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FACTORS AFFECTING MASTER'S STUDENT COMPLETION RATES

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FACTORS AFFECTING MASTER'S STUDENT COMPLETION RATES

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BY THE COMMITTEE CONSISTING OF

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Abstract

Engineering master's education is an understudied area in research. This lack of research has important ramifications to institutions, students, and society at large. Lower completion rates mean fewer qualified engineers available and a financial loss to both student and institutions. This has a society-wide impact and is important to address. As the number of students enrolled in master's programs continues to grow, it becomes critical to review, identify, and discuss factors that affect degree completion. Improvements to completion rates cannot be made and maintained without a detailed and nuanced understanding of the underlying factors. This study investigated engineering master's completion rates for students entering a large midwestern research institution from fall 2009 to spring 2014 (N=485) to identify factors affecting completion rates. Using logistic regression this study found that graduate GPA, funding, full-time enrollment, and summer enrollment affected completion rates. This study also found that prior undergraduate experience at the institution did not affect completion rates. This study also reports and compares completion rates for engineering master's programs from prior literature. Future research and policy ramifications are discussed.

Keywords: Master's completion rates; Engineering completion rates; Logistic regression

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Chapter 1: Introduction

Engineering master's students are an understudied population. Unlike undergraduate students, there are no major datasets that related to master's student completion rates. In addition to this lack of data, there is a lack of meaningful research that address factors that affect persistence, retention, and graduation for engineering master's students.

Master's level education is in high demand in the United States. The Council of Graduate Studies found that as of Fall 2016 the largest majority of graduate enrollment in the U.S. is in master's degree or graduate certificate programs (Council of Graduate Schools, 2016). More Americans have graduated with a master's degree than any other graduate degree including professional degrees such as M.D. and J.D. degrees ("Number of People With Master's and Doctoral Degrees Doubles"). Engineering has also seen a substantial growth in master's enrollment since 2002 ("How Many Degrees", 2014). The NSF in a profile of engineering found that the number of engineering master's degrees conferred has grown by 64.8% since 2002.

Roy (2018), reported that engineering master's degree enrollment has been growing at a rapid pace. In 2018, the number of students enrolled in an engineering master's degree was 93,559. Are all these students who enroll in a master's degree going to complete that degree? What factors affect these completion rates? The purpose of this thesis was to answer these questions. Little research has been performed to investigate these types of questions for engineering master's degree programs. Knowing the factors affecting degree completion is essential to improving education outcomes for master's degree students. Additionally, as master's enrollment engineering continues to grow, it is necessary and essential to focus attention on degree completion. Students who do not complete their degree face a financial loss.

Institutions who do not see students complete also lose a qualified candidate who demonstrated potential to finish.

Institutions also face a financial incentive to continue to grow and improve master's degree completion rates. Master's students pay tuition and fees, and this is a vital source of funding. Additionally, the faster a student can finish their degree the more students can be accepted into the master's program. For engineering programs, this also means students will have the opportunity to research, develop, and grow in their individual fields and contribute to society in meaningful ways.

The goal of this project was to answer the question: what factors affect engineering master's degree completion rates. Data was collected from a large midwestern university from 2009 to 2014. Literature was investigated to find possible factors that could contribute to completion rates. Factors were investigated using logistic and regression models to determine significance.

This study found the 2-year, 3-year, and 4-year completion rates for a large midwestern research institution to be higher than prior studies involving engineering completion rates. It was found that graduate grade point average (GPA), full-time enrollment, thesis research participation, assistantship funding, and demographic information such as gender were significant to completion rates. This was the first study to report completion rates for engineering master's degrees and to report factors that affect these completion rates. This technique has not been reported to be used in prior engineering completion rate studies.

This thesis is organized as follows. Chapter 2 contains a review of relevant literature and is used to identify possible factors that contribute to completion rates. Chapter 3 presents the methodology for variable selection, inclusion in the logistic regression models, data handling, and data scrubbing. Chapter 4 describes data trends and discusses the results of the regression models. The conclusion and recommendations from this study are discussed in Chapter 5.

Chapter 2: Review of Literature

In this chapter, a review of literature and relevant definitions are provided. The purpose of this review is to examine prior studies for completion rates, methodologies used, and to identify potential factors that contribute to master's degree completion rates. A review of some undergraduate retention literature is presented to identify possible variables. A summary of the identified variables and connection to this thesis is presented at the end of the chapter.

2.1 Completion Rates, Retention, and Graduate Student Measures

Haydarov, Moxley, and Anderson (2013) investigated various ways to report and monitor performance measures for master's students. They used a multi-institution, online master's program to compare measurements. They found that there is currently no consensus on what measures are being reported. They found that there is a difference in comparing attrition rates, completion rates, and drop-out rates. Without consistent measures, comparison is challenging. The authors reported that the best ways to remain consistent was to report on the 'ultimate' measures for success and failure: graduation rates, retention rates, and drop-out rates. From their study, they found a difference between online and on-campus programs with on-campus programs mostly using 150% timeframes for degrees, an example would be for a 2-year master's degree the completion timeframe should be 3 years. They suggest that the time should be extended to six years for online programs to fully capture the population of students.

2.2 Retention Models

Retention and completion rates are a heavily studied issue for undergraduate students. One of the more cited and widely accepted investigations into factors that affect completion rates and retention of undergraduate students was done by Tinto in 1975. Tinto (1975) developed a quantitative model to describe student attrition and persistence rates. Tinto's model found that students were more likely to be retained and graduate when they were socially and academically integrated with the institution, as measured through a survey of first year students. Tinto's model included academic factors such as high school GPA, major choice, and departmental culture. Tinto's research has been investigated for both 2-year and 4-year colleges (Pan, 2010). Tinto proposed a similar model for doctoral student retention (Tinto, 1993). This model uses similar metrics as the undergraduate model for but placed larger emphasis on academic integration as a factor for retention.

There has been research and literature suggesting that Tinto's model is not applicable to all student populations. Davidson and Wilson (2014) investigated other models for student retention and completion. These authors found that Tinto's model was unsuitable for commuter, native, and non-traditional student populations. Another model of retention and persistence was proposed by Bean and Metzner (1985) for undergraduate students who commuted to a community college and had an age greater than 25. Bean and Metzner identified factors that were considered critical for student retention. Some of the factors that were found to be critical include factors such as finances, hours worked, family responsibilities, major certainty, and family encouragement.

Using a model similar to the undergraduate persistence model developed by Bean and Metzner, Cohen (2012) surveyed master's students at a large northeastern U.S. university. Cohen used survey and institutionally collected data to develop a model for persistence. Cohen found factors such as age, demographics, and marital status had an impact on retention. Cohen also found that GPA and intent to leave were significant to student persistence. Cohen's study focused on all degree types. However, the data was disaggregated by major and no other literature investigating master's student persistence was found.

