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ANALYSIS OF TWO-YEAR COLLEGES: TRANSFER, RETENTION AND GRADUATION

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ABSTRACT OF DISSERTATION

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A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Business and Economics
at the University of Kentucky

By

Darshak P. Patel

Lexington, Kentucky

Director: Dr. Kenneth Troske, Sturgill Professor of Economics, Chair and Director CBER

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Investment in higher education is typically considered as a static discrete-choice problem where students make post-secondary education choices usually right after high school (Heckman et al., 2006). This is largely aligned with Becker's human capital theory. As Becker's theory holds, students' decisions can alter with the arrival of new information (Weisbrod, 1964). By relaxing the assumption certainty in the human capital model, student education decisions can be modeled using Weisbrod's option value theory. According to this theory, students reevaluate their lifetime-utility maximizing decisions based on new information acquired in a sequential nature. Students face large uncertainties due to unexpected positive and negative shocks. This dissertation benefits from utilizing student earnings while in school to proxy for these shocks and opportunity costs. Students test both the schooling and labor market to gain new information to maximize their lifetime earnings. Since higher education choices are dynamic in nature, this dissertation benefits from the use of hazard models as these models explicitly account for time. Overall, the dissertation is largely focused on estimating the effect of time-variant and time-invariant variables on the timing of student higher education investment decision. Time to dropping out or transferring is directly correlated with the cost of education. As students take longer time to transfer or shorter time to drop out, acquiring a bachelor's degree will take longer. These increases in the cost of education eventually decrease the supply of skilled labor and increase the burden on the state and taxpayers. Using a large administrative data from Kentucky Community and Technical College System (KCTCS) matched with administrative earnings data from Kentucky's unemployment insurance department, results indicate that increases in student earnings increases time to transfer, decrease time to stopout early and decrease time to graduate. The opportunity cost of continuous enrollment is high and students weigh current events more than future events. Similarly, as students age, the number of years left to enjoy full benefits from another semester of education decreases and hence students are more likely to stopout earlier or transfer later as they age. Lastly, variables that were proxy for ability promote attendance, transfer and graduation.

KEYWORDS: Community colleges, transfer, retention, stopout, hazard model

Darshak P. Patel

July 29, 2011

Date

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Dedication

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Shamil Ashokbhai Patel

1989 - 2011

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"We must address … the urgent need to expand the promise of education in America. In a global economy where the most valuable skill you can sell is your knowledge, a good education is no longer just a pathway to opportunity—it is a pre-requisite. …"

- *President Obama, 2009*

1 CHAPTER 1: DISSERTATION INTRODUCTION

Individuals who earn four-year degrees enjoy high private returns. In addition to personal benefits that accrue to those who are more highly educated, the labor literature shows a strong association between an educated populace and socially desirable outcomes (Card, 1999; Blomquist et al., 2009). That is, in addition to the private returns that accrue to more highly educated individuals, higher education's benefits also spill over to positive effects on society, through such benefits as increased production and a population that enjoys better health, lower crime rates, higher standard of living, better managed finances, and healthier lifestyles. The United States is no longer the best-educated country of the world (Organization of Economic Cooperation and Development, 2010), partially because four-year graduation rates have remained constant and time to completion has increased (Turner, 2004). If the United States is to increase the supply of skilled labor and improve both private and social returns, it must increase overall four-year graduations rates and reduce the time it takes to complete a degree. One way to improve four-year graduation rates is by increasing post-secondary retention rates. The literature shows that students who drop out or take short breaks from school face problems in the labor market and post-secondary institutions (Stratton et al., 2008).

Furthermore, with one-third of post-secondary students attending two-year colleges, a key issue of the stagnant four-year completion rate is that few students from community colleges graduate from four-year colleges (Department of Education, 2007).[1] Only 20% of students who enroll at public two-year colleges eventually transfer to four-year colleges, and approximately 50% fail to acquire a degree from either a two- or four-year college (Goldrick-Rab and Berube, 2009).[2] Researchers can identify these students by a number of personal, family, economic and institution characteristics, and most studies agree that these characteristics affect students' decisions about whether to invest in acquiring more education. This study differentiates from past studies by largely focusing on how these characteristics affect the timing of education outcomes: transfer, stopout and graduation.[3] The time of education investment significantly impacts the overall level of education attained. Time to transfer is negatively correlated with the probability that the student will attain a four-year degree and is positively related to the time the student takes to complete a four-year degree (Nutting, 2004). Stopping-out also decreases the likelihood of attaining a baccalaureate degree and increases the time to complete a degree. Similarly, postponing graduation at four-year colleges is expensive in terms of lost earnings because labor-market entry is delayed, and tuition costs of attending additional semesters increase the overall costs to obtaining a degree. Additional costs are borne by taxpayers for financing students over longer periods through the use of state funds. Recognizing these problems, I conduct this study to address issues that greatly affect education underinvestment.

[1] Students who attend for-profit two-year colleges have higher graduation rates at four-year schools compared with their colleagues who attend community colleges (Trends in College Pricing, 2010).

[2] Public two-year colleges are lagging behind in both retention and graduation rates compared with for-profit two-year colleges (Rosenbaum & Stephan, 2005).

[3] This dissertation focuses on stopout rather than dropout. These terms are distinguished by a short-term versus long-term break from school. This distinction is explained in detail in Chapter 3.1.

A novel feature of this study is that it uses a hazard model to estimate how economic, personal, family, and institution factors affect the time students take to stop-out and transfer. This study separates from past studies in terms of economic intuition, which provides a theoretical and empirical model. The labor economics literature has often modeled the human capital acquisition as a static-discrete choice problem. Becker's (1962) human capital theory suggests that students will invest in post-secondary 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. Although some may assume that students have full information about the costs and benefits of post-secondary 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 assumes that individuals lack perfect foresight, which 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, continue at the two-year college, or transfer to a four-year college. Since students can influence their timing of investments, this study contributes by estimating hazard models. The use of these models is justified as hazard models explicitly account for time. The next two chapters describe more extensively the theoretical and empirical model used in this study.

Next I describe the data used for this study. I acquired student-level data from the Kentucky Community and Technical College System (KCTCS) and matched these data with administrative earnings data from Kentucky's unemployment insurance program. Table 4.1 shows the many variables of interest. After a few basic data checks, the study included 69,233 students who entered KCTCS from 2002 to 2003 and 2003 to 2004, and followed them until fall 2008. The study excluded students in correctional facilities, under the age of 17, and over the age of 65.

Following the data chapter are two chapters that provide an empirical analysis on transfer and stopout, respectively. In both chapters, I examine the effect of the student covariates on the time to transfer from two-year colleges to four-year colleges and time to stopout using both the logistic and the hazard models. Each chapter features an introduction that describes the relevant contribution to the literature, followed with an overview of the literature review, data description, graphical presentations, empirical results, and discussions on the relationship to economic labor intuition.

Next follows an empirical analysis on competing events. Many studies analyze each student outcome as a single event. This study takes a step further by estimating a competing-risk model to consider three student outcomes: stopout, transfer, and graduation. The introduction to this chapter discusses the concerns of estimating the single-risk models. The following two sections describe the different models that can be adopted including their benefits and costs. The chapter concludes with a discussion of results.

The final chapter summarizes the dissertation and contributions from this research.

2 CHPATER 2: THEORECTICAL DISCUSSION ON ASSUMLUATING HUMAN CAPITAL

In its simplest form, Becker's (1964) human capital theory predicts that students make their post-secondary schooling decisions based on maximizing lifetime utility. Because the benefits are usually delayed, individuals weigh the net present value of benefits to the current and expected costs of education. Individuals who put more weight on current events than on future ones 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 they can maximize their lifetime earnings. According to the theory, the decision to attend post-secondary education is typically made right after completing high school. This model assumes that students have some or all knowledge of the expected value of benefits and costs of schooling.

However, in reality, benefits and costs change over time. Moreover, most if not all individuals are uncertain about the future benefits and costs of schooling. Weisbrod's (1962) option value theory builds upon Becker's human capital theory by assuming that there is a lot of uncertainty about education in regards to the costs and benefits of schooling and 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 dropout and work after each semester. These options are generated through uncertainties. There are three forms of uncertainty. One uncertainty occurs when students are unsure of their future intentions. To improve career ambitions or choices, new information is collected through college performance such as grades earned that helps alleviate some of these uncertainties. Other uncertainties come in the form of costs such as hikes 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. Once students complete a stage, students gain most up-to-date information on additional costs of education, current returns on the level of college completed plus the value of exercising the option to acquire additional schooling. Using this information, students recalculate their lifetime utility at the end of every semester to make their next investment choice.

Students can influence their timing of investment (Jacobs, 2007). Those uncertain of their schooling abilities and /or the high costs of four-year schooling may choose not to acquire post-secondary education or may choose to delay their enrollment to a four-year college. A major barrier to post-secondary education 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). However, 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 post-secondary education by enabling students to experience post-secondary schooling at a relatively lower cost than enrolling at a four-year college. This provides students with a chance to enroll and update their beliefs on their education goals sooner, rather than later. Thus, these colleges provide a sound and cost-effective education base to help marginal students determine their career paths.

Post-secondary institutions affect the accumulation of human capital through education in three ways. First, because students are provided with options to continue or drop out after completion of every stage, it encourages more students to enroll, especially those students who are marginal students. Second, this option provides those students who commit to graduating with a choice to drop out if their goals change. Lastly, 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.

This theory predicts that students make their next investment choice at the end of every stage by comparing their net benefits with their net costs. Once students update their beliefs after completing a semester or academic year, they have three options: they can stopout/dropout and join the labor force, transfer to a four-year college or receive an award (certificate, diploma, or degree). Students will transfer when they realize that their net present value is highest for the option to transfer. Similarly, students will stopout/dropout when they realize that their net present value is highest for the option to stopout/dropout. Which students exercise their option to stopout/dropout? Past studies indicate that financial aid, socioeconomic status, academic preparedness, academic and social integration, and expected future wages affect the decision to stopout (Singell, 2004; DesJardins, Ahlburg, and McCall, 2002; Vignoles and Powdthavee, 2009; Bean, 1990; Tinto, 1993; Kerkvliet and Nowell, 2005). Which students exercise their option to transfer? Past research indicates that students coming from a high family or individual socioeconomic status, who have accumulated a high number of credits, have a high GPA, have taken math and science classes, had high attendance rates, received financial aid, and were enrolled full-time were more likely to transfer (Lee and Frank, 1990; Surrette, 2001; Velez and Javalgi, 1987, Wassmer et al., 2004).

I initially focus on why some students transfer earlier than others and then examine why some students stopout earlier than others. Upon completion of a stage, students unravel new information about current returns to the completed stage of education, future costs and benefits of later stages of education and any shock to these costs and benefits (Heckman, Lochner and Todd, 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. Students investment decisions are largely influenced by unexpected positive (salary raise, promotion, etc.) or negative shocks (job loss, failing a class, etc.) while attending a post-secondary institution. Thus, this study estimates the effects of observable covariate on students' decisions to stay an additional semester at two-year colleges before transferring/stopping out. Apart from controlling for student background and ability factors, I am able to estimate the effect of students' earnings while in school on the time to transferring or stopping out. This is an important variable as it provides information on both a positive shock (increase in earnings) and a negative shock (decrease in earnings) on the decision of a student to extend enrollment at a two-year college for an additional semester.

3 CHAPTER 3: MODEL SPECIFICATION

3.1 Defining Outcomes

This dissertation is interested in investigating how individuals make their schooling choices. Students can experience one or more of the four possible outcomes. These are stopout, continued attendance, graduation, or transfer. The students can either take a short break from school (termed as stopout in the literature), dropout altogether, transfer, graduate or experience combinations of them. There have been some studies that have focused only on dropout (Singell, 2004) but recent studies have focused on both stopout and dropout (Stratton et al., 2008). Stratton et al. (2008) distinguish between the two as short-semester (usually less than a year) and long-semester dropouts (more than a year), respectively. This distinction enables researchers to study students who do not return back to school. There is limited research on the former group.[4]

It is difficult to differentiate between stopout and dropout due to data censoring at the end of sample period. One cannot tell if students who withdraw from school closer to the end of sample period return back to school. In other words, I cannot tell if a student drops out indefinitely. Therefore, this study uses stopout to describe attrition. Since some students skip the summer semester, I define stopout as students who miss two consecutive semesters.[5] Students are considered to have stopped out if 1) students miss

[4] There is no research done on evaluating when students who stopout earn a degree or transfer.

[5] Analysis was also conducted for stopouts that are defined as student missing three consecutive semesters and four consecutive semesters. Results can be provided upon request.

two consecutive semesters and do not return back to school, or 2) students who miss two consecutive semesters and return to school but do not earn a degree or transfer.

Students are identified as graduates if they earn a degree, diploma or a certificate. Students who miss two consecutive semesters of schooling but come back to school and graduate with a certificate, diploma or a degree are also considered as graduates. Students are identified as transfer if they transfer to a four-year college. Students who miss two consecutive semesters of schooling but come back to school and transfer to a four-year program are identified as transfer students. A problem arises when a student misses two consecutive semesters but returns to school and experiences graduation and transfer to a four-year program. In this case, I give precedence to the transfer outcome over the graduation outcome because a student who transfers has a higher probability of acquiring a greater education than a two-year degree. Therefore, this student is considered as a transfer student. A student who does not miss any semesters of schooling, does not transfer and does not graduate is considered as an active student.

For analyzing single events at a time, I create individual dummies for each event. I create a stopout dummy that indicates 1 for stopout and 0 for continued attendance, transfer or graduate. I create a dummy for transfer where 1 identifies students who transfer to four-year colleges and 0 identifies students who did not transfer at all. I create a dummy for graduate where 1 identifies students who graduate with a certificate, diploma or a degree and 0 otherwise. Finally, when analyzing multiple events together (discussed in Chapter 7), I use the above definitions for each events and create a single variable that denotes 0 for stopout, 1 for continuous attendance, 2 for transfer and 3 for graduation.

3.2 Single Events

The main goal of the dissertation is to examine student success in terms of transfer and persistence independently. Previous studies utilize traditional models (logit or probit models) to estimate the probability to dropping out/stopping out, transfer from two-year to four-year colleges and graduation from two or four-year colleges. These models are more convenient when the outcomes mentioned above are measured in discrete semesters – a student either drops out or does not, a student transfers or does not and a student graduates or does not. However, there are many disadvantages of using traditional models while analyzing these outcomes. First, this research is interested in the timing of these outcomes and not the probability of the outcomes occurring. Traditional models cannot exploit the timing of an event. Specifically, these models assume that a student who experiences one of the outcomes after the first semester has a higher propensity to experience the outcome than a student who experiences the outcome at a later semester. Moreover, the initial conditions are assumed to be fixed over time and the overall probability of outcome is assumed to be constant for each year/semester. Last, traditional models cannot handle right-censoring (when the outcome is unobserved during the spell due to end of sample). Traditional models either discard the censored cases or 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. All of these limitations can lead to biased estimates.

As explained earlier, option value theory states that students are faced with uncertainty. Hence, students make schooling choices sequentially when new information is revealed at the end of every stage. It is more appropriate to use hazard models for estimation which treats education choices sequentially rather than static discrete choice problems made once in a lifetime by individuals. This study uses hazard models that 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 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 adjust for the likelihood of outcomes at the end of every period. Last, hazard models can be generalized to control for unmeasured heterogeneity. Many education studies have adopted hazard models for their research due to the models' ability to account for time by treating education decisions as sequential rather than simultaneous. (Calcagno et al., 2007; DesJardins et al., 1999; Doyle, 2009). Some studies have looked at the timing to stopout. However, no studies have estimated the probability and timing of transfer using hazard models.

Hazard models are statistical models of a person over a period of time until the event occurs or when the sample period ends. Specifically, it estimates the conditional probability of an occurrence of an event at semester t given that the student has not experienced any of the events before semester t controlling for covariates collected from a post-secondary institution.[6] The time unit adopted in this dissertation is semesters. The data is in the form of person-period format where each student has one record per semester for each semester at risk or till the sample period ends. Students can experience any of the outcomes during this period. I do not observe the exact length of the duration

[6] Note that the models in this section consider one event at a time and not all the events occurring simultaneously.

of the events but rather observe when a student experiences the events at discrete moments in time. I observe whether a student stops out or transfers or graduates at the end of every semester. In other words, the time periods until the event are countable and the event is not continuous. The dissertation focuses on transfer and retention separately. Therefore, I estimate a single-risk discrete-time hazard model for each event individually. These events can also be modeled using competing-risk models. However, they are many challenges in the computation of competing models. These challenges are mentioned in detail in Chapter 7.

The dependent variable is duration until the time of the relevant event. Time to event is the fundamental outcome of interest. For example, when I am focusing on the transfer events, students who transfer will be followed up to the point of transfer. Students who do not transfer will be followed up to the end of sample. All observations are observed in discrete-time. Therefore, I observe student outcome at the end of semesters and not the instantaneous time at which a person experiences the event. Finally, all estimates are based on Maximum Likelihood Estimation. The hazard model used is:

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

where $y_i = j$ indicates student *i's* outcome in semester *j*. The condition $y_i \geq j-1, i \,\epsilon\, A_j$ states that the student *i* has not yet transferred, graduated, or stopped out from school before time semester *j* and the student is still observed at semester *j*. The probability is conditional on an event not occurring in period *j-1* or earlier. I assume that the event of interest is affected by a vector of both time-varying and time-invariant explanatory variables X_j (Table 4.1) which controls for all the observed student characteristics. This model assumes a Weibull distribution - a continuous distribution. This is a two-parameter generalization of the exponential distribution, which does not restrict the baseline hazard to be constant and allows for the hazard function to increase or decrease monotonically over time. In other words, it allows the hazard to be flexible. Manton et al. (1990) showed that the Weibull distribution is smooth, common and works for all models including discrete-time hazard model as long as there are no spikes in the data. Their solution to the spikes is to include dummy variables for the period of spike. I observe and control for transfer spikes that occur at the end of every Spring semester. The disadvantage this model is that it assumes all the determinants of the event is explained by the explanatory variables (X_j) and these effects are constant over time. The estimates will be biased if these assumptions fail. Therefore, estimates generalizing the model to include a control for unmeasured heterogeneity and allow for time-varying coefficients are also conducted (DesJardins, Ahlburg and McCall (2002)).

4 CHAPTER 4: DATA

Student record data are provided by Kentucky Community and Technical College System (KCTCS). The administrative data is then matched to administrative earnings data from the state's unemployment insurance department. KCTCS is a statewide community-college system with 16 colleges and 67 campuses all over the state of Kentucky. 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.[7] Students who are in correctional institutions, less than 17 years old or more than 60 years old as of June 1, 2002 for the 2002-03 cohort are excluded. Similar exclusions are applied to the 2003-04 cohort. Students are followed from Summer of 2002 till the Summer of 2008 so students are observed up to 20 trimesters. Students who transfer are only followed up to 13 trimesters as students in this sample transfer by the 13th trimester. A year has three trimesters: Fall, Spring and Summer.

The data include information on demographics, enrollment, course, outcomes, transfers financial aid, test scores, dual credit and earnings. Demographic data contain information on 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).

The enrollment-level data contain data on college of enrollment, enrollment semester, admittance type and the academic plan the student intends to complete while at

[7] 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 Summer of 2002, Fall of 2002, or Spring of 2003, whereas the second cohort is a sample of students who enrolled in the Summer of 2003, Fall of 2003,or Spring of 2004.

KCTCS. The course-level data include all the basic transcript information for all students who enrolled in KCTCS. These data include information by semester on grades, credits attempted and earned and whether a student acquired credits for remedial classes.

