ECONOMICS OF EDUCATION: ANALYZING POLICIES

THAT AFFECT SUCCESS IN EDUCATION

By

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To the Faculty of Washington State University.

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ECONOMICS OF EDUCATION: ANALYZING POLICIES

THAT AFFECT SUCCESS IN EDUCATION

Abstract

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The first of these three papers is an empirical study estimating the impact of peer academic support on university course grades. Results suggest that, on average, about twelve peer academic support sessions increase a student's course grade by approximately one full grade point, holding constant a student's academic ability and socioeconomic status. Supplemental instruction is potentially a more effective method of peer academic support than individual peer academic support sessions and low-performing students benefit more from peer academic support than high-performing students.

The second paper analyzes the educational impact of Native American tribal casino in Washington State. We empirically study the effect tribal casinos have on the dropout rate of schools located near tribal casinos. Next we examine the impact on the dropout rate from per capita payments. Since each federally recognized tribe is a sovereign nation, each tribe makes its own laws governing the payout of these payments. These payments are largely funded by casinos. In Washington State all tribes that make per capita payments put minor tribal member's payments in trust funds that are not technically accessible until the minor child turns 18. These trust funds are having an effect on the dropout rate of young Native American adults.

The third paper examines the effect of the gender of the student, tutor and professor on the duration between tutoring sessions. Results suggest that the female students have a shorter duration between tutoring sessions. The gender of the tutor or the gender of the instructor had no effect on our results however if the student and instructor were the same gender the duration between tutoring sessions shorter. This was true for both male and female students.

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CHAPTER ONE INTRODUCTION

The purpose of this dissertation is to analyze factors that affect student achievement. Two data sets are utilized. The first data set from Colorado State University-Pueblo is used to investigate (1) the effect of peered academic support on student achievement and (2) the effect of gender difference on peered academic support. The other data set from Washington state public high schools and Washington state Native American tribes. This study analyzes (3) the effect of trust fund payout policy on the high school dropout rates on reservations.

Dissertation Format and Content

The format of this dissertation is three related but stand-alone articles. The first study analyzes the benefits of different peered academic support offerings on various course grades. I find evidence that, on average, ten tutoring sessions increases a student's grade by approximately one-quarter of a letter grade. However, it appears that *ex ante* efforts designed specifically in preparations for tests might be more effective than *ex post* efforts, to the effect that supplementary instruction tutoring specifically designed for the preparation of tests is found to be the most effective academic support method overall, increasing a student's college-level mathematics grade by over a quarter of a letter grade. In addition, in estimating the ethnicity-specific returns to tutoring, we find that only white students have positive and significant returns in traditional courses.

The second study investigates the impact of the size and payout requirements of trust funds on the dropout rate of Native American high school students. Tribes that make per capita payments to enrolled members must decide where the per capita payments of minor children will go. Tribes can payout the funds to the minor, deposit the funds in a trust fund or payout part of the funds and deposit the rest. If the minors have trust funds, the tribe has to decide the requirements the minor must meet in order to withdraw funds. Tribes have age requirements and/or high school graduation requirements.

The third study seeks to analyze the effect gender may play in peered tutoring success. Using the data from Colorado State University we will investigate gender specific tutoring effects. Previous literature has indicated that this effect warrants further investigation. The gender specific teaching effects have found that students perform better when the teacher is the same gender. The peered aspect of the tutoring program at Colorado State University makes this study different. A final chapter draws conclusions.

CHAPTER TWO

EFFECTS OF PEER ACADEMIC SUPPORT ON UNIVERSITY COURSE GRADES

Abstract:

This study estimates the impact of peer academic support on university course grades. Results suggest that, on average, about twelve peer academic support sessions increase a student's course grade by approximately one full grade point, holding constant a student's academic ability and socioeconomic status. Supplemental instruction is potentially a more effective method of peer academic support than individual peer academic support sessions and low-performing students benefit more from peer academic support than high-performing students.

Introduction

There are many empirical studies devoted to understanding the potential factors that impact success in education. Cameron and Heckman (2001) find that parental income impacts a child's level of school attainment. Zimmerman (2003) finds that peer effects, in terms of student abilities, impact academic outcomes. The former study has implications for credit constraints and the latter study for school choices. Other topics related to success in education include the impact of socioeconomic factors (e.g., Duncan & Magnuson, 2005; Fryer, 2003; Yeung & Conley, 2008), the education level of parents (Phillips & Chin, 2004), school quality (Cook & Evans, 2000; Orr, 2003), peer effects (Hanushek et al., 2003; Sacerdote, 2001), teacher quality (Hanushek, 1971; Hanushek et al., 2005; Rivkin et al., 2005), class size (Angrist & Lavy, 1999; Hoxby, 2002), race (e.g., Clotfelter et al., 2009; Fryer & Levitt, 2004, 2011; Jencks & Phillips, 1998; Jensen, 1973; Hanushek & Rivkin, 2009), employment while in school (Ruhm, 1997; Stinebrickner & Stinebrickner, 2003), and student effort (Ehrenberg and Sherman, 1987; Hill, 1991; Schuman, 1985; Stinebrickner & Stinebrickner, 2004, 2008).

The impact of peer academic support on academic outcomes has also been analyzed. Peer academic support usually refers to students working in pairs or small groups to help one another learn material or practice an academic task. Some empirical studies measure the impact of peer academic support on a student's success using descriptive approaches. Kelley and Swartz (1976) examine the impact of peer academic support programs on student grades by quantifying the benefits of student-to-student tutoring in freshman economics courses at Duke University. Students who performed well in the course were provided with the option of either taking the final exam or tutoring students who were having difficulty in the class and being exempted from the final exam. However, students who did not perform well in the course were invited, but not required, to attend tutorial sessions. They estimate that, on average, peer tutoring raised participating students' grades by a full letter grade. Zimmer, Hamilton, and Christina (2010) study the effectiveness of the supplemental education services and educational assistance programs on students' math and reading skills in Pittsburgh's public schools. While the authors find some positive and statistical significant results that suggest benefits to tutoring, the magnitudes of the impacts are small and not robust across the various models. Munley, Vincent, and Eoghan (2012) find that approximately ten hours of tutoring per semester increased a student's grade by the equivalent of a plus or a minus change in letter grade at Lehigh University. There is an additional set of articles that uses purely descriptive approaches to examine the effect of private tutoring on academic outcomes across various counties, with some studies finding positive effects and other studies finding negative, or no effect (Buchmann, 2002; Cheo & Quah, 2005; Lee, Kim, & Yong, 2004; Lui 2012; Stevenson, Lee, & Baker, 1992).[1,2]

Using an instrumental variables (IV) approach to estimate the impact of peer academic support on university course grades is needed because the level of participation in a tutoring program is (potentially) endogenous, and thus, cannot be used as a variable to explain academic outcomes. More specifically, there is not a definitive causal role between grades (i.e., academic outcomes) and peer academic support in the underlying grade production process resulting in

[1] Some studies (Bray et al., 2003; Lee, 2007; Tansel & Bircan, 2006) also examine the determinants of demand for private tutoring. For example, Bray et al. (2003) study the demand for private tutoring in Hong-Kong to find that private tutoring appears to exacerbate social inequalities.

[2] Kunsch, Jitendra, and Sood (2007) also find that peer academic support works best when students of different ability levels work together.

potentially biased peer academic support estimates when examining the relationship from a purely descriptive perspective.

A few studies have used an IV rather than a descriptive approach. Studying the effects of private tutoring on primary grade students in Indonesia and Vietnam, Suryadarma (2006) and Dang (2007) use the proportion of classmates taking extracurricular courses and hourly tutoring fees as instruments, with the former study not finding any significant effects and the latter study finding that more spending on private tutoring significantly increases the probability that a student can be categorized as academically good or excellent. The per-hour tutoring rate used by Dang (2007) may not be exogenous because hourly tutoring rates and school quality are likely correlated through the family socioeconomic status.[3] Examining the impact of private tutoring on National College Entrance Exams in China, Zang (2013) uses the number of private tutoring participants among a student's close friends and the distance from a student's home to the nearest tutoring agency as instruments. He finds that the average effect of private tutoring to be insignificant.

The current article uses student-course data from Colorado State University – Pueblo (CSU – Pueblo) coupled with an instrumental variable (IV) strategy to estimate the impact of peer academic support on university course grades. The remainder of this paper is organized as follows: The next section presents an overview of CSU – Pueblo and its general education peer academic support services. We then present the data and discusses the amount of peer academic support utilized across the various peer academic support types and subjects. Next we present the general specification of the structural model to describe the underlying relationship between course grades and peer academic support, a description of the data, and the empirical model used to estimate the impact of peer academic support on course grades. We subsequently present the

[3] This point is also noted by Zang (2013).

results, both in general and across subjects, and the potential nonlinear effects of student academic abilities on the return to peer academic support. Finally we discuss concluding remarks and the potential for future research.

Overview of CSU – Pueblo, and its General Education Peer academic support Services

CSU – Pueblo is a public, four-year university with an enrollment of over 5,100 students, comprised of approximately 55% Caucasian, 26% Hispanic and 19% other ethnic groups. CSU – Pueblo is a fully accredited and part of the Colorado State University system, which includes CSU – Fort Collins and CSU Global campuses. CSU – Pueblo offers 27 undergraduate and seven graduate programs available through four colleges.[4]

Student Academic Services is a department within CSU – Pueblo whose mission is to provide programs and services designed to enhance the academic efficiency, effectiveness and independence of students. The General Education (Gen Ed) Tutoring Center, which includes Mathematics and Natural Sciences as well as a Humanities division, is a program within Student Academic Services that offers peer-based academic support for various general education courses. Its mission is to assist students enrolled in developmental and general education courses to become active, independent learners and achieve academic success. In AY 2011 – 12, The Gen Ed Tutoring Center employed two full-time and two part-time staff members and over fifty student workers. In 2011 – 12, the program spent approximately $178,400 on student wages.[5]

[4] http://www.colostate-pueblo.edu/IR/factbook/Pages/2011-Fact-Book.aspx

[5] The program spent $119,000 on student employee wages and employed 22 work study students per semester at an average rate of $1350 per semester. Given two semesters per year, the approximate amount of money spent on work

The Gen Ed Tutoring Center offers both supplemental instruction (SI) and individual peer academic support sessions.

SI is a form of academic intervention which utilizes peer-led study sessions. The sessions are facilitated by SI leaders who have successfully completed the course, obtained academic departmental approval, and who attend current course lectures. SI leaders regularly meet with the instructor and SI coordinator, act as model students and are trained group facilitators. SI sessions are informal and regularly scheduled seminars where students learn effective study strategies, including how to synthesize course information and prepare for exams. SI targets courses that are historically difficult, as determined by the rate of students who either earn a grade of "D", "F" or withdraw (W) from the course.[6]

Individual tutoring sessions are scheduled for fifty minutes and the student works independently with one peer tutor. Typically, students work through difficult course material with a tutor, who has successfully completed the course as well as obtained academic departmental approval to tutor. This could include assigned homework, practice quizzes and worksheets developed by the instructor. Students are not allowed to have consecutive individual sessions; however, they are allowed to access services more than once per day. Students lose appointment privileges for one semester if they do not show up for three scheduled appointments during that semester.

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study students was $59,400, for a total of $178,400 (the sum of $59,400 and $119,000). The amount of money spent on work study students was negligible in the summer.

[6]According to The International Center for Supplemental Instruction at the University of Missouri – Kansas City, SI does not have the same stigma of tutoring since SI targets "high risk" courses instead of "high risk" students (http://www.umkc.edu/cad/si/overview.shtml).

This paper focuses on data generated from the Mathematics and Natural Science division of the Gen Ed Tutoring Session across the fall 2010 to spring 2012 semesters in biology (Human Physiology and Anatomy I and II), chemistry (General Chemistry I and II), and mathematics (Mathematical Explorations, College Algebra, and Introductory Statistics) courses.[7,8] During this period of time, individual support was offered in both the mathematics and science (i.e., biology and chemistry) courses while SI was only offered in the science courses.

Empirical Approach

A general specification of the structural model to describe the underlying relationship between course grades and peer academic support can be described as follows:

$$G_{s,c,i} = \beta A_{s,c,i} + \mathbf{X}'_{\mathbf{s,c,i}}\boldsymbol{\gamma} + \varepsilon_{s,c,i} \tag{1}$$

$$A_{s,c,i} = \theta G_{s,c,i} + \mathbf{X}'_{\mathbf{sc,i}}\boldsymbol{\varphi} + \upsilon_{s,c,i} \tag{2}$$

where *s, c* and *i* denote the semester, course, and student, respectively, and $G_{s,c,i}$ and $A_{s,c,i}$ are measures of a student's grades and level of peer academic support during the s,c^{th} course. The matrix $\mathbf{X}_{\mathbf{s,c,i}}$ represents a set of student-specific covariates as well as fixed effects. The variables

[7]All students must pass at least one college-level mathematics course and complete two Natural and Physical science courses with labs to obtain their degree. See pages 62-63 of http://www.colostate-pueblo.edu/catalog/Documents/Catalog2011-2012.pdf.

[8]These courses have been identified by CSU - Pueblo as high risk courses (i.e., a 30 percent or greater DFW rate, where D, F, and W, stand for the letter grades "D," "F," and withdraw, respectively.

$\varepsilon_{s,c,i}$ and $\upsilon_{s,c,i}$ represent the residuals of the specifications. Equations (1) and (2) depict the endogeneity issue, in the form of a simultaneous relationship, between course grades and peer academic support. A student's grades potentially affect his or his utilization of peer academic support which, in turn, affects the level of grades obtained.

Assuming equations (1) and (2) are accurate representations of the underlying grade and peer academic support processes, the endogeneity (simultaneity) issue can result in potentially biased and inconsistent estimates of the grade equation (1) if estimated in isolation of the equation peer academic support equation (2). Our primary interest is the estimating of the grade equation and obtaining consistent estimates of β which is the marginal effect of peer academic support on grades. The grade equation can be estimated in a straightforward manner with an instrumental variable (IV) strategy if an observable exogenous variable, $Z_{s,c,i}$, is available and has the following properties:

$$cov\left(Z_{s,c,i}, \varepsilon_{s,c,i}\right) = 0 \text{ and,} \tag{3}$$

$$cov\left(A_{s,c,i}, Z_{s,c,i}\right) \neq 0. \tag{4}$$

One of the potential reasons that much of the research has not adopted an IV approach is difficulty with obtaining a valid instrument. Our data consists of two primary aspects that we leverage to obtain consistent peer academic support estimates in terms of course grades. The first aspect is that our data includes information relating to the level of peer academic support obtained in each of two biology and chemistry courses, and three mathematics courses from 2010 through 2012. The time series nature of our data provides us with a valid instrument for their level of peer academic support utilized at the unit of observation by using a student's previous level of peer academic support across subjects (i.e., biology, chemistry, and mathematics).[9] The second aspect is that university students have generated observable data concerning their prior intrinsic academic capabilities (i.e., American College Testing [ACT] scores) and high school grade point average [GPA]) as well as a measure of their socioeconomic status that are available for analytical purposes.[10,11] The additional information allows us to explain a student's course grades beyond their level of peer academic support and mitigate the possibility that the regression estimates are contaminated from an omitted variable bias. Collectively, the data contains multiple observations across students, as well as detailed information relating to a student's academic capability and socioeconomic status, to allow for an exogenous IV while controlling for important factors that can potential impact course grades.

Data Description

Our data set consists of student-course observations, invariant to whether they received peer academic support. Each student-course observation includes both their grade (i.e., "A," "B," "C," "D," or "F") and the number of SI and/or individual peer academic support sessions

[9] For example, we use a student's number of academic support sessions in Human Physiology and Anatomy I as an instrument for his or her number of student-specific academic support sessions in Human Physiology and Anatomy II.

[10] The ACT is a standardized test for high school achievement and college admissions in the United States produced by ACT, Inc. The ACT consists of multiple choice subject tests in English, mathematics, reading, and science reasoning with scores ranging from 1 to 36.

