Working Paper

Factors Influencing the Probability of Recent Graduates Obtaining a Job Offer

An OLS approach to the analysis of factors of job offer attainment for recent graduates from WWU in 2010

Jonathan Lee
Economics 475: Econometrics
February 21, 2023

Factors Influencing the Probability of Recent Graduates Obtaining a Job Offer

An OLS approach to the analysis of the factors influencing job offer attainment in recent graduates from WWU in 2010

Jonathan Lee
Economics 475 Student at Western Washington University
February 21, 2023

Introduction

University students make the conscious decision to bear the risk of debt and opportunity cost to aid in their search of higher education in hopes of future employment and higher future wage. This decision is the largest investment most individuals will make at that point in time of their lives. The theory of labor market polarization emphasized the "shift away from medium-skill occupations (and were) driven largely by technological change"[1]. The US has experienced substantial increases in higher-educated wage premiums over the last 30 years. However, the growth in this wage-premium has flattened over recent years, which has lowered the wage gap between college-educated working adults and high school diploma working adults.[2] Thus, lowering the value of investment of attending universities. Understanding the factors of job obtainment of recent graduates is paramount to ensure higher education providers remain a viable avenue of ensuring an individual's future employment and higher wages.

My motivation for researching the factors of job offer attainment after graduation stems from more than being a student who has invested a large amount of time and resources in obtaining a college degree. Early on, I struggled as a first generation American with learning disabilities to integrate an American lifestyle with a traditional Chinese upbringing. Learning disabilities and mental health are seen as taboo topics in Chinese culture, which led to a lack of communication in my family. This little communication I had with my parents coupled with strict discipline when I produced lower than expected grades presented itself as a lack of self-confidence required to graduate college. This lack of confidence combined with the phase of being a defiant young adult, ultimately led myself to drop out of college. The motivation behind this paper allows me to transition into its goal.

This study aims to examine the influences of graduate characteristics such as their identities (i.e. self-confidence), demographic, and educational history on the probability of obtaining *at least one job offer*

[1] Robert Valletta, *Recent Flattening in the Higher Education Wage*, (Education, Skills, and Technical Change: Implications for Future US GDP Growth, Vol 68, no. 1) (July 2014): 313-342, 314.

[2] See note 1 above.

after graduation. I specifically seek to interpret the influence that demographic and delays in graduations have on this probability. My hypothesis comes in two parts: (1) Social skills and quality attribute to on average, higher probability of obtaining a job offer. (2) Students who gain more skills during their time at university, are on average more likely to receive a job offer.

The study will be addressed using cross sectional survey data collected in 2010 by the Western Washington University's Office of Survey Research, which consists of a mixture of open-ended multiple-choice, and numerical response questions.[3] I draw structure for this paper from Denise Jackson[4] and obtain methods of analysis from both Jackson and Danielle Held[5]. This paper proceeds as follows: (1) Literature Review, (2) Data and Methods, (3) The Model, (4) Analysis, (5) Limitations of Study, (6) Results and Discussion (7) Bibliography.

1. Literature Review

The process of selecting statistically significant variables within the dataset in use, begins with a literature review of similar studies. Jackson's study[6] began her research by comparing well established models that dissect the determinants of job attainment through the concept of graduate employability.[7] It is necessary to interpret the differences in *graduate employability* and *graduate employment outcomes* in this case. Graduate employability focuses on the number of attributes, skills and knowledge that provide graduates with the ability to apply their disciplinary knowledge within a workplace. On the other hand, graduate employment outcomes are measured through achievements in the labor market.[8] With employability and employment outcomes differing in definition, the determinants selected are *institution-related factors, course quality, work experience, skill development, graduate identity, demographic characteristics and other factors, and job search strategies*.[9]

[3] John Krieg et al., *Exit Survey Of Undergraduate Students Completing Degrees in the Spring of 2010: Descriptive Statistics*, 2011-01, (Bellingham, WA: OSR, 2011), 1-142, 2, https://www.wwu.edu/faculty/kriegj/Econ475/Final%20Project%20Description.pdf.

[4] Denise Jackson, *Factors Influencing Job Attainment in Recent Bachelor Graduates: Evidence from Australia*, Higher Education 68, no. 1 (Joondalup: July 2014): 135–53, https://doi.org/10.1007/s10734-013-9696-7.

[5] Danielle Held, *The Internship Gap: The Relationship Between Internship Salary and The Probability of Receiving a Job Offe*r, (Georgetown University: Public Policy, 2016), 1-50.

[6] Jackson, *Factors Influencing Job Attainment in Recent Bachelor Graduates: Evidence from Australia,* 136-139.

[7] Dacre Pool, L., & Sewell, P. (2007). *The key to employability developing a practical model of graduate employability*. Education and Training, 49(4), 277–289, 279.

[8] See note 7 above.

[9] Jackson, *Factors Influencing Job Attainment in Recent Bachelor Graduates: Evidence from Australia, 136-139.*

The determinants for *job attainment* and graduate employability seem like reasonable ways for predicting independent variables for this studies purposes. Unfortunately, Jackson's dependent variable is job attainment, which measures recent graduates who have *accepted* employment after graduation. This is not to be misinterpreted as job offer attainment. Job attainment neglects to assess if a graduate received a job offer but ultimately declined it for reasons unknown (i.e., decided to continue to seek higher education, salary offered was too low, etc.). The purpose of this paper is to track the factors that influence the probability of graduates who receive at least one job offer, which I believe to be a fit better model in measuring graduate employability. Despite this, graduates who were successful at obtaining a job, must have received at least one job offer and are considered on average, to have a higher employability than that of graduates who did not secure a job. I plan to augment *job attainment* to *job offer attainment* and asses the viability in doing so through this literature review.

