# The Effect of Time-To-Degree on Labor Market Outcomes

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**Abstract**

Undergraduate time-to-degree functions as a proxy for speed of learning. This proxy can affect future labor market outcomes by influencing productivity. This paper examines the role of an exogenous shock of the changes in US college enrollment rates on undergraduate time-to-degree. A subset of the data collected from the National Longitudinal Survey of Youth 1997, reported time-to-degree between 2002 and 2008. Outcomes were measured from immediately after graduation to five years later. Instrumenting on colleges' average time-to-degree isolates the pure effect of time-to-degree on labor market outcomes. Extending time-to-degree negatively affects labor market outcomes. The increase in time-to-degree results in diminishing returns to learning. The effect on labor market outcomes only occurs in the first two periods after graduation. The recent changes in college enrollment rates can depress labor market success.

# 1 Introduction

College enrollment has been steadily increasing in the United States since the 1980's (Snyder and Dillow, 2012). Between 2000 and 2010 there was an 30% increase in enrollment. This is an exponential increase compared to the average of 10% in the two decades prior. It is well documented that the recent exponential shift in enrollment is due to the effects of the Great Recession (Long, 2014). Even when isolating the cyclical nature of economic conditions and college enrollment rates from the overall trend, it is still evident that college enrollment rates have increased.

One explanation for the recent expansion in college enrollment is the disparity in wages between graduates and non-college graduates. Increases in the college wage premium shift college enrollment. At the individual level, students are statistically more likely to enroll in college when they expect to earn more money than the current labor market equilibrium (Dillon, 2017). This expectation weighs the opportunity cost, or the loss in both money and time from completing an undergraduate degree, with the chance to earn higher wages. Expected earnings are higher for college graduates due to employer demand for human capital intensive skills. The continual and rapid development of new technologies replaces traditional, less human capital intensive job tasks, with computerized activities. The transformation of typical workplace duties generates demand for more knowledge-based jobs (Autor, Levy, and Murnane 2003). These jobs require skills only gained in secondary education (Valletta, 2016). Thus, increased enrollment rates are associated with the increased wage gap due to the requirements of a digitalized workplace.

In response to this trend, secondary education institutions have correspondingly experimented with implementing new programs to accommodate for increases in demand for post-high school education. The institution can either tolerate increases in student population or it can try to expedite current students' graduation dates. In regards to the former, the most common method is modifying class sizes. Strategies for the latter option include the expansion of the classes into the summer and onto the internet. Although enrollment rates are cyclical, some of these programs are being incorporated on a long term level (Seaman and Allen, 2012). It is difficult to remove a program once it has been instituted. This means that increasing college enrollment rates not only affect the immediate future, but they also have lasting consequences.

While there are merits to creating these programs, there can be detrimental effects. Extensive literature correlates poor student learning outcomes with increased class sizes (Mulryan-Kyne, 2010). These effects may be mollified if the influx of new students enroll in online classes. There is no conclusive evidence on the learning or labor market outcomes for online classes (Nguyen, 2015). If the class cannot be substituted in an online form, and the class size still cannot accommodate the influx of new students, they will need to delay registering for the class. These shortages and delays result from a decrease in funding per student when colleges do not appropriate funds properly (Bound, Lovenheim and Turner, 2007). Unforeseen economic disasters that trigger increased enrollment rates further exacerbate the issue.

The exogenous shock of increasing enrollment rates affects the length of time to complete an undergraduate degree. Time to degree can increase from enlarged class sizes and course scarcity (Kurlaender, Jackson, Howell and Grodsky, 2012). Decreasing time-to-degree, however, results in increased graduation rates and decreased costs (Attewell and Monaghan, 2016). Therefore colleges may be incentivized to decrease time-to-degree in order to mitigate the effects of college enrollment spikes.

There are definitive, albeit short term, benefits to decreasing the length of undergraduate degrees for students. Fast track programs can decrease the number of academic terms a student is enrolled in, thereby lowering student tuition costs. This may, however, cause adverse effects to students in the long term. The targeted population of stragglers, known as super-seniors, often take a fifth year to complete a minor or second major. Additionally, there are valuable internships and other opportunities only available to degree-seeking college students. Undergraduates on fast track programs may be depriving themselves of these opportunities. Thus, the efforts to curtail the number of super-seniors may decrease students' future wages. Attempts to pressure students to cap bachelor's degrees to four years can decrease human capital accumulation, which in turn causes students to have less skills and employability (Hemelt, 2009). This illustrates how time-to-degree can serve as a proxy for the speed of learning.

Understanding the effects of the programs and measures taken to change time-to-degree can help improve educational and labor outcomes. Additionally, decreasing time-to-degree will increase graduation rates and decrease other costs (Attewell and Monaghan, 2016). Demographic groups with low graduation rates and inability to pay could benefit from decreased time-to-degree. It can also help the broader labor market because increases or decreases in time-to-degree will change the supply of labor (Kurlaender, Jackson, Howell and Grodsky, 2012).

This paper aims to understand the effect of time-to-degree on future labor market outcomes through the context of increased college enrollment. Specifically, it answers the question: What is the effect of completing college in 5 years on future wages and probability of employment? This question can be reframed into a larger context for a more general question: What measures of school performance, during college, better predict labor market outcomes? Although this larger question has been researched before using standard test scores as the primary causal effect, this paper will try to encapsulate a more holistic approach to predicting labor market outcomes.