[11] We obtained the average family income levels by zip codes through the 1999 U.S. Census Bureau. The 1999 U.S. Census Bureau was the most recent zip-code income data available.

received. The data also includes each student's ACT scores, high school grade point average (GPA), high school GPA class percentile rank among their graduating class (henceforth called high school GPA percentile rank), family income, age, race, gender, and whether the student was a varsity athlete.[12] For analysis purposes, letter grades are transformed to numerical grade based on the corresponding points associated with each letter grade (i.e., four points for an A, three points for a B, two points for a C, one point for a D, and zero points for an F). The data set includes 2,220 student-course observations. However, since we seek consistent estimates of the impact of peer academic support, in terms of course grades, we use the student's previous level of peer academic support in the preceding course of a similar subject in the IV strategy resulting in a final data set of 480 student-class observations. Ninety student-class observations (65 SI and 29 individual)[13] of the total 480 student-class observations utilized peer academic support amounting to a total of 552 (410 SI and 142 individual) peer academic support sessions. Twenty of the total 169 mathematics student-course observations utilized individual peer academic support, amounting to 86 individual tutoring sessions (SI was not offered in mathematics). Forty-four (4) of the total 210 biology specific student-course observations utilized SI (individual) peer academic support amounting to 232 (21) SI (individual) support sessions. Twenty-one (5) of the total 101 chemistry specific student-class observations utilized SI (individual) amounting to 178 (35) SI (individual) support sessions. Table 2.1 presents summary statistics.

[12] An example of high school GPA class percentile rank calculation is as follows: a student whose high school GPA ranked 67 out of a graduating class consisting of 250 students has a high school GPA percentile rank of (67/250) x 100 = 26.8. High school percentile ranks range from 1 to 100 with 1 being the best and 100 being the worst rank possible.

[13] Some students utilized both types of academic support.

Although the amount of data available is reduced by using $Z_{s,c,i} = PA_{s,c,i}$, where $PA_{s,c,i}$ denotes a student's previous level of peer academic support, it is, by construction, an exogenous variable that satisfies the property $\left(cov\left(PA_{s,c,i}, \varepsilon_{s,c,i}\right) = 0\right)$, and our goal of consistent estimates of β can be obtained if $PA_{s,c,i}$ can be shown to create a valid instrument for $A_{s,c,i}$ and satisfies the property $\left(cov\left(A_{s,c,i}, PA_{s,c,i}\right) \neq 0\right)$ which will be tested in the first-stage of the IV strategy.

Empirical Model Specifications

To estimate the impact of peer academic support on course grades a number of models are nested within the following specification:

$$NA_{s,c,i} = \alpha_1 + \mathbf{S}'_{\mathbf{s,c,i}}\boldsymbol{\gamma}_1 + \mathbf{FX_c} + \lambda_1 PNA_{s,c,i} + \upsilon^1{}_{s,c,i} \tag{5}$$

$$BA_{s,c,i} = \alpha_2 + \mathbf{S}'_{\mathbf{s,c,i}}\boldsymbol{\gamma}_2 + \mathbf{FX_c} + \lambda_2 PBA_{s,c,i} + \upsilon^2{}_{s,c,i} \tag{6}$$

$$G_{s,c,i} = \alpha_3 + \beta_1 NAIV_{s,c,i} + \beta_2 BAIV_{s,c,i} + \mathbf{S}'_{\mathbf{s,c,i}}\boldsymbol{\theta} + \mathbf{FX_c} + \varepsilon_{s,c,i} \tag{7}$$

The peer academic support equations, represented by equation (5-6), are the first stages and grade equation, represented by equation (7), is the second stage of the IV strategy. The variables $NA_{s,c,i}$ and $PNA_{s,c,i}$ represent the student's number of peer academic support sessions obtained during the s,c^{th} course and its previous subject-course, respectively. The variables $BA_{s,c,i}$ and $PBA_{s,c,i}$ are an indicator variables equaling 1 if the student obtained any peer academic support during the s,c^{th} course and 0 otherwise, and its previous subject-course, respectively. The predicted values from the peer academic support equations denoted by $NAIV_{s,c,i}$, and $BAIV_{s,c,i}$ are used as instruments for peer academic support in the grade equation.

The variable $G_{s,c,i}$ is the i^{th} student numerical grade in the s,c^{th} course. The matrix $\mathbf{S_{s,c,i}}$ and $\mathbf{FX_c}$ denotes a number of student-specific covariates and subject-specific fixed effects, respectively. The student-specific covariates include the student's ACT score, their high school GPA, the high school percentile rank, the natural log of income, the natural log of the student age relative to the start of the s,c^{th} course, and indicator variables that identify whether (1) or not (0) the student is an athlete, male, and white. The subject-specific fixed effects are a complete set of indicator variables identifying the c^{th} course as mathematics, biology or chemistry course, omitting the chemistry fixed effect to avoid perfect collinearity. The terms α_1, α_2 and α_3 denote constant terms, and $\upsilon^1{}_{s,c,i}$, $\upsilon^2{}_{s,c,i}$, and $\varepsilon_{s,c,i}$, denote the residuals. The grade equation assumes constant returns, in terms of course grades, to peer academic support sessions.

The student-specific covariates control for a wide variety of factors that can potentially affect both a student's course grades as well as their usage of peer academic support such as their intrinsic academic capability as measured by previous performance on standardized tests and high school courses as well as their socioeconomic status as measured by income. The student-specific covariates also control for heterogeneity in course-grades and peer academic support across student ages, athlete/non-athletes, gender, and race factors. The subject-specific fixed controls for heterogeneity in course-grades and peer academic support across subjects.

Since we have varying amounts of peer academic support across support session types (i.e., SI and individual) and subjects, our analysis consists of both general and specific model specifications in terms of measuring the impact of peer academic support on grades. The former analysis examines the average impact of the aggregated peer academic support sessions by not distinguishing between peer academic support type (i.e., SI and individual), while the latter analysis examines the impact of type-specific peer academic support both overall (i.e., not across subjects) and across subjects. The general specifications assume constant effects of across peer academic support types and subjects, while the specific specifications allow these effects to vary.

Effects of Peer Academic Support on Course Grades

Impact of Peer Academic Support in Terms of Course Grades

This section presents our analysis of the estimated average impact of the aggregated peer academic support sessions. A total of five model specifications are estimated with each of the first four specifications increasing the number of student-specific covariates and/or fixed effects relative to the previous specification. All specifications include an IV for the number of peer academic support sessions attended $\left(NAIV_{s,c,i}\right)$. Estimated as both a traditional IV and a treatment model, the final specification also includes the IV for the indicator variable that identifies if the student attended at least one peer academic support session during the s,c^{th} course $\left(BAIV_{s,c,i}\right)$.

The first specification is the most parsimonious and includes only the IV for the number of peer academic support sessions attended ($NAIV_{s,c,i}$) as an explanatory variable. The second specification adds the student's ACT composite test score, their high school GPA, their high school percentile rank, and income variables to the first specification. The third specification further adds the age, as well as the indicator variables identifying athletes, male, and white students to the second specification. The fourth specification further adds the subject-specific fixed effects to the third specification. The fifth specification adds the binary peer academic support IV variable to the fourth specification.

First-Stage Results

Table 2.2 presents the IV first stage results for the various instruments used in the specification described earler. Columns (1-4) of Table 2.2 present the estimation results for the IV for the number of peer academic support sessions derived from equation (5). Column (5) presents the IV for the indicator variable that identifies if the student attended at least one peer academic support session derived from the equation (6). Columns (1-4) present results estimated via ordinary least squares (OLS) and column (5) presents results from a parametric Probit regression model estimated via maximum likelihood. The coefficients of the previous number of peer academic support sessions as well as the binary indicator identify whether or not previous peer academic support session were attended are positive and significant at the 0.01 level across all specifications. Regression diagnostics are reported the table footer. The adjusted R-squared statistic values are greater than 0.22 across columns (1 to 4) and the F-statistics of joint significance of the instruments of columns (2 to 4) are 30.37, 16.87, and 14.28, respectively. From the treatment model presented in column (5), the likelihood ratio test that tests whether at least one coefficient of the covariates is not equal to zero is 74.21. Each of the F-statistics and the likelihood ratio test are significant at the 0.01 level. These diagnostics provide general assurance that bias IV estimates due to low explanatory power are not likely.

IV Second-Stage Results

Table 2.3 presents the IV coefficients, as well as the coefficients of the covariates, across the five model specifications described earlier. All of the results presented in Table 2.3 are estimated via OLS. Results from a Tobit regression model that accounts for the inherent censoring of the grade data between zero and four are similar and support an identical conclusion. A Wu-Hausman test for endogeneity rejects the null hypothesis that peer academic support is exogenous (p-value = 0.0119).[14]

The IV coefficient for the number of peer academic support sessions is positive and significant at the 0.01 level in the specifications presented in columns (1 to 4) and ranges from approximately 0.0637 to 0.0804. The IV coefficients of the binary indicator variable and the number of peer academic support sessions from the specification presented in column (5) are 0.5923 and 0.0637, respectively, with the latter coefficient significant at the 0.05 level. The t-statistic for the IV binary variable is approximately 1.12. Using the IV coefficient for the number of peer academic support sessions presented in column (4), approximately 12 to 13 peer academic support sessions increases a student's course grades by a full grade point, all else constant. However, conditioned on the attendance of at least one peer academic support session during a course, students on average only attend 6.3 peer academic support sessions.

The coefficients of the covariates provide some insight into the degree to which the impacts of peer academic support extend beyond other factors that can potentially affect student grades. The magnitudes of the coefficients, and, in most cases, their associated levels of

[14] The Hausman test was tested on the specification presented in column (4) of Table 2.3. Similar results p-values are obtained across the various specifications and support the identical inference.

statistical significance, are similar across specifications. Therefore, for brevity, we restrict our discussion to the results presented in column (4) in Table 2.3. The coefficients for ACT scores and high school GPA are both positive and significant at the 0.01 level. The coefficient for high school percentile rank is approximately is negative (lower high school percentile ranks indicate better performance than higher percentile ranks) with an associated t-statistic that is approximately 1.62. The coefficients for the log of income, age, student-athlete, and male gender are all positive but not statistically significant. The coefficient for the indicator variable that identifies a student's race as white is close to zero and not statistically significant. The direction of the coefficients that estimates a student's a previous academic capabilities, as well as their socioeconomic status, are of the expected sign, with two of the key variables, ACT score and high school grade point average significant at the 0.01 level suggesting that the IV coefficients for the number of peer academic support sessions are beyond a student's intrinsic academic capability as well as other factor that can potential influence the results.

Impacts of SI and Individual Peer Academic Support across Subjects

This section presents an analysis that estimates the impact of both SI and individual peer academic support sessions across subjects with four model specifications. The first two model specifications do not distinguish the impact of peer academic support across subjects while the latter two specifications do distinguish between them. Since there are only 101 chemistry student-course observations and a total of 56 individual peer academic support sessions in biology and chemistry, we analyze the impact of type-specific peer academic support across subjects (i.e., mathematics and science) by aggregating the biology and chemistry peer academic support sessions.

In all specifications, the IVs used in the peer academic support type-specific specifications are created similarly to the general peer academic support IVs used in the Section 3. However, the student's previous level of type-specific peer academic support is used rather than their previous level of peer academic support, is used as an instrument for their level of peer academic support across SI and individual peer academic support types. In the final two specifications that estimate the impact of type-specific peer academic support across subjects, the IVs are interacted with mathematics and science specific indicator variables with the exception of the interaction between the SI IV and mathematics, since SI was not offered for mathematics courses.

In both sets of specifications presented in columns (1 and 2) and (3 and 4), two identical sets of covariates are used to control for factors that can potential influence course grades beyond peer academic support. The first set of covariates are student-specific covariates identical to the ones used in specification presented column (2) of Table 2.3, which includes ACT scores, high school grade point average, high school grade point average rank, and the (log) income variables. The second set of covariates, which is added to the first set, is a set of course-specific fixed effects.

Table 2.4 presents the type-specific peer academic support IV coefficients with columns (1 and 2) and (3 and 4) presenting the overall and across subject results, respectively. Columns (1) and (3) present the results from the specifications that include student-specific covariates, and columns (2) and (4) present the results from specifications that added the subject-specific fixed effects. The first stage of the IV strategy is omitted for brevity and is available from the authors upon request. All of the results presented in Table 2.4 were estimated via OLS.

The coefficients of the student-specific covariates are similar to their respective coefficients in Table 2.3 and support identical conclusions. We explicitly discuss only the IV coefficients for peer academic support presented in presented in columns (2) and (4). From the specifications that do not distinguish across subjects (presented in columns [2]), the impact of an additional SI (individual) peer academic support session on course grades is approximately 0.09 (0.05), and is significant at the 0.01 level (has an associated t-statistics of 1.43). Although these coefficients assume constant returns to peer academic support across subjects, the SI coefficient is entirely weighted by its impact on science courses, and the individual coefficient is heavily weighted by its impact on mathematics courses, while holding constant the course grades with fixed effects. Not accounting for varying returns to peer academic support across subjects, approximately eleven (twenty) SI (individual) peer academic support sessions on average increase a student's science course grade by one full point, holding all else constant.

From the specifications that do distinguish across subjects (presented in column 4) the impact of an additional SI (individual) peer academic support session on science grades is approximately 0.10 (-0.09) and is significant at the 0.01 level (has an associated t-statistic of 0.90). We expect that the negative coefficient of individual peer academic support sessions is a result of limited individual peer academic support science sessions observations. From the specifications that do distinguish across subjects the impact of an additional individual peer academic support session on mathematics grades is approximately 0.06, and is significant at the 0.10 level. Approximately ten (sixteen) SI (individual) peer academic support sessions on average increases a student's science (mathematics) course grades by one full point, holding all else constant.

Nonlinear Effects of Student Academic Capabilities

The analyses presented previously do not account for potential nonlinear effects in student academic abilities on their returns to peer academic support. Separate regressions were estimated for both students of high and low academically capabilities identical to the one presented in column (2) of Table 2.2 that estimated the impact of total peer academic support and includes the key student covariates. Students with high school grade point average greater than 3.22 were considered to be above students with high academic capabilities with the remainder of the students considered to be low resulting in 237 and 243 observations, respectively.[15] The coefficient and associated standard error for the peer academic support IV in the high (low) model was 0.0344 and 0.0345 (0.1000 and 0.0368), respectively. Only the coefficient for peer academic support IV for low students is significant, which it is at the 0.01 level. The coefficients of remaining variables are available from the authors upon request. These results suggest that lower-performing students may potentially benefit more from peer academic support than high-performing students. More data would allow for a more robust analysis and is an area for future research.

[15] High school grade point average of 3.3 was the mean high school grade point average in the sample of data.

Conclusions

Using the student's previous level of peer academic support to disentangle the endogenous relationship between peer academic support and course grades through an instrumental variable strategy, this study rejects the null hypothesis that peer academic support is exogenous to course grades. The estimation results of the peer academic support on the educational achievement suggest that it takes, on average, about twelve additional peer academic support sessions to increase a student's course grade by one full grade point, accounting for their academic capability and socioeconomic status. Allowing the effect to vary across peer academic support type and subjects, it takes on average approximately eleven supplemental instruction and sixteen individual peer academic support sessions to increase a student's science and mathematics course grade by one full grade point, respectively.

This study takes account of the student's academic ability with standardized test scores, high school performance, socioeconomic status as well as other student-specific effects. As a result, there is a relatively small chance that the results are influenced by an omitted variable bias. We find primary evidence that nonlinear effects across student academic levels potential exists and low performing students benefit more from peer academic support than high performing students.

The magnitude of the effects over multiple academic sessions should be interpreted with a caveat. Results are only as accurate as the model describes the underlying relationship. While it appears that we have obtained a valid measurement instrument to measure the average effect, constant returns are assumed to calculate the total impact on course grades in real terms. While our initial data set is large, it is substantially reduced in the derivation of our instrument.

Research that includes additional data could potentially create more flexible model specifications that allows for varying returns to peer academic support.

Based on our findings, we recommend further research in this area and more investment in peer-led support programs at the university level. More data would be beneficial for an econometric analysis similar to the one presented in this paper. However, it would be straightforward for peer academic support managers to design, execute, and track results from experiments relating to peer academic support programs and academic outcomes.

References for Chapter Two

Angrist, J.D., & Lavy, V. (1999). Using Maimonides' rule to estimate the effect of class size on scholastic achievement. *The Quarterly Journal of Economics*, 114(2), 533-575.

