UNIVERSITY
OF OSLO

Master thesis

Earn Knowledge or Money, Dilemma in Higher Education

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Master of Philosophy in Economics

30 ECTS study points

Department of Economics

Faculty of Social Sciences

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Thesis submitted for the degree of Master of Philosophy in Economics

Abstract

This thesis investigates the relationship between earnings of university students and time taken to finish the degree. Here earning indicates hours worked by the student. First, we investigate the relation of time taken to complete the degree for individuals with earnings and individuals with no earnings. Then we introduce controls for different groups to assess heterogeneity. Our results indicate that there is a lack of significance for most of the results. Low SES is the standout outcome that has high significance and shows a clear negative impact on time taken to finish the degree for both earning and non-earning individuals,

Acknowledgements

The Norwegian Research Council supported this research under project no. 275906. Thank you to my supervisor Edwin Leuven for his support and guidance during this work. Thank you also to my family and friends for their support and encouragement during my time in Oslo. And to my Adnan, my husband, thank you for being my best friend. Any inaccuracies or mistakes are exclusively my fault and I take sole responsibility.

Contents

1. Introduction

Students in in Norway are more likely than other European countries to partake in part-time work. Here, students spend on average 12 hours a week on paid work SSB (2018). One of the reasons that students chose work while studying is that this helps them with income of their own. However, there are many questions regarding if part time work is good for the students' wellbeing both academic and psychological. Thus, we find that the educational outcomes of working while studying has been investigated heavily across many different locations. Barbanchon et al. (2019) work is based in Uganda while Kamp (2021) bases his analyses on students at Radboud University in Nijmegen. The investigations also vary across the level of study; Rockika(2014) worked with 13-14 years olds while Jacobs (2002) works on women of 15-44 of age. In this analysis, I wanted to investigate whether students in tertiary education need more time to finish their degree when they work part time.

I follow the work by Barbanchon et al. (2019) and Tessema et al. (2014) to investigate whether the same results they found hold true in Norway, a country with an excellent welfare system and no tuitions fees. We use the data from much before 2023, and thus the change in tuition fee structure will not affect the analysis. The analysis is done through the use of multiple linear regression at 6 different levels with the same core independent variables, earning and not earning; as well as different variables which control for different categories in the other 5 regressions. We repeat the regression for a binary dependent variable called complete which takes value of 1 if the degree was finished faster, and 0 if the degree was finished slowly.

We use data from Statistics Norway (SSB) and create a smaller data set with variables pertaining personal characteristics (gender, age at start of university, immigration status, , socio-economic characteristics (gross wealth of the individual, father's earning, mother's earning, earning of the individual, parents' education level when the individual was 16) and educational variables (year of start of degree, year of completion of degree, the nus code). We want to see not only how part time work affects time to complete degree but also if this effect is different for different groups of people. We want to check for heterogeneity in the results.

Most of our results are inconclusive due to being statistically insignificant. However, we do find very strong evidence that lower socioeconomic status has detrimental impact on completion of degree in both the cases of the individual working or the individual not working.

The next section of the thesis will present a concise literature review. Section 3 will present the institutional settings and describe the data we are using. Section 4 gives us the empirical analysis that is behind the series of regression that we will conduct. Section 5 provides the results and discusses the implication of our findings. Section 6 presents the conclusion and discusses potential further work with this analysis.

2. Literature Review

There has been extensive work done in the last decade that examines the relationship between part time work and study. Two papers of high relevance are that of "The Effects of Working while in School: Evidence from Uruguayan Lotteries" by Barbanchon et al. (2019) and "Does Part-Time Job Affect College Students' Satisfaction and academic performance (GPA)? The Case of a Mid-Sized Public University" by Tessema et al. (2014).

The study on the Uruguayan Lotteries provided a unique set of data that allowed for the investigation of causal impact of students while working at school. Using regression discontinuity design and holding the lotteries as an exogenous variable, the authors were able to present results that support working while in school has a negative impact on academic performance. The paper finds that students who work more than 20 hours per week have a 0.26 standard deviation lower GPA than students who do not work at all. The effects are more detrimental for students from disadvantaged backgrounds.