The paper's structure begins with the above background (Section 1). Next, the paper reviews the scarce literature on the effect of time-to-degree on labor market outcomes (Section 2). There is a then brief exposition of the data and statistics that support the initial assumptions in the introduction to this paper (Section 3). A theoretical framework is developed for an empirical model using Two-Stage Least Squares regression (Section 4). This model is used to find the pure effect of time-to-degree on labor market outcomes (Section 5). Robustness confirms the 2SLS model (Section 6). Lastly, the paper is concluded (Section 7).

## 2 Literature Review

The literature is limited concerning the effects of time-to-degree on labor market outcomes. The lack of available research is due to this paper's inversion of the typical time-to-degree model. Previous literature in education economics focuses on the determinants of time-to-degree as a dependent variable whereas this paper uses time-to-degree as an independent variable. This paper will alternatively inspect the relationship of the total time to receive a bachelor's degree on labor market outcomes.

The following literature helped formulate the appropriate model for analyzing the effect of time-to-degree on labor market success. This specification is abbreviated here, but will be explicated in comprehensive detail in the empirical model section.

Even though there is a considerable amount of research exploring labor market outcomes, most of the prior research?involving education indicators?uses cumulative years of education as one of the main independent variables. This paper looks at the amount of time to complete a single undergraduate bachelor's degree instead of the amalgamation of schooling from preschool to college. Specifically it measures time by counting the number of academic terms it takes for an individual to graduate from college.

Although there is a lack of available literature using the model specified in this paper, previous research aids in identifying appropriate factors that contribute to time-to-degree. (Lee, 2010) measures the effects of individual characteristics like college entrance exam score, race, college GPA, and gender on the length of time-to-degree. Like Lee, this paper does not use high school GPA or quintile because these factors are not related to time-to-degree. This paper's first stage, predicting individual time-to-degree using institutional time-to-degree and other institutional characteristics, is similar to Lee's regression involving determinants of time-to-degree. Lee's paper is a useful reference for comparing coefficients and their significance to this paper's first stage regression. The results can be compared because Lee restricts the dataset to individuals who only received a bachelor's degree?the same as this paper's sample. Most importantly, Lee found that individuals enrolled in selective institutions had lower time-to-degrees. This confirms that college characteristics, like selectivity, can affect individual time-to-degree. This assumption is supported in this paper and in the robustness section.

Other variables that affect time-to-degree are institutional characteristics. (Borgen, 2016) warns of using the students' average SAT score as a proxy for the quality of each college as doing so can negatively bias time-to-degree. This paper uses SAT score as one of the two proxies for quality of education. The lack of other measures in this paper's NLSY97 data limit the ability to mitigate the downward biasing. The results of this paper will need to take into the influence of SAT scores influence on time-to-degree. Furthermore, (Borgen, 2016) explains how average SAT score has measurement error because it is not a perfect measure of a college's reputation. This will contribute to threats to identification in this paper.

(Cullinane and Lincove, 2014) examine whether student or institutional characteristics drive individual time-to-degree. They conclude that both affect time-to-degree and policy changes intended to decrease time-to-degree may have detrimental effects to graduation rates. This contradicts conventional wisdom that decreasing time-to-degree will increase graduation rates due to spending less on tuition and less burnout. This paper's model framework incorporates factors of institutional characteristics that have similar institutional effects on time-to-degree like those in (Cullinane and Lincove, 2014). Furthermore, the two authors aid this paper in determining the institutional traits, such as 2 or 4 year academic schedules, demographics of faculty, the amount spent on each student, and college entrance exam scores. (Cullinane and Lincove, 2014) also highlight the effect of transfers and other non-traditional entries into a four year university. Typically these students have higher time-to-degree, which can bias results. This paper solves this problem by removing individuals who were transfer students.

(Suhre, Jansen, Torenbeek, 2013) focus on the interaction between college characteristics and individual abilities. Specifically they measure the effect of either restricting the number of scheduled hours of lecture per week and self-studying. They find that college characteristics can affect students' motivation and discipline. Therefore, this paper needs to separate college characteristics from individual abilities, such as self-discipline, because of the correlation found in this study.

Based on these papers, time-to-degree?as an independent variable?captures a two-part effect: individual ability and school features that affect time-to-degree. Individuals with positive measured qualities will likely have a lower time-to-degree. Likewise schools with positive characteristics, like high average GPA, will tend to have a lower time-to-degree.

This paper utilizes a 2 Stage Least Squares regression model. The selected instrumental variable is the institution's average time-to-degree. (Borgen, 2015) uses an instrumental variable for school quality that is similar to the instrument used in this paper's analysis. Borgen emphasizes that most papers rely on exam scores, which might not be the best measure of school quality. This paper's measure of school quality relies on other measures like institutional time-to-degree.

After instrumenting for institution time-to-degree and controlling for other college characteristics, the individual time-to-degree is isolated as a proxy for speed of learning. Literature regarding optimum time for learning include (Melnick, 2013). Both papers explain the reasons for the parabolic shape of the learning curve. Furthermore, (Kohen, 1979) finds no difference in knowledge retention between men and women.