2.3 Completion Rates for Master's Degrees

There have been few studies into completion rates for master's degree students. Luan (1992) completed a doctoral dissertation analyzing master's student persistence and completion rates at Arizona State University. Luan investigated master's students who started in fall 1985 and analyzed four years of data to identify factors that affect persistence and degree completion. Using a logistic regression model, Luan found that there were significant factors that may have contributed to the completion rates. These factors include financial aid, gender, age, family financial support, and residency (in-state vs. out of state residency). Luan found that students who received financial aid had higher completion rates than those that did not: 68% vs. 46%. Luan also found that in-state residents had higher completion rates. Additionally, Luan found that engineering had lower completion rates compared to all other majors in the study.

Montgomery and Anderson (2007) reviewed Master of Business Administration (MBA) degree completion rates. Montgomery and Anderson used Graduate Management Admissions Test (GMAT) registrants from 1991 and 1992 who then went on to register for an MBA program. Using a logistic regression model, they investigated possible factors that could contribute to the completion rates. This study found that gender was a significant factor in degree completion rates. This study found that only 61% of students who took the GMAT enrolled in MBA programs. They also found that the completion rates were very low for GMAT registrants at 26%, which included those who did not enroll in MBA programs.

Geiske (1995) used a quantitative investigation to study nursing master's degree completion rates. Geiske used a regression model to investigate the significance of demographic information (age, sex, race, time between undergraduate and graduate degree), GRE scores, residence status, and GPA. This regression model was able to accurately predict 75% of the test data. It was found that age, gender, race, and residency were significant factors that affected completion rates.

Lightfoot and Doerner (2008) investigated completion rates for criminology students. They looked at both master's degree and doctoral degree completion and attrition across nine years and found that about two-thirds of students complete an advanced degree. It was found that the graduate records examination (GRE) scores were a significant indicator for master's degree completion rates, but not for doctoral rates. This study found that completion rates differed by gender, race, and age. Younger students with higher GRE scores finished their master's degree at a higher rate.

One of the broader investigations into Science, Technology, Engineering, and Math (STEM) completion rates was conducted by the Council of Graduate Schools (2013). This study investigated five institutions throughout the United States from 2004 to 2011. In addition to measuring completion rates, this investigation compared STEM completion rates to MBA completion rates in the same institutions. This comparison was made to determine if there is a similarity between STEM and MBA completion rates. This study classified STEM as "biological and agricultural sciences, engineering, mathematics and computer sciences, physical and earth sciences, and social and behavioral sciences" (pg. 17). To measure completion rates, this study used 2-year, 3-year, and 4-year metrics. Table 1 shows the aggregate completion rates for the five institutions and the MBA comparison. There was a significant difference (roughly

20% or more) between the MBA and engineering completion rates. This trend persisted across all STEM completion rates. This study found that women completed at a higher rate than men in STEM master's degrees.

Table 2.1: Factors Found Contributing to Master's Degree Completion (Adapted from Council of Graduate Schools, 2013, pg. 37)

Field of Study	2- year Rate	3-year Rate	4-year Rate
Biological and Agricultural Science	40%	62%	69%
Engineering	40%	60%	65%
Mathematics and Computer Science	40%	59%	66%
Physical and Earth Science	33%	59%	67%
Social and Behavioral Science	45%	60%	65%
MBA	67%	81%	86%

2.4 Financial Factors:

Financial aid has been found to impact graduate completion rates. Luan (1992) found that assistantships and scholarships were an important factor for completion rates. Luan also reported an interaction between funding and gender. Ampaw and Jaeger (2011) found that funding and assistantships are significant factors for female doctoral student time to degree. Using event history analysis, they found that the type, amount, and length of the funding impacted female science, engineering, and math doctoral students time to degree and thus would have an impact on their completion rates.

2.5 Summary:

It is important to make note that many of these studies are over 10 years old. Little recent literature was found and almost no literature was identified that discussed engineering master's students.

A useful outcome of this literature review was to identify metrics, methodologies, and factors for master's student completion rates. This review found that completion rates were the most reported metric. The most used methodology for identifying factors that contribute to completion rates was found to be logistic regression. Factors that were found to be significant can be broadly broken down to three categories: academic, demographic, and financial. Many academic factors were identified including GPA, hours attempted per semester, major, and GRE score. Demographic factors include age, gender, race, and residency. Financial factors that were found to be important include if students received assistantships, loans, or other financial support. Using the metrics, methodology, and factors identified in this review, the proposed methodology is presented in Chapter 3.

Chapter 3: Methodology

A proposed methodology to answer the research question of "what factors affect completion rates" is described in this chapter. Researcher positionality, variable identification, evaluation, and inclusion is discussed. Identification of missing variables and a brief description of the data is included. The development and implementation of variables in a logistic regression model is described. Evaluation of the model and determination of goodness of fit are addressed.

3.1 Research Positionality:

It is important to remember that researcher positionality affects research methods and outcomes. I am a master's student in engineering and this research topic is directly connected to my life experiences. Additionally, I am an academic advisor for undergraduate engineering students. In this position, I have seen students succeed and complete their undergraduate degree with institutional support. Both these positions have directed my research question and focus. As an engineering student and advisor, I want to identify factors that institutions can use to better support students.

3.2 Variable Identification, Selection, and Inclusion:

In order to answer the research question, "what factors affect completion rates," data were obtained from a large midwestern U.S. research institution. Because completion rates were found to be the most common method for measuring success, it was decided that the 2-year, 3-year, and 4-year completion rates were to be used. This metric follows the same process as the Council of Graduate School's pilot study in 2013 (Council of Graduate Schools, 2013). Data were collected for students who entered an engineering master's program from fall 2009 to spring 2014. This time selection represents 5 years of data, providing a large sample size of students. The institution of record has a policy of coursework expiring after 5 years. The spring 2014 period was selected to ensure that all students who were included would be outside the completion time metrics used in this study. The completion rate was calculated as the number of students who completed their master's degree divided by the total number of students. Years were calculated by semester. Students who started in the fall and complete in the spring semester were defined as completing in a year. Summer was considered a separate semester and a factor of 0.25 years was added to accommodate for this consideration. Starting semester (fall or spring) was included as a variable of interest. This was to determine if the policy of admitting students each semester was creating an imbalance in completion rates due to curricular structure of programs and departments.