Bray, M. & Kwok, P. (2003). Demand for private supplementary tutoring: conceptual considerations, and socio-economic patterns in Hong Kong. *Economics of Education Review*, 22, 611-620.

Buchmann, C. (2002). Getting ahead in Kenya: Social capital, shadow education, and achievement. *Research in the Sociology of Education*, 13, 133-159.

Cameron, S. & Heckman, J. (2001). The dynamics of educational attainment for black, Hispanic, and white males. *Journal of Political Economy*, 109(3), 455-499.

Cheo, R., & Quah, E. (2005). Mothers, maids and tutors: An empirical evaluation of their effect on children's academic grades in Singapore. *Education Economics*, 13(3), 269-285.

Clotfelter, C., Ladd, H. & Vigdor, J. (2009). The academic achievement gap in grades 3 to 8. *The Review of Economics and Statistics*, 91(2), 398-419.

Cook, M. & Evans, W. (2000). Families or schools? Explaining the convergence in white and black academic performance. *Journal of Labor Economics*, 18(4), 729-754.

Dang, H.-A. (2007). The determinants and impact of private tutoring classes in Vietnam,” *Economics of Education Review*, 26, 684-699.

Duncan, G. & Magnuson, K. (2005). Can Family socioeconomic resources account for racial and ethnic test score gaps? *The Future of Children*, 15 (1), 35-54.

Johnston, C. (1997). Collaborative Learning of Economics in a Peer Tutoring Context at the University of Melbourne. *Australian Economic Papers*, 36, 56-68.

Kelley, A. C., & Swartz, C. (1976). Student-to-student tutoring in economics. *Journal of Economic Education*, 8 (1), 52–55.

Kunsch, C. A., Jitendra, A. K., & Sood, S. (2007). The effects of peer-mediated instruction in mathematics for students with learning problems: A research synthesis. *Learning Disabilities Research & Practice, 22*(1), 1-12.

Ehrenberg, R. & Sherman, D. (1987). Employment while in college, academic achievement and post college outcomes. *Journal of Human Resources*, 22(1), 1-24.

Fryer, R. (2003). An Economic Approach to Cultural Capital. Unpublished manuscript, University of Chicago.

Fryer, R. & Levitt, S. (2004). Understanding the black-white test score gap in the first two years of school. *Review of Economics and Statistics*, 86 (2), 447-464.

Fryer, R. & Levitt, S. (2011). The black-white test score gap through third grade. *American Law and Economics Review*, 8 (2), 249-281.

Hanushek, E. (1971). Teacher characteristics and gains in student achievement: Estimation using micro data. *American Economic Review*, 61(2), 280-288.

Hanushek, E. A., Kain, J. F., O'Brien, D. M., & Rivkin, S. G. (2005). The market for teacher quality. (NBER Working Paper 11154). Cambridge, MA: National Bureau of Economic Research.

Hanushek, E.A., Kain, J.F., Markman, J.M. & Rivkin, S.G. (2003). Does peer ability affect student achievement? *Journal of Applied Econometrics*, 18(5), 527-544.

Hanushek, E.A. & Rivkin, S.G. (2009). Harming the best: How schools affect the black-white achievement gap. *Journal of Policy Analysis and Management*, 28 (3), 366-393.

Hill, L., Jr. (1991). Effort and reward in college: A replication of some puzzling findings. *In Replication Research in the Social Science*, J.W. Neuliep, ed., Newbury Park, CA: Sage, pp. 139-156

Hoxby, C.M. (2002). The effects of class size on student achievement: New evidence from population variation. *The Quarterly Journal of Economics*, 115(4), 1239-1285.

Jencks, C. & Phillips, M. (1998). The black-white test score gap. Brookings Institute Press.

Jensen, A. (1973). *Educability and Group Differences.* New York: Free Press.

Lee, J. (2007). Two worlds of private tutoring: The prevalence and causes of after-school mathematics tutoring in Korea and the United States. *Teachers College Record*, 109(5), 1207-1234.

Lee, J.-T., Kim, Y.-B. & Yoon, C.H. (2004). The effects of pre-class tutoring on student achievement: Challenges and implications for public education in Korea. *Journal of Educational Policy,* 1(1), 25-42.

Liu, J. (2012). Does cram schooling matter? Who goes to cram schools? Evidence from Taiwan. *International Journal of Educational Development*, 32(1), 46-52.

Munley, V G., Garvey, E. & McConnell, M.J. (2010). The effectiveness of peer tutoring on student achievement at the university level. *American Economic Review: Papers & Proceedings*, 100, 277-282.

Orr, A. (2003). Black-white differences in achievement: The importance of wealth. *Sociology of Education*, 76, 281-304.

Phillips, M., & Chin, T. (2004). School inequality: What do we know? In K. M. Neckerman, Ed., *Social inequality* (pp. 467–519). New York: Russell Sage Foundation.

Ruhm, C. (1997). Is high school employment consumption or investment? *Journal of Labor Economics*, 15(4), 735-776.

Rivkin, S.G., Hanushek, E.A., & Kain, J.F. (2005). Teachers, schools, and academic achievement. *Econometrica* 73(2), 417-458.

Schuman, H., Walsh, E., Olson, C. & Etheridge, B. (1985). Effort and reward: The assumption that college grades are affected by the quantity of study. *Social Forces*, 63, 945-946.

Stinebrickner, R. & Stinebrickner, T. (2003). Working during school and academic performance. *Journal of Labor Economics*, 21(2), 473-491.

Stinebrickner, R. & Stinebrickner, T. (2008). The causal effect of studying on academic performance. *The B.E. Journal of Economic Analysis & Policy*, 8(1), Article 14.

Stinebrickner, T.R. & Stinebrickner, R. (2004). Time-use and college outcomes. *Journal of Econometrics*, 121(1-2), 243-269

Sacerdote, B. (2001). Peer effects with random assignment: results for Dartmouth roommates. *Quarterly Journal of Economics*, 116(2), 681–704.

Suryadarma, D., Suryahadi, A., Sumarto, S., & Rogers, F. H. (2006). Improving student performance in public primary schools in developing countries: Evidence from Indonesia. *Education Economics*, 14(4), 401–429.

Stevenson, D.L. & Baker, D.P. (1992). Shadow education and allocation in formal schooling: Transition to university in Japan. *American Journal of Sociology*, 97(6), 1639-1657.

Tansel, A. & Bircan, F. (2006). Demand for education in Turkey: A Tobit analysis of private tutoring expenditures. *Economics of Education Review*, 25(3), 303-313.

Yeung, W. & Conley, D. (2008). Black-white achievement gap and family wealth. *Child Development*, 79 (2), 303- 324.

Zhang, Y. (2013). Does private tutoring improve students' national college entrance exam performance?--A Case Study from Jinan, China. *Economics of Education Review*, 32, 1-28.

Zimmer, R., Hamilton, L. & Christina, R. (2010). After-school tutoring in the context of No Child Left Behind: Effectiveness of two programs in the Pittsburgh public schools. *Economics of Education Review*, 29m 18-28.

Zimmerman, D. J. (2003). Peer effects in academic outcomes: evidence from a natural experiment. *Review of Economics and Statistics*, 85 (1), 9–23.

Table 2.1. Summary Statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Numerical grade	1.6854	1.2391	0	4
Number of total AS sessions	1.1500	4.6840	0	67
Number of SI sessions	0.8542	4.2519	0	67
Number of individual sessions	0.2958	1.9201	0	31
SI indicator	0.1354	0.3425	0	1
Individual indicator	0.0604	0.2385	0	1
Lag number of AS sessions	1.9458	5.7879	0	67
Lag number of SI	1.6125	5.2244	0	67
Lag number of IND	0.3333	2.2237	0	39
Lag tutoring indicator	0.2979	0.4578	0	1
Lag SI indicator	0.2500	0.4335	0	1
Lag individual indicator	0.0729	0.2603	0	1
Age	20.6292	1.4890	18	29
White	0.5354	0.4993	0	1
Black	0.1021	0.3031	0	1
Hispanic	0.2979	0.4578	0	1
Other	0.0396	0.1952	0	1
Male indicator	0.3646	0.4818	0	1
Athlete indicator	0.0583	0.2346	0	1
ACT score	21.0188	3.4189	11	31
high school GPA	3.2503	0.5530	1.9300	4.7500
high school GPA rank	0.3618	0.2092	0.0048	0.8728
Family Income	52650	15116	31571	139428
Math course indicator	0.3521	0.4781	0	1
Biology course	0.4375	0.4966	0	1

Note: Number of observations is 480. AS and SI denote peer academic support and supplemental instruction, respectively.

Table 2.2. IV First-Stage Regression Results

Dependent variable:	Number of Tutoring Sessions				Tutoring Indicator
	(1)	(2)	(3)	(4)	(5)
Previous number of AS sessions	0.3837***	0.3619***	0.3627***	0.3531***	
	(0.0326)	(0.0334)	(0.0336)	(0.0340)	
Previous AS indicator					0.8555***
					(0.1555)
ACT score		-0.1852***	-0.1795***	-0.2091***	-0.0924***
		(0.0606)	(0.0633)	(0.0646)	(0.0255)
High school GPA		0.4867	0.5956	0.4517	0.1873
		(0.7190)	(0.7389)	(0.7423)	(0.2943)
High school GPA rank		0.0778	0.2745	0.2223	0.3493
		(1.8911)	(1.9150)	(1.9102)	(0.7590)
Log income		1.3833*	1.4710*	1.4623*	0.3817
		(0.7747)	(0.7833)	(0.7824)	(0.2937)
Log age			-0.4600	-0.2490	0.5356
			(2.9484)	(2.9489)	(1.1135)
Athlete indicator			0.0259	0.0354	-0.0918
			(0.8199)	(0.8190)	(0.3097)
Male indicator			0.0157	-0.0897	-0.3673**
			(0.4194)	(0.4289)	(0.1753)
White indicator			-0.3809	-0.3425	-0.2184
			(0.3935)	(0.3930)	(0.1537)
Math course				-1.0704*	-0.4734**
				(0.5578)	(0.2206)
Biology course				-1.0270*	-0.3596*
				(0.5269)	(0.1936)
Constant	0.4034**	-12.2620	-12.1713	-10.7441	-5.2584
	(0.1988)	(8.4612)	(12.8199)	(12.8641)	(4.8198)
Observations	480	480	480	480	480
Model	OLS	OLS	OLS	OLS	Probit
Adjusted R-squared	0.223	0.235	0.230	0.234	
pseudo R-sq					0.160
F-stat	138.6	30.37	16.87	14.28	
LR chi2					74.21

Notes: ***, **, *, indicates significance at the 1, 5, and 10 percent levels, respectively.

Table 2.3. Impact of Peer Academic Support on Grades

	(1)	(2)	(3)	(4)	(5)
IV total number of AS session	0.0770***	0.0637**	0.0639**	0.0804***	0.0637**
	(0.0261)	(0.0255)	(0.0255)	(0.0265)	(0.0299)
IV tutoring indicator					0.5923
					(0.5277)
Act score		0.0638***	0.0654***	0.0829***	0.0922***
		(0.0181)	(0.0187)	(0.0196)	(0.0209)
High school GPA		0.4807**	0.4812**	0.5644***	0.5451***
		(0.1993)	(0.2040)	(0.2046)	(0.2008)
High school GPA rank		-0.8295	-0.8793*	-0.8506	-0.8871*
		(0.5227)	(0.5263)	(0.5254)	(0.5148)
Log income		0.1607	0.1644	0.1624	0.1262
		(0.2236)	(0.2255)	(0.2255)	(0.2228)
Log age			0.7766	0.7649	0.7364
			(0.8112)	(0.8119)	(0.7944)
Athlete indicator			0.1252	0.1392	0.1485
			(0.2255)	(0.2254)	(0.2206)
Male indicator			0.0527	0.0693	0.1269
			(0.1154)	(0.1181)	(0.1264)
White indicator			0.0067	-0.0092	0.0107
			(0.1085)	(0.1083)	(0.1074)
Mathematics course indicator				0.6121***	0.6812***
				(0.1607)	(0.1687)
Biology course indicator				0.4069***	0.4416***
				(0.1498)	(0.1497)
Constant	1.5969***	-2.7324	-5.1687	-6.1711*	-5.9769*
	(0.0652)	(2.4069)	(3.5718)	(3.5765)	(3.5019)
Observations	480	480	480	480	480
Adjusted R-squared	0.150	0.153	0.149	0.149	0.206

Notes: ***, **, *, indicates significance at the 1, 5, and 10 percent levels, respectively. AS denotes academic support.

Table 2.4. Impact of Peer Academic Support on Course Grades Across Subjects

	(1)	(2)	(3)	(4)
IV individual AS sessions	0.0522	0.0504		
	(0.0351)	(0.0352)		
IV SI AS sessions	0.0662**	0.0897***		
	(0.0318)	(0.0335)		
IV science individual AS sessions			-0.1511	-0.0933
			(0.1008)	(0.1037)
IV science SI AS sessions			0.0703**	0.0953***
			(0.0324)	(0.0339)
IV mathematics AS sessions			0.0691*	0.0626*
			(0.0367)	(0.0367)
ACT score	0.0628***	0.0787***	0.0563***	0.0733***
	(0.0176)	(0.0184)	(0.0177)	(0.0186)
High school GPA	0.4722**	0.5378***	0.4763**	0.5297***
	(0.1993)	(0.1975)	(0.1989)	(0.1975)
High school GPA rank	-0.8516*	-0.8607*	-0.8980*	-0.8935*
	(0.5165)	(0.5116)	(0.5163)	(0.5120)
Log income	0.1630	0.1573	0.1581	0.1440
	(0.2203)	(0.2183)	(0.2210)	(0.2193)
Mathematics course indicator		0.6212***		0.5615***
		(0.1610)		(0.1636)
Biology course indicator		0.3861***		0.3418**
		(0.1435)		(0.1457)
Constant	-2.6985	-3.5893	-2.4895	-3.2422
	(2.3989)	(2.3689)	(2.4094)	(2.3915)
Observations	480	480	480	480
Adjusted R-squared	0.191	0.207	0.192	0.207

Notes: ***, **, *, indicates significance at the 1, 5, and 10 percent levels, respectively. AS and SI denote academic support and supplemental instruction, respectively.

CHAPTER THREE:

THE IMPACT OF NATIVE AMERICAN CASINOS ON THE DROPOUT RATE OF NATIVE AMERICAN HIGH SCHOOL STUDENTS

Abstract:

Native American high school students have the highest dropout rates of any race in the United States. Many Native American high school students receive cash payouts from Indian Casino profits. In this article, we analyze the impact of the size and payout requirements of trust funds on the dropout rate of Native American high school students. Tribes that make per capita payments to enrolled members must decide how to distribute the per capita payments to minor children. Tribes can pay the funds to the minor, deposit the funds in a trust fund or pay part of the funds and deposit the rest. If the minors have trust funds, the tribe has to decide the requirements the minor must meet in order to withdraw funds. Tribes have age requirements and/or high school graduation requirements.

Introduction

Race and income are strong predictors of high school completion rates. The dropout rate is calculated as the percent of students who leave a school the school year without getting a high school diploma or a passing a General Educational Development (GED) test. In the 2009-10 school year, the National Center for Education Statistics found that the dropout rate was the lowest for Asian/Pacific Islander students at 1.9 percent and Caucasian students at 2.3 percent. The dropout rates for American Indian/Alaska Native, African American, and Hispanic students are 6.7 percent, 5.5 percent, and 5.0 percent, respectively. Income is another important predictor of dropout rate. In 2010, across all income levels, 7.4 percent of 16 to 24 year old high school students dropped out. The dropout rates by income quartile lowest to highest were 13.8 percent. 8.9 percent, 5.1 percent and 2.5 percent, respectively.

Historically Native Americans have been some of the poorest Americans. Indian casinos have increased the average Native American's income by providing employment and disbursing per capita payments to enrolled members. Indian casinos are built on Native American reservations, which typically have high unemployment rates. The casinos generate an increase in demand for unskilled labor. Per capita payments are paid to enrolled tribal members from profits from Indian casinos. Only about a quarter of tribes with casinos pay per capita payments[16]. This money is put in trust funds for minors and can only be accessed when the child reaches a certain age. This age ranges from 18 to 24. The amount ranges from $5,000 to $200,000 or more.