Data on outcomes identify each type of degree, certificate, and diploma awarded that are offered by KCTCS. To earn an Associate's degree, a student must complete 60 to 76 credit hours depending on the program. These are usually considered as transfer degrees. In other words, students who wish to complete a four-year degree usually acquire an Associate's degree in order maximize transfer credits. Diplomas tend to target broader areas than certificates and usually require more credits (often one year or more of full-time studies). Certificates tend to be more specialized and are completed faster than diplomas and an Associate's.

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.

Data on financial aid are provided for each student. KCTCS provides financial aid data on the type of aid, semester of aid, year of aid and the amount awarded. However, KCTCS did not provide information on whether a student applied for aid or not.

Although students who attend KCTCS are not required to take standardized tests, test scores were provided for some of the students. These included ACT and COMPASS test scores by subject. These are college placement tests that help admission officers to evaluate incoming students in different subject areas. These variables are used as a proxy for ability in the education literature. Since KCTCS does not require test scores for admission and majority of the sample constitute as non-traditional students, many students had missing test information. Due to this reason, these variables were not used for estimation. Data on students who attempted dual credits are also provided. These students are simultaneously enrolled in high school and at KCTCS. This enables them to earn certain credits well before beginning post-secondary education along with credit toward their high school graduation.

KCTCS provides employment and total wages for each student per quarter by combining student level data with the unemployment insurance department. Total wages are reported for each person and job by employers during employment per quarter. For both cohorts, earnings data were provided from the first quarter of 2000 through the third quarter of 2008 and were gathered from the state's unemployment insurance program.[8] To convert the earnings data from quarterly to a trimester format, I took the average of quarter 1 and quarter 2 to calculate earnings for Spring, average of quarter 2 and quarter 3 to calculate earnings for Summer and average of quarter 3 and quarter 4 to calculate earnings for fall. Finally, data on county-level unemployment are collected from Bureau of Labor Statistics.

4.1 Dependent and Independent Variables

The dependent variable varies depending on the outcome of interest. For estimating the time to transfer, I generate a dummy variable that is coded 1 if a student transferred to a four-year college from KCTCS during the period of sample and 0

[8] A slight limitation of these data is that it ignores self-employment, illegal employment and a few jobs that are not covered by the unemployment insurance.

otherwise. Similarly, when estimating the time to stopout, I generate a dummy variable that is coded 1 if a student stopped out from KCTCS during the period of sample and 0 otherwise. Last, when analyzing graduation, I generate a dummy variable that is coded 1 if a student graduates from KCTCS with a certificate, diploma or a degree during the period of sample and 0 otherwise. All the dependent variables are defined explicitly in Chapter 3.1.

The variables of interest to analyze each outcome are listed in Table 4.1. The independent variables included in this model are chosen based on the education literature, hypothetical considerations and theoretical predictions. Variables to control for individual background include age, age squared, race and gender. Option value predicts that younger students are more likely to transfer and also transfer at a quicker rate than the older group for two main reasons. First, older students have less time to accumulate gains of a four-year degree and therefore are less likely to attain a four-year degree. Secondly, older students tend to have more responsibilities (jobs, marriage, and children) than younger students. Both reasons decrease the overall benefits of investing in the next stage of education, holding other things constant. With the same reasoning, theory predicts that older students are more likely to stopout.

The sample consists of 78% 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 female or not. Gender and race are included in the models because the predicted sign is unclear due to conflicting results in previous work on their effects on probability to transfer. Gender also plays an important role in studying retention behavior. Over time, the gender attendance and graduation gap has diminished, and some studies indicate that women have surpassed the retention and graduation rate of men (Surette, 2001).

Student intentions are controlled for as these factors are found to be important factors in the human capital literature (DesJardin et al., 1999). Students' intentions are measured by the number of courses taken in the first KCTCS semester and a set of dichotomous variables for each student's intended 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 the student pursues an award, and what field of study is pursued. All these variables are measured in the first semester. By including controls for student intentions, I am able to compare transfer/stopout outcomes for students with very similar intentions upon entry at KCTCS. Therefore, I can address the different motivations and intentions of students who choose to acquire a degree, diploma, certificate or no degree. Students who plan to complete a degree are hypothesized to take longer to transfer than undeclared/undecided students because these students are more likely to complete a degree before transferring. These students are also more likely to have continuous attendance.

Also included is a variable indicating remedial credits earned in the first semester by a student while attending KCTCS. Students enroll in remedial credits to improve their skills in a certain subject. There have been inconclusive results in terms of the effect of remediation credits on two-year retention and graduation. Some studies show remediation to improve retention and graduation (Pascarella & Terenzini, 2005) whereas Calcagno et al. (2007) find enrolling in a remediation classes reduces the odds of graduating. No prior empirical research is found indicating whether remedial credits increase or decrease the time to transfer. Many students register for these courses and hence it is appropriate to include this variable to determine its effect on the time to transfer, time to stopout and time to graduation.

I controlled for the ability levels of students as theory predicts that higher ability students complete schooling at a more efficient rate and earn a higher rate of return than their colleagues. For these students, the net benefits of investing in the next stage of education are generally higher than the net costs. Thus, these students are more likely to persist and transfer to a four-year college. The number of credits earned in the first semester and first semester GPA are calculated and included to control for ability level upon arriving at KCTCS. Using these variables beyond the first semester would generate an endogeneity issue. Despite these concerns, some papers from the 1980s use such variables (Dougherty, 1987; Meznek, 1987; Velez and Javalgi, 1987). These variables are a proxy for a student's academic performance and hence they are hypothesized to postpone stopout and speed up transfer. 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.[9]

This research also benefits from financial aid variables. Many studies have investigated the effect of financial aid variables on an individual's investment in higher education. These variables have been used to proxy for financially constrained students

[9] The data lacks information on students' prior college experience.

as many of these aids are need based. Majority of students who qualify for the federal aid programs such as Pell Grants and Stafford Loans are students who come from a low social background. These students are more likely to spend more time outside of school. These students are hypothesized to less likely to persist or transfer. Singell (2004) shows different types of aid have different effects on education choices. Grants improve retention whereas work study programs negatively affect retention. Furthermore, since aid is not transferable from two to four-year college, I hypothesize that aid in a form of non-loan (aid that does not need to be paid back) should incentivize students to continue studying at two-year colleges and hence likely to transfer. On the other hand, aid helps in reducing current overall costs to education and therefore is predicted to increase investment in schooling. Aid in the form of loans also assists in financing education costs but increases future costs when interest payments are taken into consideration.. Therefore, students who acquire loans will continue to invest in higher education as long as the net present value of acquiring loans is greater than zero, holding other things constant. Students in this sample received aid in many formats. Therefore, I group the different types of aid into four major groups: grants, scholarship, loan and other to determine the effects of each type of aid independently. DesJardin et al. (1999) show scholarships and loans reduce the likelihood of stopping out but grants have no effect on student departure. One needs to be aware of the self-selection issue with financial aid where a student receiving aid may make different schooling decisions compared to students who do not receive aid. Since I have knowledge of the type of aid and amount of aid a student received, I am able to reduce some of the self-selection bias that this may cause. A better control for this self-selection would be controlling for whether a student applied for aid. However, KCTCS did not provide this information.

External factors that are not in the control of education institutions are also included in the model. Many students choose to attend two-year colleges or skip college altogether due to financial constraints. Students who are employed have to balance time between school and work. Students who work full time have difficulties attending school full time. Students have to make a decision on whether they value current earnings more than future earnings. Furthermore, schooling decisions are largely influenced by unexpected positive shocks (salary raise, promotion, etc.) or negative shocks (job loss, failing a class, etc.) while attending a post-secondary institution. Earnings is an important variable as it provides information on both a positive shock (increase in earnings) and a negative shock (decrease in earnings) on the decision of a student to extend enrollment at a two-year college for an additional semester or transfer to a four-year college. Therefore, option value theory hypothesizes that high opportunity costs (higher current earnings) while in school will promote stopouts and delay transfer. Thus, if students value their current earnings higher than future earnings, option value predicts that students will discount their future at a higher rate and hence are more likely to stopout and less likely to transfer. An alternative hypothesis is that earnings may have a positive impact on time to transfer especially when students value their future earnings more than their current earnings, holding other factors constant. The additional earnings further allow students to meet the expenses of four-year colleges. Thus, including a variable that controls for student earnings while in school is important. To control for the macroeconomic factors, I include the county unemployment rate. Betts and McFarland (1995) show enrollment to be counter-cyclical; that is, more people enroll during economic downturn because poor labor-market prospects lower the opportunity cost of enrollment. Therefore, during a downturn, students may choose to continue enrolling in a two-year college and take longer to transfer. Finally, dummy variables for each semester of entry are included.

This study lacks a good indicator to account for differences in ability which can have significant effects on the role of earnings in one's progress in colleges. That is, unobserved low-ability students realize that the returns to a university education are lower for them and therefore allocate more time to current income generation (working while in school) relative to future income generation (making faster progress through school). This causes low-ability students to both earn more and progress more slowly, but the earnings are not causing the slow progress. However, high-ability students are likely to be able to earn more if they do work compared to low ability students. So the effect is still unclear.[10]

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. Other variables that are unavailable for this proposal include attributes while in high school (such as GPA, etc.). Past studies show these variables to be important in the transfer and student-departure literature. Overall, the variables of interest are known

[10] Due to this issue, other identification strategies were considered by trying to exploit differences in earnings that occur for non-ability based reasons. For example, two identical individuals in different counties might both want to work X hours and earn Y dollars. But in the first county, the unemployment rate is higher and so the student from the first county earns less than the other for reasons other than those relating to his ability. This suggests using the unemployment rate as an instrumental variable (IV) for earnings (other county and period level measures of young adult employment prospects could also be used). Now the projection of earnings on these IVs will be free of ability bias. Any correlation between this projection and the rate of progress could now be interpreted as causal. However, the concern is that this IV may be too weak and there are no plausible IVs that can be used for this study.

to be important factors on the accumulation of human capital via education and hence it makes sense to use the same variables to estimate both transfer and retention behavior.

4.2 Descriptive Statistics

Student-level descriptive statistics are reported in Table 4.2. The final sample used for this analysis is 69,233 unique individuals out of which there are 31,663 men and 37,569 women. The average age of the sample is 31 years. The sample consists of 78% whites and the rest are non-whites (9%) or have missing race (13%). Students, on average, enrolled in 3 classes in the first semester, earned around 5.30 credits in the first semester and had a GPA of 2.14. The average earnings of the sample are $4,248 per semester and the county unemployment rate is 6.24%. The majority of the sample plan on acquiring some kind of degree, and 35.28% do not plan on acquiring a degree at KCTCS. Students planning on acquiring a Health degree account for 17.47% of the sample, 10.17% plan on acquiring a Vocational degree, 9.09% choose to acquire a degree in Humanities, and 13.25% of the sample is undecided. The remaining 14.74% represent students intending to acquire a Business, Services, Social Works, or Sciences degree.

A third of the sample received some type of aid over the sample period. Summary statistics on financial aid are provided only for those who received some kind of aid. Of those who received aid, 30% of them acquired grants, 94% received scholarships, and 22% received some sort of loan. Many students received aid in multiple forms: 38% received both grants and scholarships and 15% received aid in the form of grants, scholarships and loans. On average, students received $202 in grants, $1000 in scholarships and $298 in loans. Women, on average, received more dollars in all types of aid compared to men.

Mean characteristics across gender are also provided in Table 4.2. Women, on average, performed better than men in the two-year institutions. They have a higher GPA, earn more credits and a larger percentage of women graduated from high school. According to the option value theory, higher ability students, on average, accumulate higher human capital. Hence, women are more likely to transfer early. The descriptive statistics also indicate that men earn $2000 more per semester than women implying men are more likely to attend school part-time and hence take longer to transfer.

Table 4.1: 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 years
First semester GPA	First Semester GPA per student
First Semester Credits	Total Number of Credits Earned in the First Semester
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
First Semester Remedial Credits	Number of Remediation Credits earned while attending KCTCS
First Semester Classes	Total Classes attempted in First Semester
Student's Aspiration***	Whether or not to pursue an award, and what field of study in which to pursue an award
Log-Earnings****	Log of Total Earnings
Grant	Total amount of grant dollars received per semester
Scholarship	Total amount of scholarship dollars received per semester
Loan	Total amount of loan dollars received per semester
Other Financial Aid	Total amount of other dollars received per semester
County Unemployment	Unemployment rates per county per quarter
Entry Dummies	Dummy Variables for Semester of Entry (Six)

***** Reference category – White

******Reference category – Acquired High School Diploma

*** Reference category – Undeclared

**** To avoid the issue of taking a log of zero earnings, earnings are transformed by adding $1 to all observations. Separate regressions are run where the unemployed students are identified with a dummy variable. This increases the impact of the earnings variable. The other variables are consistent in both regressions.

Table 4.2: Descriptive Statistics: Whole Sample and by Gender

	Full Sample		Men		Women	
Variable	**Mean**	**S.E**	**Mean**	**S.E**	**Mean**	**S.E**
Age	30.71	10.78	30.85	11.14	30.59	10.46
Female	0.54	0.50				
White	0.78	0.41	0.77	0.42	0.79	0.41
Non White	0.09	0.29	0.07	0.26	0.11	0.31
Missing Race	0.13	0.33	0.15	0.36	0.10	0.31
First Semester Classes	2.78	1.83	2.74	1.93	2.81	1.73
First Semester GPA	2.14	1.62	1.83	1.65	2.40	1.54
First Semester Credits	5.30	5.04	4.88	5.19	5.66	4.88
GED	0.13	0.33	0.11	0.31	0.14	0.35
High School Certificate	0.80	0.40	0.78	0.42	0.81	0.39
Missing High School	0.07	0.26	0.12	0.32	0.04	0.20
Earnings	$4,248.16	$6,063.29	$5,451.10	$6,957.88	$3,305.15	$4,989.00
Grant*	$202.24	$324.57	$158.36	$304.59	$221.23	$331.05
Scholarship*	$999.87	$629.29	$914.60	$638.21	$1036.77	$621.78
Loan*	$298.16	$615.09	$239.59	$553.32	$323.52	$638.32
Other*	$0.76	$31.00	$0.40	$21.74	$0.93	$34.24
County Unemployment Rate	6.24	1.31	6.22	1.31	6.26	1.30
First Semester Remedial Credits	0.49	1.53	0.34	1.28	0.62	1.71
Student Intentions						
Business	6.32%	0.24	3.73%	0.19	8.49%	0.28
Health	17.47%	0.38	5.14%	0.22	27.81%	0.45
Humanities	9.09%	0.29	8.80%	0.28	9.34%	0.29
Sciences	0.61%	0.08	0.44%	0.07	0.75%	0.09
Services	7.13%	0.26	4.07%	0.20	9.70%	0.30
Social Works	0.67%	0.08	0.78%	0.09	0.58%	0.08
Vocational	10.17%	0.30	19.49%	0.40	2.36%	0.15
No degree	35.28%	0.48	45.77%	0.50	26.48%	0.44
Undecided	13.25%	0.34	11.77%	0.32	14.49%	0.35
Number of Students	69,233		31,663		37,570	

*Averages for students who received aid.

5 CHAPTER 5: MAKING THE LEAP: TIMING ANALYSIS OF TRASNFERS FROM TWO-YEAR COLLEGES TO FOUR-YEAR COLLEGES

5.1 Introduction

Individuals, researchers and policymakers have all shown significant interest in two-year colleges. Enrollment at two-year colleges is increasing at a significant rate. High four-year tuition rates, budget and capacity constraints on state governments, increases in the number of community-college campuses, and increases in the number of courses offered are some of the reasons for the rising enrollment at these colleges. Students who aspire to earn a four-year degree can begin at a two-year college to complete the basic required courses for an undergraduate degree at a lower cost with the expectations of transferring to a four-year college. Several studies thus focus on estimating whether or not these students transfer, finding high family or individual socioeconomic status, high GPA, completion of math and science classes, high attendance rates, receipt of financial aid and full-time enrollment to increase the probability of transfer (Lee and Frank, 1990; Surrette, 2001; Velez and Javalgi, 1987*)*. Others focus on whether transfer students are successful at four-year colleges, with studies finding conflicting results (Melguizo, 2009; Alfonso, 2006; Leigh et al., 2003; Long et al., 2009, Rouse, 1995).[11] However, to my knowledge no study has estimated the actual timing of transfers. This chapter focuses on estimating why students transfer early or late utilizing a hazard model.

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[11] Some studies find evidence for diversion effects (Rouse, 1995) i.e. attendance at community college are detrimental to acquiring a four-year degree. Other studies find evidence for democratization effects (Melguizo, 2009, Leigh et al., 2003) , i.e. attendance at community college increases overall educational attainment.

It is important to study students' actual time to transfer due to its association with accumulating additional human capital and the opportunity costs of delaying the investment in additional education. Time to transfer is negatively correlated with the probability of attaining a four-year degree (Nutting, 2004). This negative relationship is a concern as students with a bachelor's degree not only have higher returns than students with less education (Card, 1999) but also have a higher quality of life (Lochner and Moretti, 2004; Cutler and Muney, 2006, Davies, 2001). Nutting (2004) finds transfer time to have a positive relationship to the time of acquiring a four-year degree. Students often attend two-year colleges to benefit from the low tuition and fees; however, by taking more time to transfer, students' costs through actual expenditures on education and opportunity costs rise for two reasons. First, attending school for a longer period means they pay tuition for additional semesters. Second, there are increased opportunity costs in terms of lost earnings due to delayed labor market entry. The latter costs are assumed to be higher than the former. Furthermore, taxpayers also bear the cost through the use of state funds in financing these students over longer periods.

This chapter further contributes by utilizing a large and more recent administrative dataset (2000 – 2008). The earlier studies are largely restricted to students in the 1960s, 1970s, 1980s and 1990s. Much has changed in higher education since the 1990s and it is important to examine the current data for several reasons. The current student population faces a different economic and educational environment. Furthermore, the functions of community colleges have expanded over the past few decades from providing academic training to providing vocational, technical, and remedial training. Moreover, students from all backgrounds and abilities have started attending two-year institutions. Using the 2000-2008 dataset, this analysis contributes to a more recent study on two-year institutions to learn about the effects of the new roles of these colleges on transfer behavior.

Option value theory precisely models students' decisions to invest in higher education. At the end of every stage, students decide to invest in the next stage of education by weighing their overall benefits and costs of education. New information such as grades, unexpected shocks, etc. is revealed sequentially to students who incorporate this information to makes their investment choices. This theory predicts that individuals with higher ability choose to invest in additional years of education to maximize their present value of lifetime returns. Overall, any factors that help to increase the net benefits from attending higher education will promote investment in the next stage of education, holding other factors constant. This chapter examines the different post-secondary schooling decisions made across gender, race and different age groups.

Overall, estimates confirm results hypothesized by the option value theory. Student earnings while in school are negatively correlated to time to transfer. Students who work while in school attend school in a part-time basis and hence increase the time to transfer. These students value their current earnings much higher than any future earnings and hence are less likely to transfer. At the same time, increases in financial aid through grants decreases the time to transfer. However, aid in the form of scholarships delays students' transfer time. I find that women have a higher likelihood to transfer but find no differences in the probability of transfer across race. Higher ability increases likelihood of transferring, and students acquiring remedial credits increase their time to transfer.

5.2 Literature Review

My evaluation of the literature on student transfer from two to four-year college suggests that there is little research on the time to transfer. However, many studies have estimated the effects of factors on the probability of transfer. To date, most transfer functions are estimated using survey dataset. These include National Longitudinal Survey of the High School Class of 1972 (NLS: 72), High School and Beyond (HS&B), Beginning Postsecondary Students Longitudinal Study (BPS) and National Longitudinal Survey of Youth of 1979 (NLSY). Furthermore, all transfer analyses are conducted by implementing an ordinary linear regression model (Wassmer et al., 2004), logit model (Dougherty and Kienzl, 2006), a univariate probit model (Surrette, 2001) or a multivariate logistic model (Lee and Frank, 1990).

