	3.01	1.70
First Term GPA	2.30	1.55	1.89	1.64	2.64	1.39
First Term Credits	6.03	5.10	5.29	5.30	6.63	4.85
GED	0.11	0.32	0.09	0.29	0.13	0.34
High School Certificate	0.81	0.39	0.78	0.41	0.84	0.37
Missing High School	0.07	0.26	0.13	0.34	0.03	0.16
County Unemployment Rate	6.33	1.35	6.32	1.37	6.33	1.34
Earnings	$6,075	$5,582	$7,993	$6,726	$4,367	$3,523
First Term Remedial Credits	0.61	1.70	0.41	1.40	0.78	1.90
Student Intentions						
Business	6.33%	0.24	3.64%	0.19	8.50%	0.28
Health	19.44%	0.40	5.47%	0.23	30.68%	0.46
Humanities	9.51%	0.29	8.92%	0.28	9.98%	0.30
Sciences	0.69%	0.08	0.49%	0.07	0.86%	0.09
Services	7.58%	0.26	4.13%	0.20	10.35%	0.30
Social Works	0.68%	0.08	0.83%	0.09	0.56%	0.07
Vocational	9.37%	0.29	18.28%	0.39	2.20%	0.15
No degree	32.11%	0.47	45.91%	0.50	21.01%	0.41
Undecided	14.28%	0.35	12.33%	0.33	15.86%	0.37
Number of Students	71,133		32,519		38,614	

Table 3: Logistic Estimation : Marginal Effects - Elasticity			
Explanatory Variables	**1**	**2**	**3**
Log Earnings	-0.662***	-0.521***	-0.528***
	(50.95)	(40.72)	(40.75)
Female	0.023***	0.003**	0.002
	(19.56)	(2.14)	(0.50)
Nonwhite	-0.001	-0.001	-0.001**
	(0.35)	(0.73)	(2.15)
Missing Race	0.005***	0.007***	0.006***
	(11.95)	(16.33)	(15.52)
Age	-0.403***	-0.284***	-0.309***
	(19.20)	(13.58)	(14.69)
Age Squared	0.159***	0.138***	0.150***
	(16.32)	(14.27)	(15.51)
County Unemployment Rate	0.036***	0.046***	0.053***
	(6.83)	(8.75)	(10.23)
First Term GPA		0.070***	0.059***
		(40.30)	(32.65)
Number of Credits earned in first term		0.074***	0.085***
		(43.78)	(40.62)
GED		-0.003***	-0.003***
		(7.45)	(8.44)
Missing High School		-0.002***	0.002
		(4.65)	(1.36)
Number of classes attempted in first term			-0.035***
			(15.69)
First Term Remedial Credits			-0.001**
			(1.97)
Number of Observations	264,122	264,122	264,122

Note: Absolute t-Statistics in parenthesis. ***1% Level ** 5% Level * 10% Level

Table 4: Men: Logistic Estimation : Marginal Effects – Elasticity			
Dependent Variable: Attendance=1			
Explanatory Variables	**1**	**2**	**3**
Log Earnings	-0.767***	-0.606***	-0.599***
	(34.71)	(27.67)	(27.02)
Nonwhite	0.003***	0.002***	0.001***
	(5.91)	(4.61)	(2.66)
Missing Race	0.004***	0.006***	0.006***
	(5.09)	(8.08)	(7.69)
Age	-0.582***	-0.338***	-0.348***
	(16.65)	(9.63)	(9.84)
Age Squared	0.230***	0.157***	0.163***
	(13.94)	(9.58)	(9.94)
County Unemployment Rate	-0.001	0.026***	0.032***
	(0.28)	(3.20)	(3.98)
First Term GPA		0.061***	0.055***
		(27.32)	(23.61)
First Term Credits		0.065***	0.069***
		(27.02)	(23.87)
GED		-0.001*	-0.001**
		(1.85)	(2.43)
Missing High School		-0.002***	0.001
		(2.71)	(0.81)
Number of classes attempted in first term			-0.021***
			(6.84)
First Term Remedial Credits			-0.002***
			(3.47)
Number of Observations	129,900	129,900	129,900

Note: Absolute t-Statistics in parenthesis. ***1% Level ** 5% Level * 10% Level

Table 5: Women: Logistic Estimation : Marginal Effects - Elasticity			
Dependent Variable: Attendance=1			
Explanatory Variables	**1**	**2**	**3**
Log Earnings	-0.516***	-0.430***	-0.451***
	(33.25)	(28.56)	(29.60)
Nonwhite	-0.002***	-0.002	-0.002***
	(3.86)	(1.05)	(3.21)
Missing Race	0.007***	0.008***	0.008***
	(14.73)	(17.35)	(16.40)
Age	-0.349***	-0.328***	-0.395***
	(13.00)	(12.36)	(14.66)
Age Squared	0.149***	0.164***	0.193***
	(12.05)	(13.44)	(15.60)
County Unemployment Rate	0.088***	0.072***	0.084***
	(12.35)	(10.39)	(12.06)
First Term GPA		0.076***	0.056***
		(29.88)	(20.27)
First Term Credits		0.078***	0.103***
		(34.39)	(34.04)
GED		-0.004***	-0.004***
		(8.40)	(8.57)
Missing High School		-0.001***	-0.001
		(2.77)	(0.49)
Number of classes attempted in first term			-0.058***
			(17.08)
First Term Remedial Credits			0.002
			(1.21)
Number of Observations	134,222	134,222	134,222