[16] NIGA, http://www.nigc.gov/nigc/index.jsp

History of Indian Casinos

Gambling has always been a part of the Native American culture. For hundreds of years Indian tribes have played stick games, bones, and other games of chance at celebrations and tribal ceremonies. Tribes entered into large-scale gambling in the late 1970's in an attempt to bring economic activity to reservations and fund tribal governments. Tribes and states have been disputing the legalization of tribal casinos ever since. The Seminole Tribe in Florida was instrumental in securing the legal basis for Indian gaming. The Seminole Tribe opened a bingo hall in the 1970's. The sheriff of Broward County asserted that the tribal bingo was illegal because it did not follow state regulations. It was open longer hours and paid out larger prizes than allowed. The trial court ruled against the tribe, but the United States Court of Appeals of the Fifth Circuit ruled in favor of the tribe. The verdict was based on a precedent case that ruled the states could not prohibit tribal bingos because they have no regulatory power over the tribes.

This previous case was *Bryan v. Itasca*. In this case, Russell Bryan, a Chippewa Indian sued the State of Minnesota and Itasca County because the state ordered him to pay personal property taxes on his mobile home that was located on tribal trust land. The trial court ruled in favor of the state, but Bryan appealed the decision. On June 14, 1976, the U.S. Supreme Court overturned the verdict, stating that the state's jurisdiction over tribes was limited to criminal and private civil matters. This means the states cannot apply their regulatory laws within reservation borders. This was a case about the meaning of an Act of Congress (Public Law 280) that gave states some jurisdiction over tribes.[17] The states believed this Act gave them complete jurisdiction over tribes.

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[17] United States. Public Law 280. 15 Aug. 1953. 20 July 2005.

In 1987 in the *State of California v. the Cabazon Band of Mission Indians,* the U.S. Supreme Court confirmed Native American tribes are exempt from state regulatory laws by finding tribal governments have the authority to establish gaming operations independent of state regulation if gambling is allowed in that state. This allowed more tribes to enter into the gaming industry leading to the boom of tribally owned casinos in the 1990's.

In 1988, in response to the ruling in the *State of California v. the Cabazon Band of Mission Indians,* Congress passed Public Law 100-497, the Indian Gaming Regulatory Act (IGRA)[18]. This act established the legal framework for Indian gaming. The purpose of the IGRA is to provide a statutory basis for the operation and regulation of gaming, make sure gaming profit is spent as allowed by law, protect the tribes from organized crime, and ensure the gaming is fair.

Although not mandatory for most types of gaming, the majority of tribes sign Tribal-State compacts. Compacts are government-to-government legal agreements between a state and a tribe over what types of gaming the tribe will undertake. A compact contains regulations for which laws, tribal or state, will apply, licensing requirements for employees of the gaming facility and the cost of implementing the regulations. Compact negotiations are only required if the tribe is entering into Class III gaming. The IGRA divided Indian gaming into three classes. Class I gaming is social games solely for prizes of minimal value or traditional forms of Indian gaming engaged in by individuals as a part of, or in connection with, tribal ceremonies or celebrations. Class II gaming is bingo, pull-tabs, lotto, punch boards, and other games similar to

[18] Now codified as 25 U.S.C. §2701

bingo. Class III gaming is all forms of gaming that are not class I gaming or class II gaming.[19] Class III gaming is commonly referred to as casino gaming.

Literature Review

The high school dropout rate decision is effected by many factors. These include family income and the opportunity cost of attending school. A casino will affect both of these factors for American Indian students. The family income will increase if the tribe makes per capita payments. As family income increases, the dropout rate decreases. The opportunity costs of attending school include the foregone earning the student must give up in order to attend school thus local labor market conditions will affect the dropout rate. If there are decent paying jobs available for low skilled workers, the opportunity cost of attending school increases leading to some students dropping out of school in order to work. This effect is greater for American Indians because all tribes have Native preference in hiring decisions. These opposing forces make the prediction for the casinos effect on the community unclear.

Rees and Mocan (1997) use panel data estimation methods on New York public high school and found a negative relationship between the unemployment rate and high school dropout rate. They found that educational inputs such as teacher experience, students per teacher, were not predictors of the dropout rate.

Evans and Topoleski (2002) use a difference-in-difference framework to examine the economic and social impact that Indian casinos have had on reservations and the surrounding communities. They compare economic outcomes before and after tribes opened casinos to

[19] 25 U.S.C. 2703

outcomes of tribes that have not opened casinos. They found that four years after tribes open casinos, employment increased by 26 percent

Geisler and Nichols (2013) used a difference in differences model to examine the impact of Riverboat casinos on host and neighboring counties. They found that real per capita income increased and unemployment decreased in host counties. The results were similar for neighboring counties but to a lesser degree.

Wenz (2008) used a propensity score matching estimator to examine the impact of casino gambling on the welfare of local residents. He found that while casinos have no statistically significant net impact on the quality of life in their host counties, Native American casinos do increase employment is their host counties.

King and Kanzler (2002) analyzed the economic impact of Indian casinos in the state of Washington and found that tribes that opened casinos showed significant improvements in employment and median household income.

Hill and Groothius (2010) used census data to examine the effects of per capita tribal payments on work and schooling decisions of the recipients of these payments. They found that recipients work less but could draw no conclusion on educational attainment.

Conner and Taggart (2013) used census data from 1990 and 2000 and found that members of Class III gaming nations that made per capita payments had higher incomes and lower unemployment by the end of the decade.

Using restricted-use data from the1990 and 2000 Census long-form, Evans and Kim (2005) use a difference in difference model to look at the effect of Indian casinos on the demand for education. They found that opening a casinos increased employment and the dropout rates of all people living on reservations with casinos and it reduced entrance to college for all people living on reservations with casinos. This research expands on this study. Since Native American enterprises have Indian preference in employment decisions these effects would be greater for Natives.

Data Description

The first part of our data set consists of demographic and school graduation and dropout rates at the school level for all public high schools in Washington State. This data was accessed from the state of Washington Office of Superintendent of Public Instruction for the 2002-03 school year until the 2008-09 school year. The demographic data includes the school district, county, type of school (e.g. elementary, middle school, senior high school), average years of teacher experience, percentage of teachers with at least a master's degree and students per teacher. The graduation and dropout rates data has information on all, American Indian, Asian Pacific Islander, Black, Hispanic, and White, limited English, special education, low income, female, male, and state wide. The data had information at the individual school level on the number of students in each grade, number of dropouts in each grade, number continuing, number of on time graduates, size of cohort and number of late graduates for each of the different type of student listed above. Because state law requires each school to maintain a ratio of at least 46 basic education certificated instructional staff (includes teachers, teacher librarians, guidance counselors, certificated student health services staff) to one thousand annual average full-time equivalent

(FTE) students[20] schools were dropped if the number of students per classroom teacher was greater than 30.[21] This left 2911 observations.

The second part of our data set is information on the Indian casinos in Washington State. There are 29 federally recognized tribes in the state. Of those, 23 tribes have casinos and an additional 2 have tribal lotteries. Sixteen tribes make per capita payments to tribal members. Nine tribes make the payments with funds from casinos, 2 make the payments from tribal lotteries, and 5 make the payments with other sources (i.e. fishing, settlements, and timber). This data contains the tribe that owns the casino, the cities and counties of the casino and tribe, the date the casino opened and the numbers of slots and table games. This list of Indian casinos, the tribal owners and locations was compiled from the Gaming Tribe Report from the National Indian Gaming Commission. The opening date for each casino was found on Access Washington. The number of slots and table games was found on the tribal culture information website 500nations.com.

The schools were matched with a casino by county and a distance was found. If more than one casino was located in that county, then a Google maps search was conducted to find the closest casino. If there was no a casino located in that county, then every casino located in neighboring counties was checked to find the closest casino. The location of each casino within its county was also noted to check if a casino not located in an adjacent county was closer.

Each tribe was matched with the school that students who live on that reservation would attend. This was done either by tribal or school website or Google maps. Each tribe was matched

[20] Washington state law RCW 28A.150.100

[21] 1000/46= 21.73 staff members. This number includes classroom teacher, teacher librarians, guidance counselors, certificated student health serves staff and other certificated instructional staff. The number in our dataset is students per teacher so we allowed the ratio up to 30.

with a per capita payment found on a Washington State Department of Social and Health Services handout on per capita payments to each tribal member.

Unemployment rates for each county by year were downloaded from the Employment Security Department of Washington State. And a dummy variable was made for the top 10 counties by population[22] from US Census data. The summary statistics for all applicable variables are in Table 3.1.

Empirical Model

We used a nested ordinary least squares (OLS) model to describe the underlying relationship between high school dropout rate and the presence of an Indian casino. It can be describes as follows:

$$D_{s,y} = \beta_1 X_{1s,y} + \beta_2 P + \gamma Z_{s,y} + \varepsilon_{s,y} \qquad (1)$$

Where *s* and *y* denote the school and year respectively and D is the school's dropout rate. X is a matrix of different casino measures. Z is a matrix of school specific and county specific covariates as well as fixed effects. The variable ε represents the residuals of the specification.

The variable D takes many forms. In some models D is the dropout rate of all students in grades 9-12. It represents the dropout rate of only Twelfth grade students in other models. It also represents the dropout rate of only certain races, i.e. American Indian, black, white. The matrix X contains a dummy variable for if the school is located in a county with an Indian casino,

[22] The top ten counties by population were unchanged from 2000 to 2010.

distance from the school to the casino, number of years the casino has been open, and number of slot machines. *P* is a dummy variable equal to one if it is the school that students who live on a reservation would attend and if that tribe pays out a per capita payment to tribal members and zero otherwise. ***Z*** is a matrix of school specific covariates that control for a wide variety of factors that can affect the dropout rate. It includes students per teacher, number of students, a dummy variable equal to 1 if the school only contains grades 9-12, percentages of American Indian and White students, percentages of limited English and free or reduced lunch students, the county unemployment rate, and district and county fixed effects.

Empirical Results

Estimation Results for All Students

This section presents our analysis of the dropout rate of all students in grades 9-12. The results are in Table 3.2. In all specifications the casino coefficient is positive and significant at the 0.01 or .05 level. It ranges from 0.0108 to 0.0406. This shows that counties with Indian casinos have higher dropout rates. Since Indian casinos are typically built in economically depressed areas this increase in dropout rate could be from numerous factors. The coefficients for Indian casino within 10 miles are also positive and significant. To separate out the effects of the casino from other environmental factors that could affect the dropout rate fixed effects models were used. Columns 1 and 2 in Table 3.3 have school district fixed effects, and columns 3 and 4 have county fixed effects. There are 269 districts and 39 counties in our data set. In column 1, the district specification, the variable indicating the presence of a casino in the county is not significant, but the distance between the school and the closest casino is negative and significant, providing evidence that as the distance increases, the dropout rate declines and fewer students drop out. In column 3, both the casino and the distance variables are significant. The variable indicating the presence of an Indian casino is located less than ten miles away from the school is positive in both the district and county specifications. This indicates that schools with locations closer to Indian casinos have high higher dropout rates. The effect of the per capita payment variable is negative and significant only in the district specifications. This could be because tribes only payout per capita payments if the tribe is profitable. This could signify a good local economy which could translate into higher incomes for reservation residents. The county unemployment rate variable is negative and significant in all specifications. This indicates that when the unemployment rate is high, the dropout rate tends to be lower. This is consistent with previous literature. The other student and school coefficients have the expected signs.

Estimation Results for American Indians

This section presents our analysis of the dropout rate of Native American students. These results are located in Table 3.4. Columns 1 and 2 are the dropout rate for all grades. The remaining four regressions are the Native American dropout rate by grade. The demographic, school and county unemployment variables have the expected signs and are similar in magnitude to the results for all students in Table 3.2. The casino variable is positive and significant in all specification except the twelfth grade specification. The per capita payment variable is only significant for twelfth grade. Owing to rules requiring recipients of these payments to be adults, the payments only affect students who have reached eighteen years old. These results are robust across different specifications and are in Table 3.6.

Estimation Results for White Students

This section presents our analysis of the dropout rate of white students. The results are in Table 3.5. The demographic and school variables all have the expected signs and are similar in magnitude to the results for all students. The unemployment variable is only significant at one percent for all white students and twelfth grade students. (It is significant for ninth grade students at the ten percent level). The casino variable is positive and significant for all specifications. The per capita variable is not significant in any specification, as would be expected. The per capita variable should not have any effect on white students since recipients must be members of the Indian tribe that makes the payment.

Table 3.7 presents three different specifications for American Indian and white twelfth grade students. In all specifications for white students the casino in the county variable is positive and significant. The distance variable is also positive and significant in the two specification in which it is included for White students. The county unemployment rate variable is negative and significant in two specifications. This variable is not significant in the last column. This could be because the dummy variable for top ten counties by population is picking up some of this effect. All other variables for white students have the expected signs and magnitudes including the per capita dummy variable.

Neither the casino variable nor the distance variables are significant for American Indian students. The per capita dummy is positive and significant for American Indian students. This indicates that if the tribe pays out per capita payments then the dropout rate is higher for American Indian students that attend schools that are located on or near that tribe's reservation. Most likely the American Indian students who live on or near a particular tribal reservation are members of that tribe.

Estimation Results by Grade in School

This section presents our analysis of the dropout rate by grade. The results are in Table 3.6. The demographic and school variables all have the expected signs. The county unemployment variable is negative and significant for eleventh and twelfth graders. It might not be significant for younger students because with the restriction on how many hours teenagers under 16 years of age may work in a week, the teenager has no incentive to quit school to work. The casino coefficient is positive and significant in all regressions. The distance coefficient is negative and significant for all specifications. The per capita coefficient is not significant for any specification.

Conclusions

Using Washington state public school dropout rates we have found that in counties with casinos the dropout rate is higher. We controlled for the economic environment with county level unemployment and controlled for various factors in school quality including students per teacher, number of students, type of school and the percentage of low income students. We also found that this result is more profound if the school is in close proximity to the casino. We also added per capita information. As expected whether or not the tribe pays out per capita payments to tribal members only affects older Native American students. Tribes have regulations on who receives the payment and all tribes in our data set put minors' payments in trust funds that are available sometime after the child turns eighteen.

The per capita payment could affect the student's school choice in two ways. First, the payment itself could affect the students desire to stay in school. This payment is made to all enrolled members eighteen and over in a tribe that makes per capita payments. Second, the trust fund could also affect this choice as well. This fund has certain requirements. All tribes in the sample require members to be eighteen years old. Most of the tribes also require a high school diploma or GED. If the student does not graduate or get a GED, then the individual must wait until he or she is 21 years old to receive their trust fund money will still receive per capita payments. Tribes vary in their adherence to their trust fund payout policies. Many have the graduation requirement but this requirement can be waived upon request to the tribal council.

While Indian casinos have increased Native American's income through per capita payments and employment this increase has not led to a decrease in Native American dropout rates. This could be because the casino offers employment. Poor students or students that do not like school have another option. To increase graduation rates tribes could require a diploma or GED for employment. The per capita payments could also affect the student's school decision. The student could use the money to make poor choices that affect their attendance, which in turn affects their grades. This would make a student more likely to dropout. To decrease this effect, tribes could offer guidance to young tribal members about short term choices affecting long term goals or by having graduation requirements for per capita payments similar to the trust funds requirements.

A more in-depth analysis needs to be done to separate out these differing results of Indian casinos. The tribes in Washington that payout per capita payments have similar payout structures with little diversity, so expanding the sample area to a few more states would help. By law, tribes must use casino profit to benefit tribal members and their community. The increase in the dropout rate by tribal members and non-tribal members alike is an unintended consequence.

References for Chapter Three

500 Nations, http://500nations.com/Indian_Casinos.asp

Access Washington, Summary of Compact & Amendments, http://www.wsgc.wa.gov/tribal/docs/tribe-update.pdf

Bryan v. Itasca County. No. 426 U.S. 373. United States Supreme Court. 14 June 1976. 08 Aug. 2005 <http://http://www.justia.us/us/426/373/>.

California v. Cabazon Band of Mission Indians. No. 82-1708. U.S. Supreme Court. 25 Feb. 1986. 20 July 2005 <http://caselaw.lp.findlaw.com/scripts/getcase.pl?court=US&vol=480&invol=202>.