Institution-Related Factors

It is easy to argue that institution-related factors, are not applicable determinants that define the predictor variables in the dataset. Typically, high status universities exhibit higher levels of graduates who obtain job offers after graduation.[10] Due to the dataset in use being cross-sectional and observed only WWU graduates, and this paper's particular interest in WWU graduates alone. This causes notable concern due to selection bias and autocorrelation. However, I am a student expected to graduate from WWU and for this reason, I am only interested in the graduates leaving WWU. It is important to note that despite this, there will still be an observable amount of selection bias since certain types of students are more likely to respond to the survey than other types of students. Also, this data is cross-sectional, meaning each observation is on only one person at one point in time and suggests that autocorrelation should not be an issue.

Course Quality

Course quality is another determinant that cannot be accurately determined within the dataset due to the nature of the self-reported data that only accounts for course quality with opinion-based questions on satisfaction with course aspects. These subjective questions on course satisfaction most likely lack tangible implications that can be drawn on number of jobs offered to graduates. They could bias our model because I'd argue that graduates who answered "very dissatisfied" could be students who didn't apply themselves to learn to material effectively, leading to a lower GPA, and inadvertently lowering the predicted effect of people who also selected "very dissatisfied" of that student job offers. "Despite these limitations, self-report data can be both valid and reliable."[11] Course quality is an important attribute to

[10] See note 7 above, 137.

[11] Jackson, *Factors Influencing Job Attainment in Recent Bachelor Graduates: Evidence from Australia, 145.*

account for and regardless of the concerns pertaining to self-report data, I plan to include this attribute under a composite variable within skill development.

Work Experience

"Relevant work experience during undergraduate studies is a key selection criterion for graduate employers."[12] Work experience from undergraduates is typically acquired through internship opportunities and is hailed the gateway to the professional world. Aside from the consensus that internships are a medium for which students can gain real-world experience in the workplace, there is no technical definition as to what an internship can be and so, can vary greatly and does not guarantee relevant and appliable work skills. Although internships most likely being a significant predictor variable in our model, the broad definition of internships leads the determinant of work experience difficult to measure. I discuss possible responses from the dataset in the following section as to attempt to not omit variables.

Skill Development

Prior skill development is paramount for graduates to successfully enter employment. These skills are not limited to be within the field of study. Generic and social skills such as team working, communication, self-management, problem solving, analysis and self-awareness are just as desirable as hard technical skills.[13] There has been ongoing debate as to what dictates skill requirements when looking for prospect employees due to its large variation in importance across different programs and jobs. Wilton[14] argues that the lack of empirical evidence of the quality of both technical and generic skills provided by institutions combined with employers typically emphasizing soft skills suggests a higher overall outcome for all graduates. Skill development also presents itself as

Graduate Identity

Every individual has their own identity, and each student has their own pre-professional identity. I'd argue that graduate identity could be the most influential determinant in a model for predicting employability, employment outcome, or job offer attainment. Graduate identity encompasses self-esteem and confidence, professionalism, technical and social adaptability, etc.

---

[12] See note 7 above, 138.
[13] Jackson, *Factors Influencing Job Attainment in Recent Bachelor Graduates: Evidence from Australia, 138.*
[14] Nick Wilton, *The Impact of Work Placements on Skills Development and Career Outcomes for Business and Management Graduates,* (Studies in Higher Education 37, no. 5), (August 2012): 603–20, https://doi.org/10.1080/03075079.2010.532548.

Unfortunately, there has been little progress in being able to identify this characteristic despite ongoing efforts but has seen evidence of positively influencing employment outcomes.[15] In an attempt to account for this determinant and contribute to the developmental stage of the definition of this determinant, I plan to incorporate satisfaction ratings of individuals to gauge their identity specific to them alone.

Demographic characteristics and other factors

Self-reported data receives its fair share of criticism despite being widely used in empirical studies. Potentially too much as demographic information in self-reported data is generally accurate and adds to the legitimacy of using survey data. Demographic factors such as age, gender, ethnicity, etc. offer many concrete and observable insights of a dataset. For example, Wilton Purcell determines age as having a significant negative impact on graduate employability and suggests that older, more mature graduates experience more resistance in accessing employment compared to their younger counterparts.[16] Similar with age, generally, gender can also present significant impacts on job attainment. Coates and Edwards found that females are slightly less likely to succeed in job attainment one year after graduation.[17]

Job Search Strategies

Although I believe job search strategies can heavily influence a graduate's success in attaining a job offer, this variable is only accounted for in the dataset as "Which of the following best describe the current state of your job search"[18] and is only asked if the respondent answered "employment, full-time" or "employment, part-time" in the previous question. So, I will not dissect this determinant further as it is omitted in the dataset itself.

---

[15] Jonathan Winterton and Kenneth Cafferkey, *Revisiting Human Capital Theory: Progress and Prospects*. Edward Elgar Publishing EBooks, September 2019. https://doi.org/10.4337/9781786439017.00023.

[16] Purcell, K., Wilton, N., & Elias, P. (2007. *Hard lessons for lifelong learners? Age and experience in the graduate labour market.* Higher Education Quarterly, 61(1), 57–82. https://doi.org/10.1111/j.1468-2273.2006.00338.x

[17] Hamish Coates and Daniel Edwards. *The 2008 Graduate Pathways Survey: Graduates' education and employment outcomes five years after completion of a bachelor degree at an Australian university.* Camberwell: Australian Council for Educational Research.

[18] John Krieg et al., *Exit Survey of Undergraduate Students Completing Degrees in the Spring of 2010: Descriptive Statistics,16.*

1. Data and Methods

Outcome Variable

The dataset is comprised of characteristics of 2010 WWU students graduating in the spring of 2010 with total official number of observations[19], $n = 1647$ with $n = 1090$ respondents and $n = 557$ nonrespondents. However, through my preliminary data exploration, the dataset contained $n = 1707$ observations and is summarized in Table 1 in the appendix. The used sample set of this data contains $n = 674$ observations that is comprised of $n = 530$ Caucasian respondents, $n = 73$ Minority respondents, a rounded up mean age of $n = 24$ between 19-59 years of age, and $n = 251$ male respondents and $n = 423$ female respondents. Effectively removing 1033 observations due to non-responses or lack of context for our study. It is notable to mention that observation 697 was removed due to an outlier that recorded the number of job offers received as 75. This reduced the standard deviation of number of jobs offered from 4.94 to just 0.98241.