In the second paper, Tessema et al. (2014) explores the relationship between hours worked and if the student is satisfied with their results as well as the students' actual academic results. In this study, the authors used both quantitative and qualitative data to present strong evidence that that there was a significant negative relationship between the number of hours worked per week and both satisfaction with academic performance and GPA. The main result was that students who worked more than 20 hours per week reported lower levels of satisfaction with academic performance and had lower GPAs than those who worked fewer hours per week or not at all while controlling for factors such as gender, race, and major. The qualitative data, interviews and questionaries further gave backdrop to the possible causes of this lower study satisfaction.

There have been studies done investigating the link across many countries and education levels. Nyet et al. (2017) finds that among the different studies conducted, the negative relationship between work and studies is more pronounced in tertiary level (78.95%) than secondary education level (55.17%). Rokicka(2014) examined the impact of part time employment during the last year of compulsory education in England on school performance. She estimated a small detrimental effect on GCSE performance. She did find that parental aspirations and parental background has much higher impact.

Another point of interest to us is Socioeconomic status (SES). Some literature on this variable is presented here before we delve into using it. The U.S. Census Bureau (2014) reports that students have 8 times higher probability of obtaining a bachelor's degree by age 24 if they belong to high family income quartile than students coming from the lowest family income quartile. On investigating college experiences and outcomes for low and high socioeconomic status, a study found that students with lower socioeconomic status would work more and study less, and be less likely to engage in extracurricular activities. Their GPAs would also be lower than their counterparts with high SES. Moreover, the students with low socioeconomic status were found to have lower educational attainment and incomes, as well as lower graduate school attendance in comparison (Walpole, 2003). Additionally, low SES students tend to towards having lower levels of educational aspirations than their peers from higher social strata nine years post college admission. Lower SES students' ability to gain social and economic profits may be greater than that of their low SES peers who did not attend college, but it is still lower than their high SES college peers (Walpole, 2003). Low SES college graduates prefer to work full time post college graduation than attend graduate school. Aspirations towards acquiring a higher degree and attending graduate school are more common among high SES students, on the other hand, who view this as a reinvestment towards the future (McDonough, Antonio, & Horvat, 1996).

3. Institutional Setting and Data

3.1 Institutional Setting

About 35% of the adult population of Norway have higher education with women making up 60% of the students in the higher education institution SSB(2018). There are a total of 33 accredited higher education institutions in Norway (October 2019). According to NOKUT (n.d**)** there are 10 universities, 9 specialized university institutions (1 of which is an art academy) and 14 university colleges. Along with that there are alternatives such as non-accredited university colleges, and public and private vocational institutions.

Higher education has been organized as 3 years bachelors, followed by 2 year masters and a three year PhD programs (with exceptions). European standard of grading is mostly used upon completion of a course ranging from A to F (failing grade) with E being the last passing grade. Some courses may be graded as Pass/fail. A Bachelor’s level course is 180 ECT credits and a Master’s level is usually 120 ECT credits. There are also 1-year supplementary programs available at universities. Integrated 5-year programs are available for some courses such as engineering, economics, and teacher training. Other courses such as medicine include 6 years of Professional study.

<u>Work-Study Balance in Norway</u>

In Norway, it is common to have a part time job while studying. According to Statistics Norway (2018) more than 40 % Norwegian students have paid work whilst studying. An average student in Norway spends 12 hours a week on paid work which is much higher than students in the other Nordic countries and in France, Germany, and Italy.

There are small differences in the study-work ratio between different fields. This difference is more significant between different years with both bachelor and master students working on average 8 hours a week, but masters students opting to spend more hours in studying as well. Statistics Norway (2017) also found one in five students in Norway overwork which has impact on the time they have left for their studies. As the work hours increase after a limit (11 hours of work a week), the difference in time allocation between working and non-working students increases significantly.

Lastly, there are different regulations on work hours between students depending on visa status. As an EU/EEA/Swiss citizen one can work without any restriction however students outside the EU/EEA/Switzerland can work up to 20 hours a week during the semester and full-time during holidays. If you are granted a study permit, you are automatically also granted permission to work part-time.