Transfer rates have varied depending on the datasets used. Velez et al. (1987), using NLS:72, find that over 7 years, only 51 percent of the students who enrolled in community colleges transferred to four-year colleges. Lee et al. (1990), using HS&B, found that only a quarter of community-college students transfer to four-year colleges. Surette (2001), using NLSY, finds a third of sample transfer from two-year colleges to four-year colleges before they turn 25.

Most of these transfer studies agree on the factors affecting the probability of transfers. Early research has indicated that a student's integration into the campus, social and academic background, and academic performances are positively associated with transfer (Dougherty, 1987; Meznek, 1987). Using data from NLS: 72, Velez and Javalgi

(1987) find religion, academic success, class attendance, and involvement in campus activities to increase the likelihood of transferring. Students with grade averages of A in community colleges are 20 percent more likely to transfer than students with grade averages of C. Men are 18 percent more likely to transfer than women. Whites have higher odds of transferring than blacks and Hispanics, but once all covariates are controlled for, they find blacks and Hispanics to have higher probabilities of transferring compared to similar able whites by 18 percent and 13 percent, respectively. Socioeconomic status is found to have a modest but positive effect.

The HS&B dataset also indicates the student transfer rate to be just above the 50 percent mark over a period of seven years (Lee and Frank, 1990). Using a multivariate logistic approach, Lee and Frank (1990) find that students who transfer are successful in high school, of a high socioeconomic status, attended a Catholic high school, passed a high number of Math and Science classes, and are less likely to be working while attending college. Further analyses indicate minorities and females to have lower probabilities of transferring.

Surrette (2001) analyzes panel data from 1979 to 1990 of the NLSY. The data indicates that one third of students transfer from two-year colleges to four-year colleges before they turn 25. Using a multivariate probit model, results confirm previous studies. Married women are less likely to transfer than men due to family obligations such as caring for children and other household activities. Total credits increased the probability of transferring for men but have negligible effects on transfer rates for women. Wassmer et al. (2004), using an institutional dataset from all community colleges in California, finds academic preparation and socioeconomic status to strongly promote transfer but other factors have inconclusive results.

More recent research by Dougherty and Kienzl (2006) analyzes multiple variables not previously exploited to examine the likelihood of transfer for a cohort of community college students in the 1990s. Data is collected from the National Educational Longitudinal Study of the 8th Grade (NELS: 88) and Beginning Postsecondary Students Longitudinal Study of 1989-90 (BPS: 90).[12] Using a logistic model, they verify results found in the past for some factors but not all. Socioeconomic status, academic preparation, full-time enrollment and educational aspirations are positively associated with transfer, but academic and social integration variables had little or no effect on the likelihood of transfer. This study is the first to examine the effect of all ages on transfer, and they find age to be negatively correlated with the likelihood of transferring. Other results show that being single has no effect on transferring but having a child and working full time negatively affects the likelihood of transferring. There is little evidence of race and gender differences in the likelihood of transferring using the 1990 dataset unlike past results for data on the 1960s, 1970s and 1980s.

To summarize, using 1960-1990 data, the transfer literature has noted that social and academic background, institutional factors and psychological factors play an important role in the likelihood of transferring. However, community-colleges have evolved over time. Community colleges are not just academically-select institutions but also, technical and vocational institutions that prepare the students for the labor force.

[12] Both datasets are survey datasets. NELS: 88 followed students who were in the 8th grade in 1988 up to year 2000. However, it did not have any data on non-traditional students. Therefore, they utilized BPS: 90 which followed first-time students of all ages from 1989 to 1994.

This study provides a comprehensive update on the transfer behavior of students who attended two-year institutions in the 2000s and sheds light on a previously unstudied component: time to transfer.

5.3 Descriptive Statistics

Table 5.1 presents the means for the transfer and non-transfer groups on all the variables available. Overall, 19.78% of the students transferred to a four-year college. From the whole sample, more women (21.75%) transferred than men (17.26%). Of those who did transfer, 60% constituted women and 79% constituted whites. Students who transferred to four-year colleges represented a younger age group, less likely to be minority and less likely to be men. The average age of transferees is 26 whereas the non-transferees average age is 32. Students who transfer have a higher first semester GPA, earn more credits in the first semester, and are more likely to graduate from high school. The difference in earnings between the two groups is at least $2000 per semester in favor of the non-transferee group. Descriptive statistics also indicate that on average students who transfer receive more dollars in all types of aid compared to students who do not transfer.

5.4 Kaplan Meier Estimates by Gender, Race and Age

Kaplan Meier survival/failure analysis is a method of generating tables and/or plots of survival/hazard functions over time without controlling for any explanatory variables. The term hazard represents the probability (risk) of transferring. Therefore, as the hazard of an event increases over time, it implies the risk/probability of transferring increases over time. Figure 5.1, 5.2 and 5.3 show the estimates of the probability of transferring over time (failure analysis) by gender, race and age-groups. These graphs are usually upward sloping as the estimates are recalculated at the end of every semester for students who have not transferred in the previous semester. Therefore, the Kaplan Meier failure estimates illustrate when (timing) the least/greatest hazard (risk) of transferring occurs. The hazards in all figures flatten out from the 13th semester onwards because as mentioned earlier that KCTCS has transfer data for 13 semesters.

Figure 5.1 shows the empirical failure analysis for transfer by gender. The vertical axis indicates the probability of transferring and the horizontal axis indicates semesters. The curves for gender indicate that women have a higher risk of transferring than men from 1st semester onwards. In other words, women are more likely to transfer than men over the sample period. The probability of transferring increases over time as indicated by the upward-sloping hazard curve. For both groups, there is a big jump in the probability of transferring at the end of the 3rd semester (after a year in school) with the gap between the two groups increasing over time.

Figure 5.2 shows the probability of transfer by race. There are big jumps in the probability of transferring in each of the first three semesters with the highest increase in risk occurring in the 3rd semester. There seems to be very little difference among the three groups in the probability of transferring in the first few semesters. However, over time, there is a growing gap between whites and non-whites (after 3rd semester). Estimates indicate whites are more likely to transfer compared to non-whites with the difference in hazards increasing over time. However, this variation may be explained by other explanatory variables such as differences in families' socioeconomic status and student ability. Traditionally, whites come from higher socioeconomic and educated families. These factors positively increase education levels.

Figure 5.3 shows the empirical failure by different age groups. Six different age groups were 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 failure/hazard probabilities for the first three age groups. Overall, the graph indicates that the 17-20 age groups are at the highest risk to transfer from the 1st semester. The difference in risk increases over time. There is at most a 10% difference in the risks between the 17-20 and 21-25 age groups. Again, there is a large increase in the 3rd semester with the failure rate increasing from 0.08 to 0.16 for the 17-20 age groups. These large jumps indicate younger students are going to transfer earlier than the older students. The 20 - 25 age groups have a higher failure rate than the 26 - 30 age groups with the difference in the hazard rates being constant over time.

Figure 5.3 also shows similar patterns with the younger age groups having a higher hazard than the older age groups. Students aged 51-60 have very high survival rates and have the least probability of transferring. Over time, the level of risk for the oldest age group does not even increase above the 5% level. Overall, for all age groups, the hazard increases over time, and the younger group members are more likely to transfer than the older students.

5.5 Results

An analysis is conducted using logistic and a single-risk hazard model. The results for the models were reported in the form of marginal elasticity effects.[13] Marginal elasticity effects are calculated 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 from the hazard model are interpreted differently compared to a logistic model. A positive (negative) marginal elasticity implies increase (decrease) in time to transfer (or decrease (increase) in the likelihood of transferring in a given semester) whereas a positive (negative) marginal elasticity in the logistic model indicates higher (lower) likelihood of transferring.

For all models, I estimate three different specifications. Specification (1) controls for the earnings, financial aid variables, demographics variables, a macroeconomic factor and semester entry dummy variables. Specification (2) adds KCTCS first semester experiences. Finally, specification (3) further controls for intentions for attending community colleges. The results of both the logistic and hazard models are discussed below.

5.5.1 Logistic Results

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[13] Since transfer is uncertain, estimating and discussing expected duration is not fruitful. For students whose spell ends before the event, it is hard to determine when the student will transfer or if the student will transfer. Hence, the expected duration is long and in fact infinite. Therefore, it makes more sense to compute the elasticities.

The dependent variable in the logistic model is a dummy variable for transfer where it is coded 1 for a student who transfers to a four-year college and coded 0 for all students who do not transfer. This analysis was conducted by collapsing all observations per student in to one observation per student. Collapsing the data does not produce a problem for time-invariant independent variables. However, I need to redefine the computation of time-variant independent variables. For this analysis, I used the mean averages of all the time-variant variables. Another possible approach would be to use the maximum time-variant observation for each subject. These results are available upon request. Table 5.2 provides marginal elasticity effects from logit estimation for all three specifications.

The influence of earnings is significant. All three specifications indicate a strong, negative relationship between student earnings while in school and transferring. A 10% increase in earnings yields a 1.99% - 2.72% decrease in the likelihood of transferring depending on the specification. Due to time constraint, hours worked and hours spent on studying may act as substitutes. Increases in earnings are presumably correlated with increases in the number of hours of work which decreases the number of hours spent in school/studying. Hence, students who spend less time in school are less likely to transfer. Other plausible explanations are opportunity costs and option value. Increases in earnings imply increases in opportunity costs of attending college. Taking in to consideration the increased costs, option value theory states that students reevaluate their net present value of attending college and holding other costs and benefits constant, students are less likely to transfer.

This study benefits from the use of financial aid data in addition to students' earnings while in school. Student aid is broken down into four groups: loans, grants, scholarships and other. Less than 1% of the sample received aid in the form of other category. Therefore, there is no discussion on the other financial aid variable. Grants and scholarships affect transfer as hypothesized. They both negatively affect transfer in all three specifications. Focusing on the specification (3), a 10% increase in aid through grants reduces the transfer rate by 0.13%. Similarly, based on the specification (3), a 10% increase in aid through scholarships reduces the transfer rate by 0.69%. Results indicate that accumulating loans adversely affects transfers. Transfer to a four-year college may increase loan commitments and hence increase overall costs. But at the same time, by transferring early these students can reduce their loan commitments by taking out loans for a shorter period.

There is strong support for women having a higher likelihood of transferring in all three specifications. Being a woman increases the transfer rate by 8.5% - 14.2% depending on the specification. This result differs from past studies that have found women to have a lower likelihood of transferring (Lee and Frank, 1990; Velez and Javalgi ,1987) using 1970 and 1980 datasets and a study that found no differences in transfer probabilities across gender using 1990 data (Dougherty and Kienzl, 2006).

Specification (1) indicates that non-whites are less likely to transfer compared to whites. This holds among studies using the 1970s and 1980s dataset (Lee and Frank, 1990; Velez and Javalgi, 1987). However, after controlling for all covariates, results indicate that non-whites have a higher likelihood of transferring compared to whites. This result breaks from studies mentioned above and from a study on the 1990 dataset

(Dougherty and Kienzl, 2006) that finds no differences in race on transfer. This could be due to the fact that Kentucky has a lower minority population than U.S. (U.S. Census Bureau, 2011).

Age is negatively correlated to transfer when measured in its quadratic form. Evaluating at its mean, a 10% increase in age decreases the transfer by 22.06%. It is assumed that older students have many responsibilities and have less time to enjoy the full benefits of a four year degree and are therefore less likely to transfer. As students grow older, they look to maximize their lifetime earnings by increasing current earnings rather than future earnings. I do find younger students have a much larger propensity to transfer as has been found in other studies (Dougherty and Kienzl, 2006).

A high unemployment rate is negatively associated with transferring. An increase in the county unemployment rate by 10% decreases the likelihood of transferring by 2.77%, holding other variables constant. The results are consistent with studies that show enrollment to be counter-cyclical. Students facing high unemployment rates are less likely to transfer to four-year colleges to avoid the higher tuitions of four-year institutions.

There is a direct association between academic success and transfer. A more able student, as measured by first semester college performance, translates in to higher probability of transferring especially after controlling for intentions. A 10% increase in GPA increases the probability of transfer by 6.01%. In other words, students with A averages are 15.05% more likely to transfer than students with B averages. First semester credits also indicate a positive association to transfer. A 10% increase in the number of credits earned in the first semester increases the probability of transfer by 1.84%. As expected, remedial credits and transfer have a negative correlation. A 10% increase in acquiring a remedial credit in the first semester reduces the transfer rate by 0.58%. Students acquire or enroll for remedial credits to improve their knowledge on certain subjects and are assumed to have lower academic skills.

I estimate separate models for men and women because studies have shown that men and women make different human capital decisions (Surrette, 2001). These results are reported in Table 5.3 and Table 5.4 for men and women respectively. There are some noticeable differences in the magnitudes of the marginal effects in both groups. The impact of earnings for men is at least four times that of women in specification 1 and 2. For both groups, scholarships negatively affect the likelihood of transferring, women having larger effects than men. Grants have no effect on the women's probability of transferring whereas grants negatively affect men's probability of transferring. The loans variable does have a negative sign but is insignificant in specification (3) in both cases. Age is negatively correlated to transferring for both genders. Ability factors and student intentions have slightly larger positive effects on the probability of transfer for women than for men.

The logit results are comparable to past studies on transfer (Lee and Frank, 1990; Velez and Javalgi, 1987, Dougherty and Kienzl, 2006; Surrette, 2001) with some key differences. I find women and non-whites to have a higher likelihood of transferring. Using data from the 1970s, Velez and Javalgi (1987) find men were 18 percent more likely to transfer than women and blacks and Hispanics have higher probabilities of transferring compared to similarly capable whites by 18 percent and 13 percent, respectively. Using data from 1980s, Surrette (2001) find women to have a lower likelihood of transferring compared to men but the magnitude is much smaller compared to earlier studies. Finally, using the 1990 data, Dougherty and Kienzl (2006) find no significant gender or race differences on transfer. Overall, the results for other variables are similar to the results found in previous studies.

5.5.2 Survival Model Results

In this model, the data are not collapsed to one observation per person due to the interest in estimating the timing to the event. In other words, the survival analysis estimates the conditional probability of an occurrence of an event at semester *t* given that the student has not experienced any of the events before semester *t* controlling for covariates collected from KCTCS. Therefore, for each student, I generate a transfer dummy variable that is coded 0 for periods when he/she does not transfer, and it is coded 1 for the semester of transfer and all the semesters following the semester of transfer. In other words, this variable is student specific. Hence, when the code changes from 0 to 1 for a student, the timing of that semester is taken into consideration and the student is assumed to have exited the sample. I estimate a Weibull regression model that incorporates both time-variant and time-invariant variables.

Table 5.4 provides marginal elasticity effects of the single-risk discrete-time hazard model. Results indicate that students' current earnings increases time to transfer. As with the logit model, all three specifications indicate strong, negative relationships between student earnings while in school and the likelihood of transferring. A 10% increase in income increases time to transfer by 0.59%, holding other factors constant.

The magnitude increases when controlling for student intentions and college characteristics where a 10% increase in earnings increases time to transfer by 0.84%. On average, students earned $6,640 per semester. Therefore, an increase in earnings by $100 (1.5%) increases transfer time by 0.126%. Hence, in a given semester, students are less likely to transfer with increases in earnings. Increases in earnings imply that students substitute effort away from school to work by reducing course load, dropping classes or failing classes and thus transfer later than anticipated. Based on option value theory, these students weigh current earnings more than the future earnings.

Financial aid variables have mixed effects on the time to transfer. As mentioned earlier, a discussion on the other aid variables is excluded as less than 1% of the sample received aid in the form of other categories. In all three specifications, grants decreased the time to transfer. A 10% increase in grants leads to a 0.12% decrease in transfer time. Students generally do not have to payback grant money and this helps reduce certain financial difficulties and implies that students can reduce the number of hours worked. The results find grants to have a stronger effect per dollar than earnings and the correlation coefficient between grants and earnings have a negative relationship. This works to offset the effect of earnings as students can reduce the number of hours worked with any increases in grant money received.

Scholarship has an interesting effect on the time to transfer. A 10% increase in scholarship increases time to transfer by 0.16%. These scholarships are typically not transferable. Hence, students with scholarship are more likely to take more classes and delay transfer as long as the scholarship is renewed every year. Students may decide to stay until graduation or take more courses.

Loans reduce the overall time to transfer. Taking out loans may be an indicator of a student's motivation to attend school. Students are further motivated since they can also qualify for both subsidized and non-subsidized loans in four-year colleges. Results indicate that a 10% increase in loans decreases the time to transfer by 0.06%.

I find women take fewer semesters to transfer than men. The gender gap in education has diminished and more women are attending school with a plan to acquire a degree due to fewer household responsibilities compared to men. Men spend relatively more time away from school than women and therefore it is not surprising to see women transfer earlier than men. I find non-whites to take less time to transfer than whites. Age, when evaluated at its mean, is positively associated with time to transfer. A 1% increase in age increases time to transfer by 3.572%. This result is consistent with the hypothesis that younger students are more likely to transfer. Based on option value, older students have fewer years to enjoy the full benefits of a four-year degree and have many responsibilities and hence attend school on a part-time basis.

The county unemployment rate provided an unexpected result. I find that an increase in unemployment rate by 10% decreases time to transfer by 0.7% in specification (1) but has no effect in the other two specifications. I expected students to continue to enroll at two-year colleges to reduce the impact of high costs of unemployment as attending two-year colleges is a much cheaper alternative to a four-year college.

Ability as measured by performance in KCTCS has a negative impact on time to transfer. A 10% increase in GPA decreases time to transfer by 5.74%, and a 10% increase in the number of credits earned in the first semester decreases time to transfer by 1.38%.

However, students who earn remedial credits take longer to transfer. In a given semester, a 10% increase in acquiring a remedial credit in the first semester increases the time to transfer by 0.63%. Students who acquired a GED take more time to transfer than students who have a high school certificate. Policies to promote high school completion rather than a GED could help hasten transfer.

Table 5.6 shows results for men and Table 5.7 shows results for women. For both groups, increases in earnings delay transfer. As expected, students' earnings while in school have stronger positive effects on the time to transfer for men than women. In all three specifications, the magnitude of the marginal effects of earnings is higher for men than women. Women, on average, earned $2200 less than men and thus face lower opportunity costs than men and therefore take less time to transfer than men. For men, an increase in earnings by 10% increases time to transfer by 1.47% whereas for women, an increase in earnings by 10% increases time to transfer by 0.31%, holding other covariates constant. For men, scholarships have no effect on transfer, whereas for women scholarship increases the time to transfer. However, for both groups, grants and loans work to decrease the time to transfer. There are differences in the effect of non-white on timing of transfer for both groups. Results for men indicate non-whites transfer earlier than whites. There are no differences between non-whites and whites on the timing of transfer for women. In both groups increases in age delays transfer. Finally, ability factors have large negative effects on time to transfer for both genders with women having larger marginal effects than men.

5.5.3 Logistic Versus Survival

The two models look at different issues where the logistic model estimates the effect of variables on whether a student transfers or not and the hazard model estimates effect of variables on the time to transfer. The magnitudes from both models are not directly comparable but the direction of coefficients on hazard estimates provides information on the likelihood of transferring which allows for comparison to the logistic model. When a student takes longer to transfer, he/she is less likely to transfer and vice-versa. On this basis, I can compare the results from both models. Comparing the survival model and the logistic models, I find that they agree on the direction of effects for most of the variables. Earnings in all models indicate less likelihood of transferring. The models agreed on the effect of scholarships on transfer but conflicted with each other when analyzing grants and loans. The logit model indicates that grants and loans decrease the likelihood of transferring whereas the hazard model indicates otherwise for both variables. In both models, there is evidence that women and non-whites have a higher likelihood of transferring compared to their relative groups. These models diverge in the effect of county unemployment rate where the hazard model finds no effect on transfer as opposed to the logit model which finds increases in unemployment rate to decrease the probability of transferring. Finally, the models have similar conclusions on age, ability factors and remedial credits.