Predictor Variables

Skill development factors was compiled into an equally weighted composite measure across eight satisfaction reports from students on abilities gained during their time at WWU. A similar but slightly more comprehensive composite measure was used to created a composite measure for graduate identity. Graduate identity was gathered from ten different frequency questions in three categories with three different scales of measure. These responses were standardized before being weighted into a composite measure. The Cronbach alpha scores in both composite measures surpass the threshold of 0.7, indicating appropriate variables were selected in producing the composite measures. The institution related factors were heavily dissected and developed into a composite measure consisting of twelve equally weighted satisfaction with WWU related questions despite exceeding the alpha threshold.

Demographic was included using age represented in integers and gender. As for ethnicity, there is simply not enough data of specific ethnicities aside from Caucasian. This is because of those who answered the question, our sample size is comprised of almost 88% Caucasian, 55% of which are female. This leaves the entire minority group at just 12%. It was decided to not omit this aspect of demographic but instead, compile them into a generalized group named “Minorities” and is accounted for in the two groups, “Caucasian” and “Minority.” Similar to Jackson’s model[20], “Course Quality” is assested using only one question asking students about course satisfaction.

---

[19] ‘Total official number of observations’ pertains to the official summary released by the OSR.
[20] Jackson, *Factors Influencing Job Attainment in Recent Bachelor Graduates: Evidence from Australia, 147.*

The variable "joboffrd" was created to assess the number of jobs offered to students expecting either full-time or part-time employment. It was decided that the direct question related to job offers was not as accurately assessed. This question was dependent on a string of questions pertaining to the next most principal activity upon graduation and was asked to those who selected either between six different options. The number of jobs offered question tracked in the "plnempoffr" variable only asked students who selected either "employment, full-time" or "employment, part-time" followed by answering the state of their job search.[21] To explain my manipulation of this variable is simply to reiterate my research goal. This study aims to track the probability of students being offered *any number* of jobs as soon as possible. It is not to assess the factors influencing *how many* jobs offers a student may receive. So, out outcome variable is a binary variable using the previous "current state of your job search" question and plnempoffr as its parameters. 1 represents students who have received any number of job offers and 0 represents students who have received no job offers. Thus, reducing our sample size to $n = 674$.

Binary logistic regression is used for to analyze the reduced sample. Logistic regression's have an intolerance for missing data among predictor variables and so the selective deletion of observations for missing data is explained and supported in this model.

Procedures and Analysis

Variable Procedures

The outcome variable of the model was adapted from the original dataset's "plnempoffr" as explained above. It was done by generating a binary variable named "srching" that tracked only if respondents answered question B.15.b..[22] All observations with neither a 0 or 1 for thew new variable "srching" were removed due to lack of context of future plans i.e. seeking to attend graduate school, extended volunteering programs, etc..

There were many binary variables incorporated in this model as they act as descriptors of individuals within the data. The list of binary and non-binary variables is described in Table 2 of the appendix. After several attempted regressions, binary variable major department was selected over major college for offering overall lower p-values, indicating more significant measures of predicting the probability of graduates receiving a job offer. I incorporated the variables "AGE2," "GenderxSkill," and "lndebtamnt" to represent manipulations done to characteristics variables that possibly experience non-linear relationships.

---

[21] John Krieg et al., *Exit Survey of Undergraduate Students Completing Degrees in the Spring of 2010: Descriptive Statistics,16.*

[22] See note 21 above.

The variable pertaining to institutional factors, “Institutions” was originally generated as a composite measure to assess the WWU’s factor of receiving job offers. However, was ultimately removed due to the selection bias that this dataset experiences. “Graduate_Identity” and “Skill_Development” were also constructed as composite measures of student qualities. Similar to “Institutions,” “Skill_Development” was constructed the same way and consists of eight equally weighted reports on satisfaction of abilities gained through higher education at WWU. “Graduate_Identity” was trickier to handle as the questions selected were not measured on the same ranking range. So, the variable consists of ten standardized ($mean = 0, standard\ deviation = 1$) and equally weighted measures on a number of questions regarding frequency of attending events and/or meetings or collaborating with other individuals at WWU.

Instead of treating the “Institution” variable through academic prowess, I attempted to restructure it to assess “Institution Quality”. However, my efforts were fruitless as I attempted to treat the variable as a composite measure of satisfaction questions ranging from satisfaction of course availability, overall satisfaction, to satisfaction of satisfaction of advisors. I failed to the recognize the nature of this variable and concluded late in my research that this sample suffers from selection bias as it only contains observations on WWU students. So, the institutional factor is simply irrelevant in the context of this study. It may be a useful instrument to use for comparing universities but this composite measure demonstrated the lowest Cronbach alpha score just barely breaching the threshold of 0.7 at roughly 0.71.

Tests on Model

Numerous methods for assessing the efficiency and bias of the model were done. Tests done include the White’s test, Durbin-Watson Test, the Breusch-Godfrey test, and several simple residual scatterplots. There were several issues while attempting to run the DW test and BG test during my research and will be discussed in the analysis below. Unfortunately, I could not get the DW tests to work on my second model using the binary department variables due to Stata/BE only supporting matrices with up to 800 rows or columns. I attempted to resolve this by adding “, baselevels” at the end of the regression followed by “set emptycells drop” with no success. Despite this, I was able to draw implications on this issue by using “hettest, rhs fstat,” which checks for heteroskedasticity on the right-hand side by comparing the residual variances of the restricted model (where the error variance is assumed to be constant) to the unrestricted model (where the error term can vary across observations). I was only able to draw However, the model using major colleges instead of specific departments was able to draw conclusions on heteroskedasticity using all tests.

In the second model, the right-hand side BG test was inconclusive as it produced the following:

$$H_0: \alpha_i = \alpha_{i+1} \; \forall \; i$$

$$H_1 \neq H_0$$

$$F(56, 286) = 1.86$$

$$Prob > F = 0.2228$$

suggesting that there is significant evidence of my variance of the error term to be constant since my p-value is greater than my significance level of 0. When testing the heteroskedasticity using "estat vce,", it detects a large presence of heteroskedasticity between the department variables. the residual plots for model two referenced in the appendix and offer a different conclusion. I attempt to use White's correction to address this issue. Autocorrelation assumed to not be present in this data set. As the previous observations of an individual shouldn't influence the probability of another individual obtaining a job offer.