Money for higher education, loan system

Norway, being a social-democratic welfare society, has a heavily public funded education system. Education is free at all levels for Norwegian citizens and citizens of EU/EEA countries. The Norwegian Parliament, Storting, introduced tuition fees at universities for all new-coming international students from countries outside the European Economic Area and Switzerland from the academic year 2023/2024.

The Norwegian State Educational Loan Fund (Lånekassen) handles the different grant and loan schemes. These help students manage both standard of living and non-tuition related education costs.

3.2 Data

To observe the relationship between part time job and study success, we used primarily two sets of data, one pertaining to education and the other pertaining to earnings of the student. We also used data concerning socio-economic characteristics of individual from the Norwegian Population Registry. All three data sets were provided by Statistics Norway.

We draw the education variables from NUDB, National education database. We only kept the individuals who started higher education. We further refined the data set to only include those who started higher education between the age of 19 to 24; The start of education was decided to be from 1980s onwards and people were given 10 years to complete their education. Lastly, to ensure conformity of data, we allowed for only those students who start in August, i.e. are regular students in the academic year. We merged in income variables from the income data set starting from 1993 onwards. All the data sets are linked through a unique identifier for every individual.

Variables

The following variables are included in the final dataset and are used in the ensuing regressions.

First of all we use unique identifiers for individuals as well as unique identifiers for parents across our data set.

NUDB has created the NUS2000 codes as a way to easily access education identifier. The NUS stands for "The Norwegian Standard Classification of Education". This has been put into use from 1970 onwards. The codes are generally a mix of alphabets and numbers and are in this dataset are 6 characters long. We use the following 3 NUS codes. "**nus2000"** which is the NUS code for the level and category of education the individual has, "**nus2000_far_16"**, which is the NUS code for the highest education the father had when the individual was 16, and "**nus2009_mor_16"** which is the NUS code for the highest education the mother had when the individual was 16.

For every individual the age at higher education start is included as the variable "**agestart**". Our dependent variable is based on the years taken to complete study. To find this we use the variables "**ystart**" (year when first enrolled in higher education) and "**ycomplete**" (year first completed higher education). For the "**ycomplete**" variable we make it so that if the individual has missing data (they didn't complete their education, then the variable becomes non applicable for those individuals

We also have a more general variable indicating the parents' education level when the individual is 16 years of age, which is called "**sosbak**". The variable codes for social background through education of the parents and has five categories.

Table 1. Explanation of the code "sosbak"

Code	**Explanation of code**
1	Mother or father or both have education at level 7 or 8
2	Mother or father or both have education at level 6
3	Secondary school. Mother or father or both have education at level 3, 4 or 5
4	Elementary school. Mother or father or both have education at level 0, 1 or 2
9	Unspecified. Both parents have unspecified education.

We also use “**kjoenn**” to assign gender. This is a binary variable with 1 for men and 2 for women. Another variable we use is “**invkat**” to show the immigration background. The following are the different categories for immigration background.

Table 2. Explanation for “invkat” as “X”

A	Without immigration background
B	First-generation immigrant without a Norwegian background
C	Person born in Norway to two foreign-born parents
D	The code is not in use. (Foreign adopted)
E	Born abroad with a Norwegian parent
F	Norwegian-born with a foreign parent
G	Born abroad to Norwegian-born parents

What we do know is that financial situation of the students heavily impacts both their choice to work as well as their study success Walpole(2003). We use the variables “**earnings0**” (earnings at the start of study year), “**wealth0**” (gross taxable wealth in year of study start), “**fearnings0**” (father’s earnings in year of study start), “**fwealth0**” (gross taxable wealth in year of study start), “**mearnings0**” (mother’s earnings in year of study star) and “**mwealth0**” (gross taxable wealth in year of study start). Figure 1 shows the distribution of logearnings across the dataset. For convenience, 0 earnings have been removed from the histogram.