5.6 Conclusion

Community-colleges are of major interest to policymakers. Their popularity is on the rise and they are quickly becoming a major source of U.S. workforce. Researchers have largely focused on promoting transfers and the success of these students at a four-year college. However, transfer studies have failed to account for the actual time to transfer. Although it is important to promote transfer and draw up policies to improve overall success at post-secondary institutions, it is equally important to promote transfer at an efficient rate. Time to transfer should be a great concern to policymakers because of its negative association with the receipt of a four-year degree and positive association to the costs of education for both individuals and taxpayers (Nutting, 2004). Using a large administrative data from KCTCS, I focus on the actual timing of transfer to gain further understanding on schooling decisions made by this large transfer group.

I use a hazard model to estimate the relation between the observable covariates and the time to transfer. The results agree with the predictions of the schooling model of human capital as described by the option value theory. Students' current earnings delay the time to transfer. Higher earnings arise from increasing the number of hours of work which leads students to attend school in a part-time capacity, thus lengthening the time to transfer. Furthermore, transferring comes with a high opportunity cost. Students may have to quit their job or decrease the number of hours at work because they have to put in more effort in a four-year college. The recent dataset also separates itself from past studies on schooling decisions made by women. I find women transfer earlier and have a higher propensity to transfer. However, I find no differences in the time to transfer across race. As expected, ability is negatively associated with time to transfer. More able individuals transfer quickly and finish schooling faster and hence face lower costs of continued education. Students with high school degrees transfer earlier than students with GEDs, and acquiring remedial credits is associated with longer transfer time.

This chapter benefits by investigating a variable that has not been used in previous studies – student's current earnings while in school. Based on the results, earnings have a large impact on the time to transfer. Financial costs in terms of opportunity costs of attending post-secondary schooling strongly affect transfer. Living expenses which make up a large part of families' budgets. Students struggle to cover their living expenses even when government programs such as financial aid help cover schooling costs. Policymakers need to draw up policies that reduce the need to work while in school. One such policy would be to increase the overall amount of grant dollars available to students who attend two-year colleges. This chapter does indicate that grants counter the effect of earnings. According to the College Board, students attending a four-year college receive on average $11,500 in aid with at least $6,000 accounted for by grants. Furthermore, a report from the Brookings Institution (2009) indicated that a Full Time Equivalent (FTE) four-year student receives 300% more aid than a two-year FTE ($2,600 versus $790). At the same time, student overall expenses (tuition plus expenses) of attending four-year college is only 150% higher than attending a two-year college (National Center for Education Statistics, 2009). Students who attend two-year colleges receive less money compared to their peers who attend four-year colleges. Providing these students with the same amount of total aid money with a condition to attempt four-year schooling may have the potential to cut transfer time and increase transfer to four-year colleges. This increases the likelihood of improving the four-year graduation rates. .

Lastly, a vast amount of resources need to be invested in providing information to students about earnings differences between a two-year degree and a four-year degree, transfer scholarships, financial aid availability and the positive spillover benefits from higher education to increase student knowledge on the benefits of a four-year degree.

Table 5.1: Descriptive Statistics: Transfers Vs. Non-Transfers

	Transfer		Non Transfer	
Variable	**Mean**	**S.E**	**Mean**	**S.E**
Age	26.14	8.09	31.85	11.06
Female	0.60	0.49	0.53	0.50
White	0.79	0.41	0.78	0.42
Non White	0.09	0.28	0.09	0.29
Missing Race	0.12	0.33	0.13	0.34
First Semester Classes	2.64	1.75	2.81	1.84
First Semester GPA	2.82	1.34	1.97	1.64
First Semester Credits	6.07	4.76	5.11	5.09
GED	0.05	0.22	0.15	0.35
High School Certificate	0.92	0.28	0.77	0.42
Missing High School	0.03	0.17	0.09	0.28
Earnings	$3,156.33	$4,727.22	$4,565.06	$6321.28
Grant*	$211.55	$328.93	$155.92	$297.65
Scholarship*	$1009.87	$640.03	$950.09	$570.15
Loan*	$305.71	$622.29	$260.59	$576.47
Other Financial Aid*	$0.80	$32.66	$0.59	$20.81
County Unemployment Rate	6.20	1.24	6.25	1.32
First Semester Remedial Credits	0.32	1.22	0.54	1.60
Student Intentions				
Business	5.03%	0.22	6.64%	0.25
Health	11.67%	0.32	18.91%	0.39
Humanities	12.94%	0.34	8.13%	0.27
Sciences	1.15%	0.11	0.48%	0.07
Services	7.84%	0.27	6.96%	0.25
Social Works	0.60%	0.08	0.69%	0.08
Vocational	5.20%	0.22	11.41%	0.32
No degree	39.30%	0.49	34.28%	0.47
Undecided	16.27%	0.37	12.50%	0.33
Number of Students	13,638		55,594	

*Summary statistics for students who received aid.

Table 5.2: Logit Results - Transfer (Marginal elasticities effects reported)

Dependent Variable: Transfer Dummy – 1 if Transfer, 0 Otherwise

Explanatory Variables	**1**	**2**	**3**	**Explanatory Variables**	**1**	**2**	**3**
Log Earnings	-0.199***	-0.263***	-0.272***	**First Semester Classes**			-0.131***
	(12.09)	(15.15)	(15.29)				(5.61)
Grant	-0.017***	-0.017***	-0.013**	**Remedial Credits**			-0.058***
	(3.74)	(3.55)	(2.64)				(15.43)
Scholarship	-0.059***	-0.077***	-0.069***	**Missing Race**	0.001	0.001	-0.014***
	(9.00)	(11.27)	(9.79)		(0.91)	(0.48)	(2.64)
Loan	-0.01*	-0.010***	-0.006**	**Missing High School**		-0.027***	-0.036***
	(1.94)	(3.34)	(2.09)			(7.46)	(9.70)
Female	0.142***	0.085***	0.094***	**Business**			-0.033***
	(15.09)	(8.51)	(8.55)				(12.04)
Non White	-0.018***	0.01	0.017**	**Health**			-0.136***
	(2.66)	(1.42)	(2.34)				(24.13)
Age	-4.559***	-4.031***	-2.890***	**Humanities**			0.010*
	(22.38)	(18.68)	(12.89)				(1.66)
Age Squared	1.410***	1.233***	0.684***	**Sciences**			0.002***
	(14.10)	(11.59)	(6.16)				(3.01)
County Unemployment Rate	-0.242***	-0.259***	-0.277***	**Services**			-0.016***
	(4.86)	(4.94)	(5.12)				(5.88)
First Semester GPA		0.642***	0.601***	**Social Work**			-0.004***
		(41.63)	(36.51)				-(4.83)
First Semester Credits		-0.033***	0.184***	**Vocational**			-0.103***
		(2.87)	(10.87)				(23.89)

Table 5.2: Continued

GED		-0.099***	-0.084***		**Undecided**			-0.019***
		(21.24)	(17.61)					(4.76)
Number of Observations	69,233	69,233	69,233		**Number of Observations**	69,233	69,233	69,233

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 5.3: Men: Logit Results - Transfer (Marginal elasticities effects reported)

Dependent Variable: Transfer Dummy – 1 if Transfer, 0 Otherwise

Explanatory Variables	**1**	**2**	**3**	**Explanatory Variables**	**1**	**2**	**3**
Log Earnings	-0.385***	-0.452***	-0.462***	**First Semester Classes**			-0.184***
	(13.92)	(15.38)	(15.38)				(5.11)
Grant	-0.017***	-0.017***	-0.014***	**Remedial Credits**			-0.030***
	(3.71)	(3.53)	(2.91)				(6.78)
Scholarship	-0.001	-0.017**	-0.020*	**Missing Race**	- 0.026***	-0.035***	-0.040***
	(0.44)	(2.30)	(1.92)		(2.69)	(3.47)	(3.92)
Loan	-0.001	-0.010	-0.001	**Missing High School**		-0.064***	-0.068***
	(0.68)	(1.59)	(1.37)			(7.40)	(7.73)
Female				**Business**			0.006**
							(2.11)
Non White	0.02	0.050***	0.044***	**Health**			-0.013***
	(1.52)	(4.08)	(3.42)				(3.51)
Age	-5.074***	-4.015***	-3.370***	**Humanities**			0.027***
	(14.56)	(10.81)	(8.80)				(6.13)
Age Squared	1.530***	1.140***	0.850***	**Sciences**			0.003***
	(8.82)	(6.12)	(4.43)				-(3.57)
County Unemployment Rate	-0.541***	-0.473***	-0.486***	**Services**			0.001
	(6.60)	(5.46)	(5.43)				(0.17)
First Semester GPA		0.604***	0.572***	**Social Work**			0.001
		(28.76)	(25.64)				(1.14)
First Semester Credits		-0.049***	0.156***	**Vocational**			-0.179***
		(2.92)	(6.39)				(17.30)

Table 5.3: Continued

GED		-0.108***	-0.097***	**Undecided**			0.014**
		(14.90)	(13.20)				(2.45)
Number of Observations	31,633	31,633	31,633	**Number of Observations**	31,633	31,633	31,633

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 5.4: Women: Logit Results - Transfer (Marginal elasticities effects reported)

Dependent Variable: Transfer Dummy – 1 if Transfer, 0 Otherwise

Explanatory Variables	1	2	3	Explanatory Variables	1	2	3
Log Earnings	-0.060***	-0.127***	-0.131***	**First Semester Classes**			-0.088***
	(2.95)	(6.00)	(5.98)				(2.77)
Grant	-0.010	-0.010	-0.010	**Remedial Credits**			-0.084***
	(1.51)	(1.44)	(0.63)				(14.27)
Scholarship	-0.111***	-0.128***	-0.114***	**Missing Race**	0.017***	0.011**	0.001
	(10.77)	(11.80)	(10.24)		(3.40)	(2.12)	(0.22)
Loan	-0.010	-0.012***	-0.010	**Missing High School**		-0.010*	-0.011***
	(1.56)	(2.68)	-(1.40)			(1.80)	(3.94)
Female				**Business**			-0.078***
							(16.86)
Non White	-0.037***	-0.010	0.001	**Health**			-0.273***
	(4.61)	(1.39)	(0.13)				(26.73)
Age	-4.171***	-3.956***	-2.355***	**Humanities**			-0.017***
	(16.59)	(14.96)	(8.44)				(4.38)
Age Squared	1.304***	1.245***	0.472***	**Sciences**			0.001
	(10.68)	(9.67)	(3.45)				(0.33)
County Unemployment Rate	-0.050	-0.130*	-0.158**	**Services**			-0.038***
	(0.77)	(1.89)	(2.30)				(9.04)
First Semester GPA		0.661***	0.602***	**Social Work**			-0.006***
		(29.70)	(25.03)				(5.56)
First Semester Credits		-0.030*	0.215***	**Vocational**			-0.020***
		(1.62)	(9.04)				(9.30)

Table 5.4: Continued

GED		-0.095***	-0.075***	**Undecided**			-0.053***
		(15.32)	(11.71)				(9.62)
Number of Observations	37,570	37,570	37,570	**Number of Observations**	37,570	37,570	37,570

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 5.5: Time to Transfer (Hazard marginal elasticities effects reported)

Failure Variable: Transfer

Explanatory Variables	1	2	3
Log Earnings	0.059***	0.083***	0.084***
	(4.82)	(6.83)	(6.99)
Grant	-0.011***	-0.011***	-0.012***
	(6.20)	(6.08)	(6.58)
Scholarship	0.023***	0.025***	0.016***
	(7.47)	(7.98)	(5.22)
Loan	-0.006***	-0.005***	-0.006***
	(4.64)	(3.53)	(4.59)
Female	-0.117***	-0.053***	-0.069***
	(12.01)	(5.45)	(6.81)
Non White	0.001	-0.009***	-0.012***
	(0.95)	(3.17)	(4.27)
Age	7.615***	6.877***	5.374***
	(36.73)	(33.32)	(25.61)
Age Squared	-2.801***	-2.541***	-1.802***
	(26.41)	(23.82)	(16.43)
County Unemployment Rate	-0.070*	-0.06	-0.06
	(1.63)	(1.49)	(1.36)
First Semester GPA		-0.640***	-0.574***
		(40.74)	(35.89)
First Semester Credits		0.093***	-0.138***
		(8.28)	(8.63)

Explanatory Variables	1	2	3
First Semester Classes			0.160***
			(6.77)
Remedial Credits			0.063***
			(15.60)
Missing Race	0.001	-0.007**	0.001
	(0.24)	(2.05)	(0.03)
Missing High School		0.024***	0.034***
		(5.64)	(8.10)
Business			0.035***
			(12.33)
Health			0.158***
			(25.93)
Humanities			0.001
			(0.10)
Sciences			-0.001**
			(2.07)
Services			0.020***
			(7.90)
Social Work			0.004***
			(4.62)
Vocational			0.114***
			(23.25)

Table 5.5: Continued

GED		0.114***	0.094***	**Undecided**			0.028***
		(20.18)	(16.75)				(7.88)
Number of Observations	69,233	69,233	69,233	**Number of Observations**	69,233	69,233	69,233

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 5.6: Men: Time to Transfer (Hazard marginal elasticities effects reported)

Failure Variable: Transfer

Explanatory Variables	1	2	3	Explanatory Variables	1	2	3
Log Earnings	0.125***	0.141***	0.147***	**First Semester Classes**			0.207***
	(6.42)	(7.27)	(7.61)				(5.99)
Grant	-0.005***	-0.004***	-0.005***	**Remedial Credits**			0.030***
	(2.88)	(2.73)	(3.20)				(7.22)
Scholarship	0.001	0.001	0.001	**Missing Race**	0.010*	0.000	0.010
	(0.41)	(1.47)	(0.59)		(1.93)	(0.05)	(1.59)
Loan	-0.005***	-0.003**	-0.004***	**Missing High School**		0.061***	0.068***
	(3.55)	(2.72)	(3.31)			(6.28)	(6.95)
Female				**Business**			-0.004
							(1.61)
Non White	-0.009***	-0.019***	-0.017***	**Health**			0.018***
	(2.71)	(5.49)	(5.05)				(4.96)
Age	8.218***	7.091***	6.173***	**Humanities**			-0.017***
	(24.59)	(21.20)	(18.21)				(4.70)
Age Squared	-2.992***	-2.592***	-2.156***	**Sciences**			-0.001***
	(17.32)	(14.78)	(12.05)				(2.72)
County Unemployment Rate	0.060	0.001	-0.010	**Services**			0.001
	(0.88)	(0.03)	(0.14)				(1.37)
First Semester GPA		-0.538***	-0.495***	**Social Work**			0.001
		(27.21)	(24.30)				(1.35)
First Semester Credits		0.076***	-0.132***	**Vocational**			0.190***
		(4.98)	(6.01)				(17.42)

Table 5.6: Continued

GED		0.113***	0.099***	**Undecided**			0.001
		(13.79)	(12.21)				(0.38)
Number of Observations	31,633	31,633	31,633	**Number of Observations**	31,633	31,633	31,633

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 5.7: Women: Time to Transfer (Hazard marginal elasticities effects reported)

Failure Variable: Transfer

Explanatory Variables	1	2	3	Explanatory Variables	1	2	3
Log Earnings	0.000	0.034**	0.031**	**First Semester Classes**			0.118***
	(0.16)	(2.21)	(2.06)				(3.64)
Grant	-0.018***	-0.018***	-0.019***	**Remedial Credits**			0.096***
	(5.86)	(5.82)	(6.14)				(14.13)
Scholarship	0.046***	0.046***	0.030***	**Missing Race**	-0.010	-0.011***	-0.010
	(8.67)	(8.44)	-(5.64)		(1.51)	(2.84)	(1.63)
Loan	-0.008***	-0.006***	-0.008***	**Missing High School**		0.001	0.007**
	(3.50)	(2.72)	-(3.55)			(0.26)	(2.46)
Female				**Business**			0.088***
							(16.28)
Non White	0.015***	0.001	-0.010	**Health**			0.322***
	(3.35)	(0.28)	(1.06)				(27.30)
Age	7.228***	6.738***	4.641***	**Humanities**			0.019***
	-(27.24)	(25.62)	(17.28)				(5.31)
Age Squared	-2.680***	-2.503***	-1.479***	**Sciences**			0.001
	(19.91)	(18.62)	(10.61)				(0.23)
County Unemployment Rate	-0.157***	-0.100*	-0.070	**Services**			0.043***
	(2.76)	(1.78)	(1.26)				(10.25)
First Semester GPA		-0.711***	-0.611***	**Social Work**			0.006***
		(29.76)	(25.31)				(5.09)
First Semester Credits		0.112***	-0.155***	**Vocational**			0.022***
		(6.82)	(6.76)				(8.83)

Table 5.7: Continued

GED		0.120***	0.091***	**Undecided**			0.061***
		(14.98)	(11.52)				(11.58)
Number of Observations	37,570	37,570	37,570	**Number of Observations**	37,570	37,570	37,570

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Figure 5.1: Kaplan Meier Sample Failure Estimates of Transfer by Gender