2. Results and Discussion

The outstanding variables in the logit regression include "Graduate_Identity," "Skill_Development," "Minority," "majsatqual," and numerous "Dept_...." These outstanding variables do not contain zero in their confidence intervals, leading me to believe they are reasonable predictors along with their p-values being lower than the confidence level of 0.05. We use a logit regression to identify the odds ratio and the marginal effects of the original robust regression to identify the change in odds given a change in a variable.

To my surprise, in the logit regression, "Graduate_Identity" had a coefficient of 0.79, p-value of 0.019 with a Cronbach alpha of 0.7379, 0.379 above the threshold of 0.7. It also had a mfx p-value of 0.032, indicating it as a significant estimator for the probability of a graduate student receiving at least one job offer. This means that on average, a student who attended more events and meetings with advisors or professors at WWU, have roughly a $e^{0.7379}$ odds ratio of being offered a job. Using the mfx table, this means that on average a student who attends more events, etc. are roughly 10.8% more likely to receive a job offer. This could be due to a high social adaptability, networking, and outgoing charisma that adds to the probability of acquiring a job offer. However, with my chi-squared value being zero, this means that my model is likely overfitting the data and may not generalize new data well.

The "Skill_Development" had a coefficient of roughly -4.677, a p-value of 0.05 and a Cronbach alpha score of 0.7991. Interpreting this, on average an increase by one unit in skill leads roughly a $e^{-4.67}$ odds ratio of receiving a job offer. In other words, (using the mfx table) a student who is more satisfied with their skills gained from WWU is on average, 20% less likely to acquire a job offer. The interpretation here is inconsistent with what I originally predicted. This could be an issue of self-report data in which a student over states their ability. The more likely reason is that in the mfx regression, "Skill_Development" has a high p-value of 0.236, indicating that it may not be the best fit estimator.

Again, in the logit regression, "Minority" had a coefficient of roughly -1.05 and a p-value of 0.025. This means this is a significant estimator within our odds ratio regression. Although, the mfx regression presents a p-value of 0.051, barely rejecting the null hypothesis suggesting that this variable may not be able to estimate this probability accurately. Only, focusing on the mfx regression, the only significant estimators presented in this model are "Graduation_Identity," "majsatqual," Dept_7," and "Dept_15."

It is important to emphasize this is self-reported data, which should warrant concern due to selection bias of a pool of people all attending the same university during the same year. Despite this, the study's aim seeks to analyze the probability that a WWU graduate receives any number of job offers depicted in *Figure 1-4*. I concluded presence of heteroskedasticity and was mitigated by performing a no constant White correction. Despite this, the model still suffered from noticeable patterns in its residuals. A number of binary variables were omitted due to either no observations seen or significant collinearity.

3. Conclusion

This study attempted to identify the factors that influence recent graduates at WWU in 2010. The findings suggest that graduates who attend events at Western or meetings with advisors are on average, more likely to receive a job offer following graduation. It also identifies that minorities are roughly and on average 6% less likely to receive a job offer. According to the mfx, which analyzes the slope of our OLS regression for categorical variables, Canadian/American Studies have roughly a 133% higher chance of receiving a job offer than all other students. Oddly, the the logit regression study identifies a strong negative relationship on a student's odds ratio of receiving a job. The mfx for skill development was inconclusive on the mfx table as it failed to reject the null, indicating that its marginal effect is equal is of little statistical significance on our dependent binary variable.

Unfortunately, with my results for analyzing the effects of skill development, which was comprised of student satisfaction in abilities gained at WWU was inconclusive as it failed to reject the null in our mfx regression. Despite being statistically significant in our logit regression, I must assume the second part of my hypothesis is inconclusive and in need of further research.

Social adaptability was essentially captured in “Graduate_Identity.” As it tracked student responses on the frequency of attending social and professional events. Our composite variable for graduate identity or qualities was proven to be significant. Thus supporting half of my hypothesis. An interesting discovery here was within graduate identity. My composite variable returned statistically significant values for all my regressions. Leading me to be convinced that the variables were somewhat chosen appropriately and deserves to be looked into.

APPENDIX

Table of Variables

VARIABLE	DEF	MEASUREMENT
plnempoffr	Number of job offers	0-7
joboffrd	Binary variable indicating success in job offer attainment	0=no job offers 1=job offered
UG_WWU_GPA	GPA	0-4.0
Graduate_Identity		
Skill_Development		
AGE	age	19-59
FemaleBin	Gender	0=Male 1=Female
ethnic_1	Caucasian	0=not Caucasian 1=Caucasian
ethnic_2	African	0=Not African 1=African
ethnic_3	Hispanic	0=Not Hispanic 1=Hispanic
ethnic_4	Asian	0=Not Asian 1=Asian
ethnic_5	Native American	0=Not Native American 1=Native American
ethnic_6	Unknown	0=Known 1=Unknown
ethnic_7	International	0=Not International 1=International
ethnic_8	Other/Multicultural	0=Not other 1=Other/Multicultural
Major_college_4	College of Business and Economics	0=Not in CBE BU=CBE Student
Major_college_5	Woodring College	0=Not in Woodring ED=Woodring Student
Major_college_6	Fairhaven	0=Not in Fairhaven FA=Fairhaven Student
Major_college_7	College of Fine Performing Arts	0=Not in CFPA FI = CFPA Student
Major_college_8	College of Humanities Social Science	0=Not in CHSS HS=CHSS Student
Major_college_9	Huxley College	0=Not in Huxley HU=Huxley Student
Major_college_10	College of Science and Technology	0=Not in CST ST=CST Student

q0_b	“How often did you worked with classmates outside of class to prepare class assignments”	Scale of 1-5 1=Not Often 5=Often
q0_c	“How often did you Put together ideas or concepts from different courses when completing assignment?”	Scale of 1-5 1=Not Often 5=Often
q1_a	Student satisfaction of peers?	Scale of 1-7 1=Unfriendly 7=Friendly
majsatavail	Student satisfaction of class availability	Scale of 1-5 1=Very dissatisfied 5=Very Satisfied
engfreqcar	Frequency of meeting with advisors	1=Not Often 5=Often
engfreqevnt	Frequency of attending events	1=Not Often 5=Often
ttdexpec	Graduation delays	1=Not Often 5=Often
debtamnt	Debt accrued	
fgen	First Generation Student Binary Variable	1= first gen 0= first gen
abilconwrit	Student Confidence in Writing skills	
abilconoral	Student confidence in oral skills	
abilconcrit	Student confidence in critical thinkingskills	
abilconind	Student confidence in working independently	
abilconcoop	Student confidence in cooperation skills	