Conner, T. W., & Taggart, W. A. (2013). Assessing the Impact of Indian Gaming on American Indian Nations: Is the House Winning? *Social Science Quarterly*, *94*(4), 1016-1044

Department of Health and Social Services, Tribal Income, available at http://www.dshs.wa.gov/pdf/manual/Tribal%20Income.pdf

Evans, W., & Kim, W. (2006). The Impact of Local Labor Market Conditions on the Demand for Education: Evidence from Indian Casinos. *US Census Bureau Center for Economic Studies Discussion Paper*, 06-14.

Employment Security Department of Washington State, Local Unemployment Statistics, Annual averages. Available at https://fortress.wa.gov/esd/employmentdata/reports-publications/regional-reports/local-unemployment-statistics

Evans, William N., and Julie H. Topoleski. 2002. The Social and Economic Impact of Native American Casinos. *NBER Working Paper No. 9198*.

Geisler, Karl R. and Nichols, Mark W., (2013) Riverboat Casino Gambling Impacts on Employment and Income in Host ,and Surrounding Counties. UNR Economics Working Paper Series Working paper No. 13-005

Hill, James R., Groothuis, Peter A.,(2012) The effects of Per Capita Tribal Payments on the Fertility, Education, and Labor Force Participation of Tribal Members, Business and Economic Research Vol.2 No.2

King, Cheryl, Simrell; Kanzler, Casey, Background to Dream: Impacts of Tribal Gaming in Washington State. First American Education Project, 2002.

National Indian Gaming Commission. 01 July 2005 <http://www.nigc.gov/nigc/index.jsp>.

National Indian Gaming Commission, Gaming Tribe Report. http://www.nigc.gov/Portals/0/NIGC%20Uploads/readingroom/listandlocationoftribalgamingops/state1.pdf

Rees, D., Mocan, H., (1997) Labor Market Conditions and the High School Dropout Rate: Evidence from New York State, *Economics of Education Review*, 16, 2, 103-109.

State of Washington Office of Superintendent of Public Instruction https://www.k12.wa.us/DataAdmin/default.aspx

Stillwell, R,. Sable, J. (2003). Public School Graduates and Dropouts from the Common Core of Data: School Year 2009-10: First Look (Provisional Data) (NCES 2013-209rev). U.S. Department of Education. Washington, DC: National Center for Education Statistics. Retrieved March 4, 2014 from http://nces.ed.gov/pubsearch

Snyder, T.D., and Dillow, S.A. (2013), Digest of Education Statistics 2012 (NCES 2014-015). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, D.C.

Washington State Department of Transportation, Population Growth in Relation to the State's Counties.

Wenz, M. (2008). Matching estimation, casino gambling and the quality of life. *The Annals of Regional Science, 42*(1), 235-249.

Table 3.1 Dropout Summary Statistics

Variable	Obs	Mean	Std. Dev.
annual dropout rate	2911	0.070689	0.098973
9th grade dropout rate	2805	0.053935	0.113241
10th grade dropout rate	2889	0.058431	0.101672
11th grade dropout rate	2884	0.072447	0.115186
Twelfth grade dropout rate	2867	0.094484	0.149054
American Indian dropout rate	2574	0.093978	0.16268
9th grade American Indian dropout rate	1977	0.0676	0.170544
10th grade American Indian dropout rate	2164	0.076682	0.182576
11th grade American Indian dropout rate	2120	0.092093	0.193987
Twelfth grade American Indian dropout rate	2004	0.118432	0.23067
White dropout rate	2902	0.066751	0.099883
9th grade White dropout rate	2754	0.048617	0.115284
10th grade White dropout rate	2852	0.053061	0.107192
11th grade White dropout rate	2848	0.067893	0.117968
Twelfth grade White dropout rate	2828	0.08884	0.150006
distance to nearest American Indian casino	2911	34.97918	29.76224
schools with only grades 9-12	2911	0.722776	0.447705
number of students	2911	675.01	644.7336
students per classroom teacher	2911	16.06046	5.061456
county unemployment rate	2911	0.066437	0.020596
tribe pays per capita	2911	282.406	1732.431
TOP10	2911	0.59842	0.490302
< 10 miles to casino	2911	0.184816	0.388215

Table 3.2 Estimation Results for Dropout Rate: All Students

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Casino	0.0133**	0.0108**	0.0566***	0.0406***			
	(0.0053)	(0.0049)	(0.0076)	(0.0078)			
Distance between school and closest casino			-0.0146***	-0.0097***			
			(0.0019)	(0.0019)			
Less than10 miles to casino					0.0269***	0.0311***	0.0251***
					(0.0049)	(0.0046)	(0.0046)
Tribe pays per capita		0.0036	-0.0037	0.0047		-0.0057	0.0026
		(0.0087)	(0.0086)	(0.0086)		(0.0087)	(0.0086)
County unemployment rate	-0.2555***	-0.3398***	-0.2402***	-0.0920	-0.2037**	-0.2864***	-0.0912
	(0.0893)	(0.0839)	(0.0840)	(0.0853)	(0.0887)	(0.0831)	(0.0847)
Student-teacher ratio		0.0507***	0.0459***	0.0395***		0.0487***	0.0403***
		(0.0054)	(0.0054)	(0.0054)		(0.0054)	(0.0054)
Number of students		-0.0359***	-0.0360***	-0.0376***		-0.0362***	-0.0380***
		(0.0017)	(0.0017)	(0.0017)		(0.0017)	(0.0017)
Schools with only grades 9-12		0.0444***	0.0425***	0.0386***		0.0447***	0.0396***
		(0.0046)	(0.0046)	(0.0046)		(0.0046)	(0.0046)
TOP10				0.0321***			0.0359***
				(0.0041)			(0.0039)
Constant	0.0762***	0.1224***	0.1313***	0.1318***	0.0797***	0.1301***	0.1333***
	(0.0074)	(0.0138)	(0.0137)	(0.0135)	(0.0063)	(0.0134)	(0.0132)
Observations	2911	2911	2911	2911	2911	2911	2911
Adjusted R-squared	0.004	0.139	0.157	0.174	0.012	0.151	0.174

Notes: ***, **, *, indicates significance at the 1, 5, and 10 percent levels, respectively.

Table 3.3. Estimation Results for Dropout Rate (Fixed Effects)

	(1)	(2)	(3)	(4)
Variable	District		County	
Casino	0.0279		0.0184*	
	(0.0194)		(0.0095)	
Distance between school and closest casino	-0.0136**		-0.0046*	
	(0.0060)		(0.0026)	
Less than10 miles to casino		0.0275***		0.0130***
		(0.0092)		(0.0049)
County unemployment rate	-0.3573***	-0.3725***	-0.3666***	-0.3617***
	(0.0895)	(0.0893)	(0.0992)	(0.0989)
Student-teacher ratio	0.0090	0.0093	0.0304***	0.0307***
	(0.0061)	(0.0061)	(0.0056)	(0.0056)
Number of students	-0.0471***	-0.0471***	-0.0383***	-0.0384***
	(0.0018)	(0.0018)	(0.0017)	(0.0017)
Only grades 9-12	0.0441***	0.0440***	0.0387***	0.0391***
	(0.0058)	(0.0058)	(0.0046)	(0.0046)
Tribe pays per capita	-0.0309**	-0.0323**	-0.0041	-0.0052
	(0.0146)	(0.0147)	(0.0090)	(0.0090)
Constant	0.4043***	0.3917***	0.1624***	0.1606***
	(0.0279)	(0.0273)	(0.0221)	(0.0211)
Observations	2911	2911	2911	2911
Adjusted R-squared	0.367	0.366	0.210	0.212

Notes: ***, **, *, indicates significance at the 1, 5, and 10 percent levels, respectively.

Table 3.4. Estimation Results for Dropout Rate: American Indian Students

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	9th	10th	11th	Twelfth
Casino	0.0211**	0.0615***	0.0596***	0.0350**	0.0816***	0.0314
	(0.0092)	(0.0139)	(0.0169)	(0.0170)	(0.0180)	(0.0221)
distance between school and casino		-0.0136***	-0.0140***	-0.0078*	-0.0175***	-0.0050
		(0.0034)	(0.0041)	(0.0042)	(0.0045)	(0.0055)
Tribe pays per capita		-0.0018	-0.0050	-0.0038	-0.0038	0.0395*
		(0.0150)	(0.0167)	(0.0172)	(0.0184)	(0.0220)
County unemployment rate	-0.516***	-0.5309***	-0.1228	-0.4870**	-0.4173**	-0.7543***
	(0.1563)	(0.1568)	(0.1895)	(0.1947)	(0.2083)	(0.2597)
Student-teacher ration		0.0914***	0.0743***	0.0748***	0.0848***	0.1218***
		(0.0120)	(0.0167)	(0.0166)	(0.0174)	(0.0218)
Number of students		-0.0429***	-0.0321***	-0.0381***	-0.0421***	-0.0468***
		(0.0038)	(0.0054)	(0.0052)	(0.0055)	(0.0069)
Only grades 9-12		0.0272***	0.0126	0.0171	0.0203*	0.0128
		(0.0088)	(0.0113)	(0.0116)	(0.0124)	(0.0154)
Constant	0.1101***	0.1001***	0.0455	0.1161***	0.1066***	0.0968*
	(0.0129)	(0.0283)	(0.0374)	(0.0379)	(0.0407)	(0.0502)
Observations	2574	2574	1977	2164	2120	2004
Adjusted R-squared	0.005	0.058	0.023	0.026	0.035	0.027

Notes: ***, **, *, indicates significance at the 1, 5, and 10 percent levels, respectively.

Table 3.5. Estimation Results for Dropout Rate: White Students

	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	9th	10th	11th	Twelfth
Casino	0.0127**	0.0553***	0.0318***	0.0364***	0.0501***	0.0786***
	(0.0054)	(0.0078)	(0.0098)	(0.0087)	(0.0096)	(0.0122)
School-casino distance		-0.0143***	-0.0111***	-0.0109***	-0.0143***	-0.0153***
		(0.0019)	(0.0024)	(0.0021)	(0.0024)	(0.0030)
Tribe pays per capita		-0.0095	-0.0092	-0.0097	-0.0058	-0.0047
		(0.0089)	(0.0110)	(0.0099)	(0.0110)	(0.0138)
Unemployment rate	-0.2449***	-0.2328***	-0.1757*	-0.0947	-0.1674	-0.4410***
	(0.0903)	(0.0860)	(0.1063)	(0.0953)	(0.1052)	(0.1333)
Student-teacher ratio		0.0428***	0.0343***	0.0525***	0.0401***	0.0661***
		(0.0056)	(0.0071)	(0.0064)	(0.0070)	(0.0090)
Number of students		-0.0337***	-0.0268***	-0.0339***	-0.0347***	-0.0495***
		(0.0017)	(0.0022)	(0.0020)	(0.0022)	(0.0029)
Only grades 9-12		0.0374***	0.0360***	0.0370***	0.0426***	0.0405***
		(0.0047)	(0.0059)	(0.0053)	(0.0058)	(0.0073)
Constant	0.0721***	0.1265***	0.1005***	0.0863***	0.1382***	0.1737***
	(0.0075)	(0.0141)	(0.0177)	(0.0159)	(0.0176)	(0.0223)
Observations	2902	2902	2754	2852	2848	2828
Adjusted R-squared	0.003	0.136	0.056	0.097	0.089	0.110

Notes: ***, **, *, indicates significance at the 1, 5, and 10 percent levels, respectively.

Table 3.6. Estimation Results for Dropout Rate: By Grade

	(1)	(2)	(3)	(4)
variable	9th	10th	11th	12th
Casino	0.0323***	0.0339***	0.0513***	0.0941***
	(0.0094)	(0.0080)	(0.0092)	(0.0118)
School-casino distance	-0.0100***	-0.0114***	-0.0150***	-0.0178***
	(0.0023)	(0.0020)	(0.0022)	(0.0029)
Tribe pays per capita	-0.0084	-0.0083	-0.0008	0.0096
	(0.0104)	(0.0090)	(0.0103)	(0.0132)
Unemployment rate	-0.1561	-0.1094	-0.2078**	-0.3671***
	(0.1021)	(0.0882)	(0.1006)	(0.1294)
Students per teacher	0.0387***	0.0559***	0.0472***	0.0746***
	(0.0066)	(0.0058)	(0.0066)	(0.0086)
Student-teacher ratio	0.0387***	0.0559***	0.0472***	0.0746***
	(0.0066)	(0.0058)	(0.0066)	(0.0086)
Number of students	-0.0316***	-0.0356***	-0.0379***	-0.0530***
	(0.0021)	(0.0018)	(0.0021)	(0.0028)
Only grades 9-12	0.0478***	0.0389***	0.0433***	0.0439***
	(0.0056)	(0.0048)	(0.0055)	(0.0071)
Constant	0.1081***	0.0951***	0.1443***	0.1612***
	(0.0167)	(0.0145)	(0.0166)	(0.0213)
Observations	2805	2889	2884	2867
Adjusted R-squared	0.081	0.122	0.113	0.134

Notes: ***, **, *, indicates significance at the 1, 5, and 10 percent levels, respectively.

Table 3.7. Estimation Results for Dropout Rate: Twelfth Grade

	(1)	(2)	(3)	(4)	(5)	(6)
variable		American Indian			White	
Casino	0.0166	0.0314	0.0199	0.0303***	0.0786***	0.0518***
	(0.0148)	(0.0221)	(0.0227)	(0.0078)	(0.0122)	(0.0124)
Casino distance		-0.0050	-0.0014		-0.015***	-0.0069**
		(0.0055)	(0.0057)		(0.0030)	(0.0031)
PC	0.0415*	0.0395*	0.0466**	0.0026	-0.0047	0.0113
	(0.0219)	(0.0220)	(0.0222)	(0.0137)	(0.0138)	(0.0137)
Unemployment rate	-0.794***	-0.754***	-0.6216**	-0.541***	-0.441***	-0.1741
	(0.2561)	(0.2597)	(0.2661)	(0.1325)	(0.1333)	(0.1349)
Student-teacher ratio	0.1226***	0.1218***	0.1178***	0.0716***	0.0661***	0.0538***
	(0.0218)	(0.0218)	(0.0218)	(0.0090)	(0.0090)	(0.0090)
Number of students	-0.047***	-0.047***	-0.050***	-0.049***	-0.050***	-0.053***
	(0.0069)	(0.0069)	(0.0071)	(0.0029)	(0.0029)	(0.0029)
Only grades 9-12	0.0136	0.0128	0.0099	0.0426***	0.0405***	0.0330***
	(0.0153)	(0.0154)	(0.0154)	(0.0073)	(0.0073)	(0.0073)
TOP10			0.0298**			0.0588***
			(0.0132)			(0.0066)
Constant	0.0960*	0.0968*	0.1049**	0.1611***	0.1737***	0.1825***
	(0.0502)	(0.0502)	(0.0503)	(0.0223)	(0.0223)	(0.0220)
Observations	2004	2004	2004	2828	2828	2828
Adjusted R-squared	0.027	0.027	0.029	0.102	0.110	0.134

Notes: ***, **, *, indicates significance at the 1, 5, and 10 percent levels, respectively.

CHAPTER FOUR:

THE EFFECT OF GENDER ON THE DURATION BETWEEN TUTORING SESSIONS

ABSTRACT

This study seeks to analyze the effect gender may play in peer tutoring success. Using the data from Colorado State University Pueblo, we investigate gender specific tutoring effects. Previous literature has indicated that this effect warrants further investigation. The gender specific teaching effects have found that students perform better when the teacher is the same gender. The peered aspect of the tutoring program makes this study different.

Introduction

Education is universally accepted as one of the most important factors in the quality of life as such educational success is always a hot topic. There are many studies that explore student success in but most focus on socioeconomic factors like, income [Cameron and Heckman (2001)], race [Fryer & Levitt (2004 and 2011) and Duncan & Magnuson (2005)], parental education level [Phillips & Chin (2004)], and school and/or teacher quality [Angrist & Lavy (1999)Cook & Evans (2000), Orr (2003), Hanusheck et at. (2005) Rivkin et al., (2005)] While this paper does not focus on academic outcome directly it focuses on the decision to attend another tutoring session. Our models focus on students who have already made the decision to attend at least one tutoring session. We examine how the gender of the student, tutor and instructor affects the decision to return to peer lead tutoring.