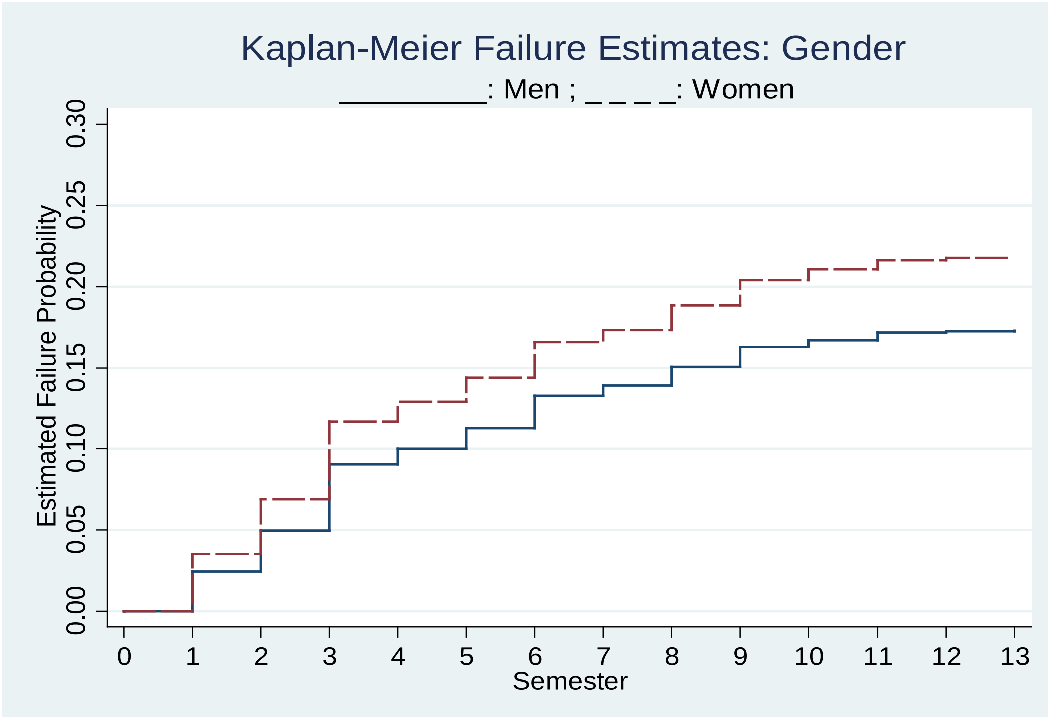


Figure 5.2: Kaplan Meier Sample Failure Estimates of Transfer by Race

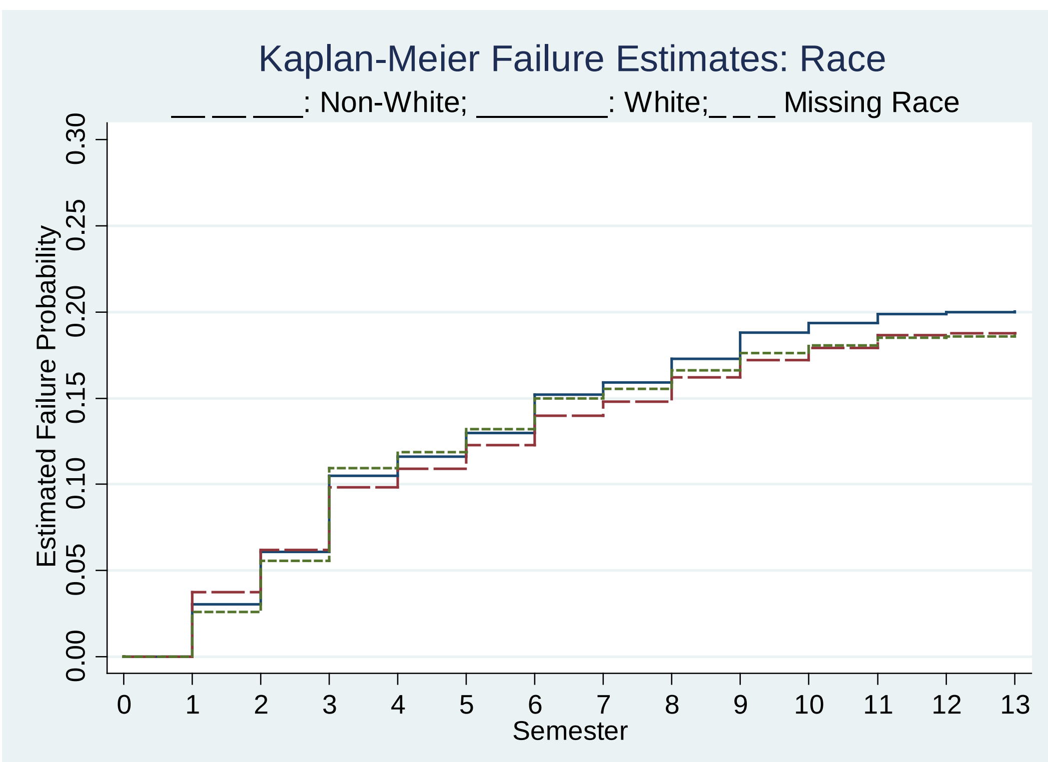
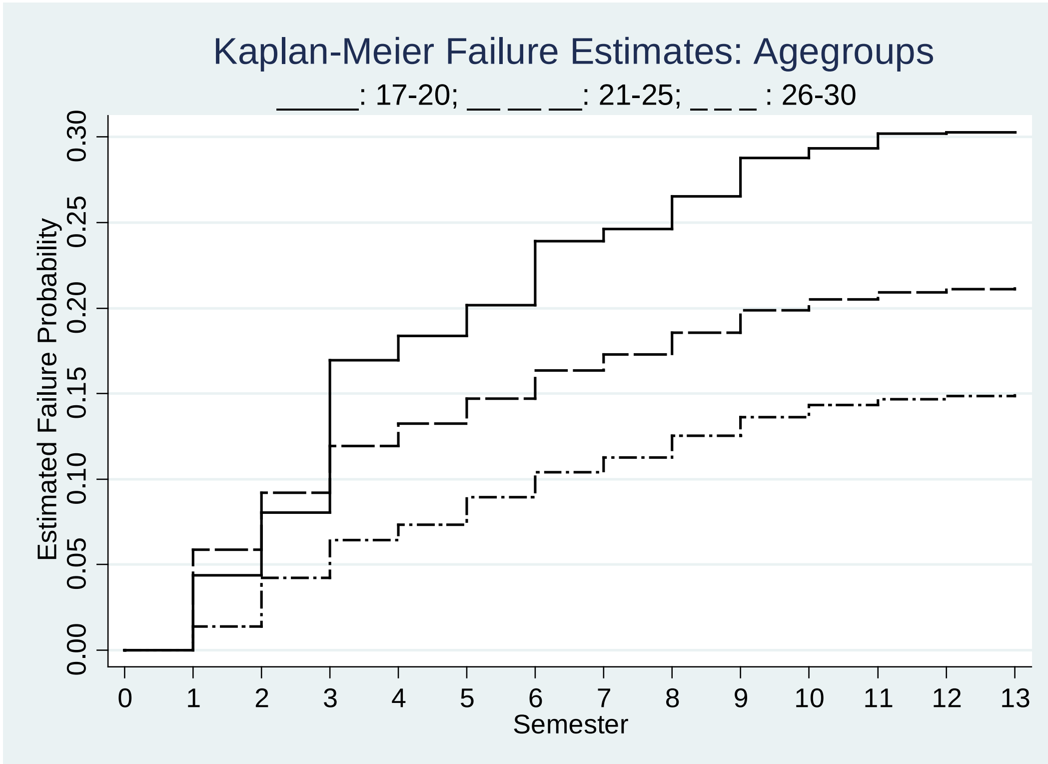
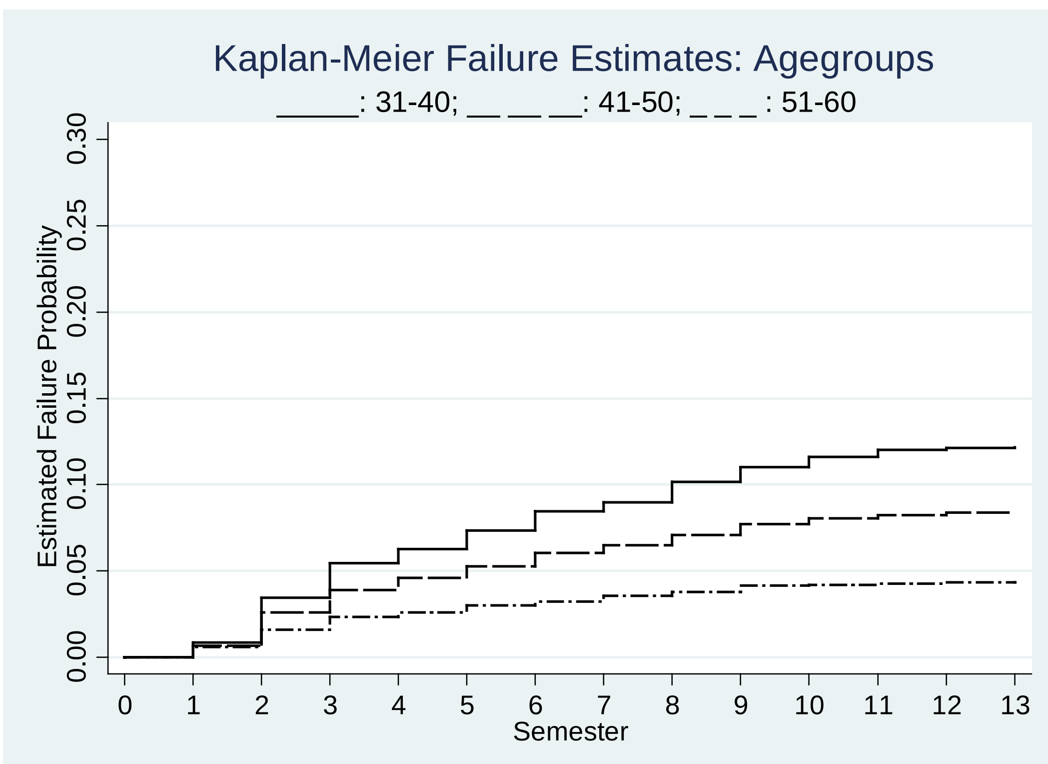


Figure 5.3: Kaplan Meier Sample Failure Estimates of Transfer by Age





6 CHAPTER 6: AN EXPLORATORY ANALYSIS OF THE REALTIOSNSHIP BETWEEN STUDENT EARNINGS AND POSTSECONDARY RETENTION

6.1 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. There is an absolute need to understand better the obstacles to college completion to help students achieve their education in a swift and efficient manner. This chapter 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).

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 post-secondary retention will assist policy makers in designing education policies that help alleviate poverty by encouraging post-secondary completion rather than just postsecondary attendance.

Again, students who attend two-year colleges are the focal point of this study. Popularity of two-year colleges is on the rise with over 6 million students currently attending two-year colleges. As states face budget cuts, state governments are encouraging students to begin their higher education at a two-year college. Moreover, president Obama recently pledged two billion dollars to the development of community colleges to increase the number of graduates (Kanter, 2011). As enrollment at the community colleges increases at a tremendous rate and two-year dropout rates peak at 50% (Goldrick-Rab and Berube, 2009), it is important to study the attendance behavior of students who attend these colleges.

Using administrative data from KCTCS, results indicate that student earnings are negatively correlated with student retention in Kentucky community colleges. The preferred hazard model indicates that a 10% increase in earnings reduces time to stopout with a probability of 0.56%, holding other covariates constant. Aid in the form of grants unexpectedly hastens the time to stopout but this effect is close to zero. Scholarships and loans, on the other hand, promote continuous attendance. Ability as measured by first semester GPA in KCTCS and credits earned in the first semester positively affects retention.

6.2 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 (Bean, 1990), 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 and therefore he introduces the importance of student intentions in determining student persistence. Thus, retention is modeled as a function of academic, social and institutional culture of the universities. Results indicate 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) expands on Tinto's (1993) model by incorporating financial variables. They model retention as a function of 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. This study suffers from endogeneity issues due to the choice of certain academic variables used for estimation.

Desjardin et al. (2002) focus largely on 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. This study improves over other studies by adopting a hazard model that better control for factors that vary over time such as financial aid. After controlling for time-varying effects and unobserved heterogeneity, they find that grants and scholarships 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. A bivariate model is used to estimate the effect of observed covariates on retention conditioned on the effects of unobserved covariates that affect enrollment. This model produces less biased results by controlling for the correlation between enrollment and retention. Estimates indicate that family income and median household income have no effect on retention. Subsidized aid positively affects persistence but unsubsidized aid has the opposite effect. Furthermore, retention behavior largely differs between needy and non-needy students, with needy students having higher probability of enrolling even after controlling for ability.

Kerkvliet et al. (2005) study student persistence using data from two different universities: Weber State University (WSU) and Oregon State University (OSU). They improve on past literature by controlling for students' intentions to remain enrolled or not in the following year and wage-based opportunity costs. Retention is modeled as a function of background characteristics, academic and social integrations, opportunity cost of attending school and financial aid. Opportunity cost wage is measured as a self-reported wage rate when not attending school. The percentage of tuition paid by student and family is included to control for direct costs and a dummy variable for each type of aid is included to control for financial aid. Using a negative binomial model for WSU dataset, they find wage to be inversely related to retention. Veteran's aid and guaranteed student loans show weak support for retention, and academic variables have no significant effect. 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 at lower wages but lower retention at 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 work for school 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 and their wealthier counterparts. Their main variable of focus is students' 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 in professional occupations 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.

Dadgar and Weiss (2011) have a very rich administrative data of students who attend Washington State of Board of Community and Technical Colleges who are also matched with the unemployment insurance records. Their data can be used as a robustness check on this study mainly because their data has information on the number of hours worked by each student and a good proxy for SES.

Many studies have focused on the issue of finance on the probability of retention. Some studies have found conflicting results of student's self-reported wages on retention

(Kerkvliet et al., 2005) whereas some studies find finance to play no role in persistence (Powdthavee et al., 2009). However, none of the studies have explored a more robust measure of student finance - 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) using a more appropriate model – hazard model. Furthermore, this study benefits from a large administrative dataset.

6.3 Descriptive Statistics

Table 6.1 provides details on students who stopout versus non-stopout. Students are considered to have stopped out if 1) students miss two consecutive semesters and do not return back to school, or 2) students who miss two consecutive semesters and return to school but do not earn a degree or transfer. The rest are assumed to have continuous enrollment. Based on the definition of stopout, 65% of the sample stopped out. Out of the 35% who were considered to be continuously enrolled, 56% constitute students who transfer to four-year colleges, 43% represent graduates and 1% represent students who did not transfer or graduate. Students who stopout are on average older than students who do not stopout. Women are more likely to persist. Of those who stopout, 50% were women and 76% were white. Of those who did not stopout, women represented 62% and whites represented 82%. As expected, students in the non-stopout group do better academically than their peers in the stopout group. These students take more classes in the first semester, have a higher first semester GPA, earn more credits in the first semester, and are more likely to have a high school certificate. Students in the stopout group earned considerably more than the non-stopout group and received less money in terms of aid. Only 29% of students who stopped out received some kind of aid compared to 41% of the non stopout group.

6.4 Kaplan Meier Estimates by Gender, Race and Age.

In this section, I present Kaplan Meier survival estimates unlike the failure estimates discussed in section 5.4 as I am more interested in probability of persistence over time. Survival graphs are downward sloping as the probability of surviving (persistence) decreases over time. Note, a student is said to have stopped out when he/she misses two consecutive semesters. This definition implies that if the student attends the 1^{st} semester but misses the next two, he/she is said to have stopped out after the 1^{st} semester.

Figure 6.1 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 a student has 100% probability of persisting. The downward sloping curves (survival estimates) hence indicate that students' likelihood of stopping out increases over time, i.e. students are less likely to survive in school over time. The curves for gender indicate that for both men and women, there is a high likelihood of stopping out after completing the 1^{st} 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 completion of the third semester after which the probability of continuous enrollment is higher for women than men for the rest of the sample time period.

Figure 6.2 shows the empirical survival for stopout by race. The curves for race also indicate that there is a high probability of stopping out especially right after completing the 1st semester, and the probability of stopping out increases over time as indicated by the downward-sloping survival estimates. The curves indicate that whites have a higher probability of continuous enrollment compared to the non-whites. The closeness of the curves indicates that the race differences in semesters of enrollment are minimal.

Figure 6.3 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 6.3 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 youngest age group has a survival probability of 70% after the 1st semester compared to 60% for the other age groups. Over time, the estimates are converging around the 0.40 mark for the youngest age group indicating these students are 60% more likely to stopout and for the other age groups the estimates are converging around the 0.30 mark indicating these students are 70% likely to stopout. The bottom panel of Figure 6.3 shows similar patterns with students aged 51-60 having a high likelihood of stopping out rates from the end of third semester 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.

In summary, the gender descriptive hazards indicate that female students have lower conditional probability of stopping out in all time periods. The probabilities are very similar for the different races. However, in both cases the largest stopout occur at the end of the 1st semester, indicating institutions need to pay more attention to students during initial enrolment to ensure continuous persistence. 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. In all cases, the graphs never fall to zero. This is due to the way stopout is defined. Students who graduate and transfer are considered not to stopout.

6.5 Results

For both models, I estimated three different specifications. Specification (1) controls for the earnings, financial aid variables, demographics variables, county unemployment rates and semester entry dummy variables. Specification (2) adds KCTCS first-semester experiences. Finally, specification (3) 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 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 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 higher (lower) likelihood of attendance.

6.5.1 Logistic Results

The dependent variable is a dummy variable for continuous enrollment which is coded 1 for a student who is continuously enrolled and 0 otherwise. This analysis was conducted by collapsing all observations per student in to one observation per student. Collapsing the data does not produce a problem for time-invariant independent variables. However, I need to redefine the computation of time-variant independent variables. For this analysis, I used the mean averages of all the time-variant variables. Another possible approach would be to use the maximum time-variant observation for each subject. These results are available upon request.

Table 6.2 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 enrollment Specification (1) indicates a 10% increase in earnings leads to 0.47% decrease in persistence, holding other factors constant. Even after controlling for student intentions and college characteristics, a 10% increase in earnings reduces attendance by 0.82%. 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.

All aid variables are positively correlated with attendance. A 10% increase in grant money increases the likelihood of attendance by 0.21% to 0.25% depending on the specification. Similarly, a 10% increase in scholarship money increases the likelihood of attendance by 0.13% to 0.58% depending on the specification. Aid in the form of loan also positively affects attendance. Aid in any form reduces the financial burden of attending school and hence increases persistence.

I find that women are less likely to stopout. Being a woman increases attendance rates by 10.2%, holding other factors constant. Non-whites have a lower likelihood of transferring than whites. After controlling for all covariates, being non-white decreases the probability of continuous enrollment in the following semester by 2.2%. Age is inversely correlated to attendance. Evaluated at its mean, a 10% increase in age decreases the likelihood of attendance by 11.84%, holding other covariates constant.

Specification (1) indicates that an increase in the county unemployment rate by 10% decreases the probability of continuous enrollment by 1.17%, holding other variables constant. After controlling for all the covariates, the magnitude falls slightly to 1.04%. The results conflict with a study by Betts and McFarland (1995) who show attendance to be counter-cyclical - more people enroll during economic downturns. Increasing unemployment rates due to economic downturn should increase enrollment as poor labor-market prospects lower the opportunity cost of enrollment.

College characteristics are strongly correlated to enrollment. A 10% increase in GPA increases the probability of enrollment by 5.73%, and a 1% increase in the number of credits earned in the first semester increases the probability of enrollment by 0.411%. A remedial credit earned in the first semester has a negative effect on attendance. Registering for remedial credits may be an indicator of low ability students.

I further estimate separate models for men and women. Table 6.3 and Table 6.4 show analysis of men and women respectively. Earnings have a negative effect on stopping out for men but positively affect women's attendance in specification (1) but have a small and insignificant effect for women in specification (2) and (3). In this sample, men do earn significantly more than women per semester and women are more motivated to pursue their educational goals. Financial aid variables have positive effects on attendance for both men and women. For men, I find no race effects whereas for women I find non-whites to more likely to stopout. Unemployment rate has a negative effect on attendance for men but no effect in the attendance rates for women. All other variables affect both groups similarly but with different magnitudes.

Although some estimates from this study agree with previous studies (e.g. ability), estimates of financial aid and work variables conflict with past studies. Wetzel et al. (1993) find financial aid factors to have little or no effects whereas Desjardin et al. (2002) found that grants and scholarship positively affected retention with scholarships having the largest impact on retention. Powdthavee et al. (2009) finds no evidence that financial aid works to promote persistence and they recommend that polices should be directed in improving high school and remedial education rather than focusing on finance. Kerkvliet et al. (2005) focus on the effect of self-reported wages on retention at two different universities. They found contradictory results at both universities where at WSU, students substitute work for school when faced with higher wages, and in OSU higher wages encourage retention. This study finds earnings to generate breaks in schooling. However, aid in any form improves persistence among the students.

6.5.2 Survival Model

In this model, the data are not collapsed to one observation per person due to the interest in estimating the timing to the event. In other words, the survival estimates the conditional probability of an occurrence of an event at semester *t* given that the student has not experienced any of the events before semester *t* controlling for covariates collected from a post-secondary institution. Therefore, for each student, I generate a dummy variable that is coded 1 for periods when the student is enrolled and is coded 0 from a student's first stop out onwards. In other words, this variable is student specific. Hence, when the code changes from 1 to 0 (enrolled to stopout) for a student, the timing of that semester is taken into consideration and the student is assumed to have exited the school. Students who transfer and graduate are treated as coded as 1 as well. I estimate a Weibull regression model that incorporates both time-variant and time-invariant variables.

Table 6.5 shows the marginal elasticity effects of independent variables on retention. As noted before, this model is more appropriate for the education data and is the preferred model for this analysis. As with the logit, all three specifications indicate strong, negative relationships between student earnings while in school and attendance as predicted by the option value theory. Substituting work for school increases overall costs of education and thus students are more likely to stopout at the end of this stage of education, holding net benefits constant. Specification (1) indicates a 10% increase in earnings decreases time to stopout by 0.79%, holding other factors constant. Even after controlling for student intentions and college characteristics, a 10% increase in earnings decreases time to stopout by 0.55%. Hence, in a given semester, students are more likely to stopout with increases in earnings.