PLOTS AND REGRESSIONS

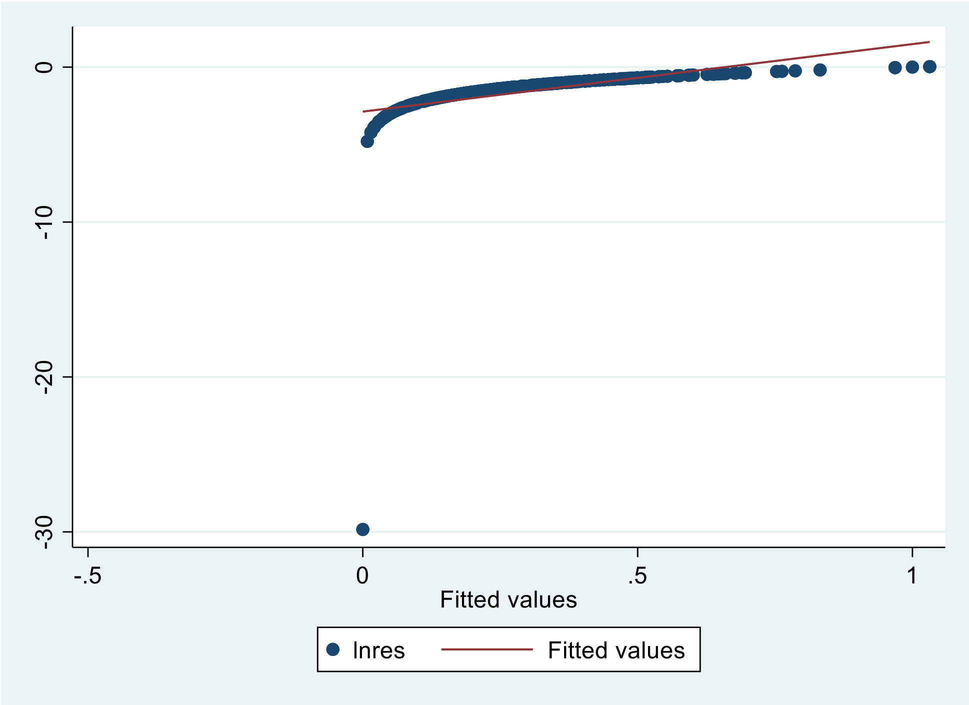

Figure 1 Robust Model 2 lnres vs yhat

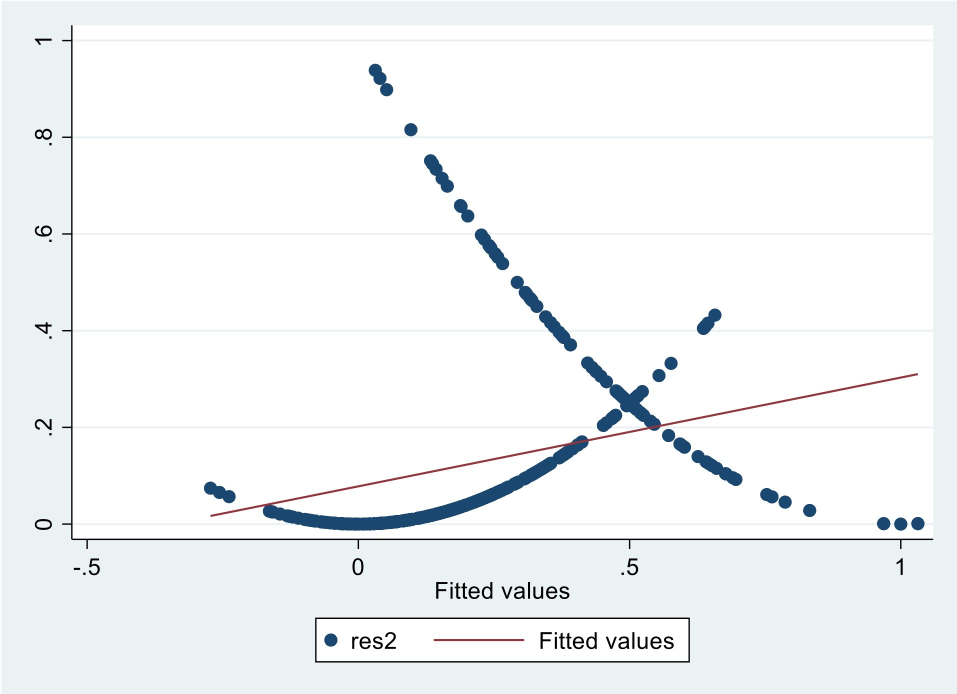

Figure 2 Robust Model 2 res2 vs yhat.