The variables identified in Chapter 2 were retrieved for these students. To investigate academic integration from Tino's model, it was decided to examine students who attended the institution for their undergraduate degree. As another way to investigate integration and to determine if there were internal differences at the institution of investigation, department level data were used. Another variable that was considered was the role of a thesis research project on completion rates. To determine this role, both thesis research participation and completion were included in this study. Prior to retrieving any data, this research was approved by the Institutional Review Board (IRB) as exempt (OU IRB #10455). The data retrieval was completed by the Institutional Research and Reporting (IRR) department. This retrieval resulted in data for 549 students. To preserve confidentiality, all personally identifying data were removed. Financial aid information was restricted to assistantship funding and completion of the free application of federal student aid (FAFSA) only. As an additional measure of confidentiality, departments were coded to remove the possibility of identifying a student and race was defined as white, non-white, does not wish to report, and non-US citizen.

The variables retrieved were guided by the variables listed in Chapter 2. A full list of the variables gathered, data type, and a brief description for each can be found in Appendix A. The variables were investigated for missing values and general completeness. Each student's transcript was also evaluated individually to ensure accuracy of each variable as well as to verify prior institution attendance, average number of hours attempted each semester, enrollment status, thesis hours enrollment, thesis completion, and summer enrollment. The definition for part-time enrollment was enrollment in less than 6 credit hours per semester without enrollment in thesis research hours. Full-time enrollment was defined as 6 or more credit hours per semester with the exception for students enrolled in thesis research hours who are considered full time when enrolled in these hours. After reviewing the variables for accuracy and completeness, the following variables were removed due to a large number of missing entries: GRE scores and the Free Application for Federal Student Aid (FAFSA).

Students who did not meet the criteria of entering an engineering master's degree during fall 2009 to spring 2014 were removed from the dataset. Students who were enrolled in a master's degree but started a Ph.D. program without receiving a master's degree were removed from the dataset. The reason for this removal is due to the uncertainty of knowing if these students initially started as Ph.D. students and were miscategorized or chose to pursue a different degree. Students who participated in a reciprocal exchange program were also removed. These students did not fully complete their degree at the institution of investigation and do not represent typical master's students at this institution. After all the outliers were identified and removed, there were 485 students who met the criteria.

3.3 Logistic Regression:

Because the objective of this study was to find the factors that contribute to the completion of a master's degree, the outcome variables are 2-year, 3-year, and 4-year graduation. These were binary (Y/N) in nature. This makes logistic regression an appropriate method for modeling these variables. Logistic regression has been used in many studies (Beemer et al., 2015; Geiske, 1995; Luan, 1992; Montgomery, 2007). Logistic regression has an advantage in being easier to describe the effect of each factor in the overall model and can be used to categorize factors. Logistic regression has assumptions that must be considered when applying this method. The variables must be independent in nature in order to solve for the associated probability. Additionally, regression models can be easily skewed by outliers and incomplete datasets due to the general nature of fitting a line to datasets.

In general cases, logistic regression calculates the probability of a binary variable occurring (Kleinbaum et al., 2010). Equation 3.1 shows the general probability calculation. In this equation, $\beta_1 \ldots \beta_n$ are the regression coefficients of the variables, and $X_1 \ldots X_n$ are the predictor variables. Using this equation, the impact or likelihood of a factor affecting the binary outcome variable can be expressed. This is shown in Equation 3.2 with the same definitions of variables in Equation 3.1, with α defined as the intercept. For this study the outcome variable was the binary outcome of graduation. Equation 3.2 would then be used to calculate the impact factors have on 2-year, 3-year, and 4-year graduation.

$$P(X) = \frac{1}{(1+ e^{-\left(\sum_{i=1}^{n} \beta_i X_i\right)})} \tag{3.1}$$

$$Z = \exp\left(\alpha + \sum_{i=1}^{n} \beta_i X_i\right) \tag{3.2}$$

The logistic regression models were created using an R programming environment (R Core Team, 2016). A logistic regression model was created for each of the completion variables using the glmnet package (Friedman & Tibshirani, 2010). Data were broken into two sets with a random subset of 70% of the data being set aside to train the regression models and 30% of the data being set aside for testing goodness of fit and accuracy of model predictions. All variables were included in the logistic regression models and the significances and p-values were determined in R and are presented in Chapter 4. An r^2 value was also calculated and is presented in Chapter 4 as part of the goodness of fit evaluation.

Chapter 4: Results

The 2-year, 3-year, and 4-year master's degree completion rates by department from this study are found in Table 4.1. To preserve anonymity, departments are coded as Departments A – H. Only percentages of the total number in the department are provided for these completion rates.

	Total Number of Students	2 Year Completion Rate (%)	3 Year Completion Rate (%)	4 Year Completion Rate (%)
Department A	66	50.00	68.18	72.73
Department B	8	87.50	100.00	100.00
Department C	54	44.44	79.63	89.89
Department D	28	60.71	100.00	100.00
Department E	117	53.85	79.49	81.20
Department F	80	61.25	81.25	87.50
Department G	124	43.55	77.42	84.68
Department H	8	37.50	75.00	75.00
TOTAL Engineering	485	51.55	79.18	84.12

Table 4.1: Completion Rates Broken Down by Department

There was a large variance in the number of students enrolled across departments. Departments B and H had few students during the period investigated, whereas Department G had over 100 students. From this tabular data, it appears that a difference can be observed between departments for 3-year and 4-year completion rates. This was verified with a Kruskal-Wallis significance test with a p-value rejection criteria of 0.10. The p-values for these tests can be found in Table 4.2.

Table 4.2: Kruskal-Wallis Significance Test for Department Effect on Completion Rate

	2 Year Completion Rate	3 Year Completion Rate	4 Year Completion Rate
P-Value	0.0656	0.0384	0.025

The completion rates for thesis and non-thesis students are given in Table 4.3. There were two students who did not finish their thesis in the 4-year period of the study. The completion rates for students who participated in thesis research but did not have a thesis on record are given in Table 4.4 (presumably they did not complete the thesis research). Additionally, there are differences between having completed thesis research without a thesis on the transcript and no thesis research completed. The 2-year and 3-year completion rates are lower for students who participated in research, but this discrepancy changes at the 4-year metric. The lower rates could be explained with students participating in research but deciding to change to a non-thesis track during the research project resulting in a longer time to degree. Students who received assistantship funding finished at a higher rate than students who did not receive funding. In fact, the discrepancy between those who did not receive funding and those who did receive funding only grew in the additional time frames.