Aid in the form of grants provides an unexpected result. All three specifications indicate that increase in grant aid reduces the time to stopout. The effect is reduced when ability and intentions are controlled for. This is a somewhat surprising result as students who receive aid in any form are assumed to have continuous attendance due to the lower financial burden. However, three-quarters of students who received grants received it in the form of Federal Pell Grants. Recipients of these grants are typically students who come from a low socio-economic status. The magnitude of the effect is so minimal that the above reasons could be cancelling the overall effect of grants. Students who receive aid in the form of scholarship and loans are more likely to have continuous attendance. A 10% increase in scholarship increases the time to stopout by 0.85% and a 10% increase in loans increases time to stopout by 0.28%.

The effects of gender, race and age are similar to that of the logit model. Specification (1) indicates that being a woman increases time to stopout by 11.3%, holding other factors constant. Specification (2) and specification (3) provide similar intuition but with smaller probabilities. I do find non-whites to have a higher likelihood of stopping out than whites. Attendance and age are negatively correlated. The results indicate that the older students have a higher probability of stopping out. A 1% increase in age decreases time to stopout by 0.021%.

The two models agree on the sign for the unemployment variable. In the hazard model, all three specifications indicate unemployment to be associated with an increase in the time to stopout. After controlling for all the variables, an increase in the county unemployment rate by 10% increases the time to stopout by 2.98%, holding other variables constant. The logit model indicates that increases in unemployment rate increase the likelihood of stopping out. Results from the hazard model 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 10% increase in GPA increases continuous enrollment by 4.46%, and a 10% increase in the number of credits earned in the first semester increases the time to stopout by 4.19%. However, students taking remedial credits are less likely to remain enrolled. In a given semester, a 10% increase in acquiring a remedial credit in the first semester increases the likelihood of stopping out by 0.32%. Students who acquire a GED are more likely to stopout compared to students with a high school certificate.

Table 6.6 and Table 6.7 show analysis for men and women respectively. Earnings have a negative impact on attendance for both men and women. All three specifications indicate earnings have a larger impact for men than women. For men, an increase in earnings by 10% decreases time to stopout by 0.61%, holding other covariates constant. However, for women, an increase in earnings by 10% decreases time to stopout by 0.51%, holding other covariates constant. For both groups, scholarships and loans promote attendance. For women, grants decrease the time to stopout but have no effect for men's time to stopout. The two groups also differ in regarding race effects. I find no race effects for men but find non-white women to have a lower likelihood of stopping out. Both groups also differ in their age effects. Older men are less likely to have continuous enrollment but age has no effect on women's attendance. Ability factors have large positive effects on retention for both genders with women having larger effects than for men.

6.5.3 Logistic versus Survival

The two models look at different issues where the logistic model estimates the effect of variables on whether a student transfers or not and the hazard model estimates effect of variables on the time to transfer. The magnitudes from both models are not directly comparable but the direction of coefficients on hazard estimates provides information on the likelihood of transferring which allows for comparison to the logistic model. When a student takes longer to stopout, it implies that he/she is less likely to stopout and vice-versa. On this basis, I can compare the results from both models. Comparing the survival model and the logistic models, I find, in some part, these models conflict with each other. The earnings variable in both models is positively correlated with stopping out. The models slightly differ in their results for the financial aid variables. Estimates from the logit model find financial aid in all forms to promote persistence. In the hazard model, grants are positively correlated with stopping out whereas scholarship and loans promote persistence. These models agree on the gender and race effect where women and whites are more likely to persist. However, the models disagree in the effect of unemployment. The logit model finds unemployment to negatively affect retention whereas the hazard model finds unemployment to promote continuous enrollment. All other variables have consistent effects across models.

6.6 Conclusion

Using administrative data from postsecondary institutions matched with administrative earnings data from the state's unemployment insurance department, I find student earnings to be negatively correlated to student retention in Kentucky community colleges. Increases in earnings can come through increase in number of hours at work, increase in salary, or through any work unrelated circumstances. This dissertation is unable to infer the causes of changes in earnings but it does show that earnings severely hurt students' accumulation of human capital even after controlling for student intentions. Aid in the form of grants provides an unexpected result. Grants hasten the time to stopout whereas scholarships and loans promote continuous attendance.

Overall, this chapter contributes to the retention literature 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 gaining popularity in the education literature and that is suited for the education data. Earlier studies have tried to proxy working with self-reported wages. However, self-reported wages have large measurement errors and have provided conflicting results. By matching students to the unemployment insurance program, this study benefits by studying a more robust measure of students' time spent at work.

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. Financial aid variables have mixed effects on stopping out. While scholarships and loans promote persistence, it is unclear why grants have essentially zero effect. Financial aid helps alleviate some costs of schooling. However, this represents a small portion of a family's overall budget. For many students overall living expenses constitute a large portion of their budgets, and therefore students are more likely to make attendance decisions based on overall earnings rather than financial aid. Providing subsidized aid to alleviate some of the living expenses may incentivize students to substitute school for work which may promote persistence. In general, students are valuing current earnings much higher than future earnings. Overall, 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.

Table 6.1: Descriptive Statistics: Stopouts Vs. Non-Stopouts

	Stopouts		Non-Stopouts	
Variable	**Mean**	**S.E**	**Mean**	**S.E**
Age	32.12	11.14	28.14	9.17
Female	0.50	0.50	0.62	0.48
White	0.76	0.43	0.82	0.39
Non White	0.24	0.43	0.18	0.39
Missing Race	0.14	0.35	0.10	0.30
First Semester Classes	2.61	1.77	3.10	1.88
First Semester GPA	1.69	1.63	2.97	1.21
First Semester Credits	4.11	4.51	7.55	5.23
GED	0.15	0.36	0.08	0.28
High School Certificate	0.75	0.43	0.89	0.31
Missing High School	0.10	0.30	0.03	0.16
Earnings	$6,294.34	$5,901.28	$4,939.83	$4,013.81
Grant*	$55.85	$94.93	$90.69	$126.04
Scholarship*	$296.35	$270.89	$420.70	$337.68
Loan*	$0.20	$6.12	$0.38	$9.38
Other Financial Aid*	$77.67	$180.51	$140.35	$245.45
County Unemployment Rate	6.24	1.12	6.25	1.09
First Semester Remedial Credits	0.52	1.58	0.51	1.54

Student Intentions				
Business	6.00%	0.24	6.93%	0.25
Health	15.61%	0.36	20.98%	0.41
Humanities	8.53%	0.28	10.12%	0.30
Sciences	0.50%	0.07	0.81%	0.09
Services	6.65%	0.25	8.04%	0.27
Social Works	0.57%	0.08	0.87%	0.09
Vocational	9.44%	0.29	11.63%	0.32
No degree	39.97%	0.49	26.36%	0.44
Undecided	12.73%	0.33	14.25%	0.35
Number of Students	45010		24223	

*Summary statistics for students who received aid.

Table 6.2: Logit Results - Retention (Marginal elasticities effects reported, t-statistics in parenthesis)

Dependent Variable: Retention – 1 if enrolled, 0 otherwise

Explanatory Variables	**1**	**2**	**3**	**Explanatory Variables**	**1**	**2**	**3**
Log Earnings	-0.047***	-0.070***	-0.082***	**First Semester Classes**			-0.163***
	(4.42)	(5.68)	(6.61)				(9.26)
Grant	0.021***	0.023***	0.025***	**Remedial Credits**			-0.052***
	(8.04)	(7.79)	(8.48)				(22.57)
Scholarship	0.058***	0.013***	0.021***	**Missing Race**	0.008**	0.010	0.001
	(14.52)	(2.92)	(4.64)		(2.42)	(1.28)	(0.46)
Loan	0.026***	0.025***	0.025***	**Missing High School**		-0.026***	-0.028***
	(14.59)	(13.17)	(12.92)			(10.63)	(11.28)
Female	0.135***	0.089***	0.102***	**Business**			-0.006***
	(21.83)	(12.58)	(12.88)				(3.39)
Non White	-0.054***	-0.027***	-0.022***	**Health**			0.001
	(11.99)	(5.34)	(4.29)				(0.58)
Age	-1.896***	-1.725***	-1.724***	**Humanities**			0.001
	(16.27)	(12.69)	(12.44)				(0.95)
Age Squared	0.552***	0.559***	0.540***	**Sciences**			0.001
	(9.98)	(8.62)	(8.18)				(0.90)
County Unemployment Rate	-0.117***	-0.160***	-0.104***	**Services**			-0.005**
	(3.68)	(4.34)	(2.78)				(2.31)
First Semester GPA		0.628***	0.573***	**Social Work**			0.001
		(54.40)	(47.93)				(1.22)
First Semester Credits		0.270***	0.411***	**Vocational**			0.001
		(33.29)	(33.08)				(0.62)

Table 6.2: Continued

GED		-0.062***	-0.058***	**Undecided**			-0.010***
		(22.62)	(20.80)				(3.34)
Number of Observations	69,233	69,233	69,233	**Number of Observations**	69,233	69,233	69,233

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 6.3: Men - Logit Results - Retention (Marginal elasticities effects reported, t-statistics in parenthesis)

Dependent Variable: Retention – 1 if enrolled, 0 otherwise

Explanatory Variables	1	2	3	Explanatory Variables	1	2	3
Log Earnings	-0.173***	-0.190***	-0.197***	**First Semester Classes**			-0.169***
	(9.21)	(8.54)	(8.79)				(5.86)
Grant	0.012***	0.013***	0.014***	**Remedial Credits**			-0.034***
	(4.07)	(4.06)	(4.36)				(11.29)
Scholarship	0.071***	0.020***	0.024***	**Missing Race**	-0.010	-0.010	-0.020*
	(14.05)	(3.79)	(4.37)		(1.57)	(1.55)	(1.85)
Loan	0.015***	0.012***	0.012***	**Missing High School**		-0.069***	-0.066***
	(6.79)	(5.20)	(5.25)			(10.58)	(10.13)
Female				**Business**			0.001
							(1.30)
Non White	-0.034***	0.001	0.001	**Health**			0.011***
	(3.79)	(0.24)	(0.12)				(4.02)
Age	-2.670***	-2.162***	-2.384***	**Humanities**			0.015***
	(12.96)	(8.88)	(9.62)				(3.91)
Age Squared	0.808***	0.715***	0.801***	**Sciences**			0.001
	(8.18)	(6.11)	(6.73)				(1.60)
County Unemployment Rate	-0.315***	-0.290***	-0.230***	**Services**			0.001
	(5.82)	(4.49)	(3.53)				(0.30)
First Semester GPA		0.603***	0.559***	**Social Work**			0.002**
		(36.31)	(32.94)				(2.02)
First Semester Credits		0.310***	0.409***	**Vocational**			0.017**
		(24.40)	(22.09)				(2.41)

Table 6.3: Continued

GED		-0.062***	-0.060***	**Undecided**			0.001
		(13.96)	(13.37)				(0.71)
Number of Observations	31,633	31,633	31,633	**Number of Observations**	31,633	31,633	31,633

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 6.4: Women - Logit Results - Retention (Marginal elasticities effects reported, t-statistics in parenthesis)

Dependent Variable: Retention – 1 if enrolled, 0 otherwise

Explanatory Variables	1	2	3	Explanatory Variables	1	2	3
Log Earnings	0.044***	0.010	-0.010	**First Semester Classes**			-0.153***
	(3.56)	(0.64)	(0.37)				(6.99)
Grant	0.029***	0.029***	0.033***	**Remedial Credits**			-0.062***
	(7.50)	(6.89)	(7.49)				(19.57)
Scholarship	0.048***	0.010	0.020***	**Missing Race**	0.014***	0.010***	0.007**
	(8.47)	(1.48)	(3.06)		(4.39)	(2.74)	(1.99)
Loan	0.034***	0.034***	0.033***	**Missing High School**		-0.004**	-0.006***
	(13.49)	(12.36)	(11.99)			(2.27)	(3.64)
Female				**Business**			-0.017***
							(6.21)
Non White	-0.061***	-0.037***	-0.032***	**Health**			-0.023***
	(12.54)	(6.81)	(5.75)				(3.52)
Age	-1.356***	-1.380***	-1.195***	**Humanities**			-0.009***
	(9.77)	(8.77)	(7.40)				(3.24)
Age Squared	0.376***	0.436***	0.335***	**Sciences**			0.001
	(5.72)	(5.85)	(4.38)				(0.53)
County Unemployment Rate	0.010	-0.080*	-0.040	**Services**			-0.012***
	(0.18)	(1.94)	(0.93)				(4.28)
First Semester GPA		0.622***	0.555***	**Social Work**			0.001
		(39.87)	(33.73)				(0.45)
First Semester Credits		0.231***	0.404***	**Vocational**			-0.005***
		(22.31)	(24.48)				(4.00)

Table 6.4: Continued

GED		-0.061***	-0.055***	**Undecided**			-0.024***
		(17.88)	(15.84)				(6.19)
Number of Observations	37,570	37,570	37,570	**Number of Observations**	37,570	37,570	37,570

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 6.5: Time to Stopout (Hazard marginal elasticities effects reported)

Failure Variable: Stopout

Explanatory Variables	1	2	3	Explanatory Variables	1	2	3
Log Earnings	-0.079***	-0.049***	-0.055***	**First Semester Classes**			-0.099***
	(15.02)	(10.74)	(12.12)				(13.89)
Grant	-0.005***	-0.003**	-0.001*	**Remedial Credits**			-0.032***
	(2.80)	(2.46)	(1.89)				(23.35)
Scholarship	0.122***	0.078***	0.085***	**Missing Race**	-0.012***	0.001*	0.001
	(38.83)	(29.24)	(31.62)		(9.63)	(1.83)	(1.06)
Loan	0.037***	0.028***	0.028***	**Missing High School**		-0.006***	-0.007***
	(21.81)	(19.11)	(19.35)			(11.52)	(12.75)
Female	0.113***	0.041***	0.047***	**Business**			-0.006***
	(24.61)	(10.19)	(10.60)				(5.30)
Non White	-0.014***	-0.005***	-0.003***	**Health**			-0.005**
	(12.39)	(4.67)	(3.45)				(2.46)
Age	-0.120*	0.163***	0.135**	**Humanities**			0.003**
	(1.79)	(2.72)	(2.25)				(2.32)
Age Squared	-0.073**	-0.114***	-0.115***	**Sciences**			0.001
	(2.36)	(4.25)	(4.28)				(0.21)
County Unemployment Rate	0.366***	0.288***	0.298***	**Services**			-0.006***
	(18.00)	(16.58)	(17.10)				(5.32)
First Semester GPA		0.488***	0.446***	**Social Work**			0.001
		(67.82)	(58.91)				(1.52)
First Semester Credits		0.297***	0.419***	**Vocational**			-0.008***
		(46.08)	(50.65)				(5.27)

Table 6.5: Continued

GED		-0.032***	-0.029***	**Undecided**			-0.013***
		(31.11)	(27.83)				(8.03)
Number of Observations	69,233	69,233	69,233	**Number of Observations**	69,233	69,233	69,233

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 6.6: Men - Time to Stopout (Hazard marginal elasticities effects reported)

Failure Variable: Stopout

Explanatory Variables	1	2	3	Explanatory Variables	1	2	3
Log Earnings	-0.101***	-0.058***	-0.061***	**First Semester Classes**			-0.061***
	(13.57)	(9.23)	(9.67)				(6.52)
Grant	-0.001	-0.001	-0.001	**Remedial Credits**			-0.019***
	(0.81)	(0.74)	(0.45)				(11.83)
Scholarship	0.091***	0.051***	0.054***	**Missing Race**	-0.014***	0.005***	0.004**
	(24.86)	(16.98)	(17.80)		(6.75)	(2.95)	(2.50)
Loan	0.021***	0.014***	0.014***	**Missing High School**		-0.012***	-0.012***
	(12.30)	(9.89)	(10.03)			(12.14)	(12.09)
Female				**Business**			0.001
							(0.43)
Non White	-0.004***	0.001	0.001	**Health**			0.003**
	(2.76)	(0.01)	(0.36)				(2.19)
Age	-0.212**	0.276***	0.217***	**Humanities**			0.008***
	(2.33)	(3.56)	(2.78)				(4.24)
Age Squared	-0.05	-0.166***	-0.148***	**Sciences**			0.001
	(1.27)	(4.90)	(4.34)				(0.63)
County Unemployment Rate	0.296***	0.256***	0.263***	**Services**			-0.003***
	(10.88)	(11.14)	(11.40)				(3.17)
First Semester GPA		0.379***	0.355***	**Social Work**			0.002***
		(42.55)	(38.30)				(3.03)
First Semester Credits		0.300***	0.368***	**Vocational**			-0.010
		(34.68)	(34.15)				(1.80)

Table 6.6: Continued

GED		-0.024***	-0.023***	**Undecided**			-0.005**
		(19.14)	(17.90)				(2.57)
Number of Observations	31,633	31,633	31,633	**Number of Observations**	31,633	31,633	31,633

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 6.7: Women - Time to Stopout (Hazard marginal elasticities effects reported)

Failure Variable: Stopout

Explanatory Variables	1	2	3	Explanatory Variables	1	2	3
Log Earnings	-0.054***	-0.042***	-0.051***	**First Semester Classes**			-0.152***
	(7.24)	(6.31)	(7.74)				(13.44)
Grant	-0.007***	-0.006**	-0.005**	**Remedial Credits**			-0.044***
	(2.71)	(2.54)	(2.10)				(20.43)
Scholarship	0.148***	0.103***	0.115***	**Missing Race**	-0.011***	0.001	0.001
	(30.22)	(24.57)	-(27.09)		(6.66)	(0.20)	(0.72)
Loan	0.049***	0.038***	0.039***	**Missing High School**		-0.002***	-0.003***
	(17.93)	(16.08)	-(16.21)			(3.40)	(4.66)
Female				**Business**			-0.013***
							(7.12)
Non White	-0.023***	-0.008***	-0.007***	**Health**			-0.021***
	(13.73)	(5.64)	(4.57)				(4.99)
Age	-0.030	0.010	0.070	**Humanities**			0.001
	-0.33)	(0.06)	(0.75)				(1.09)
Age Squared	-0.090*	-0.040	-0.086**	**Sciences**			0.001
	(1.88)	(0.91)	(2.03)				(0.49)
County Unemployment Rate	0.436***	0.310***	0.323***	**Services**			-0.011***
	(14.35)	(11.82)	(12.30)				(5.62)
First Semester GPA		0.588***	0.515***	**Social Work**			0.001
		(52.71)	(43.16)				(0.93)
First Semester Credits		0.296***	0.484***	**Vocational**			-0.004***
		(31.10)	(38.13)				(4.64)

Table 6.7: Continued

GED		-0.039***	-0.034***	**Undecided**			-0.022***
		(24.32)	(20.90)				(8.77)
Number of Observations	37,570	37,570	37,570	**Number of Observations**	37,570	37,570	37,570

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Figure 6.1: Kaplan Meier Sample Survival Estimates of Stopout by Gender