In regards to the broader question of discerning the measures of school performance affecting labor market outcomes, there is an abundant amount of available literature. (Borgen, 2015) summarizes the current state of determinants of school performance on labor market outcomes. (Borgen, 2015) finds that most studies use samples obtained in the United States with standard test scores as the main independent variable with controls for gender, race, parental education and parental income. These variables act as a measure for quality of school performance. Nevertheless, a majority of the papers report a small effect of test scores on wages, occupational status, and career mobility with low explanatory ability (Borgen, 2015). This paper will deemphasize test scores as the primary determinant of labor market outcomes and it will seek to find other alternative variables. Shifting the focus away from test scores does not downplay the apparent effect of test scores on deducing measures of school performance on labor market outcomes. Instead this paper will seek to find new areas of academic achievement that affect labor market outcomes.

# 3 Data

The primary dataset comes from the National Longitudinal Survey of Youth 1997. This panel data set is provided by the US Department of Labor's Bureau of Labor Statistics. It a national survey of people born between 1980 and 1984. The 8,984 individuals were interviewed from 1997 to the present. The panel data set reported variables for information on every college, term, and course. The survey oversampled certain demographic groups of the US population. This did not affect the results of the paper because the selected sample did not increase when the oversampled groups were added.

The sample was restricted to bachelor degree holding participants. Each individual sampled did not complete an associate's degree or some secondary education before entering a four-year university. The individuals only received one bachelor's degree and may have received a graduate degree. The variable definition of ?time-to-degree,' as the summation of the number of academic terms, necessitated choosing one type of academic term. Only people enrolled in semester systems were selected because the ratio of people enrolled in semesters to quarters was 10 to 1. The sample was further restricted to people who earned a degree between 2001 and 2010. The upper bound for the sample was cut off at 2010 in order to properly display the unique trends of the effects of time-to-degree around the five year mark. The threshold allows for the ability to look at long term wage trends of at least 5 years.

The panel data set did not provide cumulative statistics for each variable. Instead, this paper created variables by conditioning on the course being in the correct term that corresponded to the correct university. For example, the number of remedial and failed courses for a student were only counted for the terms in which the they were attending the university that they would receive their degree from. A majority of the variables were created using transcript copies obtained by the surveyors. The college entrance exam was created using the SAT and not the ACT. The SAT was selected due to discrepancies in the data between the ACT composite score and the summation of the individual ACT subject areas. Parental education was created using the residential instead of biological parents' information. Although residential parents typically had more education, there was more variation compared to biological parents' information. This bias did not affect the sample too much as the differences in highest grade completed for residential and biological only differed by 10%. It made more sense to include the residential parent as they were most likely supporting and paying for the student's tuition and expenses. Nevertheless, time-to-degree is biased because an inability to support someone's education may decrease their time-to-degree. The GPA variable was created by conditioning on the the school in which the individual received a bachelor's degree. Since students can receive a bachelor's degree and graduate degree at the same school, the GPA was calculated for schools where the individual only received a bachelor's degree. The major area type is split into four categories: STEM, humanities, arts and skills, and social sciences. STEM was selected as the base group in the regression analysis because certain STEM majors, like engineering, typically have increased time-to-degree compared to other majors. Double majors, minors, and the number of credits were selected based on transcript reported data. Some transcripts reported two majors as one which under-represents the total number of double majors.

Institutional variables were created to isolate pure time-to-degree from an individual abilities after instrumenting. The specific methodology will be covered in the Empirical Model section. Institutional variables were created by averaging the specific statistic across individuals at the university. The institution region was selected during the year before the student graduated. There may be some error if the student was studying abroad.

Time-to-degree is measured as the number of academic terms (e.g., semesters) between the first enrollment term and the term when the bachelor's degree was conferred. Figure 1 displays the trend of academic terms between the graduation dates of 2002 and 2008.The normal number of academic terms for a bachelor's degree is 8. The trend line is above the average throughout 2002 to 2008. This could be due the overall increase in time-to-degree for highly ranked institutions (Bound, Lovenheim, and Turner 2010). time-to-degree deviates beginning in 2007. This coincides with the beginning of the 2007 financial crisis and recession. When prospective job outlooks are bleak, people face lower opportunity costs to enroll or continue their education. If there is massive unemployment, it might be more attractive to stay in college for a few more academic terms to get another degree. As the economy improved in the following years, time-to-degree decreased as job prospects improved.

Alternative measurements included the time difference between the date of first enrollment and the date of graduation. The date of degree, however, may not correspond to the last term of enrollment. Therefore, electing only the terms in which the individual reported attending is preferable to measuring the difference in years or months. Figure 2 shows time-to-degree in years instead of academic terms. The patterns in this figure track well with the academic terms time-to-degree in Figure 1. Thus, it is reasonable to use academic terms as a measure of the time-to-degree.

The dependent variables, wages and employment status were calculated immediately after graduation to five years later. Wages is the total amount of earnings through salary, tips, and commissions before deductions in taxes. The top 2% of wages were averaged by the surveyors. Figure 3 presents the average yearly income between graduation dates of 2002 and 2008. As the years increase after graduation, the average yearly income increases. When the recession hit in 2007, there was a decrease in the average yearly income across all cohorts except immediate graduates. This could be attributed to new college graduates willing to take lower paying jobs.