Note: Absolute t-Statistics in parenthesis. ***1% Level ** 5% Level * 10% Level

Table 6: Hazard of Retention - Marginal Effects - Elasticity			
Event: Time to Stopout			
Explanatory Variables	**1**	**2**	**3**
Log Earnings	-1.767***	-1.050***	-1.050***
	(24.26)	(16.66)	(16.48)
Female	0.162***	0.068***	0.064***
	(21.96)	(10.07)	(8.91)
Nonwhite	0.002	0.002	0.002
	(0.29)	(1.29)	(0.42)
Missing Race	0.007	0.007***	0.007***
	(1.11)	(3.80)	(3.78)
Age	0.896***	1.077***	1.040***
	(7.76)	(10.52)	(10.05)
Age Squared	-0.454***	-0.434***	-0.415***
	(8.91)	(9.71)	(9.17)
County Unemployment Rate	0.06*	0.03	0.05**
	(1.80)	(1.20)	(1.95)
First Term GPA		0.370***	0.348***
		(34.54)	(30.91)
First Term Credits		0.326***	0.340***
		(31.80)	(25.57)
GED		-0.012***	-0.014***
		(7.01)	(7.60)
Missing High School		-0.012***	-0.011***
		(11.92)	(10.22)
Number of classes attempted in first term			-0.035***
			(3.01)
First Term Remedial Credits			-0.012***
			(4.87)
Observations	264,122	264,122	264,122

Note: Absolute t-Statistics in parenthesis. ***1% Level ** 5% Level * 10% Level

Table 7: Men: Hazard of Retention - Marginal Effects – Elasticity			
Event: Time to Stopout			
Explanatory Variables	**1**	**2**	**3**
Log Earnings	-1.736***	-0.952***	-0.856***
	(17.13)	(10.83)	(9.65)
Nonwhite	0.015***	0.011***	0.009***
	(5.64)	(4.95)	(3.87)
Missing Race	-0.009**	0.006**	0.007**
	(2.89)	(2.01)	(2.31)
Age	-0.07	0.552***	0.519***
	(0.44)	(4.09)	(3.80)
Age Squared	-0.100	-0.256***	-0.236***
	(1.55)	(4.39)	(4.01)
County Unemployment Rate	-0.082**	-0.040	-0.020
	(2.14)	(1.21)	(0.61)
First Term GPA		0.309***	0.294***
		(24.55)	(22.76)
First Term Credits		0.304***	0.263***
		(22.41)	(15.69)
GED		-0.008***	-0.009***
		(3.48)	(4.15)
Missing High School		-0.018***	-0.015***
		(9.14)	(7.73)
Number of classes attempted in first term			0.020
			(1.27)
First Term Remedial Credits			-0.010*
			(1.78)
Observations	129,900	129,900	129,900

Note: Absolute t-Statistics in parenthesis. ***1% Level ** 5% Level * 10% Level

Table 8: Women: Hazard of Retention - Marginal Effects – Elasticity			
Event: Time to Stopout			
Explanatory Variables	**1**	**2**	**3**
Log Earnings	-1.402***	-1.010***	-1.077***
	(13.28)	(10.91)	(11.53)
Nonwhite	-0.016***	-0.007***	-0.007***
	(5.50)	(2.58)	(2.72)
Missing Race	0.008**	0.012***	0.012***
	(2.43)	(4.12)	(4.01)
Age	1.724***	1.541***	1.485***
	(9.41)	(9.24)	(8.77)
Age Squared	-0.723***	-0.574***	-0.556***
	(8.72)	(7.67)	(7.32)
County Unemployment Rate	0.268***	0.141**	0.164***
	(5.40)	(3.23)	(3.72)
First Term GPA		0.401***	0.344***
		(22.68)	(17.76)
First Term Credits		0.344***	0.457***
		(22.37)	(21.23)
GED		-0.020***	-0.018***
		(7.01)	(6.49)
Missing High School		-0.005***	-0.004***
		(4.03)	(3.58)
Number of classes attempted in first term			-0.140***
			(6.68)
First Term Remedial Credits			-0.021***
			(5.13)
Observations	134,222	134,222	134,222