Table 4.3: Completion Rates Broken Down by Thesis Completion

	2 Year Completion Rate (%)	3 Year Completion Rate (%)	4 Year Completion Rate (%)
Thesis (On Transcript)	56.44	91.58	99.01
Non-Thesis	48.06	70.32	73.50

Table 4.4: Completion Rates Broken Down by Thesis Research

	2 Year Completion Rate (%)	3 Year Completion Rate (%)	4 Year Completion Rate (%)
Thesis Research Only	45.21	68.49	75.34
No Thesis Research	49.05	70.95	72.86

The completion rates for US citizens and non-citizens are given in Table 4.5. Completion rates for students who had prior experience at the institution investigated are compared in Table 4.6. The completion rates for students who received graduate assistantship funding are provided in Table 4.7. There is a strong correlation between thesis completion and (degree) completion rates. This makes sense, since students who finish their thesis will have completed degree requirements. Non-US citizens completed at a higher rate than US citizens. This study found that students who attended the institution prior had lower completion rates in all three metrics. This trend was unexpected. Following Tinto's model, the students who had prior experience could be considered already familiar with departments, faculty, and general academic expectations, but these did not lead to higher completion rates than students who did not attend the institution prior to starting a master's degree.

Table 4.5: Completion Rates Broken Down by Citizenship

	2 Year Completion Rate (%)	3 Year Completion Rate (%)	4 Year Completion Rate (%)
US Citizen	45.30	69.61	75.69
Non-US Citizen	55.26	84.87	89.14

Table 4.6: Completion Rates Broken Down by Prior Experience

	2 Year Completion Rate (%)	3 Year Completion Rate (%)	4 Year Completion Rate (%)
Prior Experience at Institution	47.41	72.41	78.45
No Prior Experience	52.85	81.30	85.91

Table 4.7: Completion Rates Broken Down by Funding Status

	2 Year Completion Rate (%)	3 Year Completion Rate (%)	4 Year Completion Rate (%)
GA Funded	54.87	87.01	91.88
Non-Funded	45.76	65.54	70.62

A comparison of the completion rates for starting semester are given in Table 4.8. The completion rates for race are found in Table 4.9, to preserve anonymity due to small sample sizes, categories were aggregated to white, non-white, and non-US citizen. Those who did not report were excluded from this table. The completion rates for gender are presented in Table 4.10. Starting semester did not have a marked difference in completion rates. This was verified with a Kruskal-Wallis significance test with a p-value of 0.10 used as the rejection criteria. The results for each test can be found in Table 4.11. Gender played a role in completion rates. Students who identified as female completed at a consistently higher rate than male identifying students. This follows the similar trend found in the CGC pilot study from 2013.

Table 4.8: Completion Rates Broken Down by Starting Semester

	2 Year Completion Rate (%)	3 Year Completion Rate (%)	4 Year Completion Rate (%)
Fall Start	52.62	77.96	84.30
Spring Start	48.36	82.79	83.61

Table 4.9: Completion Rates Broken Down by IPEDS Race Category

	2 Year Completion Rate (%)	3 Year Completion Rate (%)	4 Year Completion Rate (%)
Non-US Citizen	55.26	84.87	89.14
White	49.24	71.21	78.03
Non-White	31.58	63.16	65.79

Table 4.10: Completion Rates Broken Down by Gender

	2 Year Completion Rate (%)	3 Year Completion Rate (%)	4 Year Completion Rate (%)
Male	49.49	76.92	82.31
Female	60.00	88.42	91.58

Table 4.11: Kruskal-Wallis Significance Test Results for Starting Semester

	P-Value
Starting Semester and 2-year completion rate	0.075
Starting Semester and 3-year completion rate	0.091
Starting Semester and 4-year completion rate	0.208

A comparison of enrollment status is provided in Table 4.12. There is a strong difference between full-time and part-time completion rates. This trend was expected since part-time enrollment is less hours completed each semester and thus a longer time to degree.

Table 4.12: Completion Rates Broken Down by Enrollment Status

	2 Year Completion Rate (%)	3 Year Completion Rate (%)	4 Year Completion Rate (%)
Part-Time Enrollment	0.00	43.90	53.66
Full-Time Enrollment	56.31	82.43	86.94

To better understand contributing factors and to further develop the role factors play in completion rates, a logistic regression model was created for the 2-year, 3-year, and 4-year completion rates. The standard error, and p-value are included as well. For this study, the rejection criteria for determining if a factor was statistically significant in the model was a p-value less than 0.10. Factors with a significant p-value were considered to reject the null hypothesis of not impacting the outcome for the modeled graduation. Only significant variables are presented in the tables. These models are presented in Table 4.13, Table 4.14, and Table 4.15. For binary variables, the coded default value is indicated in each table. The full models are presented in Appendix B.

Table 4.13: 2-Year Graduation Regression Model

2-Year Graduated Model	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-2.93248	1.82266	-1.609	0.1076
Age	-0.09931	0.04240	-2.342	0.0192
Graduate GPA	1.73412	0.39549	4.385	1.16e-05
Thesis Research Participation (Y)	-0.85875	0.34361	-2.499	0.0124
Summer Enrollment (Y)	0.54332	0.27985	1.941	0.0522

Table 4.14: 3-Year Graduation Regression Model

3-Year Graduated Model	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-6.45536	2.25091	-2.868	0.00413
Age	-0.09358	0.04081	-2.293	0.02184
Graduate GPA	3.37568	0.57227	5.899	3.66e-09
Gender (Male)	-1.22319	0.57509	-2.127	0.03343
Assistantship (Y)	0.66316	0.39023	1.699	0.08924
Thesis Research Participation (Y)	-0.71411	0.44141	-1.618	0.10571
Enrollment Status (Part-Time)	-1.78763	0.56454	-3.167	0.00154

Table 4.15: 4-Year Graduation Regression Model

4-Year Graduated Model	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-9.93168	2.82974	-3.510	0.000449
Graduate GPA	3.92729	0.70953	5.535	3.11e-08
Gender (Male)	-1.40533	0.77232	-1.820	0.068817
Summer Enrollment (Y)	0.89032	0.48973	1.818	0.069069
Enrollment Status (Part-Time)	-1.68442	0.64193	-2.624	0.008690

For logistic regression models with a lot of factors, interpretation can be challenging. The sign and magnitude for each factor was used to determine how each factor contributes to the overall model. One common factor in all models was the graduate retention GPA. For all models, students with a higher GPA were more likely to graduate in the specified model. This makes sense since GPA is a metric for performance and students who do well complete their degree. The institution of record also has a policy preventing enrollment for students who do not meet specific GPA requirements. Another common factor was the lack of significance of department in all models. Departments had no significant effect on the specified graduation metrics. There is a large standard error for Departments B and G. This is due to the large discrepancy in size between the departments. Prior experience at the institution of investigation was found to not be significant in any of the regression models. Department was also found to not contribute to any of the regression models.