Similar trends appear for the probability of employment in Figure 4. The probability of employment is measured as a binary variable for whether the individual is employed. Employment statistics were provided at the weekly level. A person with employment records for all 52 weeks of the year was counted as employed. Across all years, the number of individuals employed for all 52 weeks was close to 80% of the entire survey population. Regressions were also run using employment for only 26, but the results were not statistically significant for all years post graduation.

# 4 Empirical Model

The two primary labor market outcomes are wages and probability of employment. After controlling for other factors, these outcomes are determined by the worker productivity. Increases in productivity will shift the labor demand curve out. A more productive worker can produce more output more efficiently. Thus the shift in the labor demand curve represents employers willingness to increase wages and the number of workers employed.

An exogenous shock, such as college enrollment increasing, affects the level of productivity. Growth of college enrollment results in changes to students' time-to-degree. The direction of the change in time-to-degree affects the productivity of graduates. Therefore, by influencing productivity, time-to-degree can alter labor market outcomes. If increases in time-to-degree positively affect productivity, then the labor demand curve would shift to the right. This upward shift in the demand curve raises the wage and increases the number of employees desired.

Time-to-degree is defined as the the number of academic terms enrolled in the bachelor's degree-conferring institution. This variable is a function of individual abilities and college traits. An individual with positive abilities, such as high GPA or college entrance exam score, likely will have a shorter time-to-degree. On the other hand, colleges have certain characteristics that produce a different time-to-degree. For example, for profit institutions or "diploma mills" are incentivized to have a longer time-to-degree compared to public universities. Since both factors? individual abilities and college traits?affect time-to-degree, they also impact productivity and labor market outcomes.

This basic correlational model predicting labor market outcomes using individual time-to-degree is insufficient. Endogeneity arises from individual abilities affecting the main independent variable, time-to-degree, and the independent variable productivity. Positive individual abilities, like a good work ethic, can allow a student to complete a more rigorous course schedule earlier. A good work ethic, however, will also increase productivity and thus labor market outcomes. An individual's dual effect on time-to-degree and labor market outcomes indicates that time-to-degree is not the sole influencer of productivity.

The effect of time-to-degree on labor market outcomes can be isolated from the spurious relation through experimentation, or implementation of an instrumental variable. Since time-to-degree is essentially a choice for each individual, the former method randomly assigns varying levels of time-to-degree to participants. If the dataset contained information on prerequisite exam scores for institution-specific advanced classes, then the sample would only include those who barely passed or barely failed. This pass rate is near random, which helps eliminate possible bias.

The infeasibility and unethical experiment necessitates utilizing an instrumental variable. Selection of the instrument was based on two criteria: lack of correlation with the error term and nonzero correlation with the main dependent variable time-to-degree. The best instrument that fits the constraints of the data is institutional time-to-degree. The institution's average time-to-degree is correlated with individual time-to-degrees. The environmental factors of the institution, like college selectivity or rigorousness, influence the individual's length of degree completion. In contrast, institutional time-to-degree does not affect labor market outcomes. Institutional time-to-degree changes based on institution characteristics. For example, large class sizes may affect institutional time-to-degree but larger class sizes, and thus institution time-to-degree, do not influence an individual's wages post-graduation.

Utilizing an instrumental variable requires two stages: predicting the main independent variable using the instrument, and performing a regression on the labor market outcomes using the predicted main independent variable. The first stage in equation (1), predicting individual time-to-degree using $T_c$ or institution c's average time-to-degree after controlling for college characteristics, and individual controls in $X_{i,t}$. Individual i's controls include gender, race, and parental education. The first and second stage were run for $t = 0, 1, 2, 3, 4$, and 5 years after graduation.

$$(time)_c = \pi_0 + \pi_1 T_c + \beta X_{i,t} + v_c \tag{1}$$

The second stage in equation (2) measures the effect of predicted individual time-to-degree on log wages and the probability of employment. New regressors are added in order to isolate the effect of pure time-to-degree. $A_{i,t}$ is individual i's abilities that affect productivity and individual time-to-degree, but do not affect institution time-to-degree. The abilities in $A_{i,t}$ include SAT scores, GPA, number of remedial and failed classes, second major or minor, and the number of credits. College characteristics $C_c$ is the average GPA and SAT for college $c$. The main independent variable, $(time)_{i,c,t}$, is the predicted individual time-to-degree. $(time)_{i,c,t}$ is the instrument variable, college time-to-degree, after controlling for college traits.

$$ln(Wage)_{i,t} = \alpha_{i,t} + \beta X_{i,t} + \gamma A_{i,t} + \lambda C_c + \delta(time)_{i,c,t} + \epsilon_{i,t} \tag{2}$$

Equation (3) replicates the second stage model but uses the probability of employment instead of log wages as the dependent variable. The probability of employment is a binary variable. Time-to-degree's effect is represented in percentage points increases in the probability of employment.

$$Employment_{i,t} = \alpha_{i,t} + \beta X_{i,t} + \gamma A_{i,t} + \lambda C_c + \delta(time)_{i,c,t} + \epsilon_{i,t} \tag{3}$$

After controlling for other college traits like institution GPA and instrumenting, the effect of time-to-degree, $\delta$ is isolated. This pure time-to-degree captures an individual's speed of learning. There are increasing returns to learning associated with low amounts of learning. After a certain point, however, any additional learning negatively impacts the student. This point demarcates when benefits to extra learning are not proportional to the amount of additional learning. (Melnick, 2013) explain that this "point of criterion" marks diminishing returns to learning because there is a decrease in the cognitive exertion and variability of learning. This can be applied to time-to-degree wherein additional time in school may not grow new skills to boost productivity. Instead, excessive time-to-degree may cause productivity to remain stagnant.