Many studies have pointed to the effectiveness of peer lead tutoring. Cohen and Kulik (1982) provides a meta-analysis of 65 independent studies on school tutoring programs and showed that these programs have positive effects on academic performance and attitudes. Tutoring effects were larger in more structured programs and also the effects were larger when math rather than reading was the subject. There are several other papers such as Kelly and Swartz (1976), Blowers et al. (2003), Nestel (2003), Topping (2005) Mynard and Almarzouqi (2006) and Munley et al (2010) that have empirically studied the effect of peered tutoring at the university level and all found improvements in student performance and/or retention. The improvements in performance ranged from very small to a full letter grade or more. Arco-Tirado, Fernandez-Martin and Fernandez-Balboa (2011) found that participation in peer tutoring not only provided short term gains in grade point average, performance rate and success rate among first-year Civil Engineering, Economics, Pharmacy and Chemical Engineering college students, participation also had long term effects in learning strategies and social skills.

Others have examined whether underrepresented students benefit from instructors with similar characteristics. Ehrenberg and Brewer (1995) used data from the U.S. Department of Education's "High School and Beyond longitudinal survey" to study if school and/or teacher characteristics influence the probability that public school students drop out of high school between their sophomore and senior years and, for those who do not drop out, whether these characteristics influence the extent to which students' scores on achievement tests increase during the 2-year period. They found that school and teacher characteristics appear to influence test scores more than the dropout rate. Specifically, they found that African-American students who have African-American instructors have higher test scores. This has been interpreted as evidence that same-group instructors act as role models. This role model effect could be because they serve as examples to same-group students or because they can better empathize with the same-group particular needs. Similarly, Rask and Bailey (2002) studied college students' choice in majors and found role model effects for women, minorities and men.

Other studies have examined gender bias in teaching. Some of these studies have examined whether female role models affect educational outcomes. The results have been mixed. Rothstein (1995) found a positive relationship between female students post graduate education and the proportion of female faculty but were unable to rule out the possibility that female students and female faculty self-selecting into academic environments that are supportive of women. Neumark and Gardecki (1998) studied role model and mentoring effects in Economics Ph.D. programs in the U.S. and found no evidence that a larger proportion of female faculty or a female dissertation chair positively affected future success for female students. Holmlund and

Sund (2008) found that girls outperform boys in upper-secondary education in Stockholm, Sweden. They tested their hypothesis that the gender performance gap could be attributed to the fact that the teacher profession is female dominated. They found that while the gender performance gap is larger in subjects where the share of female teachers is higher, this effect cannot be interpreted as causal due to the same self-selection possibility as Rothstein (1995).

Bettinger and Long (2005) explored whether the instructor's gender in introductory college courses affected the student's choice to take other classes in that field. The results were mixed, but they concluded that there was strong support for the role model hypothesis in mathematics, statistics, geology, sociology and journalism.

Data Description

We use data from Colorado State University – Pueblo's (CSU – Pueblo) Student Academic Services. This is a department within CSU – Pueblo whose mission is to provide programs and services designed to supplement classroom instruction to enhance student learning. CSU-Pueblo is a fully accredited public, four-year university with an enrollment of over 5,100 students.

Our data is from the General Education (Gen Ed) Tutoring Center, which provides services for Mathematics and Natural Sciences as well as a Humanities classes. The GenED Tutoring Center is a program within Student Academic Services that offers peer-based academic support for various general education courses. In AY 2011 – 12, The Gen Ed Tutoring Center employed two full-time and two part-time staff members and over fifty student workers. The Gen Ed Tutoring Center offers both supplemental instruction (SI) and individual peer academic support sessions. SI sessions are regularly scheduled thus the student does not choose the time between sessions so we focus on individual tutoring.

Individual tutoring sessions are scheduled by the student. Each session lasts for up to fifty minutes and the student works independently with one peer tutor. Typically, students work through difficult course material with a tutor, who has successfully completed the course as well as obtained academic departmental approval to tutor. This could include assigned homework, practice quizzes and worksheets developed by the instructor. Students are not allowed to have consecutive individual sessions; however, they are allowed to access services more than once per day. Students lose appointment privileges for one semester if they do not show up for three scheduled appointments during that semester.

This paper focuses on data generated from the Mathematics and Natural Science division of the Gen Ed Tutoring Session across the fall 2010 to spring 2012 semesters in biology (Human Physiology and Anatomy I and II), chemistry (General Chemistry I and II), and mathematics (Mathematical Explorations, College Algebra, and Introductory Statistics) courses.[23,24] During this period of time, individual tutoring sessions were offered in both the mathematics and science (i.e., biology and chemistry) courses.

Our data has tutor and instructor gender and student specific traits such as the students American College Testing (ACT) scores, final grade in the class, if the student is a college

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[23] All students must pass at least one college-level mathematics course and complete two Natural and Physical science courses with labs to obtain their degree. See pages 62-63 of http://www.colostate-pueblo.edu/catalog/Documents/Catalog2011-2012.pdf.

[24] These courses have been identified by CSU - Pueblo as high risk courses (i.e., a 30 percent or greater DFW rate, where D, F, and W, stand for the letter grades “D,” “F,” and withdraw, respectively.

athlete, student gender, in which class they are getting tutored, and what day(s) they went to tutoring. With this we calculated the duration between tutoring sessions.

The duration start time was the day the student went to tutoring. The end time was either the day the student went to their next tutoring session or the last day of the academic quarter. The failure event was attending another tutoring session. If the student did not go to any more tutoring sessions the observation was censored. This resulted in multiple observations for students who attended three or more tutoring sessions. If a student withdrew from the class the student was dropped because we did not have information on when the student withdrew. We needed this information to calculate when this observation was censored.

Our final data set consisted of 1701 observations. Of these, there were 1362 failures (student attended another tutoring session), the time at risk was 16968 days and the incidence rate was 0.0803. The summary statistics are in Table 1.

Empirical Specifications

We employ survival analysis to examine the duration of time between individual tutoring sessions. Our data set only includes students who attended at least one tutoring sessions. In the context of our paper the event is returning to tutoring. Thus, the survival function, $S(t) = Pr(T>t)$, is the probability of a student surviving (not returning to tutoring) t units of time from the last time the student went to tutoring.

First, we use nonparametric methods such as graphing the hazard function and the Nelson-Aalen cumulative hazard curve and using graphing and comparing survival functions with the Kaplan-Meier estimator and the log rank test. Second, we use parametric and semi-parametric regression models to estimate coefficients and hazard rates. Third, we further explore the gender effect by examining female and male students separately.

We first nonparametric method we employ is the estimate of the smoothed hazard rate[25]. This is the estimate of the probability that the duration will end after time *t*, conditional on survival until time *t*. Then we calculate the Nelson-Aalen estimator of the cumulative hazard function. This is calculated by summing up the hazard functions over time. It is:

$$\widetilde{H}(t) = \sum_{t_i \leq t} \frac{h_i}{n_i} \tag{1}$$

where h_i is the number events at time t_i and n_i is the total number at risk at t_i.

$$\hat{S}(T_k) = \prod_{i=1}^{k} \frac{n_i - h_i}{n_i} = \frac{n_i - h_i}{n_1} \tag{2}$$

Next we calculate the Kaplan Meier product limit estimator for all observations and by groups. This strictly empirical estimate of the survivor function is:

$$\hat{S}(T_k) = \prod_{i=1}^{k} \frac{n_i - h_i}{n_i} = \frac{n_i - h_i}{n_1} \tag{3}$$

[25] This estimate is calculated as a weighted kernel-density estimate using the estimated hazard contributions, $\Delta H\widehat{(t_j)} = H\widehat{(t_j)} - \widehat{H}(t_{j-1})$.

where there are K distinct survival times in the data, denoted T_k, n_k is the total number at risk at t_k and h_k is the number of events at time T_k. The final nonparametric test we use is the log rank test. This tests the equality of survivor functions between groups by computing the expected number of events at each time in each group if there were no difference between groups and comparing it to the observed number of events in each group.

The parametric models we use are Exponential, Weibull and Gompertz models. Parametric models impose assumptions on the hazard function and the effect of any covariates. The survival function of the exponential distribution is $S(t)=exp(-\lambda t)$. With the exponential distribution model the hazard rate is constant over time. The survival function of the Weibull distribution model is $S(t) = exp(-\lambda t)^{\gamma}$. The survival function of the Gompertz is $S(t) = exp[-(e^{n}-1)e^{\lambda}\gamma^{-1}]$.

We use the semi-parametric Cox proportional hazard model to analyze the effect of covariates on the hazard rate, $\lambda(t)$. In this model the hazard function is made up of two separate parts. The first part, $\lambda_0(t)$, is the baseline hazard. It represents the hazard when all of the independent variables ($X_1, X_2, \ldots, X_p$) are equal to zero. The second part is a function of the independent variables. It takes the form $exp(x'\beta)$ where x is a vector of observations on an individual's characteristics and β is a parameter vector. The hazard function being estimated is:

$$\lambda(t) = \lambda_0(t)\exp(x'\beta) \tag{4}$$

Results: The Effects of Gender on Duration between Tutoring Sessions

Nonparametric Methods

Nonparametric methods do not impose strong assumptions thus are helpful for data exploration and description. Figure 4.1 contains the estimate of the hazard function for the duration between tutoring sessions. The hazard rate shows the probability of having the event (going back to tutoring) going down from about 6.5% to about 1% over 60 time periods (days).

Figure 4.2 contains the Nelson-Aalen cumulative hazard estimate. It shows that the cumulative H(77)=2.11[26]. This means that if the event was repeatable, we would expect two events for a person in 77 days.

The Kaplan-Meir Method is used to estimate the Survival curve. This method estimates the curve from the survival times without assuming an underlying probability distribution. Figure 4.3 shows the results for all students. The probability of survival is 0.8097[27] to the second day of the study period. In the fifth day this probability declines to 0.5293. The probability of survival is 0.1056 on the 77th day (the last day of the study).

Figures 4.4, 4.5 and 4.6 show the results by student gender, tutor gender and instructor gender respectively. Note that the curves by tutor gender and instructor gender cross multiple times. This indicates a clear departure from proportional hazards consequently the Kaplan-Meier survival curves graphs cannot be used to estimate a difference in these survival curves. The Kaplan-Meier curves by student gender are roughly parallel therefore the difference between the curves can be examined. The curves indicate that female students have a longer duration between

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[26] From the list of the Nelson-Aalen estimate of the cumulative hazard function.

[27] All probabilities of survival are from life tables.

tutoring sessions. The probability of survival to the second day for male (female) students is 0.7825 (0.8311). The male (female) probability of survival on the last day of the study is 0.0832 (0.1258).

Figures 4.7 (4.8) show the results by if the student and tutor (instructor) are the same gender. Since the student and tutor gender curves cross multiple times we will only examine the curves for student instructor gender. The curves indicate that if the student and instructor are different genders the duration between tutoring sessions is longer. If the student and instructor are different (same) genders then the probability of survival to the second day is 0.8842 (0.7492). The probability of survival on the last day of the study if the student and instructor are different (same) genders is 0.1155 (0.1004).

To further compare the survival curves of Figures 4.4 and 4.8, we use the log rank test. This test will only detect a difference if proportional hazards apply therefore it is not applicable with the other groups. The null hypothesis is that there is no difference between the survival curves of the two groups. The results are in Table 4.2. The log rank test by student gender indicates that the survival times are different for male and female students. The p-value is zero and the chi-square statistic is 19.25 with one degree of freedom therefore we reject the null hypothesis that the survivor functions are equal. The log rank test by student and instructor gender indicate that the survival function for students with instructors of the same gender differ from the survival functions for students with instructors of the different gender. The p-value is 0 and the chi-square statistic is 39.89 with one degree of freedom, therefore we reject the null hypothesis.

Parametric and Semi-parametric Models

Parametric survival analysis models explicitly state a functional form of the hazard rate. We begin with the exponential distribution. This model assumes that the hazard rate is flat with respect to time therefore this model also assumes proportional hazards. The hazard equation is

$$\lambda(t)= \lambda \tag{5}$$

This means the hazards are invariant to time. Table 4.3 contains the estimation results of the exponential regression coefficients. In all models the ACT score, athlete and science class indicator variables are significant. The ACT variable is negative and significant at the 1% level ranging from -1.4506 to -1.3531 indicating that students with higher ACT scores have longer durations between tutoring sessions. The athlete (science) indicator is positive and significant at the 1% level ranging from 0.6794 to 0.7419 (0.2135 to 0.2972) indicating that student athletes (science students) have shorter durations between tutoring sessions.

Models 2, 3 and 4 are specifications with indicator variables for student, tutor and instructor gender respectfully. Similar to our results with nonparametric estimates, only student gender is significant. The estimate for the indicator variable for female students is negative and significant at the 1% level. The coefficient estimate is -0.3919 which indicates that female students have longer durations between tutoring sessions. The indicator variable for the student and instructor being the same gender is positive and significant at the 1% level. The coefficient estimate is 0.4674 indicating that when the students and instructor are the same gender they have a shorter duration between tutoring sessions than when the genders are different. We will further explore this in the following section.

Table 4.4 contains the exponential hazard ratio estimates of the duration between tutoring sessions. Students with a higher ACT score are less likely to go back to tutoring. Athletes (science students) have about 100% (30%) increase in there hazard rate, meaning they are more likely to go back to tutoring. Female students have 32% decreasing in there hazard rate, meaning females are less likely to go back to tutoring. Students with the same gender as their instructor are 60% more likely to go back tutoring. This means they are more likely to go back to tutoring.

Tables 4.5 and 4.6 contain coefficients for the parametric estimates of models for the student gender and student/instructor the same gender variables respectfully. The first column models report the Exponential results. The second column reports the Weibull model regression results. The Weibull distribution can model hazard functions that are constant or monotonically decreasing or increasing. The hazard function is

$$\lambda(t)= \lambda\, \gamma\, t\, \gamma^{\gamma-1} \tag{6}$$

where $\gamma>0$ and $\lambda>0$. If $\gamma>1(\gamma<1)$ the hazard increases (decreases) over time. If $-\gamma = 1$ this is the exponential distribution so the hazard function is constant.

The third column contains the Gompertz model regression coefficients. The Gompertz distribution models hazard rates that increase or decrease exponentially. The hazard function is

$$\lambda(t)= \lambda \exp(\gamma\, t) \tag{7}$$

If $-\gamma > 0$ ($-\gamma < 0$) the hazard function increases (decreases) exponentially over time. If $-\gamma = 0$ the hazard is constant thus is also the exponential distribution.

The coefficients are in all models are consistent with the estimates in table 3 therefore I will not go in detail

Column 4 of Tables 4.5 and 4.6 contain the hazard rates for the Cox proportional hazard model. With this semi-parametric model the hazard function is composed of two separate parts. The first part is a function of time. The second part is only a function of explanatory variables. The hazard function is:

$$\lambda(t) = \lambda_0(t) expx'\beta \qquad (8)$$

This model assumes proportional hazards but does not need a specific probability distribution of the hazard. This means that while the hazards may change with time but the proportional difference between the two groups does not change. These results are similar to the results in table 3 therefore I will not go into detail about these estimates.