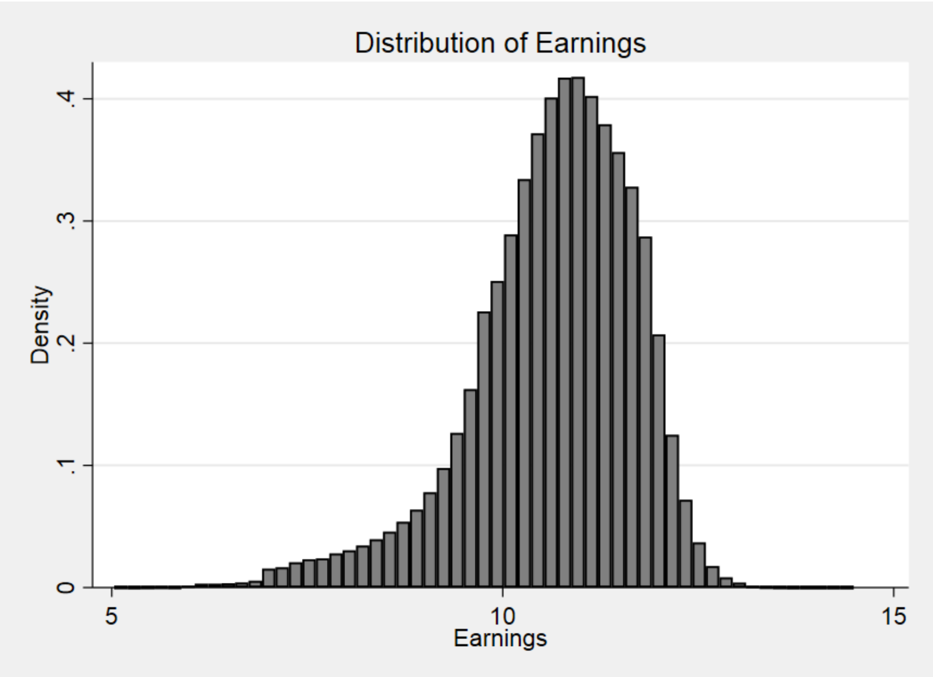

Figure 1. Distributing of Earnings (log) across the data set

The final data sample has 378 803 observations. The summary statistics is shown below. The mean age for the data set is 20.34 years old and the median being a bit lower at 20.

Table 3. Summary Statistics

Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Age at Start	378,803	20.34365	1.371383	19	24
Year of Start	378,803	2000.854	4.650649	1993	2008
Year Completed	235,759	2005.617	5.209962	1993	2018
Gender	378,803	1.598454	.4902117	1	2
No Earnings	378,803	.0848779	.2787003	0	1
Earnings (log)	375,393	9.724651	3.144193	0	14.48783
Wealth (log)	337,311	10.0503	1.48346	6.907755	19.77206
Log of Father's Earning (log)	334,144	12.69955	.8474109	0	17.6974
Mother's Earning (log)	333,828	12.16879	.8807302	0	16.69042
Father's Wealth (log)	347,203	13.00943	1.260179	6.907755	21.16728
Mother's Wealth (log)	340,591	11.65841	1.66271	6.907755	21.37961

4. Empirical analysis

In this section, we explain the various multiple linear regressions used to investigate the relationship between study success and work done, and how fixed effect regression models operate in panel data. Lastly, we show potential heterogeneity issues and how they are resolved here.

Our primary question is if there is a relation between a student's study success and their part time work. Both Barbanchon et al. (2019) working on Uruguayan students and Tessema et al. (2014) work at a midsized Midwestern university support the hypothesis that students who worked more had lower academic performances. While both the authors relied on surveys and questionnaires along with administrative data, in this paper we will be using administrative data only. This paper also exclusively uses multiple linear regression for the analysis. Unlike both the previously mentioned works, our observation size is much larger and over a longer period. The larger data size allows for more accurate estimations of the coefficients with a multiple regression analysis.

However, there is quite a bit of difficulty in establishing correlation between part time work and study success. There might be other underlying factors which may cause both study success and part time work to move in a certain way. For example, children from poor families may both need to work to support themselves as well as the stress of their environment may contribute to bad study habits. To correct for these sorts of confounding variables, we included several of these variables as covariates.