A positive slope ($\delta > 0$) for the pure time-to-degree curve represents gains to productivity due to more skills. Positive effects of increases in time-to-degree include spending extra time to complete a double major or minor. But, after a certain point, having a high time-to-degree may be detrimental ($\delta < 0$) to productivity due to poor knowledge retention or learning outdated material. Therefore, the sign of $\delta$ will explain the relationship between time-to-degree and labor market outcomes.

The main threat to identification is measurement error. There are no perfect measures of college quality. (Borgen, 2015) advises against using college entrance exam scores as proxies for institutional quality. Due to the confidential limitations of nature of the data set, other college factors are missing which could be used to alleviate this issue. The measure of school quality will be biased, but the 2 Stage Least Squares Regression framework can decrease its debilitating effects.

# 5 Empirical Results

The effect of individual time-to-degree on labor market outcomes is negative for the first two periods after graduation. The statistically significant effects are quite large. Table 2 displays log wages and probability of employment immediately after graduation and one year later. Increasing time-to-degree by one academic term is associated with a 38.81% increase in log wages immediately after graduation. One year later, log wages decrease by 42.96% for a one unit increase in time-to-degree. Time-to-degree's effect on probability of employment is a lot lower compared to log wages. A one unit increase in time-to-degree will decrease the probability of employment by 21.37% after graduation whereas the same one unit increase in time-to-degree will decrease probability of employment only 12.27% one year after graduation.

The OLS results in Table 1 show the positive caused by the endogeneity by individual abilities. The time-to-degree coefficients are all positive except for probability of employment one year after graduation. After instrumenting for individual abilities in Table 2, the effect of time-to-degree is negative. Additionally, the 2 Stage Least Squares regression made the time-to-degree coefficients statistically significant.

The non-significant effect of time-to-degree on labor market outcomes for years two through five are reported in Table 3 and 4. As time from graduation increases, the effect of time-to-degree is more positive on respective labor market outcomes. Time-to-degree did not become positive for log wages because the magnitude of the negative effect immediately after graduation was greater for log wages than probability of employment. Time-to-degree on log wages may have a greater magnitude because wages continually increases as the number of years from graduation increases (Figure 3). The probability of wages converges together two years after graduation.

The first stage results are presented in Table 5. Increasing the institution's average time-to-degree by 1 is associated with a 0.7296 unit increase in individual time-to-degree. The instrument is statistically significant at the 99% level. The signs of the coefficients are better in the first stage compared to the second stage. Increasing the number of failed and remedial classes, and the number of credits are associated with increases in individual time-to-degree. But, like (Lee, 2010) a lot of the variables are statistically insignificant. The amount of variation explained by the regression is 40%. This means that the use of an instrumental variable after controlling for college characteristics was moderately able to capture the pure time-to-degree. The second stage in Table 6 illustrates the fact that few coefficients are statistically significant aside from the main independent variable time-to-degree.

The two main limitations of the analysis are the sample selected and the statistically insignificant co-regressors. A larger sample size of individuals can add more variability in graduation dates. Most individuals graduated between 2004 and 2007. The statistically insignificant regressors, such remedial classes, and additional majors have incorrect signs. A few variables were highly collinear with each other. This paper was not unique in finding statistically insignificant independent variables when time-to-degree is measured. Individual characteristics, except being a Native America, were found to have no statistically significant relationship with time-to-degree in (Lee, 2010).

These results demonstrate the importance of policies designed to alter students' time-to-degree. College's efforts to reduce time-to-degree, because of rising enrollment rates, do not affect student outcomes immediately. It is preferable to decrease time-to-degree when considering immediate labor market success.

# 6 Robustness

There are two main qualifications for a good instrumental variable. There needs to be correlation between the instrument and the main regressor, and there should be no correlation between the instrumental variable and the error term. In regards to the former, the OLS regression coefficient was positive 0.7296. The instrumental variable, institutional time-to-degree, has a positive effect on individual time-to-degree For the later, it is impossible to measure the correlation with a variable that is unmeasurable. An alternative is to measure the correlation between the institution time-to-degree and the institutional characteristics: SAT and GPA. Both had low correlation. Therefore, the data supports the appropriateness of the instrument.