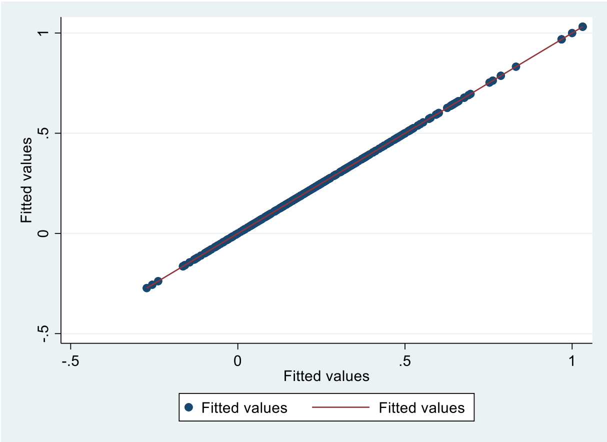

Figure 3 Robust Model 2 res vs yhat

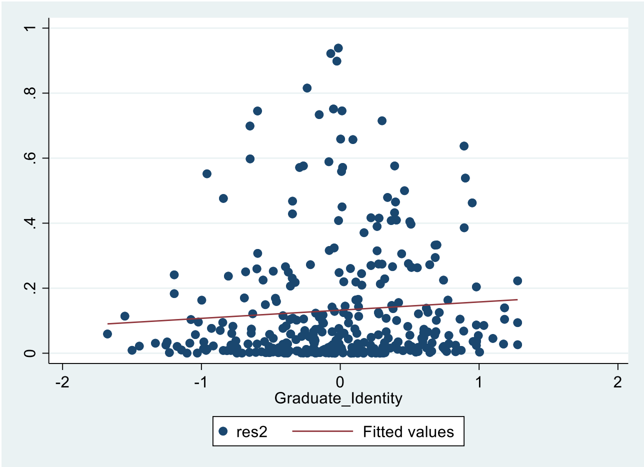

Figure 4 Robust Model 2 res2 vs Graduate_Identity

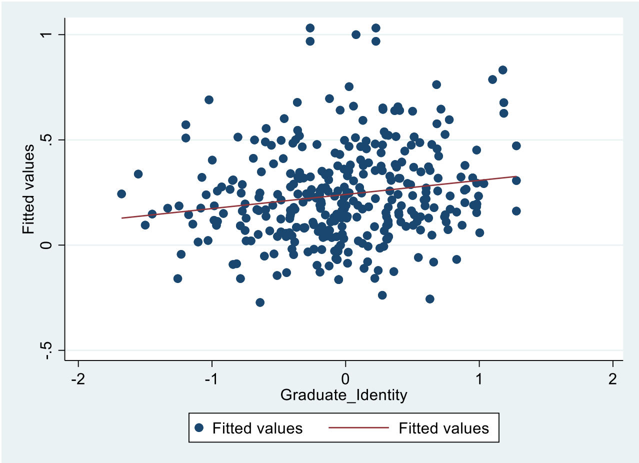

Figure 5 residuals vs Graduate_Identity

Linear regression						
	Number of obs	=	343			
	F(56, 285)	=	.			
	Prob > F	=	.			
	R-squared	=	0.4484			
	Root MSE	=	.3984			

joboffrd	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
Graduate_Identity	.1084429	.049586	2.19	0.030	.0108417	.2060441
Skill_Development	-.2682572	.2108397	-1.27	0.204	-.6832577	.1467434
majsatqual	-.0630441	.0326779	-1.93	0.055	-.1273647	.0012765
Minority	-.1149439	.0580715	-1.98	0.049	-.2292473	-.0006405
AGE	-.0445344	.03409	-1.31	0.192	-.1116346	.0225658
UG_WWU_GPA	-.0358485	.064422	-0.56	0.578	-.1626517	.0909547
Dept_1	2.719753	.9518012	2.86	0.005	.8463009	4.593205
Dept_2	0	(omitted)				
Dept_3	2.856933	.9514042	3.00	0.003	.9842621	4.729603
Dept_4	2.713728	.9452106	2.87	0.004	.8532485	4.574207
Dept_5	3.099971	.9663953	3.21	0.001	1.197793	5.002148
Dept_6	0	(omitted)				
Dept_7	3.848341	.9536082	4.04	0.000	1.971332	5.725349
Dept_8	3.048416	.9697073	3.14	0.002	1.139719	4.957112
Dept_9	3.154097	.9748629	3.24	0.001	1.235252	5.072941
Dept_10	3.329905	.9708069	3.43	0.001	1.419043	5.240766
Dept_11	2.970429	.9618399	3.09	0.002	1.077218	4.86364
Dept_12	3.010444	.9739433	3.09	0.002	1.09341	4.927479
Dept_13	2.825063	.9585497	2.95	0.003	.9383278	4.711798
Dept_14	2.919242	.9479814	3.08	0.002	1.053309	4.785176
Dept_15	3.806777	.963568	3.95	0.000	1.910164	5.70339
Dept_16	2.820331	.9468722	2.98	0.003	.956581	4.684081
Dept_17	2.589961	.9427706	2.75	0.006	.7342841	4.445637
Dept_18	2.940919	.991805	2.97	0.003	.9887273	4.893112
Dept_19	2.979928	.9569899	3.11	0.002	1.096263	4.863593
Dept_20	3.089124	.9663533	3.20	0.002	1.187029	4.991219
Dept_21	3.029917	.9990793	3.03	0.003	1.063407	4.996428
Dept_22	2.982029	.957474	3.11	0.002	1.097411	4.866646
Dept_23	2.870879	.9541397	3.01	0.003	.9928242	4.748934
Dept_24	2.89561	.9506444	3.05	0.003	1.024435	4.766784
Dept_25	2.712054	.9332636	2.91	0.004	.87509	4.549017
Dept_26	3.239008	.9910708	3.27	0.001	1.288261	5.189755
Dept_27	2.946916	.9421361	3.13	0.002	1.092488	4.801343
Dept_28	3.372563	.969898	3.48	0.001	1.46349	5.281635
Dept_29	2.907774	.9535966	3.05	0.003	1.030788	4.78476
Dept_30	3.336186	.9775351	3.41	0.001	1.412081	5.26029
Dept_31	2.730453	.9403844	2.90	0.004	.8794729	4.581432
Dept_32	2.711022	.9615888	2.82	0.005	.8183052	4.603739
Dept_33	2.509999	.9429234	2.66	0.008	.6540212	4.365976
Dept_34	2.956395	.9704083	3.05	0.003	1.046319	4.866472
Dept_35	2.957149	.9685653	3.05	0.002	1.0507	4.863598
Dept_36	2.81165	.9749291	2.88	0.004	.8926754	4.730625
Dept_37	2.901128	.9996033	2.90	0.004	.9335858	4.868669
Dept_38	2.73909	.9557286	2.87	0.004	.8579083	4.620273
Dept_39	2.987135	.9675548	3.09	0.002	1.082675	4.891595
Dept_40	0	(omitted)				
Dept_41	2.889689	.9901606	2.92	0.004	.9407337	4.838645
Dept_42	3.139908	.9675467	3.25	0.001	1.235464	5.044352
Dept_43	2.943759	.9668428	3.04	0.003	1.040701	4.846818
Dept_44	3.827493	.9651763	3.97	0.000	1.927715	5.727271
Dept_45	3.304257	.9672519	3.42	0.001	1.400393	5.208121
Dept_46	2.836466	.9702572	2.92	0.004	.9266869	4.746245
Dept_47	3.314544	.9749896	3.40	0.001	1.39545	5.233638
Dept_48	2.711124	.9717284	2.79	0.006	.7984491	4.623799
FemaleBin	-.2153509	.3908858	-0.55	0.582	-.9847403	.5540385
GenderxSkill	.015495	.0978686	0.16	0.874	-.1771419	.2081319
lndebtamnt	-.1107761	.0358646	-3.09	0.002	-.1813692	-.040183
GradExpec_2	.0869535	.0868181	1.00	0.317	-.0839325	.2578394
GradExpec_3	.0006097	.2721465	0.00	0.998	-.5350623	.5362818
AgexSkill	.0097342	.008398	1.16	0.247	-.0067959	.0262642
AGExGradExpec_3	.0013822	.0102588	0.13	0.893	-.0188105	.0215749