The first regression analyzes the core variables that impact the time a student takes to complete their education. The following regressions are applied.

$$Complete = \beta 0 + \beta 1 noearnings0 + \beta 2 logearnings0 + \beta 3 i.agestart + \beta 4 i.ystart \qquad \text{Equation (1)}$$

In this equation, "*Complete*" refers to the duration taken to complete the education. Here, we compute complete from time taken to complete the degree (*timetodegree*) which is *"ycomplete-ystart*". The variable is treated such that it is binary and 1 if the individual completed their degree faster and 0 is the individual took more time to complete their degree. The "*noearnings*" is also a binary variable and is 0 when there are some earnings. We also include the age at the start of education as well as the year of start of education to get a general picture of the trends in education and earnings.

We conduct the same analysis but this time making our dependent variable "*timetodegree*" to see the relation when the dependent variable takes a more quantitative form.

$$Timetodegree = \beta 0 + \beta 1noearnings0 + \beta 2logearnings0 + \beta 3i.agestart + \beta 4i.ystart$$

Equation (2)

The next thing we want to see is the relation between the time to finish the degree and earning while controlling for the different education levels and categories (the nus2000 code) constant. This will allow us to account for the individual's education choices and the impact of those choices over time. If not controlled for, this could have led to omitted variable bias.

We control the first three digits of the nus code, which codes for a narrower field of education. We chose this specification for our variable as the third digit is most relevant to our analysis. The first nus codes for levels of education. We have already specified that we are working with university students. The second nus digit would add information about the field of study, but it would be in a more general sense like "primary industries". However, the third nus digit allows for the academic programs to be grouped such that they deviate little with respect to academic content (Barrabés & Østli, 2017).

We do this twice with the dependent variable being "Complete" and Y being "time to degree". We are interested to know the impact both on time taken on complete degree and the effect of completion of degree. We will do the same for every regression that follows henceforth in this analysis.

We use a fixed effect regression model to account for unobserved heterogeneity due to education field,

$$Y = \beta 0 + \beta 1noearnings0it + \beta 2log(earnings0it) + \beta 3agestartit + \beta 4ystartit + \alpha i + uit$$

Equation (3)

Where "αi" now stands for the for the third digit of education ("d3nus"), which is a narrower field of education.

We also want to see the trends in heterogeneity for other variables for this data set; we chose to check for the variables gender, socioeconomic status, and immigration status. Here, we introduce interaction effects.

The general formula that we use in consecutive regressions is as follows,

$$Y = \beta 0 + \beta 1X + \beta 2Z + \beta 3(Z \times X) + \sum \beta_k C_k + \alpha + \varepsilon \qquad \text{Equation (4)}$$

Here, “Y” is the dependent variable (Time taken to finish the degree or Degree Completion, and “X” is the main independent variable, Earnings. “Z” here is the binary variable that helps us investigate different factors of heterogeneity. In this analysis Z is gender, socio-economic status (SES) and immigration status. “Z×X” is the interaction term. For example when “Z” is gender, “Z×X ” shows how effect of earning on time taken to complete degree differs for men and women .

For our analysis with gender as a covariate, we assign the variable female to be 0 and male to be 1. In the case of SES which was not originally binary, we are using the variable “lowses” here. We know from the data section, a higher “sosbak” means lower parents’ education. For the regression analysis, we let low SES “lowses” to be defined by “sosbak” being greater than 2. Now all low SES individuals take the value of 1 and higher SES individuals take the value of 0. Lastly, in our analysis concerning immigration background, we do not need the many different categories of immigrants. Thus, we transform “invkat” into the variable “native” such that all native individuals take the value of 1 (that is category A found in data) and people with immigration background take the value of 0.

Lastly, I will explain the 6 models of regression in brief. This is as follows;

Model 1 is the simplest model with “noearnings0” and “logearnings0” are the independent variables, and agrestart and ystart are included as fixed effects. Model 2 introduces the fixed effect pertaining the education fields. This allows us to control for heterogeneity that doesn’t change with time, i.e., variations that exist within the education fields will not cause variation in the regression model. Model 3 adds more controls including “sosbak” and “female” and “migrant” and some wealth variables. The wealth variables are grouped together and a subset of them is introduced in the regression model. Model 4, Model 5 and Model 6 introduce the interaction terms for “female”, “lowses” and “native” respectively.