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## Figures and Tables


Figure 1: Average Time-To-Degree Between 2002 and 2008 (In Number of Academic Terms)


Figure 2: Average Time-To-Degree Between 2002 and 2008 (In Number of Years)

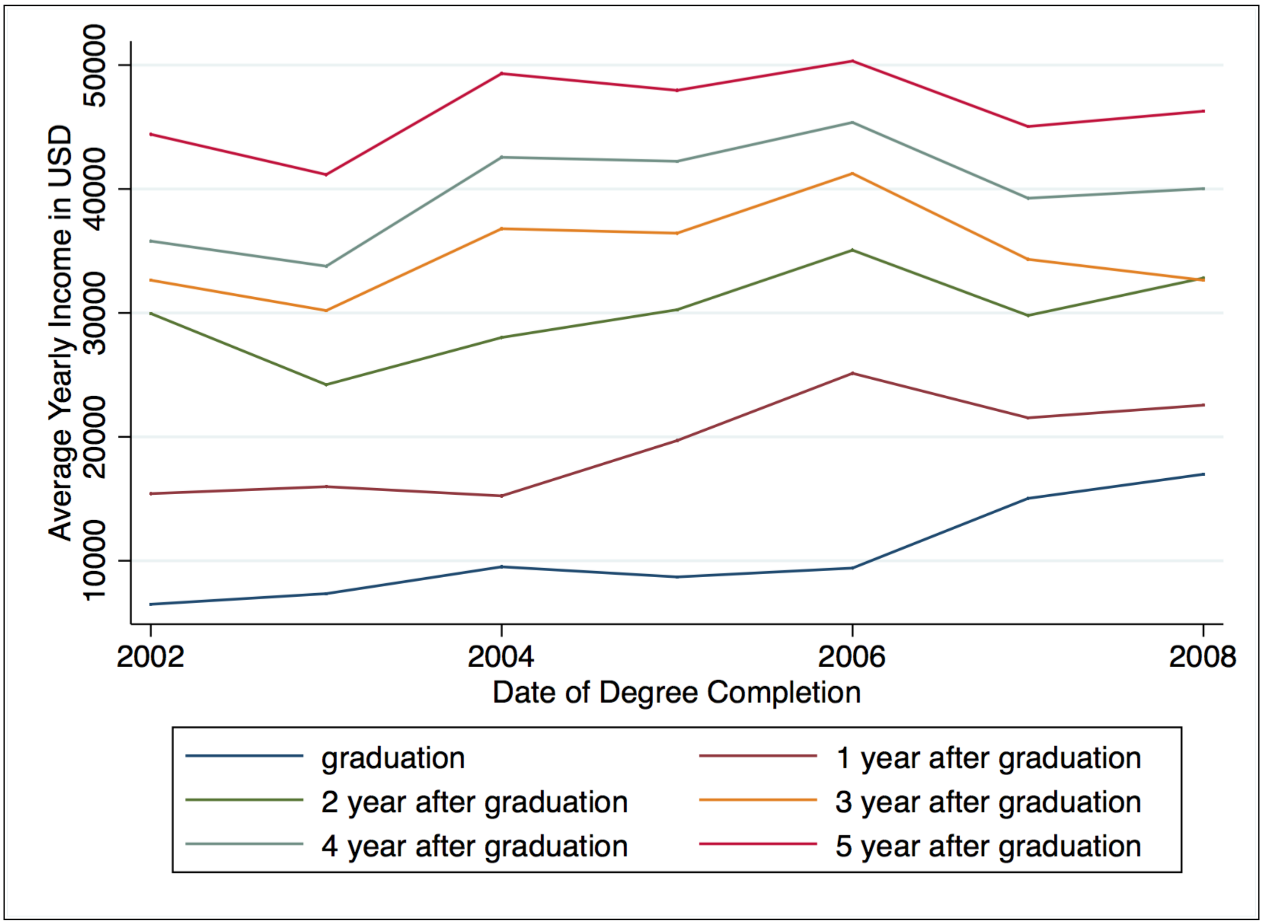


Figure 3: Average Yearly Income Between 2002 and 2008 (In USD)