Figure 6 Model 2 Robust

Marginal effects after regress
y = Fitted values (predict)
= .23906706

variable	dy/dx	Std. err.	z	P>|z|	[95%	C.I.]	X
Gradua~y	.1084429	.04959	2.19	0.029	.011256	.20563	-.024955
Skill_~t	-.2682572	.21084	-1.27	0.203	-.681495	.144981	3.96408
majs~ual	-.0630441	.03268	-1.93	0.054	-.127092	.001003	4.03499
Minority*	-.1149439	.05807	-1.98	0.048	-.228762	-.001126	.204082
AGE	-.0445344	.03409	-1.31	0.191	-.11135	.022281	24.3557
UG_WWU~A	-.0358485	.06442	-0.56	0.578	-.162113	.090416	3.17274
Dept_1*	2.719753	.9518	2.86	0.004	.854257	4.58525	.023324
Dept_3*	2.856933	.9514	3.00	0.003	.992215	4.72165	.046647
Dept_4*	2.713728	.94521	2.87	0.004	.861149	4.56631	.011662
Dept_5*	3.099971	.9664	3.21	0.001	1.20587	4.99407	.017493
Dept_7*	3.848341	.95361	4.04	0.000	1.9793	5.71738	.005831
Dept_8*	3.048416	.96971	3.14	0.002	1.14782	4.94901	.017493
Dept_9*	3.154097	.97486	3.24	0.001	1.2434	5.06479	.023324
Dept_10*	3.329905	.97081	3.43	0.001	1.42716	5.23265	.020408
Dept_11*	2.970429	.96184	3.09	0.002	1.08526	4.8556	.020408
Dept_12*	3.010444	.97394	3.09	0.002	1.10155	4.91934	.011662
Dept_13*	2.825063	.95855	2.95	0.003	.94634	4.70379	.03207
Dept_14*	2.919242	.94798	3.08	0.002	1.06123	4.77725	.029155
Dept_15*	3.806777	.96357	3.95	0.000	1.91822	5.69534	.002915
Dept_16*	2.820331	.94687	2.98	0.003	.964496	4.67617	.014577
Dept_17*	2.589961	.94277	2.75	0.006	.742164	4.43776	.014577
Dept_18*	2.940919	.9918	2.97	0.003	.997017	4.88482	.058309
Dept_19*	2.979928	.95699	3.11	0.002	1.10426	4.85559	.067055
Dept_20*	3.089124	.96635	3.20	0.001	1.19511	4.98314	.020408
Dept_21*	3.029917	.99908	3.03	0.002	1.07176	4.98808	.023324
Dept_22*	2.982029	.95747	3.11	0.002	1.10541	4.85864	.029155
Dept_23*	2.870879	.95414	3.01	0.003	1.0008	4.74096	.049563
Dept_24*	2.89561	.95064	3.05	0.002	1.03238	4.75884	.029155
Dept_25*	2.712054	.93326	2.91	0.004	.882891	4.54122	.008746
Dept_26*	3.239008	.99107	3.27	0.001	1.29654	5.18147	.020408
Dept_27*	2.946916	.94214	3.13	0.002	1.10036	4.79347	.09621
Dept_28*	3.372563	.9699	3.48	0.001	1.4716	5.27353	.008746
Dept_29*	2.907774	.9536	3.05	0.002	1.03876	4.77679	.008746
Dept_30*	3.336186	.97754	3.41	0.001	1.42025	5.25212	.005831
Dept_31*	2.730453	.94038	2.90	0.004	.887333	4.57357	.011662
Dept_32*	2.711022	.96159	2.82	0.005	.826343	4.5957	.040816
Dept_33*	2.509999	.94292	2.66	0.008	.661903	4.35809	.002915
Dept_34*	2.956395	.97041	3.05	0.002	1.05443	4.85836	.017493
Dept_35*	2.957149	.96857	3.05	0.002	1.0588	4.8555	.014577
Dept_36*	2.81165	.97493	2.88	0.004	.900824	4.72248	.005831
Dept_37*	2.901128	.9996	2.90	0.004	.941941	4.86031	.008746
Dept_38*	2.73909	.95573	2.87	0.004	.865897	4.61228	.008746
Dept_39*	2.987135	.96755	3.09	0.002	1.09076	4.88351	.034985
Dept_41*	2.889689	.99016	2.92	0.004	.94901	4.83037	.008746
Dept_42*	3.139908	.96755	3.25	0.001	1.24355	5.03626	.029155
Dept_43*	2.943759	.96684	3.04	0.002	1.04878	4.83874	.037901
Dept_44*	3.827493	.96518	3.97	0.000	1.93578	5.7192	.005831
Dept_45*	3.304257	.96725	3.42	0.001	1.40848	5.20004	.026239
Dept_46*	2.836466	.97026	2.92	0.003	.934797	4.73814	.005831
Dept_47*	3.314544	.97499	3.40	0.001	1.4036	5.22549	.014577
Dept_48*	2.711124	.97173	2.79	0.005	.806571	4.61568	.008746
Female~n*	-.2153509	.39089	-0.55	0.582	-.981473	.550771	.658892
Gender~l	.015495	.09787	0.16	0.874	-.176324	.207314	2.63315
lndebt~t	-.1107761	.03586	-3.09	0.002	-.181069	-.040483	9.82189
GradEx~2*	.0869535	.08682	1.00	0.317	-.083207	.257114	.536443
GradEx~3*	.0006097	.27215	0.00	0.998	-.532788	.534007	.41691
AgexSk~l	.0097342	.0084	1.16	0.246	-.006726	.026194	96.6517
AGExGr~3	.0013822	.01026	0.13	0.893	-.018725	.021489	10.3528