For the 2-year model, the largest contributor was graduate GPA. The second largest factor was thesis research. Students who participated in thesis research were less likely to graduate in two years. The third largest factor was summer enrollment. Students who took a course in the summer were more likely to finish in two years. Age was found to be significant with younger students more likely to finish in two years.

For the 3-year model, the largest contributor was the graduate GPA. Age played a small role for the 3-year model. Younger students were more likely to graduate, which supports literature (Cohen, 2012; Montgomery and Anderson, 2007). Students who were funded via a graduate assistantship were more likely to graduate in 3-years. Enrollment status was important for this model with part-time students less likely to graduate in 3 years. Male students were less likely to graduate in 3 years in this model. Thesis research may have played a role but is beyond the rejection criteria.

For the 4-year model, the largest contributor was the graduate retention GPA. Gender had a negative effect on graduation. Students who identified as male were less likely to graduate in 4 years. This follows similar trends with the Council of Graduate Schools pilot study (CGS, 2013). Summer continued to play a positive role in this model. Students who were part time were less likely to complete their degree in 4 years.

The r^2 values for the models are presented in Table 4.16. Using test data, the models' prediction accuracy were evaluated and are presented in Table 4.17. The logistic regression models were evaluated for goodness of fit by reviewing the prediction accuracy and r^2 values. The 2-year regression model was the least accurate and least correlated with a low r^2 value. The 3-year and 4-year models were more accurate and better correlated with the data. The collinearity of the variables was investigated by using the variance inflation factor (VIF) for each model. In general, variables with a VIF of 5 or greater are considered highly collinear and should be excluded. In all models and for all variables the VIF was less than 2.50.

Table 4.16: r^2 Values for Regression Models

	2-Year Model	3-Year Model	4-Year Model
r^2 Value	0.2332	0.3584	0.4562

Table 4.17: Regression Model Accuracy

	2-Year Model (%)	3-Year Model (%)	4-Year Model (%)
Accuracy	69.86	85.38	89.73

Graduate retention GPA played a large role in all the models. To investigate this further, a histogram was created and is found in Figure 4.1. There is a skew toward the upper end of GPA and few counts below 2.50. Students with a GPA less than 3.00 were unlikely to graduate. At the institution of investigation, there is a policy of preventing student enrollment with a GPA less than 3.00. To determine if this policy was a contributing factor, a histogram of number of graduate semesters for students who had a GPA less than 3.00 was created and is found in Figure 4.2. From Figure 4.2, it is apparent that students with GPA less than 3.00 do not continue beyond the first year at a high rate. Only one student graduated with a GPA of less than 3.00.

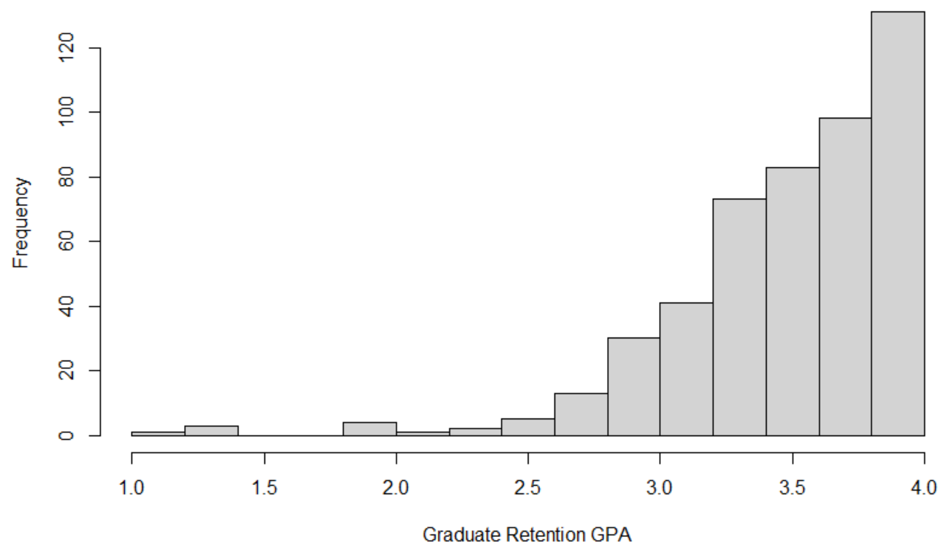

Figure 4.1: Histogram of Graduate Retention GPA

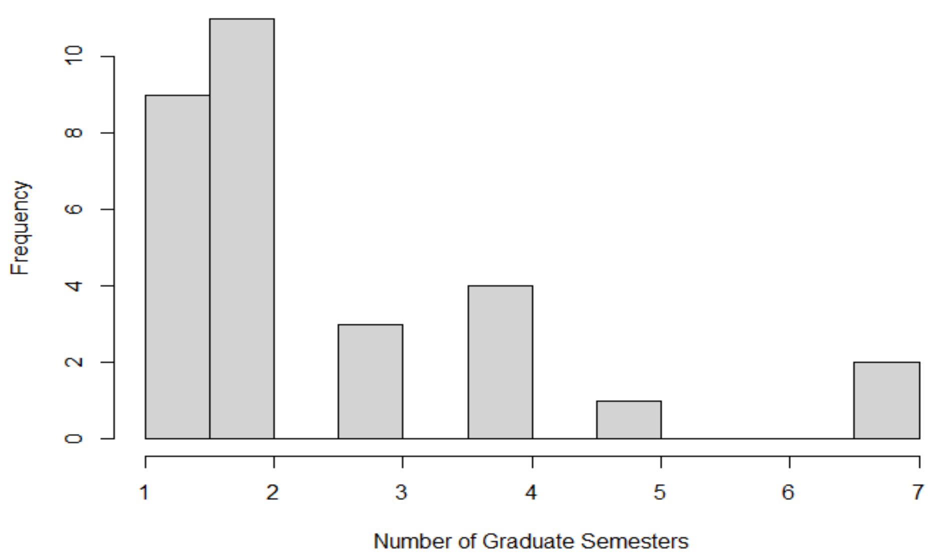

Figure 4.2: Histogram of Number of Semesters for GPA < 3.00

The average time to degree for students who graduated was 2.23 years. The role of a thesis project was investigated to determine if it hindered time to degree for engineering master's students. 202 students of the 485 included in this study had a thesis project as part of their degree plan. To investigate the role of the thesis project on the time to degree, a box and whisker plot was created and can be found in Figure 4.3. The average time to degree is the same for both full-time students who have a thesis and full-time students who did not participate in a thesis project. To verify this result, a Kruskal-Wallis test was calculated. The p-value of 0.4186 was calculated and thus the null hypothesis of no difference between the means cannot be rejected. The interaction between enrollment status and thesis research was also investigated. A box and whisker plot was created for part-time and full time thesis research and can be found in Figure 4.4. The average time to degree in years for part-time students with a thesis was 4.33 years, compared to 3.15 years for part-time students without a thesis. From Figure 4.4, it can be seen that a thesis research project does affect time to degree for part time students. This was also verified with a Kruskal-Wallis test with a p-value of 0.09, which is below the rejection criteria and the null hypothesis of no difference between the means is rejected.