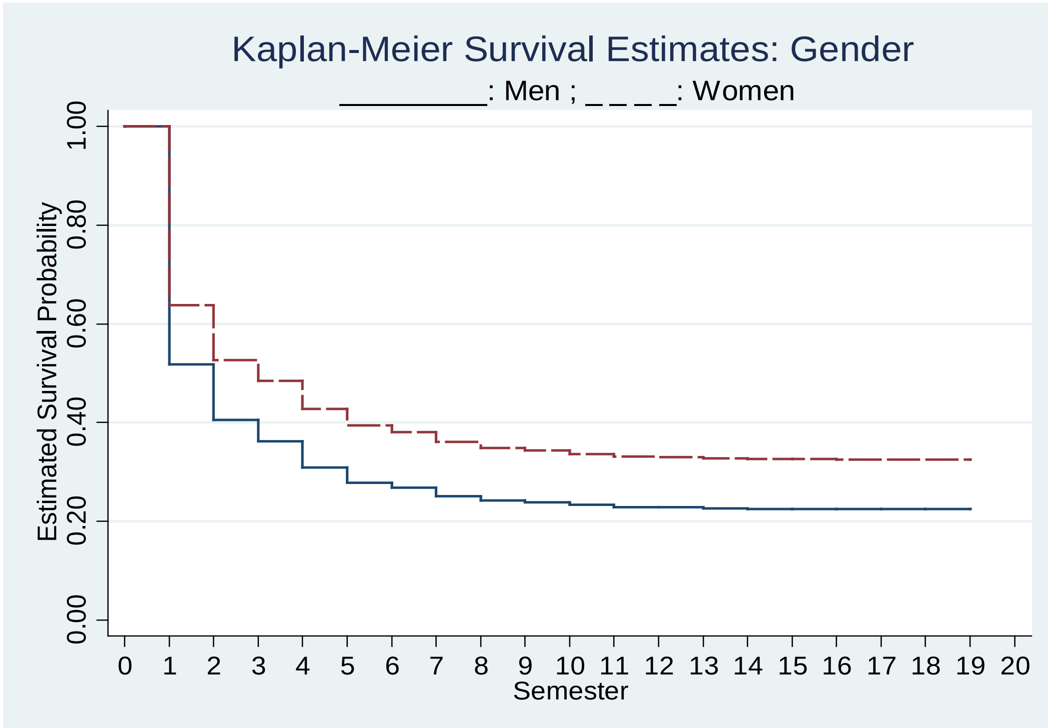


Figure 6.2: Kaplan Meier Sample Survival Estimates of Stopout by Race

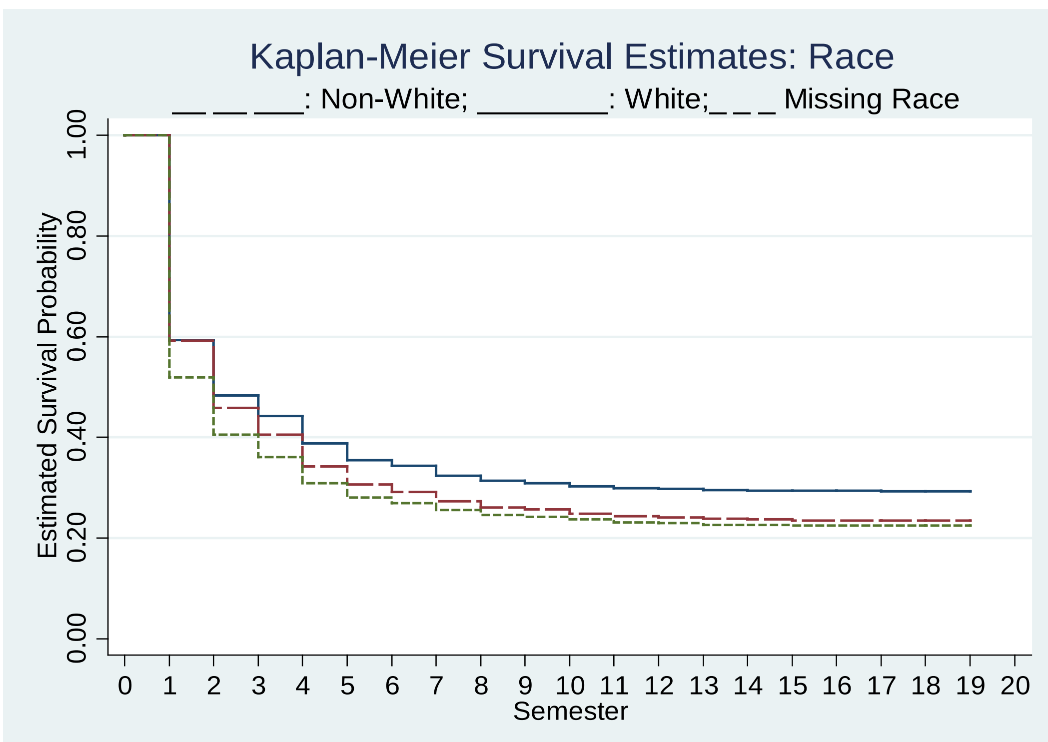
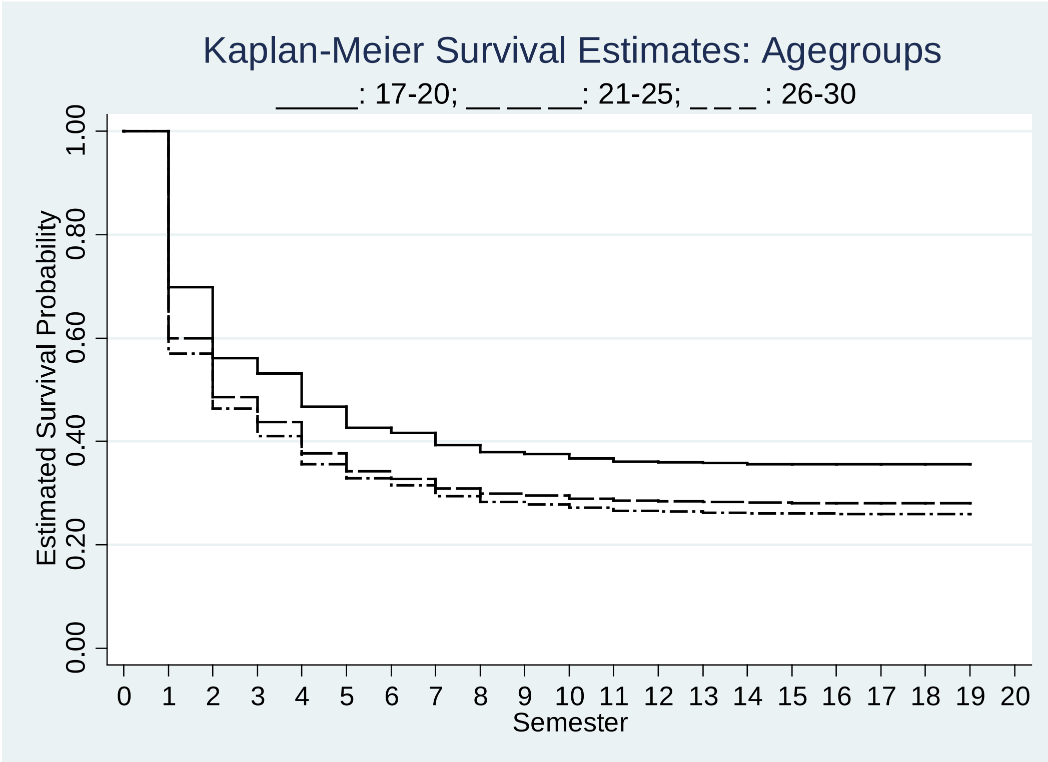
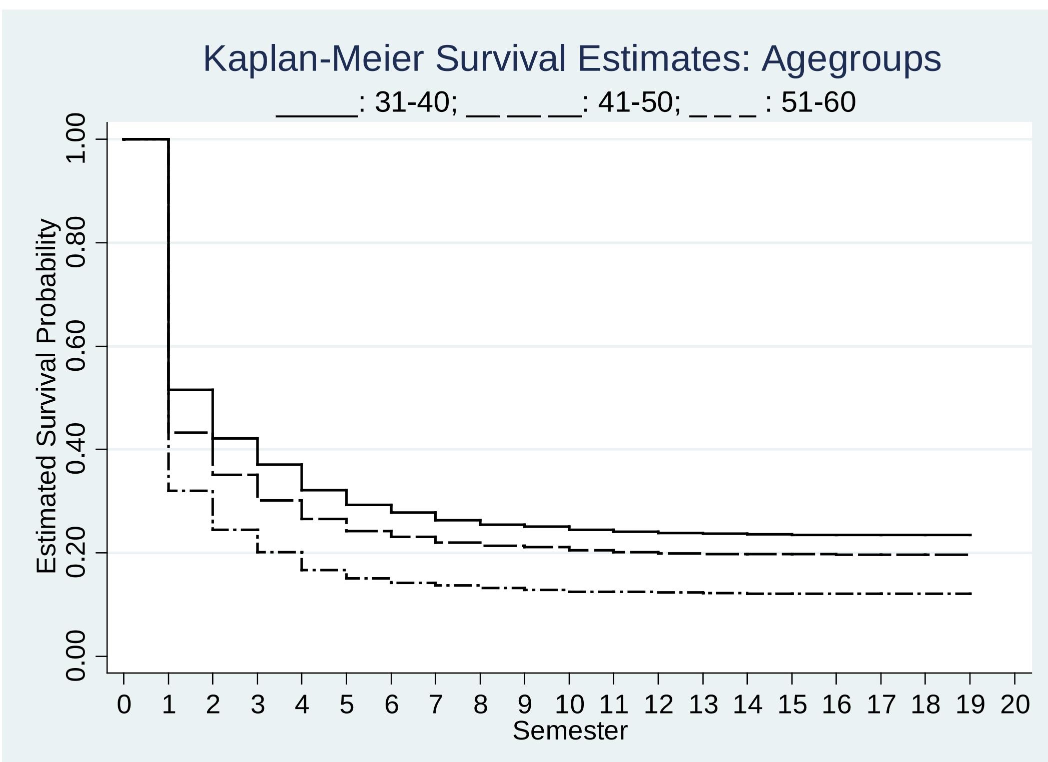


Figure 6.3: Kaplan Meier Sample Survival Estimates of Stopout by Age





7 CHAPTER 6: COMPETING EVENTS

7.1 Discussion

This dissertation has so far focused on single events, mainly transfer and stopout. However, there is a possibility of correlated outcomes while estimating single-risk models. Students can experience many outcomes while attending post-secondary schooling. Students can either dropout, transfer, graduate or even experience two events or more in a lifetime. When a student experiences one event, the probability of experiencing another event is affected. Furthermore, it is difficult to determine a student's final outcome due to right censoring of data. Some studies have data that cutoff when a student experiences a certain event. For example, if a student drops out, there are no observations after the dropped out date for that student. Some studies have benefited from observations until the graduation date. In this study, sample data cuts off at Fall 2008 for all students regardless of when an event occurs. In other words, students are still observed after an occurrence of an event until the end of sample time period. If a student stops out or graduates, I can still follow these students until the end of sample period to observe any transfer behavior. Similarly, if a student stops out or transfers, I can still follow these students until the end of sample period to observe any award receipt. Students who have not experienced any outcome experience right censoring only at the end of the data collection period. Hence, these data provide more precise estimates than datasets described above. However, estimates will still be biased if the separate events are not independent of each other i.e. whether estimates of one event are driven by other events. This implies that as long as transfer, stopout and graduation are considered independent events in this sample the single-risk models should provide robust estimates. However, if these events are not independent events than results from a single-risk model may be biased. This is an important assumption for competing-risk models as well but these models are estimated to allow for the correlated risks. This is discussed in the next section.

Note that explanatory variables can affect all competing risks, so correlation per se is not a problem. There must be unmeasured factors (disturbances) which affect several outcomes, or the outcomes have direct causal impact on each other. Examples would be motivation to study from parents, or stopping out disrupting the acquisition and maintenance of study skills. While such problems are somewhat present with high probability, the quality of the explanatory variables reduces the problem.

The assumption of independent outcomes is essentially the same as the assumption in a multinomial logit model of several possible outcomes called the independence of irrelevant alternatives. Unmeasured factors are assumed to be uncorrelated.

7.1.1 Competing Risk Models

To overcome the issues of correlated events, some studies have implemented competing risk models. DesJardin et al. (1999) estimated a competing-risk model to test the specification sensitivity of their single-risk model that studied student departure. In this setting, students are followed over time until they experience one of the events. In their study, the main outcomes of interest are stopout, dropout and graduation. Each outcome is defined such that there is only one outcome per person. In other words, outcomes are defined to ensure that an individual cannot have more than one outcome because to conduct a conventional competing-risk model, failure mechanisms need to be independent. A student is said to have stopped out when he/she experiences a first break from school. A graduate is when a student graduates within the time period regardless of any break from school. Lastly, a student is a dropout when a student takes time off from school and does not return at all. This way each student only has one outcome. However, these definitions assume that a student who stops out or drops out does not increase or decrease the probability to come back to graduate. Defining the outcomes as described earlier makes no statement about independent events. In summary, there is no competing-risk model present so the issue is avoided at the cost of stopping the analysis.

Similarly, in my sample, I have students who stopout, transfer without a degree, transfer with a degree or obtain a degree. However, I do not estimate a competing risk model as these models assume single spells with unique endpoints which are drawn from a set of discrete possibilities. Such models cannot accommodate multiple endpoints, alternative paths through the endpoints, or what appear to be multiple spells for a given person. In the present case, Associate, Associate to transfer, and transfer alone, are separable technically but not analytically, and it would be very inaccurate to treat Associate to transfer as independent of the others. That is, no competing risk model is present. In addition, it is difficult to control for unobserved heterogeneity and impose distributional assumptions when estimating a competing-risk model. A multivariate distribution of unmeasured heterogeneity would result. Given that the goal is to model each individual event (especially transfer), these constraints have more costs than benefit.

Hence, the data is not set up for a competing risk unless I make an audacious assumption that the above outcomes are independent given the explanatory variables.

The only way I can estimate a competing risk model is as a sequence of single-risk models for all outcomes.[14] Therefore, results from the single-risk model and competing-risk model are virtually the same. Hence, I do not discuss these results in this section. It is not clear how DesJardin et al. (2009) estimated their competing-risk model but they obtained virtually the same results for both specifications. Given the lack of discussion of unmeasured heterogeneity, presumably that was assumed not to exist, and therefore was not correlated. Although I did not estimate a competing-risk model due to all the above reasons, I did estimate a traditional model to analyze these competing events to act as a robustness check on the single-risk estimations and as a comparison to previous literature.

7.1.2 Traditional Models[15]

Since there are more than two events, I can use a generalization of the logit and probit models to estimate the different outcomes. Calcagno et al. (2007) implement a multinomial logit model (MNL) to serve as a robustness check to their single-risk discrete hazard model. Their model has four outcomes: dropout, transfer, certificates and

[14] Stata9 does not have capabilities to estimate a competing-risk model. The only way to compute estimations is through a sequence of single-risk models. These provide the exact same result as the estimating the single-risk models. Stata11 has competing-risk capabilities but one cannot control for unmeasured heterogeneity and make any assumptions on the distribution.

[15] Traditional models also have the same limitations as the competing-risk models as explained in section 7.1.1.

Associates. However, they did not discuss the transfer results because their main outcome of interest was college completion. Furthermore, they have very limited information on transfer.

Multinomial models are generalized as a function of the observable covariates and a separate error term for each alternative. These models assume students make schooling choices simultaneously. These models act as an extension to the binary models with many alternatives: attendance, stopout, transfer or graduate. When estimating these models, one alternative is used as a base outcome. Each alternative is then modeled as a function of individual specific characteristics and is compared to the base outcome. These models have the same limitations as the logistic model explained earlier. In other words, it does not consider the events to be dynamic. The disturbances (unmeasured factors) are assumed to be independent across outcomes. That can be relaxed in a nested logit, but it is not clear what nesting structure would make sense. They are not geographical regions or types of schools.

The two multinomial models differ based on the assumptions made concerning the error terms. If the error terms are assumed to follow independent log Weibull distributions, then one can estimate the MNL model based on theory; alternatively one can assume probabilities are proportional to exponentiated single indices. In other words, differences in the error semesters are assumed to have a logistic distribution. These models are easy to compute as the errors are independently and identically distributed. However, this also creates a problem as assuming the errors are independently distributed imposes the independence of irrelevant alternatives (IIA) property. The IIA property assumes that when odds of two alternatives are estimated, including another alternative or other characteristics does not affect those odds. In this context, it implies that a student's relative risk of transfer or retention should not change if another alternative (graduation) is added or dropped in the analysis, net of the explanatory variables. MNL incorrectly specifies a model when this assumption is violated. In other words, the model cannot produce accurate estimates of the marginal effects of the choices in hand. This assumption is very likely to fail using the education data as outcomes in this dataset do affect each other. In other words, if any outcome was taken away from the choice set, the odds of the alternative outcomes are bound to change, and students are affected by unmeasured family, personal and academic supports and stressors. In this case, the MNL model may not be the most suitable model. There are many tests available to test the IIA property to determine the suitability of the MNL model. Either Hausman or Small-Hsiao tests can be used to test this property. Unfortunately, these tests look for differences in coefficients, not models of unmeasured factors. They do not provide a solution to the problem.

A more appropriate choice of model is the MNP model. This model assumes that the error terms distributed multivariate-normally with a covariance matrix Z. This model avoids the IIA issue as it is assumed that the errors semesters are correlated across the different outcomes. However, the model assumes that the covariance matrix (Z) is not restricted to be a diagonal matrix (Train, 2003). This model's main limitation is that it has a high computational cost. In other words, they take long time and a lot of computing power to estimate. That is true even in modern times with large data sets. An additional problem is that the estimation of variances and covariances of many unobserved disturbances is difficult. The multinomial probit procedure in Stata continues to assume independence, like multinomial logit. Stata assumes that the error terms are assumed to be independent, standard normal, random variables. Even two-variable probits with one covariance can fail to converge. In sum, this is a difficult numerical problem.

7.2 Literature Review

This chapter introduces graduation as one of the competing events. Several studies have analyzed graduation as a single event. Turner (2004) identifies individual, state and institution characteristics as possible factors that affect graduation levels. Light & Strayer (2000) estimated a MNP to estimate the effect of observable factors on graduation rates. Using data from National Longitudinal Survey of Youth (NLSY), they find strong women, mother's education level, receipt of financial aid and AFQT scores positively affect college completion. Overall, a mismatch of student's ability level with the school's quality level negatively affects completion. DesJardin et al (1999) compute a competing-risk model that includes graduation but do not discuss their results. Calcagno et al. (2007) implement a multinomial logit model (MNL) using dropout, transfer, certificates and Associates as their outcomes. Their results indicate that women are more likely to complete a degree whereas non-whites have a lower likelihood of completion. Higher able students have higher graduation probabilities. They find older students to have a lower likelihood of college completion but after controlling for math, this effect reverses. They conclude that the lower completion rates for older students are largely due to the break from schooling rather than age. Remediation also decreases the likelihood of graduation as these credits do not count towards the degree and hence increases the time to degree. Doyle (2009) uses a Cox hazard model to estimate the hazard rate for completing a bachelor's degree. Using data from National Center for Education Statistic's Beginning Postsecondary Students study, he finds students who begin postsecondary education at a community college have a lower risk of college completion. After controlling for selection bias by matching community college students to four year college students, the hazard level further decreases.

7.3 Results

In order to estimate a traditional competing model, I generate a categorical variable that that denotes 0 for stopout, 1 for continuous attendance, 2 for transfer and 3 for graduation. This separates all the alternatives. The breakdown of the separate categories is provided in Table 7.1. In this sample, around 64% of the sample stopped out at some point in their college years, 20% transferred and 15% graduated with a two-year degree but did not transfer. Students who are continuously enrolled but have not transferred or graduated made up less than 1% of the sample. It will be incorrect or unfruitful to estimate this as one of the categories. Since the aim of this estimation is to determine if the binary logistic models are biased, I estimate MNP using all four categories.

I provide results estimated using a MNP model. A MNL model was also estimated but the IIA tests provided inconclusive evidence on whether the IIA assumptions affect the results. Therefore, I did not report the MNL results. However, the results are very similar to MNP and can be provided upon request.[16] To estimate the MNP, I collapse the sample to one observation per student. Collapsing the data does not produce a problem for time-invariant independent variables. However, I need to redefine the computation of time variant independent variables. For this analysis, I used the mean averages of all the time-variant variables. Another possible approach would be to use the maximum time-variant observation for each subject.[17] These results are available upon request. Table 7.2 provides marginal elasticity effects from MNP for attrition, transfer and graduation respectively. The base outcome is stopping out as I am interested in estimating favorable outcomes versus the unfavorable (stopout). I run the same three specifications as the other analysis in previous chapters.