Student Gender-Specific Regressions

Tables 4.7 and 4.8 are parametric regressions for male students and female students respectively. These regressions investigate student-instructor same gender coefficient for male students separately from female students. The coefficients for ACT score for male (female) students are significant at the 1% level and range from -2.7598 to -1.6946 (-0.9806 to -0.6785). All of the coefficients for ACT scores for male students are larger in magnitude than for female students from male students. This suggests that as Act scores increase the duration between sessions increase. The magnitude of the male students ACT score coefficient relative to female student magnitude indicate that males students' durations are more sensitive to their ACT scores. The athlete indicator variable coefficients for male students are not significant in any models. The athlete results for female students are significant at the 1% level and range from 0.5261 to 1.0442. Indication female student athletes are more likely to tend tutoring. The science indicator variable coefficients for males are significant at the 1% level and range from 0.3488 to 0.6305. The science indicator variable coefficients for female students are not significant. This indicates that male science students are more likely to attend tutoring. The student and instructor the same gender indicator variables for male (female) students are significant at the 1% level and range from 0.2602 to 0.4201 (0.2934 to 0.3622) This indicates that students with instructors the same gender then to go back to tutoring

Conclusions

We have examined the duration between tutoring sessions. Female students tend to have a longer duration between tutoring sessions. The reason behind this needs to be further explored. Also male students with male instructors as well as female students with female instructors tend to have shorter durations between tutoring sessions. This also needs to be explored. The General Education tutoring center at Colorado State University-Pueblo focuses mainly on classes that are historically difficult. These are classes with the highest rates of students either earning a "D", "F" or "W" from the course. These are classes where tutoring could make a difference between students passing or failing a class. If gender, either student gender or instructor gender, enters the decision process of a student deciding whether or not to go to tutoring then it is an effect worth exploring. Based on our findings, we recommend further research in the area of gender and the tutoring decision. Data from multiple locations would enrich our understanding of the gender effect.

References for Chapter Four

Angrist, J.D., & Lavy, V. (1999). Using Maimonides' rule to estimate the effect of class size on scholastic achievement. *The Quarterly Journal of Economics*, 114(2), 533-575.

Arco-Tiradeo, F & Fernández-Martín, F. & Fernández-Balboa, J. (2011) The impact of a peer-tutoring program on quality standards in higher education. *Higher Education*, 62(6) 773-788

Bettinger, E. & Long, B. (2005), Do Faculty Serve as Role Models? The Impact of Instructor Gender on Female Students. *American Economic Review,* 95(2), 152-157

Blowers, S., Ramsey, P., Merriman, C., & Grooms, J. (2003). Patterns of peer tutoring in nursing. *Journal of Nursing Education*, 42(5), 204-211

Cameron, S. & Heckman, J. (2001). The dynamics of educational attainment for black, Hispanic, and white males. *Journal of Political Economy*, 109(3), 455-499.

Cohen, P. A., Kulik, J. A., & Kulik, C. L. C. (1982). Educational outcomes of tutoring: A meta-analysis of findings. *American educational research journal*, *19*(2), 237-248

Cook, M. & Evans, W. (2000). Families or schools? Explaining the convergence in white and black academic performance. *Journal of Labor Economics*, 18(4), 729-754.

Duncan, G. & Magnuson, K. (2005). Can Family socioeconomic resources account for racial and ethnic test score gaps? *The Future of Children*, 15 (1), 35-54.

Ehrenberg, R. & Brewer, D. (1994) Do School and Teacher Characteristics Matter? Evidence from the High School and Beyond. *Economics of Education Review,* 13(1), 1-17

Fryer, R. & Levitt, S. (2004). Understanding the black-white test score gap in the first two years of school. *Review of Economics and Statistics*, 86 (2), 447-464.

Hanushek, E. A., Kain, J. F., O'Brien, D. M., & Rivkin, S. G. (2005). The market for teacher quality. (NBER Working Paper 11154). Cambridge, MA: National Bureau of Economic Research.

Holmlund H. &Sund, K. (2008). Is the gender gap in school performance affected by the sex of the teacher? *Labour Economics*, 15(1), 37-53

Kelley, A. C., & Swartz, C. (1976). Student-to-student tutoring in economics. *Journal of Economic Education*, 8 (1), 52–55.

Munley, V G., Garvey, E. & McConnell, M.J. (2010). The effectiveness of peer tutoring on student achievement at the university level. *American Economic Review: Papers & Proceedings*, 100, 277-282.

Mynard, J., & Almarzouqi, M. (2006). Investigating peer tutoring. *ELT Journal*, 60(1), 13-22.

Nestel, D., & Kidd, J. (2003). Peer tutoring in patient-centered interview skills: Experience of a project for first-year students. *Medical Teacher*, 25(4), 398-403.

Neumark, D. & Gardecki, R., (1998), Women Helping Women? Role Model and Mentoring Effects on Female Ph.D. Students in Economics, *The Journal of Human Resources,* 33(1), 220-246

Orr, A. (2003). Black-white differences in achievement: The importance of wealth." *Sociology of Education*, 76, 281-304.

Phillips, M., & Chin, T. (2004). School inequality: What do we know? In K. M. Neckerman, Ed., *Social inequality* (pp. 467–519). New York: Russell Sage Foundation.

Rask, K. & Bailey, E. (2002), Are Faculty Role Models? Evidence from Major Choice in an Undergraduate Institution, *Journal of Economic Education*, 33(2), 99-124

Rivkin, S.G., Hanushek, E.A., & Kain, J.F. (2005). Teachers, schools, and academic achievement. *Econometrica* 73(2), 417-458.

Rothstein, D. (1995), Do Female Faculty Influence Female Students' Educational and Labor Market Attainments?, *Industrial and Labor Relations Review*, 48(3), 525-530

Topping, K. J. (2005). Trends in peer learning. *Educational Psychology,* 25(6), 631-645

Table 4.1. Summary Statistics

	Mean	Std. Dev.	Min	Max
Duration	9.97531	14.5027	1	77
Event	0.80071	0.39959	0	1
ACT math	17.0741	2.88267	6	28
Athlete	0.07525	0.26387	0	1
Science class	0.18519	0.38856	0	1
Student gender	0.55791	0.49678	0	1
Tutor gender	0.38036	0.48562	0	1
Instructor gender	0.44680	0.49731	0	1
Tutor/student same gender	0.51911	0.49978	0	1
Instructor/student same gender	0.55262	0.49737	0	1

Note: 1701 observations for all variables

Table 4.2. Long Rank Test for Equality of Survivor Functions

student gender	**events observed**	**events expected**
male	627	553.3
female	735	808.7
total	1362	1362
	$chi^2(1)$ =	19.45
	Pr>chi2 =	0.000

instructor/student gender	**events observed**	**events expected**
same	581	688.34
not the same	781	673.66
total	1362	1362
	chi2(1) =	39.89
	Pr>chi2 =	0.000

Table 3. Exponential Coefficient Estimates of the Duration Between Tutoring Sessions

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ACT math	-1.3587***	-1.4506***	-1.3701***	-1.3665***	-1.3531***	-1.4527***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Athlete	0.7336***	0.7419***	0.7269***	0.7301***	0.7357***	0.6794***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Science class	0.2135***	0.2989***	0.2173***	0.2235***	0.2161***	0.2972***
	(0.0028)	(0.0000)	(0.0024)	(0.0023)	(0.0025)	(0.0000)
Female student		-0.3919***				
		(0.0000)				
Female tutor			-0.0793			
			(0.1572)			
Female instructor				0.0353		
				(0.5275)		
Tutor and student same gender					0.0464	
					(0.3943)	
Instructor and student same gender						0.4674***
						(0.0000)
Constant	1.2464***	1.7176***	1.3088***	1.2509***	1.2058***	1.2579***
	(0.0025)	(0.0000)	(0.0015)	(0.0025)	(0.0038)	(0.0033)
Observations	1701	1701	1701	1701	1701	1701

Note: ***, **, *, indicates significance at the 1%, 5%, and 10% levels, respectively.

Table 4.4. Exponential Hazard Ratio Estimates of the Duration Between Tutoring Sessions

Variable	(1)	(2)	(3)	(4)	(5)	(6)
ACT math	0.2570***	0.2344***	0.2547***	0.2250***	0.2585***	0.2339***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Athlete	2.0826***	2.1000***	2.0695***	2.0753***	2.0876***	1.9727***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Science class	1.2380***	1.3484***	1.2422***	1.2504***	1.2408***	1.3461***
	(0.0028)	(0.0000)	(0.0024)	(0.0023)	(0.0025)	(0.0000)
Female student		0.6758***				
		(0.0000)				
Female tutor			0.9261			
			(0.2400)			
Female instructor				1.0360		
				(0.5275)		
Tutor/student same gender					1.0490	
					(0.3943)	
Instructor/student same gender						1.5958***
						(0.0000)
Observations	1701	1701	1701	1701	1701	1701

Note: ***, **, *, indicates significance at the 1%, 5%, and 10% levels, respectively.

Table 4.5. Parametric Regression Model Coefficients for Student Gender

	Exponential	Weibull	Gompertz	Cox proportional hazard
ACT math	-1.4506***	-1.1976***	-1.0650***	-0.9865***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Athlete	0.7419***	0.5516***	0.4307***	0.3901***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Science class	0.2989***	0.2087***	0.1578**	0.1188
	(0.0000)	(0.0040)	(0.0294)	(0.1016)
Female student	-0.3919***	-0.3137***	-0.2729***	-0.2584***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	1.7176***	1.7166***	1.3123***	
	(0.0000)	(0.0001)	(0.0022)	
Ln p constant		-0.3028***		
		(0.0000)		
Gamma constant				-0.757***
				(0.0000)

Notes: ***, **, *, indicates significance at the 1%, 5%, and 10% levels, respectively. 1701 observations for all models

Table 4.6. Parametric Regression Model Coefficients for Student/Instructor Same Gender

	Exponential	Weibull	Gompertz	Cox Proportional Hazard
ACT math	-1.4527***	-1.2129***	-1.0809***	-1.0045***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Athlete	0.6794***	0.4903***	0.3686***	0.3317***
	(0.0000)	(0.0000)	(0.0003)	(0.0011)
Science class	0.2972***	0.2033***	0.1514**	0.1118
	(0.0000)	(0.0053)	(0.0371)	(0.1244)
Instructor and student same gender	0.4674***	0.3833***	0.3494***	0.3299***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	1.2579***	1.3758***	1.0195**	
	(0.0033)	(0.0016)	(0.0195)	
Ln_p constant		-0.2991***		
		(0.0000)		
Gamma constant			-0.0753***	
			(0.0000)	

Notes: ***, **, *, indicates significance at the 1%, 5%, and 10% levels, respectively.
1701 observations for all models

Table 4.7. Parametric Regression Model Coefficients for Male Students

Variables	Exponential	Weibull	Gompertz	Cox Proportional Hazard
ACT math	-2.7598***	-2.2194***	-1.8645***	-1.6946***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Athlete	0.0324	0.0260	0.0386	0.0367
	(0.8734)	(0.8982)	(0.8496)	(0.8571)
Science class	0.6305***	0.4899***	0.4139***	0.3488***
	(0.0000)	(0.0000)	(0.0003)	(0.0027)
Instructor and student same gender	0.4201***	0.3473***	0.2765***	0.2602***
	(0.0000)	(0.0001)	(0.0014)	(0.0027)
Constant	5.1496***	4.2524***	3.3528***	
	(0.0000)	(0.0000)	(0.0000)	
Ln_p constant		-0.2402***		
		(0.0000)		
Gamma constant			-0.0716***	
			(0.0000)	

Notes: ***, **, *, indicates significance at the 1%, 5%, and 10% levels, respectively.
752 observations for all models

Table 4.8. Parametric Regression Model Coefficients for Female Students

Variables	Exponential	Weibull	Gompertz	Cox Proportional Hazard
ACT math	-0.9806***	-0.8311***	-0.7318***	-0.6785***
	(0.0000)	(0.0001)	(0.0005)	(0.0014)
Athlete	1.0442***	0.7597***	0.5822***	0.5261***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Science class	0.0701	0.0162	-0.0067	-0.0311
	(0.4874)	(0.8736)	(0.9470)	(0.7586)
Instructor and student same gender	0.3622***	0.3088***	0.3049***	0.2934***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Constant	-0.1450	0.2668	-0.0331	
	(0.8023)	(0.6496)	(0.9552)	
Ln_p				
Constant		-0.3136***		
		(0.0000)		
Gamma Constant			-0.0742***	
			(0.0000)	

Notes: ***, **, *, indicates significance at the 1%, 5%, and 10% levels, respectively.
949 observations for all models

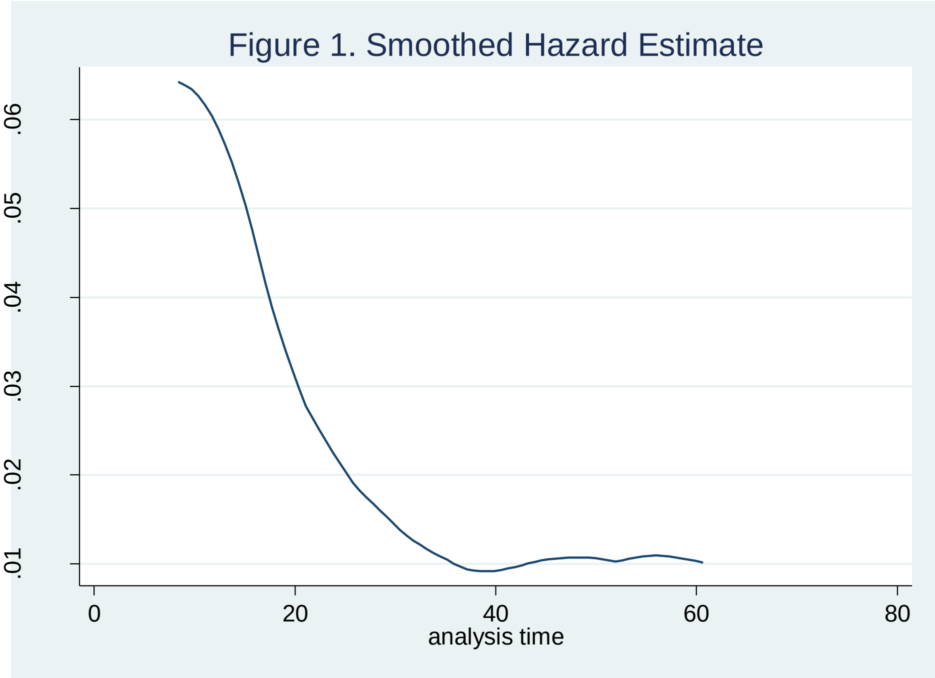


Figure 1. Smoothed Hazard Estimate
.01
.02
.03
.04
.05
.06
0
20
40
60
80
analysis time

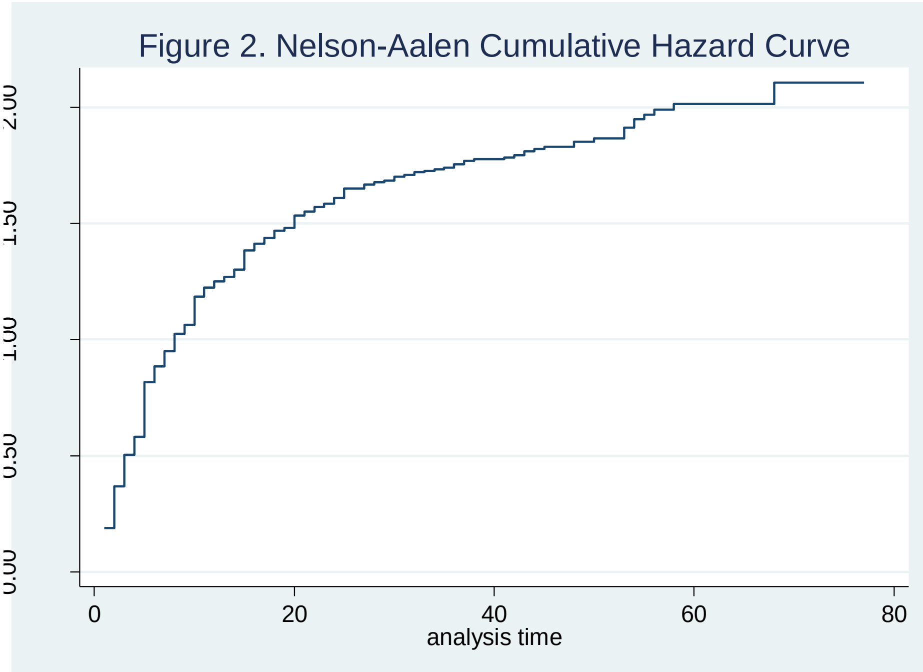


Figure 2. Nelson-Aalen Cumulative Hazard Curve
0.00
0.50
1.00
1.50
2.00
0
20
40
60
80
analysis time