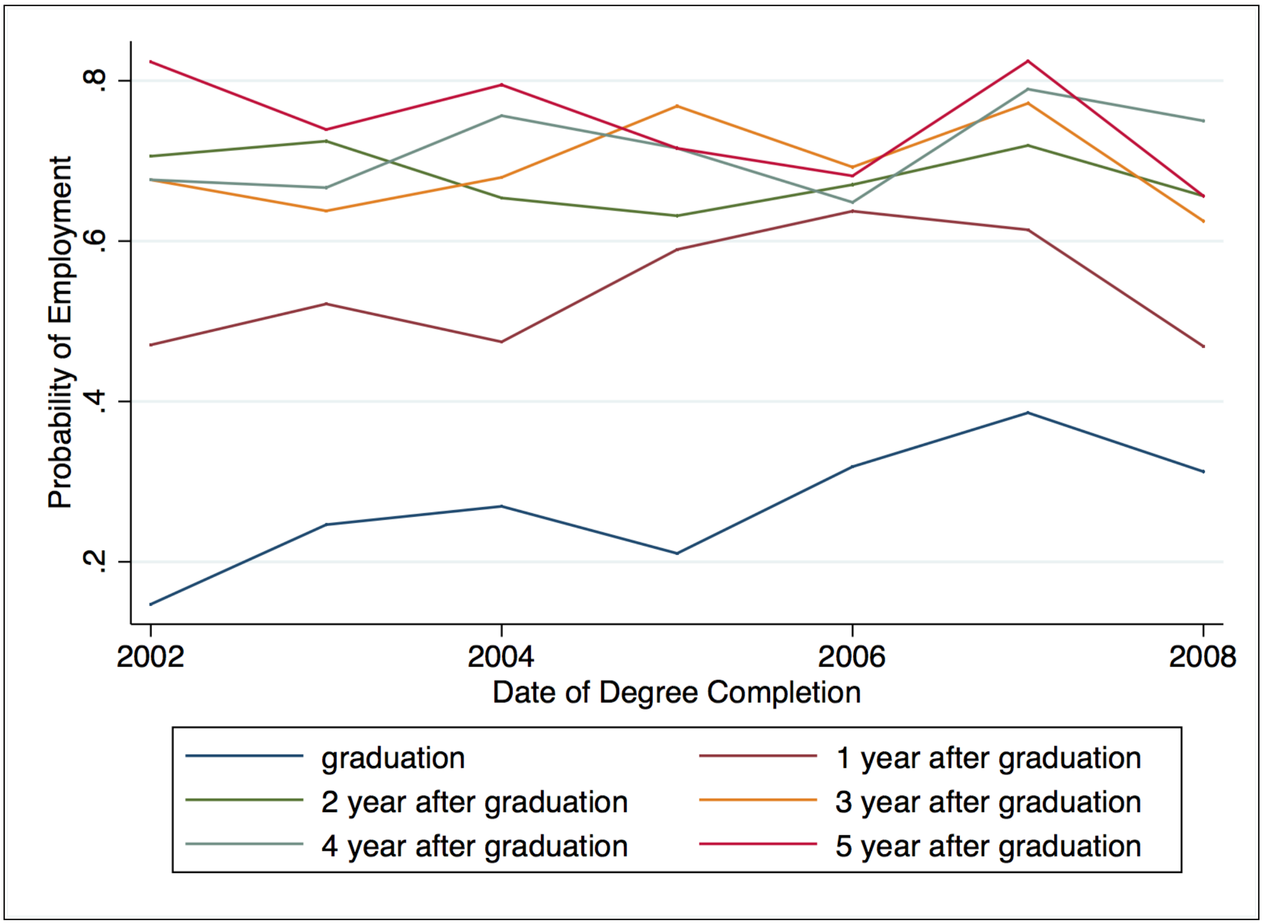


Figure 4: Average Probability of Employment Between 2002 and 2008 (In Percent)

Table 1
OLS Regression Time To Degree for 0 and 1 years after graduation

| | lwage0 | lwage1 | emp0 | emp1 |
|---|---|---|---|---|
| Time To Degree | 0.0364 | 0.0084 | 0.0421* | −0.0154 |
| | (0.0458) | (0.0375) | (0.0225) | (0.0272) |
| $R^2$ | 0.2916 | 0.2722 | 0.1354 | 0.1974 |

Table 2
IV Regression Time To Degree for 0 and 1 years after graduation

| | lwage0 | lwage1 | emp0 | emp1 |
|---|---|---|---|---|
| Time To Degree | −0.3881** | −0.4296** | −0.2137*** | −0.1227** |
| | (0.19) | (0.18) | (0.08) | (0.06) |

* = Significant at 90%, ** = Significant at 95%, *** = Significant at 99%

Table 3
IV Regression Time To Degree on Log Wages for 0-5 years after graduation

| | lwage0 | lwage1 | lwage2 | lwage3 | lwage4 | lwage5 |
|---|---|---|---|---|---|---|
| Time To Degree | $-0.3881^{**}$ | $-0.4296^{**}$ | $-0.1004$ | $-0.2640$ | $-0.1051$ | $-0.0818$ |
| | (0.08) | (0.06) | (0.08) | (0.17) | (0.15) | (0.09) |

Table 4
IV Regression Time To Degree on Employment for 0-5 years after graduation

| | emp0 | emp1 | emp2 | emp3 | emp4 | emp5 |
|---|---|---|---|---|---|---|
| Time To Degree | $-0.2137^{**}$ | $-0.1227^{**}$ | 0.0218 | 0.0245 | $0.1149^{*}$ | $0.1366^{*}$ |
| | (0.08) | (0.06) | (0.07) | (0.06) | (0.06) | (0.06) |

* = Significant at 90%, ** = Significant at 95%, *** = Significant at 99%

Table 5
First Stage Regression Part 1
* = Significant at 90%, ** = Significant at 95%, *** = Significant at 99%