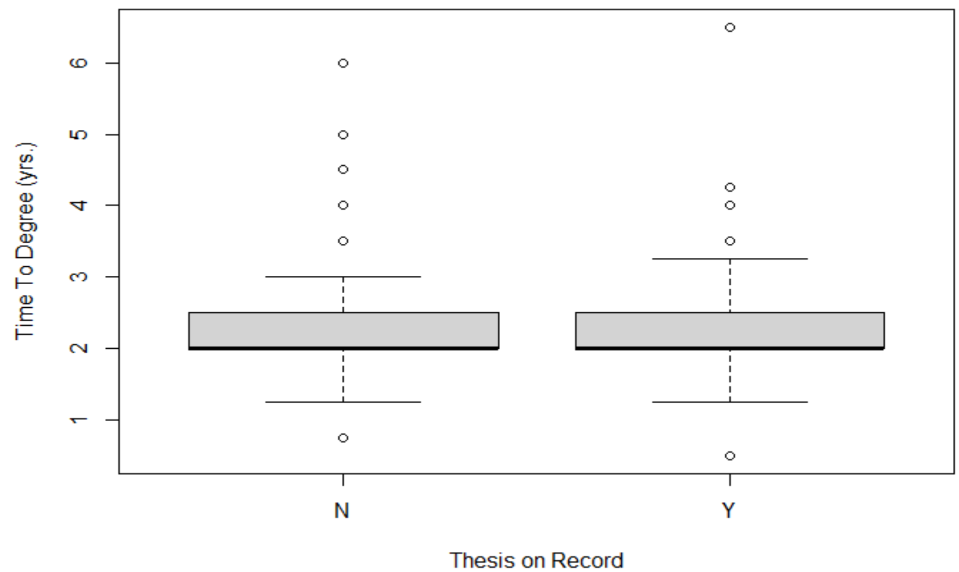

Figure 4.3: Boxplot of Thesis on Record vs. Time to Degree in Years

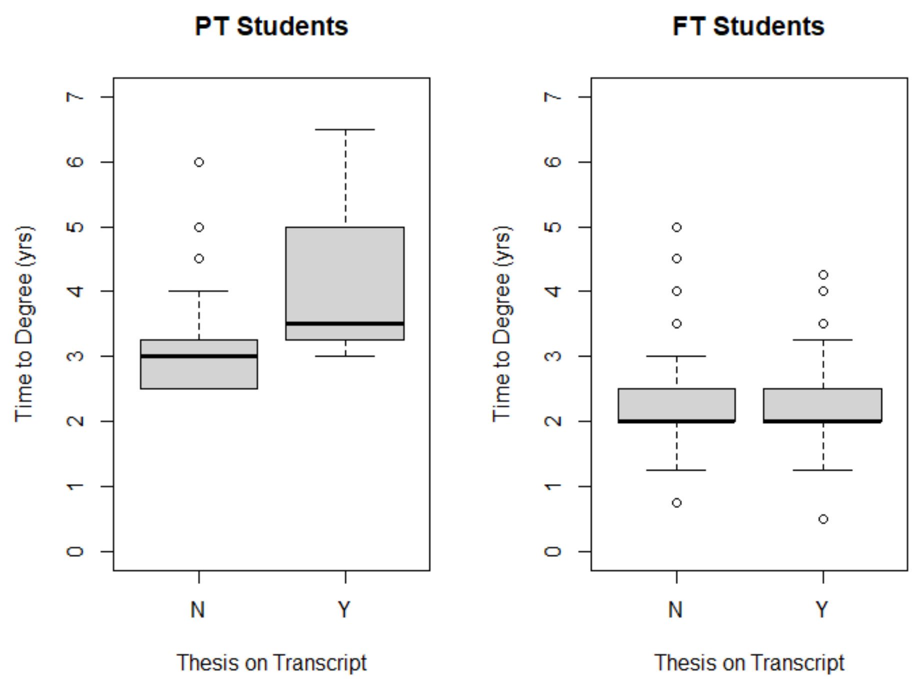

Figure 4.4: Boxplot of Full Time and Part Time Thesis Time to Degree

Chapter 5: Summary and Recommendations

Chapter 5 summarizes the results in view of the body of knowledge that exists in literature. In turn, the core research question is answered. Future research and policy recommendations are addressed.

5.1 Summary of Key Findings:

The research question for this study was, "what factors affect engineering master's degree completion rates?". From the results in Chapter 4, it was discovered that graduate GPA, enrollment status, funding, gender, summer coursework, and thesis completion were significant factors. It was also found that department and prior experience at the institution were not significant factors. Graduate GPA was an indicator for 2, 3, and 4-year completion rates. This correlates with undergraduate predictors as well. Gershenfeld et. al. (2016) used first semester undergraduate GPA to demonstrate that a lower initial GPA is an indicator for lower graduation rates.

This study found that the starting semester was not a significant contributor to completion rates. It is of note to see that it did not matter if a student started in the fall or spring to completing in a timely manner. This demonstrates that the institution of investigation had established a way to allow students to start in any semester for a degree without a delay to their completion timeframe.

Funding was an indicator for student completion rates. Students who received an assistantship were more likely to finish and more often finished faster than those who did not receive funding. A Kruskal-Wallis test was performed to verify the correlation between graduation and assistantship. A p-value of $2.6 * 10^{-13}$ was calculated, and the null hypothesis of no correlation was rejected. This result supports Ampaw and Jaeger's research. Unfortunately, the current study was unable to differentiate between a research assistantship and a teaching assistantship. This study was unable to investigate alternative sources of funding as factors for completion rates due to lack of institutional data kept at the institution of investigation.

Students who enrolled as part time were less likely to graduate. This is similar to the undergraduate experience as reported by Klempin (2014). Summer was found to be a contributor for completion rates with students who participated in summer finishing at a higher rate and faster.

Whether a student had participated in thesis research hours was a factor. This factor had multiple implications for completion rates. Students who participated in a thesis project did not experience a delay in their time to degree when enrolled full time.