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Figure 7 Mfx Model 2

Logistic regression

Number of obs = 300
Wald chi2(43) = 90.86
Prob > chi2 = 0.0000

Log pseudolikelihood = -134.20259

joboffrd	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
Graduate_Identity	.7907336	.3371919	2.35	0.019	.1298496	1.451618
Skill_Development	-4.677537	2.384315	-1.96	0.050	-9.350709	-.004366
majsatqual	-.4448972	.2147455	-2.07	0.038	-.8657907	-.0240038
Minority	-1.045991	.4674999	-2.24	0.025	-1.962274	-.129708
AGE	-.860772	.4511075	-1.91	0.056	-1.744926	.0233825
UG_WWU_GPA	-.3697114	.4761643	-0.78	0.437	-1.302976	.5635534
Dept_1	0	(omitted)				
Dept_2	0	(omitted)				
Dept_3	28.99734	11.15627	2.60	0.009	7.131459	50.86323
Dept_4	0	(omitted)				
Dept_5	31.15542	11.19098	2.78	0.005	9.221499	53.08934
Dept_6	0	(omitted)				
Dept_7	0	(omitted)				
Dept_8	30.79637	11.18018	2.75	0.006	8.883626	52.70911
Dept_9	31.08633	11.23792	2.77	0.006	9.06041	53.11224
Dept_10	32.24189	11.32894	2.85	0.004	10.03759	54.4462
Dept_11	30.26156	11.2594	2.69	0.007	8.193549	52.32958
Dept_12	30.59419	11.2967	2.71	0.007	8.453062	52.73532
Dept_13	29.36994	11.1904	2.62	0.009	7.43716	51.30271
Dept_14	30.01978	11.14023	2.69	0.007	8.185326	51.85423
Dept_15	0	(omitted)				
Dept_16	28.5554	10.98619	2.60	0.009	7.022873	50.08793
Dept_17	0	(omitted)				
Dept_18	30.18209	11.37615	2.65	0.008	7.885252	52.47892
Dept_19	30.40634	11.23418	2.71	0.007	8.387741	52.42493
Dept_20	30.76046	11.2569	2.73	0.006	8.697343	52.82358
Dept_21	30.63417	11.21994	2.73	0.006	8.643497	52.62484
Dept_22	30.52189	11.34831	2.69	0.007	8.279625	52.76416
Dept_23	29.61879	11.13258	2.66	0.008	7.799335	51.43825
Dept_24	29.73394	11.0725	2.69	0.007	8.032226	51.43565
Dept_25	0	(omitted)				
Dept_26	31.77036	11.25194	2.82	0.005	9.716963	53.82376
Dept_27	30.06395	11.10245	2.71	0.007	8.303544	51.82435
Dept_28	33.01014	11.7539	2.81	0.005	9.972925	56.04736
Dept_29	0	(omitted)				
Dept_30	32.39406	11.2474	2.88	0.004	10.34956	54.43855
Dept_31	0	(omitted)				
Dept_32	28.13871	11.20177	2.51	0.012	6.183638	50.09378
Dept_33	0	(omitted)				
Dept_34	30.05397	11.17163	2.69	0.007	8.157983	51.94996
Dept_35	30.44771	11.40608	2.67	0.008	8.0922	52.80323
Dept_36	0	(omitted)				
Dept_37	29.70719	11.34722	2.62	0.009	7.467039	51.94734
Dept_38	0	(omitted)				
Dept_39	30.44037	11.22557	2.71	0.007	8.438646	52.44209
Dept_40	0	(omitted)				
Dept_41	29.58619	11.20119	2.64	0.008	7.632259	51.54013
Dept_42	31.27959	11.26238	2.78	0.005	9.205734	53.35344
Dept_43	30.00848	11.41559	2.63	0.009	7.634332	52.38262
Dept_44	0	(omitted)				
Dept_45	32.09078	11.28112	2.84	0.004	9.980187	54.20137
Dept_46	0	(omitted)				
Dept_47	31.98866	11.24193	2.85	0.004	9.954894	54.02243
Dept_48	0	(omitted)				
FemaleBin	-1.732831	2.401734	-0.72	0.471	-6.440143	2.974481
GenderxSkill	.1737466	.6003635	0.29	0.772	-1.002944	1.350437
lndebtamnt	-.7567656	.237154	-3.19	0.001	-1.221579	-.2919524
GradExpec_2	.8075192	.79092	1.02	0.307	-.7426555	2.357694
GradExpec_3	.522264	.8425874	0.62	0.535	-1.129177	2.173705
AgexSkill	.1906337	.1029291	1.85	0.064	-.0111036	.3923711

Figure 8 Logit Regression of Model 2