| | Time To Degree By Number of Terms |
|---|---|
| Intercept | 5.930 |
| | (11.3803) |
| College Time To Degree IV | 0.7296*** |
| | (0.1900) |
| Gender | −0.2057 |
| | (0.3428) |
| White | −0.8544 |
| | (0.5330) |
| Mom Highest Grade | 0.0319 |
| | (0.0568) |
| Dad Highest Grade | 0.0339 |
| | (0.0660) |
| SAT Math | −0.0010 |
| | (0.0024) |
| SAT Verbal | −0.0010 |
| | (0.0024) |
| GPA | −1.6064 |
| | (0.5308) |
| Remedial Classes | 0.3800 |
| | (0.9275) |
| Classes Failed | 0.0880*** |
| | (0.0297) |
| Minor Degree | 0.0709 |
| | (0.4637) |
| Double Major | −0.3133 |
| | (0.4536) |
| Humanities | −0.2600 |
| | (0.5184) |
| Art and Skills | 1.6351 |
| | (1.2153) |
| Social Sciences | 0.6058 |
| | (0.6041) |
| Number of Credits | 0.0163** |
| | (0.0079) |
| Institution Northeast | −0.8508* |
| | (0.4484) |
| Institution North Central | −0.0764 |
| | (0.5397) |
| Institution West | −0.9527 |
| | (0.6720) |
| Institution GPA | −0.7969 |
| | (2.8138) |
| Institution SAT Math | −0.0001 |
| | (0.0206) |
| Institution SAT Verbal | 0.0057 |
| | (0.0291) |
| $R^2$ | 0.40 |

Table 6
Second Stage Regression for 0 and 1 years after graduation
* = Significant at 90%, ** = Significant at 95%, *** = Significant at 99%

| | lwage0 | lwage1 | emp0 | emp1 |
|---|---|---|---|---|
| Intercept | 7.5248 | 24.2385*** | −3.0043*** | 1.9020 |
| | (10.4050) | (9.3271) | (4.1810) | (3.0665) |
| Time To Degree | −0.3881** | −0.4296** | −0.2137*** | −0.1227** |
| | (0.1940) | (0.1773) | (0.1051) | (0.0571) |
| Gender | −0.2850 | −0.3022 | −0.0794 | −0.2230** |
| | (0.2344) | (0.2161) | (0.1051) | (0.0969) |
| White | −0.5584 | 0.1766 | −0.1973 | −0.2015 |
| | (0.4169) | (0.4532) | (0.1840) | (0.1326) |
| Mom Highest Grade | −0.0147 | 0.0114 | 0.0118 | −0.0066 |
| | (0.0370) | (0.0352) | (0.0180) | (0.0174) |
| Dad Highest Grade | −0.0396 | 0.0562 | 0.0005 | −0.0074 |
| | (0.0390) | (0.0401) | (0.0231) | (0.0172) |
| SAT Math | 0.0014 | −0.0004 | 0.0002 | 0.0002 |
| | (0.0017) | (0.0018) | (0.0007) | (0.0006) |
| SAT Verbal | −0.0001 | 0.0012 | −0.0005 | −0.0011* |
| | (0.0017) | (0.0019) | (0.0007) | (0.0006) |
| GPA | −1.2257* | −1.2611*** | −0.4076* | −0.1836 |
| | (0.5199) | (0.4922) | (0.2269) | (0.1719) |
| Remedial Classes | −0.1090 | 0.1115 | −0.0487 | −0.1836 |
| | (0.5560) | (0.4184) | (0.2282) | (0.2203) |
| Classes Failed | 0.0438* | 0.0350 | 0.0327*** | 0.0050 |
| | (0.0247) | (0.0350) | (0.0115) | (0.0087) |
| Minor Degree | −0.2502 | −0.2623 | −0.1039 | −0.0977 |
| | (0.3009) | (0.2643) | (0.1413) | (0.1197) |
| Double Major | −0.3917 | −0.4777* | −0.0532 | −0.0271 |
| | (0.3484) | (0.2558) | (0.1700) | (0.1042) |
| Humanities | −0.1012 | −0.0570 | 0.0260 | 0.1379 |
| | (0.3101) | (0.3233) | (0.1439) | (0.1173) |
| Art and Skills | 0.7540 | 0.1035 | 0.6231 | 0.1913 |
| | (1.3569) | (1.3118) | (0.4951) | (0.2002) |
| Social Sciences | 0.2123 | 0.6446 | 0.3963* | 0.1186 |
| | (0.3590) | (0.4045) | (0.2411) | (0.1890) |
| Number of Credits | 0.0215*** | 0.0147* | 0.0031 | 0.0040* |
| | (0.0071) | (0.0081) | (0.0035) | (0.0022) |
| Institution Northeast | −0.0411 | 0.0858 | −0.1777 | −0.1497 |
| | (0.3414) | (0.3174) | (0.1557) | (0.1217) |
| Institution North Central | 0.0481 | −0.0453 | 0.0380 | −0.1375 |
| | (0.3815) | (0.3150) | (0.1836) | (0.1349) |
| Institution West | 0.3753 | 0.3017 | −0.2479 | 0.0767 |
| | (0.4421) | (0.4017) | (0.2180) | (0.1566) |
| Institution GPA | 0.6253 | −4.4273 | 0.8630 | −0.0491 |
| | (2.6501) | (2.1974) | (0.9953) | (0.7512) |
| Institution SAT Math | −0.0085 | 0.0167 | −0.0045 | 0.0063 |
| | (0.0152) | (0.0147) | (0.0072) | (0.0056) |
| Institution SAT Verbal | 0.0174 | −0.0093 | 0.0112 | −0.0044 |
| | (0.0209) | (0.0203) | (0.0100) | (0.0077) |
| $R^2$ | 0.01 | 0.01 | 0.01 | 0.3 |