This study did not find prior experience at the institution of investigation to be a contributing factor to completion rates. This contradicts Tinto's model for academic integration (1993) and Cohen's (2012) model for master's student persistence.

Demographic factors played a role in completion rates. It was found that non-US citizens complete at a higher rate than all other categories. This may be due to the fact that non-US citizens made up the majority of the dataset. This study found that non-White US citizens completed at a lower rate than White US citizens. Gender was found to be significant in completion rates. Students who identified as female were more likely to complete than students who identified as male. This supports the trend found by the Council of Graduate Schools pilot study. (Baker, 1998; CGS, 2013; Gayles, 2014; Yingyi and Yan, 2017).

5.2 Recommendations:

Funding was a crucial factor for completion rates. This study found students who received funding completed their degree at a higher rate. This study supported Luan's (1992) research about funding and completion rates. Consideration should be placed on the type of funding as well. Luan found that scholarships were more important for completion and more sources of funding should be included in future research. Ampaw and Jaeger (2011) found that female graduate students who received research assistantships were more likely to finish sooner than those who received teaching assistantships. This shows that care and thought should be placed when adding more funding to allow for more equity and diversity in improving master's completion rates. Institutions should also begin to keep records for the type of funding and include outside sources of funding to ensure better understanding of the students attending.

Summer enrollment can play an important role in completion time. It was found that students who took summer coursework finished at a higher rate. It is recommended that programs review their summer offerings and work to ensure that courses can be offered in the summer to allow students to complete their degree sooner. To make an incentive for summer enrollment, it is recommended to follow an undergraduate model of banded or flat banded tuition (Klempin, 2014). Flat banded tuition uses a capped tuition to create an incentive for students to either enroll as a full-time graduate student or take summer courses. With the average number of hours taken being 6.912, there is room to allow students to take 6 credit hours each semester and have an option for tuition to be "banked" for the summer. This would allow for more flexibility in student planning and allow for students to take advantage of every semester available. Summer also allows for part time enrolled students to continue their education inside the classroom and may be a way to bridge the gap found in completion rates.

This study found that students who took the thesis research option had the same time to degree when enrolled full time. Little research has been done on the role the thesis project plays on time to degree for engineering master's students. It is strongly recommended that future research for engineering master's students include thesis research. It is also recommended for departments to review and implement a milestone program into their research and thesis courses. Massyn (2018) found that implementing a milestone program improved thesis completion for Master of Business Administration (MBA) students by 30% as part of a case study. A milestone program would need to be structured to include specific criteria, deadlines, and mentorship opportunities. Little research has been conducted in master's student mentorship and the role mentorship plays for non-thesis students.

5.3 Future Research:

This study is a starting point to investigate factors and has limitations, so more research is required to further develop these factors. Since this study only investigated one university, there is a limit to the generalizability of the findings. To bring more generalizable information to these factors, including more research institutions would be strongly recommended. This inclusion would allow for stronger data analysis with more data to show trends and identify outliers. It is also suggested to look at other programs of study beyond engineering to determine other factors. This will also increase the data analysis power and may allow for more factors to be identified. Online programs should also be investigated. This study only investigated in person and on campus programs. There may be a difference between online engineering programs and in person programs. Future research should also include additional data from financial support to allow for more direct understanding of the role funding plays beyond assistantships.This study was entirely quantitative in nature. Additional research should include a qualitative portion and approach. Qualitative factors are important and critical in understanding persistence and completion of degrees. Qualitative research will bring the human experience to the investigation. One recommended start for research could involve the mentorship of master's students. It was found in this study that research played a crucial part in completion rates, but was that due to the role of a mentor? Mentorship plays a critical role for doctoral students (Noy 2012). Little research has been done about mentorship for master's degree students in engineering.

Studies that involve qualitative research should also include research that investigates student experience and intent. Cohen's study and model focused on intent to persist. Future studies that investigate student experiences would allow for a fuller view of the master's student experience and for the refinement of Cohen's model. This study found that institutional experience was not an important factor in completion rates. This contradicts undergraduate models and prior studies for graduate student persistence. This result should be further investigated using qualitative and quantitative means. Further research could also look into the discrepancy between non-White and White completion rates. Future research will also need to include the intersectionality of citizenship, gender, and race. It was found that race and gender influenced completion rates. Further research should be dedicated to developing and identifying how the intersection of gender and race affect completion rates.

5.4 Conclusion:

The purpose of this study was to answer the research question "what factors affect engineering master's degree completion rates?" and found that graduate GPA, funding, full time enrollment, gender, and summer enrollment were significant factors in 2, 3, and 4-year completion rates. To the best of the author's knowledge, this study is the first to report engineering master's completion rates and identify factors that contribute to those completion rates. This study contributes to the body of knowledge in finding factors such as gender, thesis research, funding, and enrollment status to improve completion rates. This study found that women were more likely to complete than men. This study found that prior attendance at the investigated institution was not a contributing factor for completion rates. To identify and support these findings this study reviewed current literature on master's completion rates. To determine significance, this study reviewed tabular results of completion rates and statistical significance in logistic regression models. From these findings, policy suggestions were made. Future research is suggested including further developing and improving these models and expanding with qualitative research.

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Appendix A: Feature Names

Variable Name	Variable Type	Variable Description
YEAR	Numeric	The year the student started their degree (2009-2014)
SEMESTER	Numeric	The semester the student started their degree 1 – Fall; 2 – Spring
ID	Numeric	The unique ID for each student
PERSON_UID	Numeric	An ID for each student used to join tables
Starting_Semester	Numeric	The semester started.
IPEDS_RACE	Categorical	The IPEDS defined race for the student (self-reported by student in application)
IPEDS_RACE_DESC	String	The description of IPEDS_RACE.
GENDER_DESC	Categorical	The gender reported by student in application
US_Citizen	Binary	A binary indicator for US citizenship (Y/N)
BIRTH_DATE	Date	The date the student was born
RACE_WHITE	Binary	Indicator for the student reported White as a race.
RACE_BLACK	Binary	Indicator for the student reported Black or African American as a race.
RACE_ASIAN	Binary	Indicator for the student reported Asian as a race.
RACE_PACIFIC	Binary	Indicator for the student reported Pacific Islander/Native Hawaiian as a race.
RACE_AMER_INDIAN	Binary	Indicator for the student reported American Indian or Alaskan Native as a race.
ETHNIC_HISPANIC	Binary	Indicator for the student reported Hispanic as a race.
MAJOR_CODE	String	Code for the major. MXXX
MAJOR_DESC	String	The description for the major code