5. Results and discussion

5.1 Results

In this section, the results of the regression analysis will be presented. First, a scatter plot of time taken to finish the degree against log of earning would be presented. Then, we will present the findings from regression analysis based on Equation (2), (3) and (4). Here the dependent variables would be time taken to complete the degree. The next part would present the findings from a regression analysis based on Equation (1), (3) and (4) with the dependent variable being the binary variable "Complete".

First, to investigate a general trend through the years, a scatter plot of the time taken to finish degree when earning is presented. As we see, the plot shows a nonlinear relationship but when the line of best fit is drawn, the line is slightly downward sloping. This means that as earnings increase, the time taken to finish a degree decreases. Tessema et al. (2014) has already established that this is not the case. Our results may be due to extreme outliers, or the presence of confounding variables just as previously mentioned in empirical analysis.

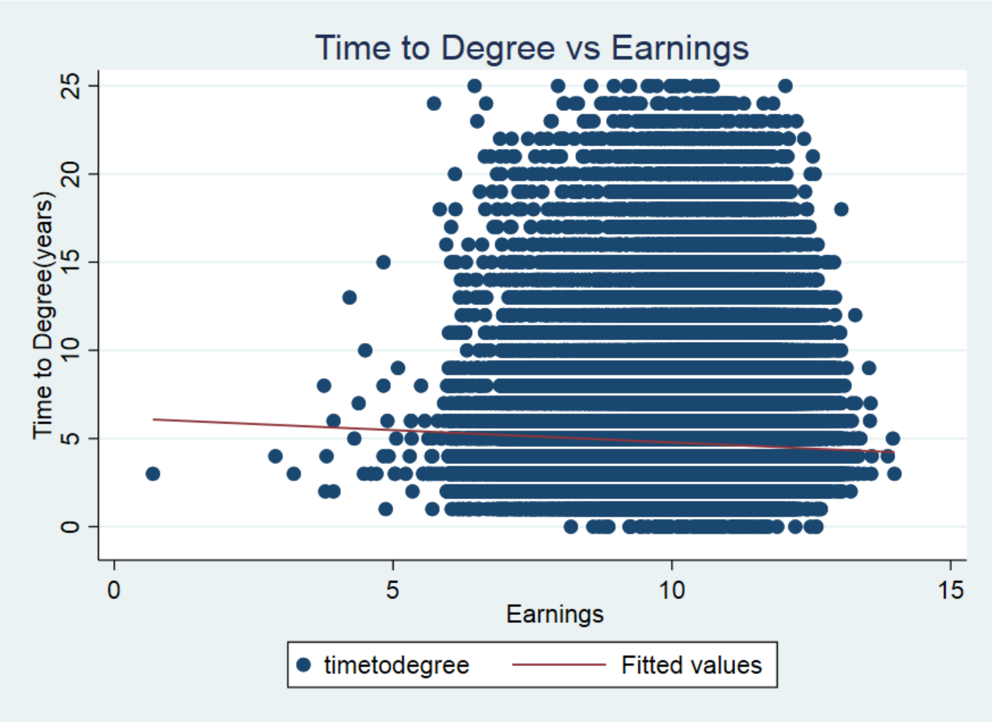

Figure 2. Scatter plot of Time to Complete Degree Vs Log Earnings

Next, we come to our main investigations. We wanted to know how working part time impacts study success. Here, we show two different parameters for study success, time taken to finish the degree and whether the degree was completed or not.

We now use regression to analyze the time taken to finish a degree in relation to earnings, gender, socioeconomic status, and immigration background. The coefficients are of particular interest to us as they explain by how much and in what way a variable may affect the time taken to finish degree. The interacting terms also explain to us how two different variables may combine to affect the duration taken to finish degree. We also control unobserved heterogeneity in the fields of education (d3nus) through fixed time effect. This is to ensure that we are analyzing changes in duration to finish education due to impact of earnings, gender, socio economic status and immigration status, rather than the impact of differences that arise due to students studying different fields.