Note: Absolute t-Statistics in parenthesis. ***1% Level ** 5% Level * 10% Level

FIGURE 1. *Kaplan Meier Sample survival estimates of stopout by gender*

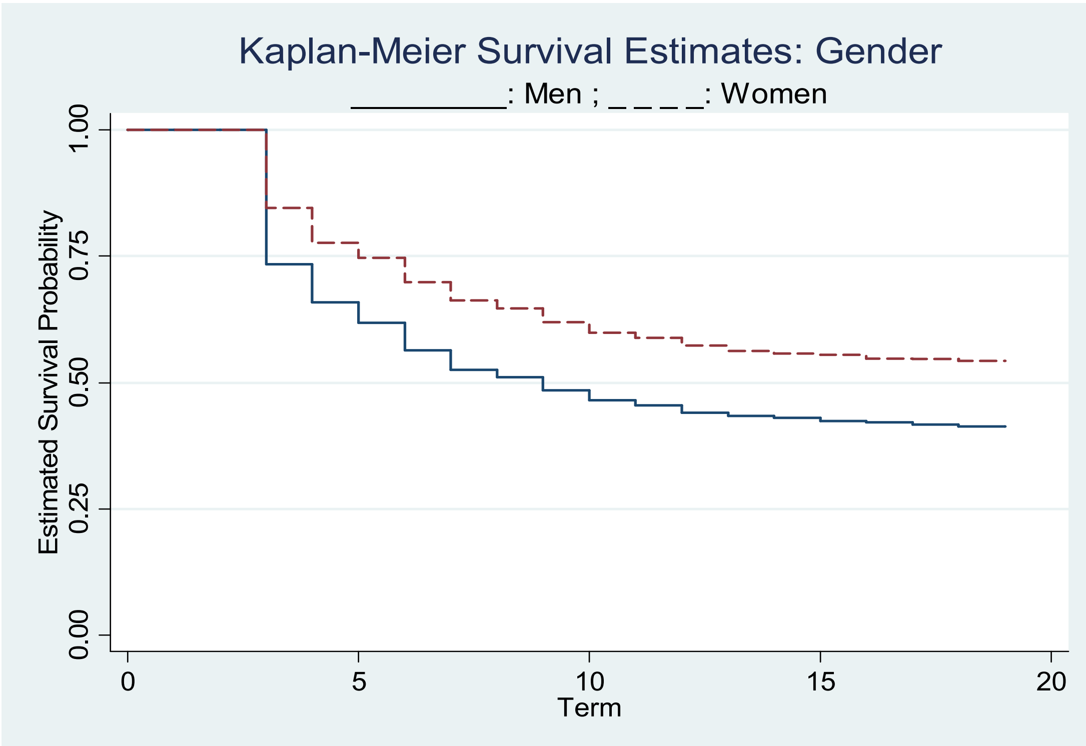

FIGURE 2. *Kaplan Meier Sample survival estimates of stopout by race*

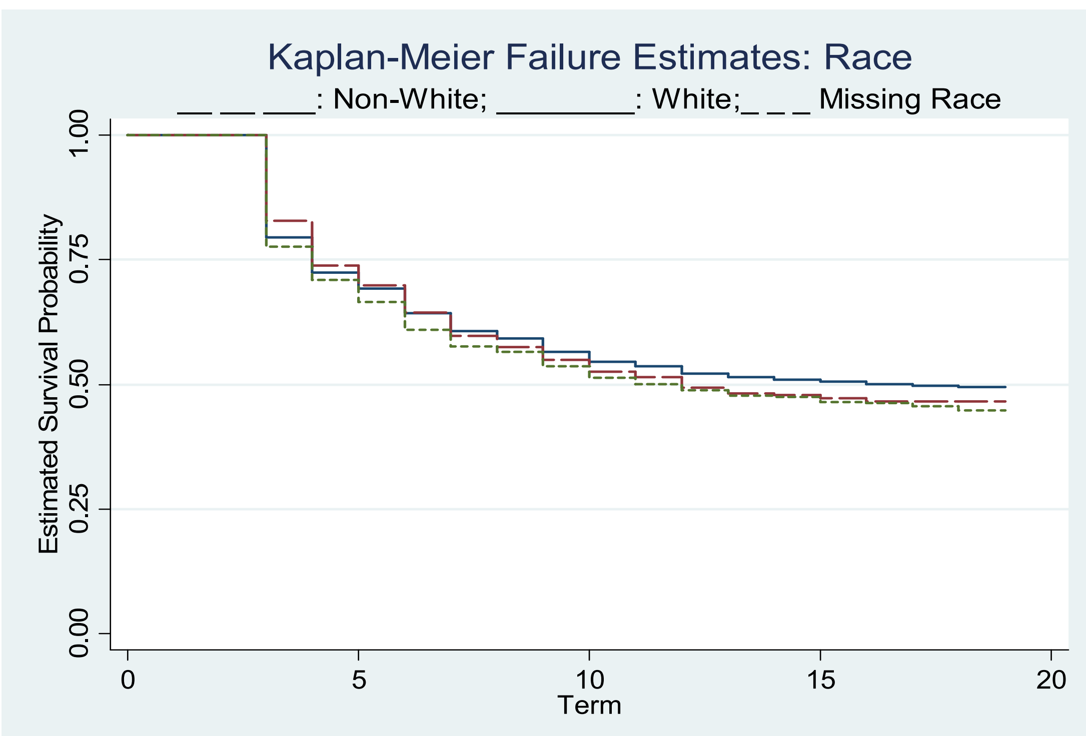

FIGURE 3. *Kaplan Meier Sample survival estimates of stopout by age*