DEPARTMENT_CODE	Categorical	Code for the department (EN00-EN07)
DEPARTMENT_DESC	String	The description for the department code
GA_IND	Binary	An indicator for students who participated in a Graduate Assistantship during their studies. This includes Teaching and Research Assistantships.
PHD_START_TERM	Numeric	The term the student started a PhD at this institution.
Status_1	String	An indicator for the graduation status for the student after one year. (Enrolled, Not Enrolled, Completed, Unknown)
Status_2	String	An indicator for the graduation status for the student after two years. (Enrolled, Not Enrolled, Completed, Unknown)
Status_3	String	An indicator for the graduation status for the student after three years. (Enrolled, Not Enrolled, Completed, Unknown)
Status_4	String	An indicator for the graduation status for the student after four years. (Enrolled, Not Enrolled, Completed, Unknown)
Status_5	String	An indicator for the graduation status for the student after five years. (Enrolled, Not Enrolled, Completed, Unknown)
accl	Binary	An indicator for the student who participated in a shared undergraduate and graduate MS program.
COMB_RETN_GRAD_GPA	Numeric	The Graduate Grade Point Average (GPA) of the student with all academic forgiveness policies applied.

COMB_RETN_GRAD_HOURS	Numeric	The number of hours used in the COMB_RETN_GRAD_GPA
COMB_RETN_UG_GPA	Numeric	The Undergraduate Grade Point Average (GPA) of the student with all academic forgiveness policies applied.
COMB_RETN_UG_HOURS	Numeric	The number of hours used in the COMB_RETN_GRAD_GPA
DEGREE_CODE	String	The code for the degree granted
DEGREE_DESC	String	The description for the degree granted
ACADEMIC_PERIOD_GRADUATION	Numeric	The term degree was granted.
FAFSA_IND	Binary	An indicator for if the student submitted a FAFSA to the institution

Table A.1: Initial Variables in Dataset

Feature Name	Feature Type	Feature Description
BirthYear	Numeric	The year the student was born
AgeAtEntrance	Numeric	The age the student started program.
ThesisHours	Binary	An indicator for if the student had thesis research hours on their account.
NumberGradSemesters	Numeric	The number of graduate semesters the student took for their master's degree
ContinuousEnrollment	Binary	An indicator for if the student was enrolled continuously. Summer was not counted for Continuous enrollment.
SUMMER	Binary	An indicator for if the student took a summer course.
Graduated	Binary	An indicator for if the student graduated with their declared master's degree.
2YearGraduation	Binary	An indicator for if the student graduated within 2 years of start date.
3YearGraduation	Binary	An indicator for if the student graduated within 3 years of start date.

4YearGraduation	Binary	An indicator for if the student graduated within 4 years of start date.
HoursPerSemester	Numeric	The average number of hours taken each semester.
ThesisOnTranscript	Binary	An indicator for if the student has a thesis on their transcript.
Part-Time Enrollment	Binary	An indicator for if the student was enrolled as a full-time or part-time student

Table A.2: Created Variables in Dataset

Appendix B: Full Model Tables

2-Year Graduated Model	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-2.93248	1.82266	-1.609	0.1076
Department A	0.41293	0.96119	0.430	0.6675
Department B	0.52072	0.95627	0.545	0.5861
Department C	-0.63179	0.94614	-0.668	0.5043
Department D	0.11471	0.91066	0.126	0.8998
Department E	-0.29204	0.89084	-0.328	0.7430
Department F	0.61353	0.92425	0.664	0.5068
Department G	17.77133	2231.49810	0.008	0.9936
Age	-0.09931	0.04240	-2.342	0.0192
Graduate GPA	1.73412	0.39549	4.385	1.16e-05
Prior Institutional Experience (Y)	-0.14157	0.38783	-0.365	0.7151
US Citizen (Y)	0.18854	0.36172	0.521	0.6022
Gender (Male)	-0.50684	0.33523	-1.512	0.1306
Assistantship (Y)	0.08587	0.32072	0.268	0.7889
Thesis Research Participation (Y)	-0.85875	0.34361	-2.499	0.0124
Summer Enrollment (Y)	0.54332	0.27985	1.941	0.0522
Enrollment Status (Part-Time)	-17.83485	626.72278	-0.028	0.9773

Table B.1: 2-Year Graduation Regression Full Model

3-Year Graduated Model	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-6.45536	2.25091	-2.868	0.00413
Department A	-0.24072	1.12036	-0.215	0.82987
Department B	17.46851	1120.04121	0.016	0.98756
Department C	-1.14783	1.08755	-1.055	0.29123
Department D	0.65733	1.06656	0.616	0.53769
Department E	-0.50847	1.02722	-0.495	0.62060
Department F	0.24608	1.08030	0.228	0.81981
Department G	16.55846	3740.67321	0.004	0.99647
Age	-0.09358	0.04081	-2.293	0.02184
Graduate GPA	3.37568	0.57227	5.899	3.66e-09
Prior Institutional Experience (Y)	-0.11738	0.47603	-0.247	0.80524
US Citizen (Y)	-0.53193	0.48533	-1.096	0.27307
Gender (Male)	-1.22319	0.57509	-2.127	0.03343
Assistantship (Y)	0.66316	0.39023	1.699	0.08924
Thesis Research Participation (Y)	-0.71411	0.44141	-1.618	0.10571
Summer Enrollment (Y)	0.10616	0.37312	0.285	0.77602
Enrollment Status (Part-Time)	-1.78763	0.56454	-3.167	0.00154

Table B.2: 3-Year Graduation Regression Full Model

4-Year Graduated Model	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-9.93168	2.82974	-3.510	0.000449
Department A	0.38424	1.26567	0.304	0.761446
Department B	17.52432	1089.17572	0.016	0.987163
Department C	-0.14122	1.25021	-0.113	0.910067
Department D	1.39069	1.20852	1.151	0.249838
Department E	0.48318	1.16110	0.416	0.677307
Department F	1.17376	1.23475	0.951	0.341808
Department G	16.32692	3663.29536	0.004	0.996444
Age	-0.04880	0.04449	-1.097	0.272685
Graduate GPA	3.92729	0.70953	5.535	3.11e-08
Prior Institutional Experience (Y)	-0.29267	0.56535	-0.518	0.604684
US Citizen (Y)	-0.79198	0.60422	-1.311	0.189945
Gender (Male)	-1.40533	0.77232	-1.820	0.068817
Assistantship (Y)	0.65473	0.46211	1.417	0.156537
Thesis Research Participation (Y)	0.07640	0.51932	0.147	0.883045
Summer Enrollment (Y)	0.89032	0.48973	1.818	0.069069
Enrollment Status (Part-Time)	-1.68442	0.64193	-2.624	0.008690

Table B.3: 4-Year Graduation Regression Full Model