7.3.1 Continuous Enrollment

MNP estimates on attendance are available in the first column of Table 7.2. Remember, I define stopout as students who take a break from school for two consecutive semesters, who do not graduate and/or transfer. Results indicate that student earnings are positively correlated to their attendance. These results disagree with the logit results in Table 6.2 where I found that earnings decrease the likelihood of continuous

[16] Separate MNP estimations by gender were conducted but not discussed. I was more interested in the effect of factors on the difference alternatives using the full sample to see if the logit estimations on transfer were driven by the other outcomes. The gender results can be provided upon request.

[17] The results from using maximum time-variant approach differed slightly from the mean results. The maximum approached found earnings to have no effect on retention and scholarship to have a negative effect on retention. The rest of estimates were consistent in both models. Similar differences are found when the mean MNL model is compared to maximum MNP model.

enrollment.[18] All three specifications indicate strong, positive significance between student earnings while in school and attendance. Even after controlling for student intentions and college characteristics, a 10% increase in earnings increases attendance by 9.30%. This result is not what was expected. 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. However, this is not what the estimates found. Based on the definitions of the outcomes, less than 1% of students are defined in this category. It does not make sense to estimate the effects on continuous enrollment and the results may not be appropriate or correct to present.

Financial aid in form of grants and scholarships are found to promote attendance in the first two specifications but have no effect in specification (3) when intentions are controlled for. Loans have a positive relationship with continuous enrollment in all three specifications. These results agree with those found in the single event logistic regression. I find no gender differences on attendance. There are some race differences found in the specification (3) which indicates that non-whites are more likely to stopout than whites. The logit model, on the other hand, found women to have a lower likelihood of stopping out and non-whites to have a higher likelihood of stopping out in all three specifications.

Other variables that contradict with the logistic regression include age, first semester credits and first semester remedial credits. The MNP model indicates students are more likely to stopout when they are younger, when they earn more credits in the first

[18] Note that the binary logit model and MNP model are different. Even though the magnitudes cannot be comparable, the direction of the estimations can be. This helps in determining the direction/type of bias caused by ignoring correlated outcomes.

semester and acquire few remedial credits. The rest of the variables agreed with the logistic regression.

7.3.2 Transfer

Column (2) of Table 7.2 report MNP marginal effects for various specifications for the likelihood of transferring. All three specifications indicate coefficients that are negatively correlated with the probability of transferring. Specification (3) indicates that a 10% increase in earnings decreases the probability of transferring by 2.53%. These results agree with that of the single event logit model. Financial aid variables have mixed effects on transfer. Grants and loans have no effect on transfer but scholarships have a negative effect on transfer. On the other hand, the binary logistic model identifies all the financial aid variables to decrease the probability of transferring.

All other variables of interest are consistent in both the models except for remedial credits in the first semester. The MNP model shows that increases in remedial credits acquired in the first semester increases the probability of transfer whereas the logistic model indicated otherwise. Overall, for those variables of interest that agreed on both models, the marginal effects were of very similar magnitudes.

7.3.3 Graduate

The previous two analyses show that average student earnings while in school increase attendance and decrease the likelihood of transferring. However, results indicate that increases in earnings motivate students to complete a two-year degree. Column (3) in Table 7.2 provides estimates for graduation from two-year colleges. The results from the MNP model fully agree with the results from a binary logistic model provided in Table 7.4.[19] In all three specifications in the MNP model, earnings while in school have a large positive impact on graduation. A 10% increase in earnings increases completion rates by 1.44% - 2.52% depending on the specification. Although earnings have a negative relationship with probability to transfer, they encourage students to at most complete a two-year degree without transferring. Although students substitute work for school, these students are motivated to complete their degrees.

Grants, scholarships and loans positively affect the likelihood of graduation. All three specifications are significant at the 1% level. This is a good sign indicating that students who acquire or need aid do in fact complete some kind of degree and hence, financial aid help promote completion at two-year colleges.

Women have a higher likelihood of completing at a two-year institution. This was as expected as women have surpassed the attendance and graduation rates as compared to men. Non-whites have a lower likelihood of completion than comparable whites. I find age to be positively associated with graduation. As per specification (3), 10% increase in age increases graduation by 55%. County unemployment rate has no significant effect on graduation.

Ability is positively correlated to completing two-year schooling. More able students, identified by first semester GPA and first semester credits are more likely to complete schooling. Acquiring a GED compared to high school diploma is detrimental to

[19] Hazard model results for graduation are provided in Table 7.3 but are not discussed.

two-year completion rates. However, attempting remedial credits does promote student completion levels.

7.4 Conclusion

Due to correlated events the results from the binary and single-risk models may produce biased results. Studies have used different models to overcome this issue. Calcagno et al. (2007) estimate a MNL model and DesJardin et al. (1999) estimate a competing-risk model. However, both models have many limitations as explained earlier in the chapter. However, I did estimate a MNP which provides a robustness test for the single events (mainly logit results). Results show that students' earnings decrease the likelihood of stopping out, decrease the likelihood of transferring to a four-year college but increase the likelihood of completing a degree. MNP analysis for continuous enrollment differs significantly from the binary logit model. This model finds a positive association between earnings and persistence, unlike the binary model. They further differ in terms of gender effects, age, first semester credits and remedial credits.

Women have lower probability of dropping out, higher probability of transferring and higher probability of graduating. Variables that were proxy for ability promote attendance, transfer and graduation. Overall, both the MNP and logit results look very similar but differ significantly in the effects of earnings. MNP earnings estimates promote persistence and eventually graduation whereas the linear probability model finds attendance and earnings to be negatively correlated.

Hence, controlling for other outcomes does matter. For one, the effect of earnings on retention changes signs when estimating a competing model. This could be largely due to the fact that the enrollment category is represented by less than 1% of the sample. Conducting a MNP with this category does not provide any fruitful results.

Table 7.1: Tabulation of the Four Categories

	Number of Students	%
Stopout	44,761	64.65%
Continuous Enrollment	259	0.37%
Transfer	13,638	19.70%
Graduate	10,575	15.27%
	69,233	100.00%

Table 7.2: Multinomial Probit Results (Marginal elasticities effects reported)

Base Outcome: Stopout

	Continuous Enrollment			Transfer			Graduate		
Explanatory Variables	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Log Earnings	0.806***	0.766***	0.930***	-0.197***	-0.243***	-0.253***	0.144***	0.250***	0.252***
	(5.36)	(5.05)	(5.25)	(12.05)	(14.28)	(14.66)	(7.69)	(10.98)	(10.43)
Grant	0.063***	0.063***	0.020	-0.005	-0.004	-0.005	0.035***	0.038***	0.026***
	(2.80)	(2.78)	(0.80)	(1.19)	(1.01)	(1.16)	(9.05)	(8.70)	(5.80)
Scholarship	0.128***	0.111***	0.067	-0.043***	-0.059***	-0.054***	0.169***	0.106***	0.094***
	(3.34)	(2.88)	(1.54)	(6.81)	(8.95)	(7.99)	(27.63)	(15.19)	(12.81)
Loan	0.113***	0.111***	0.111***	0.004	0.002	0.005*	0.040***	0.043***	0.038***
	(10.81)	(10.66)	(9.77)	(1.41)	(0.78)	(1.83)	(16.77)	(16.22)	(13.76)
Female	0.086	0.025	-0.131	0.144***	0.090***	0.091***	0.143***	0.120***	0.129***
	(1.06)	(0.31)	(1.27)	(15.34)	(9.19)	(8.50)	(13.18)	(9.23)	(8.16)
Non White	-0.077	-0.075	-0.165**	-0.016**	0.003	0.005	-0.101***	-0.075***	-0.093***
	(1.36)	(1.33)	(2.47)	(2.49)	(0.45)	(0.69)	(12.74)	(8.08)	(9.50)
Age	3.568**	3.681**	6.202***	-4.350***	-3.641***	-2.631***	1.375***	1.514***	0.459*
	(2.37)	(2.43)	(3.46)	(22.73)	(18.15)	(12.77)	(6.78)	(6.14)	(1.72)
Age Squared	-1.397*	-1.397*	-2.385***	1.361***	1.122***	0.644***	-0.589***	-0.500***	0.015
	(1.95)	(1.94)	(2.78)	(14.65)	(11.49)	(6.40)	(6.08)	(4.23)	(0.12)
County Unemployment Rate	-1.106**	-1.019**	-1.780***	-0.241***	-0.244***	-0.301***	0.067	0.016	0.024
	(2.46)	(2.27)	(3.33)	(4.88)	(4.76)	(5.76)	(1.23)	(0.24)	(0.35)
First Semester GPA		0.402***	0.505***		0.574***	0.556***		0.730***	0.719***
		(3.37)	(3.56)		(38.18)	(35.08)		(32.85)	(29.02)

Table 7.2: Continued

First Semester Credits		-0.036	-0.574***		0.017	0.145***		0.652***	0.519***
		(0.37)	(3.32)		(1.52)	(8.74)		(45.19)	(23.08)
GED		-0.016	-0.019		-0.090***	-0.079***		-0.028***	-0.041***
		(0.60)	(0.60)		(22.04)	(18.95)		(6.15)	(8.41)
First Semester Classes			-0.119			-0.098***			-0.158***
			(0.52)			(4.48)			(5.16)
Remedial Credits			0.736***			0.026***			0.194***
			(16.98)			(4.00)			(25.56)
Missing Race	0.109***	0.108***	0.157***	0.005	0.001	-0.007	0.002	0.001	0.016**
	(2.78)	(2.77)	(3.43)	(1.12)	(0.18)	(1.44)	(0.29)	(0.11)	(2.22)
Missing High School		-0.013	0.014		-0.023***	-0.031***		-0.027***	-0.011**
		(0.54)	(0.52)		(6.90)	(9.31)		(5.58)	(2.13)
Business			-0.007			-0.035***			0.038***
			(0.30)			(13.33)			(11.05)
Health			0.062			-0.128***			0.192***
			(1.32)			(24.00)			(26.18)
Humanities			-0.054*			-0.003			0.008
			(1.73)			(1.15)			(1.59)
Sciences			-0.005			0.001*			-0.001
			(0.64)			(1.92)			(1.18)
Services			0.014			-0.019***			0.027***
			(0.59)			(7.33)			(7.23)
Social Work			0.006			-0.003***			0.007***
			(1.18)			(4.70)			(9.00)

Table 7.2: Continued

Vocational			-0.021			-0.088***				0.133***
			(0.55)			(22.43)				(26.80)
Undecided			-0.018			-0.031***				0.023***
			(0.47)			(8.05)				(3.73)
Number of Observations	69,233	69,233	69,233	69,233	69,233	69,233		69,233	69,233	69,233

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 7.3: Time to Graduate (Hazard marginal elasticities effects reported, t-statistics in parenthesis)

Explanatory Variables	1	2	3	Explanatory Variables	1	2	3
Log Earnings	-0.160***	-0.184***	-0.175***	**First Semester Classes**			0.096***
	(20.52)	(23.72)	(23.25)				(7.31)
Grant	-0.011***	-0.008***	-0.007***	**Remedial Credits**			0.022***
	(18.09)	(13.84)	(13.38)				(14.19)
Scholarship	-0.056***	-0.041***	-0.039***	**Missing Race**	0.036***	0.020***	0.015***
	(43.89)	(33.42)	(33.14)		(13.02)	(7.53)	(5.68)
Loan	-0.010***	-0.010***	-0.009***	**Missing High School**		0.019***	0.010
	(24.76)	(24.16)	(22.80)			(6.31)	(1.55)
Female	-0.091***	-0.045***	-0.063***	**Business**			-0.032***
	(14.37)	(7.29)	(8.81)				(20.38)
Non White	0.021***	0.012***	0.012***	**Health**			-0.111***
	(10.68)	(6.10)	(6.43)				(31.39)
Age	-1.156***	-0.961***	-0.231*	**Humanities**			-0.026***
	(9.90)	(8.31)	(2.05)				(10.27)
Age Squared	0.558***	0.354***	0.03	**Sciences**			-0.001**
	(9.92)	(6.39)	(0.50)				(2.72)
County Unemployment Rate	-0.249***	-0.201***	-0.266***	**Services**			-0.029***
	(9.73)	(8.06)	(10.92)				(15.88)
First Semester GPA		-0.443***	-0.381***	**Social Work**			-0.004***
		(36.23)	(30.82)				-(13.53)
First Semester Credits		-0.295***	-0.291***	**Vocational**			-0.070***
		(48.80)	(31.09)				(31.93)

Table 7.3: Continued

GED		0.013***	0.016***	**Undecided**			-0.043***
		(6.09)	(7.72)				(13.46)
Number of Observations	69,233	69,233	69,233	**Number of Observations**	69,233	69,233	69,233

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

Table 7.4: Logit Results – Graduate (Marginal elasticities effects reported, t-statistics in parenthesis)

Dependent Variable: Graduate – 1 if graduated, 0 otherwise

Explanatory Variables	1	2	3	Explanatory Variables	1	2	3
Log Earnings	0.121***	0.224***	0.210***	**First Semester Classes**			-0.185***
	(7.20)	(11.30)	(10.32)				(6.98)
Grant	0.025***	0.026***	0.029***	**Remedial Credits**			-0.055***
	(7.38)	(6.86)	(7.42)				(16.94)
Scholarship	0.180***	0.117***	0.120***	**Missing Race**	0.000	0.000	0.010
	(33.80)	(19.53)	(19.57)		(0.54)	(0.13)	(1.24)
Loan	0.032***	0.034***	0.030***	**Missing High School**		-0.031***	-0.015**
	(14.81)	(14.23)	(12.61)			(6.46)	(3.13)
Female	0.154***	0.119***	0.128***	**Business**			0.045***
	(15.85)	(10.50)	(9.55)				(15.37)
Non White	-0.107***	-0.070***	-0.075***	**Health**			0.191***
	(14.61)	(8.51)	(8.85)				(30.08)
Age	0.958***	1.322***	-0.15	**Humanities**			0.045***
	(5.23)	(6.05)	(0.67)				(11.29)
Age Squared	-0.505***	-0.485***	0.18	**Sciences**			0.002**
	(5.74)	(4.60)	(1.64)				(3.11)
County Unemployment Rate	0.131**	0.09	0.249***	**Services**			0.048***
	(2.72)	(1.56)	(4.29)				(15.17)
First Semester GPA		0.839***	0.777***	**Social Work**			0.007***
		(39.57)	(34.28)				-(9.34)
First Semester Credits		0.664***	0.682***	**Vocational**			0.115***
		(53.37)	(35.69)				(26.99)

Table 7.4: Continued

GED		-0.040***	-0.048***	**Undecided**			0.064***
		(9.81)	(11.54)				(12.24)
Number of Observations	69,233	69,233	69,233	**Number of Observations**	69,233	69,233	69,233

Absolute value of t statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

8 CHAPTER 8: GENERAL DISCUSSION AND CONCLUSION

Although much research has studied the effect of personal, economic, and institutional characteristics on education outcomes, in this study I report research that contributes by estimating the effects of these characteristics on the timing of different education outcomes: stopout, transfer, and graduation. This work assumes education investment is not static; rather it is dynamic. Students have the goal of maximizing their lifetime earnings by incorporating new information acquired at different investment stages. Based on this assumption, this work differs from existing research by adopting hazard models that solve these sequential choice problems.

This study further contributes by implementing a competing-risk model that considers all education outcomes simultaneously. When a student experiences one event, the probability of experiencing another event is affected. Assuming each event is independent and ignoring alternative outcomes may bias results. There are several models that can be utilized as robustness check on the single-event models. This study estimates a MNP using stopout as the base outcome. However, due to a small sample of students in the continuous enrollment category, the estimates from this study may not be consistent. Future research needs to be conducted using models that relax the IIA property to reduce the overall bias caused by unmeasured factors.

Moreover, many studies have solely focused on the schooling market factors or solely on labor market factors, but no study considers both markets simultaneously. When controlling for labor market factors, several studies have used proxies for student earnings, but to the best of my knowledge, no study has controlled for student's earnings while in school. In this study, earnings data are collected by matching students in the dataset with the administrative earnings data from

Kentucky’s unemployment insurance program. This is an important contribution; estimating the earnings effect provides information on the short-term positive (increase in earnings) and negative (decrease in earnings) shocks on students’ investment choices. This dissertation combines both the schooling and labor market and finds that students value current events more highly than they value future events, particularly when it comes to finances. When analyzing each education outcome separately, I find student earnings increase the time to transfer and decrease the time to stopout. This can also be inferred as earnings decrease the likelihood of transferring and increase the likelihood of stopping out. Conversely, the competing event model finds earnings to promote persistence. While students are less likely to transfer, working outside school does not deter them from obtaining a degree at a two-year school. However, since the students in the continuous enrollment sample made up of only 0.50% of the sample, these results need further investigation.

The study establishes other characteristic that influence student education decisions: personal factors (ability, gender, race, age) and economic factors (financial aid, unemployment rates). Financial aid has mixed effects on each event. Focusing on single events, grants promote early transfer and stopout, although the effect on stopout is close to zero. Students who received grants received them in the form of Pell Grants, which are usually provided to students from low socioeconomic backgrounds. Hence, it is not surprising that these students stopout early. Scholarships, which are typically not transferrable, delay the time to transfer but promote retention; students with scholarship are more likely to take more classes and delay transfer as long as the scholarship is renewed yearly. Loans work to promote transfer and persistence.

Gender, race, and age also play a major role in the timing of investments. I find that women take fewer semesters to transfer and are more likely to persist than men. This is not surprising as earnings differences in the sample between the genders indicate that men spend relatively more time in the labor market. I find non-whites to take less time to transfer than whites but are also more likely to stopout early. As expected, age is positively correlated to the time to transfer and inversely correlated to the time to stopout. Option value theory predicts that older students delay transfer or stopout early because they have fewer years to enjoy the full benefits of a four-year degree, have many responsibilities, and spend fewer hours in school-related activities.

Confirming human capital literature, this study finds that ability is important at all levels. First semester GPA, a proxy for ability, postpones stopout and promotes early transfer and graduation. Many students register for remedial credits to improve their understandings of certain subjects and can be identified as low-ability students. I find that they are more likely to stopout and less likely to transfer. Finally, students who acquire GEDs rather than high school certificates are less likely to invest in additional post-secondary education.

Policymakers may want to construct programs that address issues that can improve transfer and retention rates. The goal is to identify causes and find remedies. This dissertation finds that students who fail to acquire high school certification invest less in post-secondary education. Increasing or providing students with mentoring, counseling, and tutoring programs could be an initial step.

Economic factors have the largest impact on student's decision to attain additional education. Increases in student earnings strongly and negatively affect education outcomes.

Living expenses that absorb a large part of the family budget can be identified as one influence as students weigh in making decisions about the state of earnings. Students struggle to cover their living expenses even when government programs such as financial aid help cover schooling costs. Policymakers should devise policies that reduce the need for students to work while in school. One such policy would be to increase the availability of subsidized aid to alleviate living expenses, distributed based on factors including household size, number of dependents, and socioeconomic status. This may incentivize students to substitute school for work.

In this dissertation I have demonstrated that short-term events affect students' education plans even when long-term plans are controlled for. Students are willing to earn more today at a cost of acquiring higher education. Though, their behavior does not change with the availability of financial aid, aid does motivate them to advance their education by a few steps. By using option value theory as the foundation explaining why individuals invest in human capital, this dissertation shows that time is consequential. This adds support for the use of hazard models in analyzing education outcomes. Future research will include an estimation of a competing-risk model and following these students at a four-year college and estimating the overall impact of delayed investments in education on students' future educational and labor-market outcomes.

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