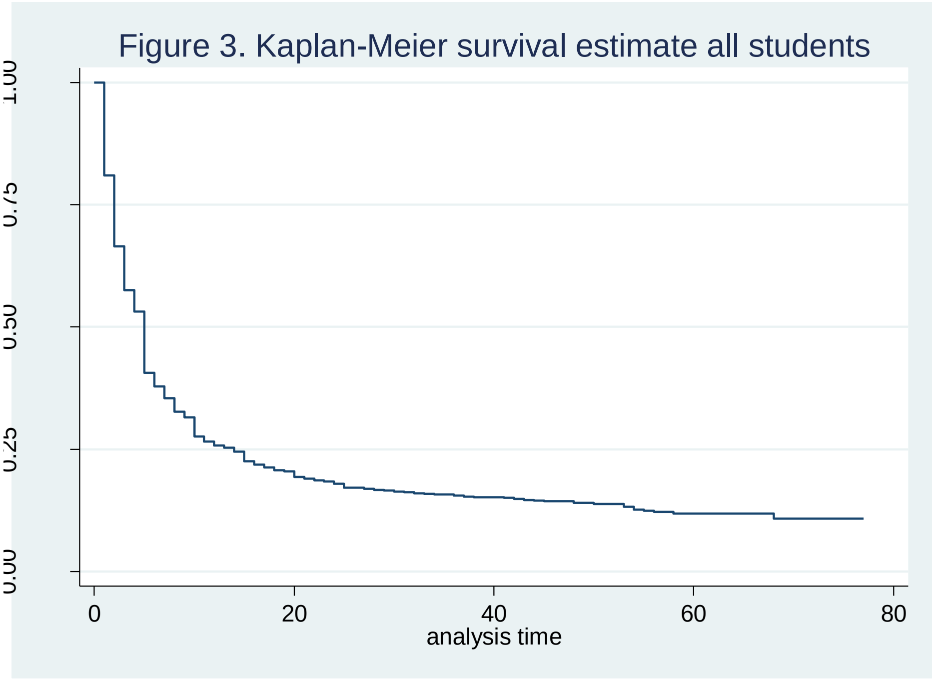


Figure 3. Kaplan-Meier survival estimate all students
1.00
0.75
0.50
0.25
0.00
0
20
40
60
80
analysis time

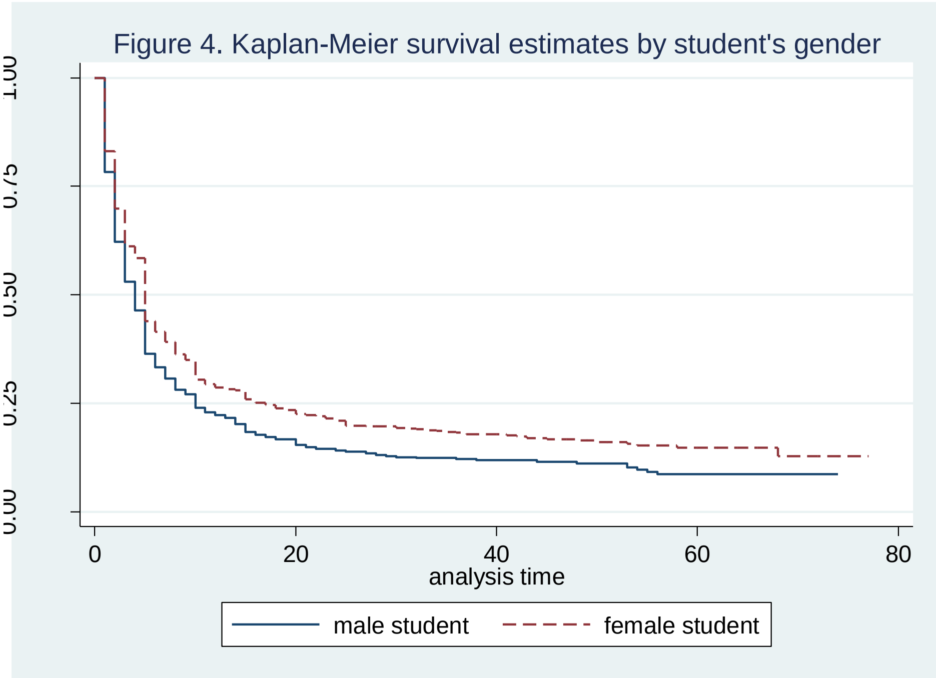
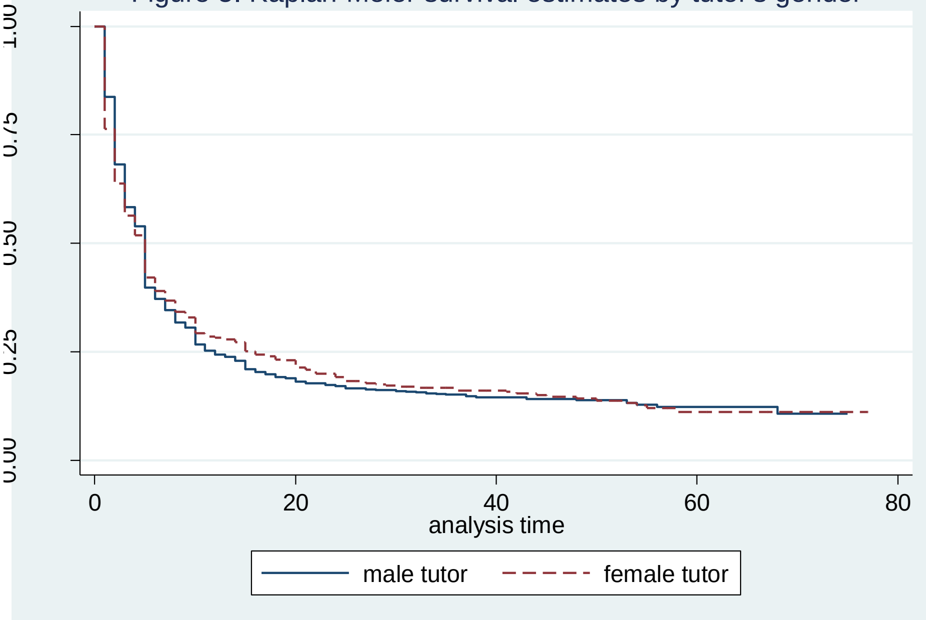


Figure 4. Kaplan-Meier survival estimates by student's gender
0.00
0.25
0.50
0.75
1.00
0
20
40
60
80
analysis time
male student
female student

Figure 5. Kaplan-Meier survival estimates by tutor's gender



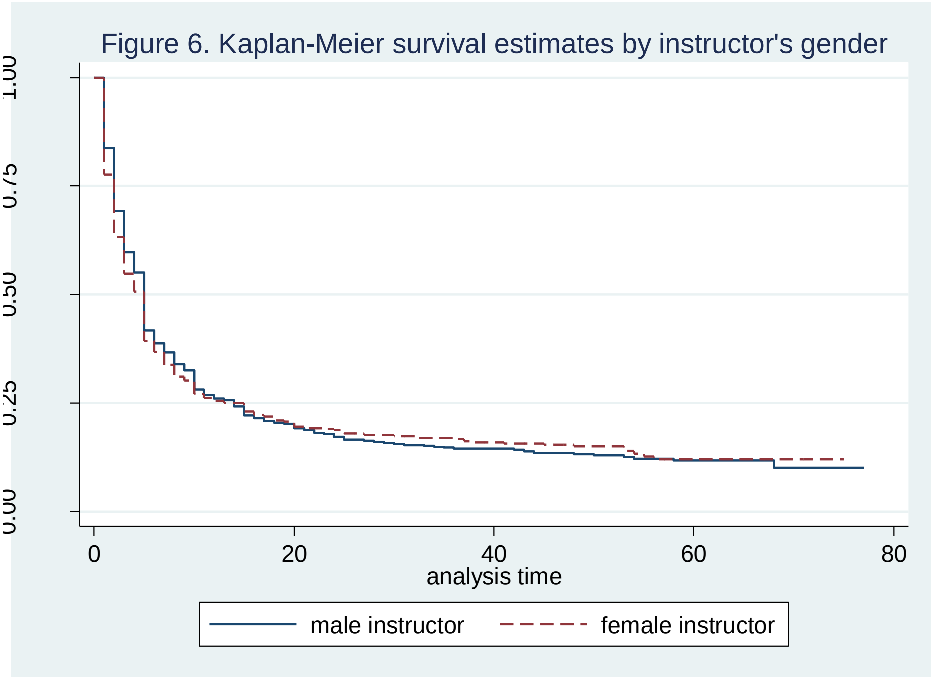


Figure 6. Kaplan-Meier survival estimates by instructor's gender
1.00
0.75
0.50
0.25
0.00
0
20
40
60
80
analysis time
male instructor
female instructor

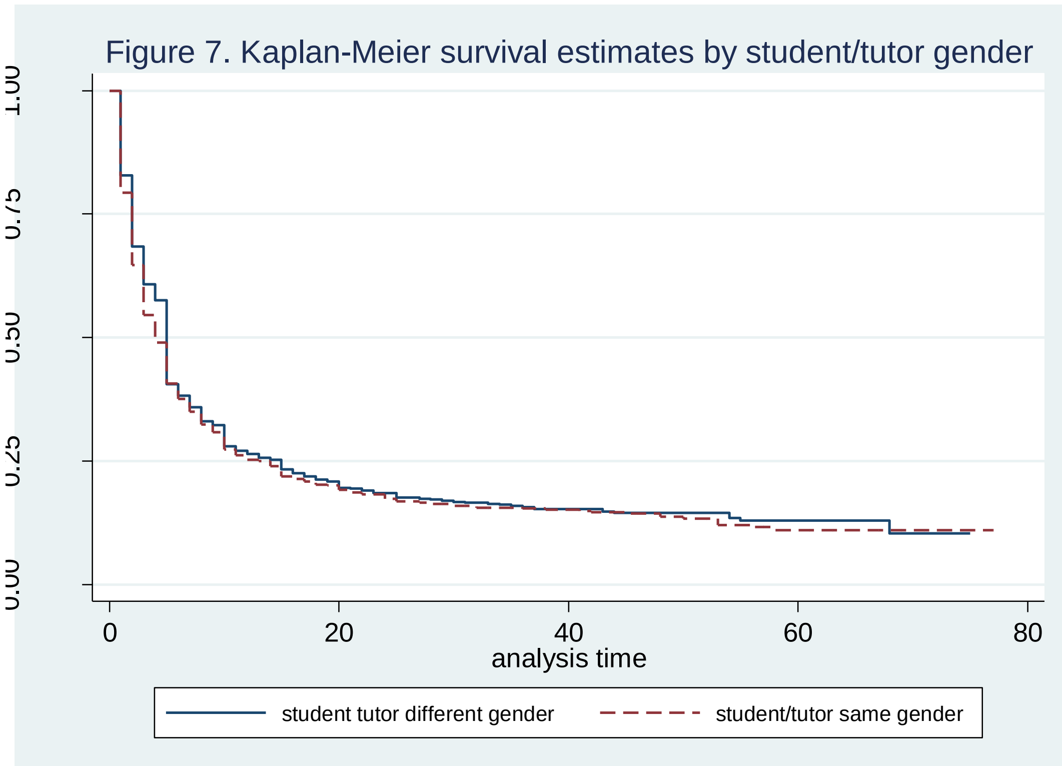
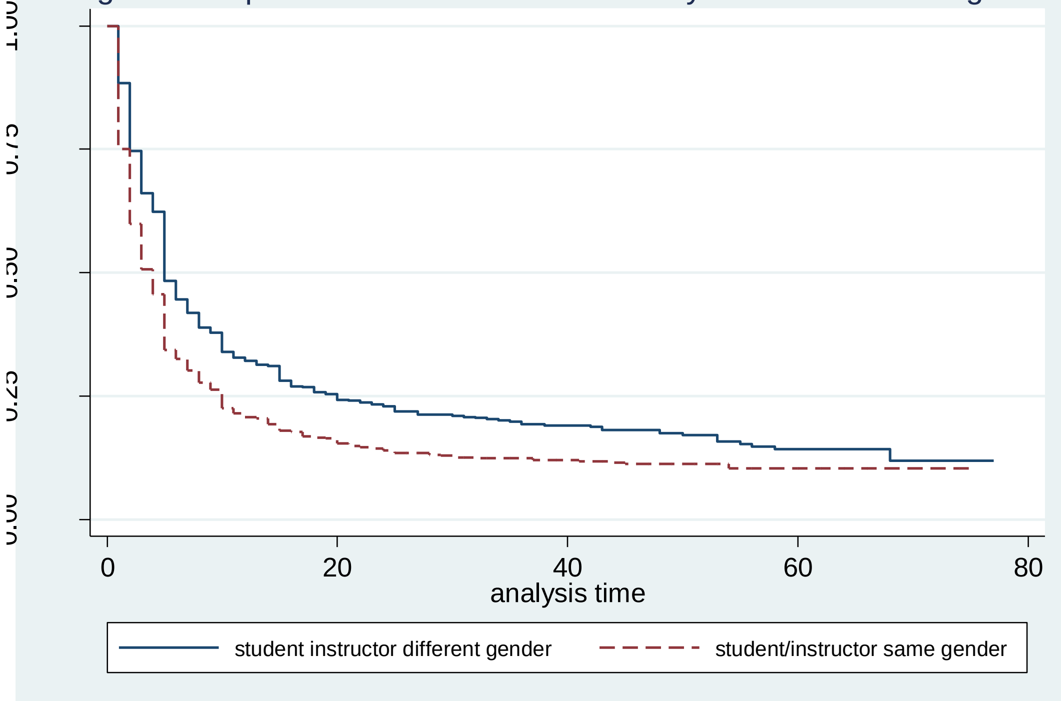


Figure 7. Kaplan-Meier survival estimates by student/tutor gender
0.00
0.25
0.50
0.75
1.00
0
20
40
60
80
analysis time
student tutor different gender
student/tutor same gender

Figure 8. Kaplan-Meier survival estimates by student/instructor gender



CHAPTER FIVE:

DISSERTATION CONCLUSIONS

We have approached measuring success in education three different ways. First we measured the impact of peer tutoring in historically challenging college math and science classes and found that if students attended 12 tutoring classes there was an increase of one full letter grade. This breaks down to about one tutoring session a week. This is a rather large commitment from the student but since the classes are classes with large withdrawal rates and large failure rates the commitment potentially has great individual rewards.

Next we examined the effect of tribal casinos. Tribal casinos necessarily located on Indian reservation which have extremely high rates of poverty. Tribal casinos could be inadvertently increasing the dropout rate among tribal members and non-tribal members alike. Casinos require a lot of employees thus increasing the demand for unskilled labor. Adding the increased job supply to the rampant poverty could possibly lead to a greater number of high school students, both Native American and non-Native American, tempted to drop out of school to make money. Native American students face another potential influence to drop out. Tribes with successful casinos often pay tribal members per capitas. Each tribe decides requirements for disbursement of these funds. Many tribes have graduation requirements but some do not. Tribes whose only requirement is for tribal members to turn 18 to receive fund are missing out on a potential incentive they could use to potentially keep young tribal members in school. If they changed their payout requirements more tribal members would stay in school.

Last we looked at the effect gender had on students returning to tutoring. The results suggest that students have a shorter duration if the teacher was the same gender as the student. This could possibility be a “role model” effect discussed by several papers in the introduction section of this paper. This paper did not have the endogeneity problem as the first paper since we only examined students who had attended at least one tutoring session but examining such a small data set has its own set of problems.

Recommendations

Based on the findings of this dissertation, I recommend the following strategies. Gather more data for all papers. For the peer tutoring paper having information from more classes and class types would allow for a deeper understanding of the peer tutoring effect. Also information from different universities would aid in uncovering how effective each tutoring type is in different areas of study.

For the tribal casino paper data from more than one state would allow the researcher to explore different payout structures. Most tribes in Washington are similar in payout structure in that they start paying out proceeds from the casino to tribal members who are 18 years or older. Tribes in different states have different payout structures. Some tribes make tribal members wait until they are 21 or 25. Also tribes in Washington are small in relation to tribes from around the country. This could have an effect on the availability of tribal members getting waivers on the payout policy.

For the final paper, more information about the tutor and instructor quality would allow us to control for these things allowing us to further examine the gender effect. Also it would allow us to compare the gender effect by subject. STEM class success for women is a hot topic since women tend to be under represented in these fields.