Table 4. Analysis for Time Taken to Complete Degree (Continuous)

	Time to Complete Degree					
	(1)	(2)	(3)	(4)	(5)	(6)
No earnings	-0.215**	0.145	0.417***	0.203	0.361**	-0.009
	(0.074)	(0.090)	(0.089)	(0.186)	(0.109)	(0.294)
Earnings (log)	-0.044***	-0.001	0.031**	0.012	0.021*	0.007
	(0.007)	(0.010)	(0.009)	(0.019)	(0.010)	(0.027)
No earning when women				0.395*		
				(0.193)		
Earnings (log) when women				0.035		
				(0.019)		
No Earnings when individual comes from low SES					0.099	
					(0.124)	
Earnings (log) when individual comes from low SES					0.019	
					(0.012)	
No Earnings for Native Individuals						0.476
						(0.304)
Earnings (log) for Native Individuals						0.026

						(0.027)
N	234600	234598	216840	216840	216840	216840

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I shall now analyze the coefficients of the various variables. First, we notice that the impact of not earning on time taken to finish degree changes both in sign and magnitude across the 6 models. This tells us that the time to finish a degree may also be highly influenced by other variables. For example, an individual with no earnings would take 21.5% less time to finish the degree according to Model 1, however when other variables are added we see an individual with no earnings also increase time taken to finish the degree by 36.1% in Model 5. Looking at Log Earnings, we see a similar pattern emerge where both significance levels and coefficients display variations across the models.

Now we observe how time taken to finish education changes when working for different groups.

First, we check the how time taken to finish education is different between men and women. From Model 4, we see that the effect of not earning (i.e., not working) on time to finish degree is 39.5 % more positive for women than men. This is statistically significant at 5% level. We also found that the impact of earnings (in log) on time taken to finish degree for women relative to men is not significant according to the analysis.

Secondly, we can not find evidence for impact of both earning or not earning on the time taken to finish degree when coming from a lower SES. Both the coefficients are not significant at any level. Lastly, we find that immigration status has no statistically significant effect on time taken to finish degree for both earning and not earning variables.

For the second part of our core analysis, we use regression to analyze how completing of degree is influenced by earnings, gender, socioeconomic status, and immigration background.

Table 5. Analysis for Completion of Degree (Binary)

	Completion of Degree					
	(1)	(2)	(3)	(4)	(5)	(6)
No earnings	0.095*** (0.010)	-0.005 (0.020)	-0.057* (0.022)	-0.056 (0.040)	-0.014 (0.021)	-0.037 (0.022)
Earnings (log)	0.021*** (0.001)	0.006* (0.002)	-0.004 (0.002)	-0.005 (0.004)	-0.001 (0.002)	-0.003 (0.002)
No earning when women				-0.010 (0.047)		
Earnings (log) when women				0.002 (0.005)		
No Earnings when individual comes from low SES					-0.094*** (0.020)	
Earnings (log) when individual comes from low SES					-0.007*** (0.002)	
No Earnings for Native Individuals						-0.023 (0.032)
Earnings (log) for Native Individuals						-0.001 (0.003)
N	375393	375389	342235	342235	342235	342235

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We treat the regression in the same way as Table 4 with just our dependent variable changing to completion of degree. One thing to remember is that completion of degree is a binary variable. We see that both gender and immigration status have no significant impact on the way earnings affect completion of degree. However, we do that SES has a significant effect as a covariate. We find that for individuals from low SES relative to individuals from high SES, there is 9.4% decrease associated with completing the degree faster when not earning. Even when earning, we see the that the effect of higher earnings on completing the degree faster is smaller for people from low SES.

Lastly, we see that in this analysis Model 1 provides us with statistically significant results for Earning and not Earning on completion of degree. This is a simple model and does not include covariates. We see that not earning leads to a 9.5% higher chance of completing degree faster. Interestingly, a unit increase in earning (and thus working) also leads to a higher chance (2.1%) of completing degree faster .

5.2 Discussion

In this section, the results will be reviewed in relation to the literature review. Then, we will have a brief discussion about the real-life implications. Finally, we will present the limitations of this analysis.

From Table 4, we found that even when not working, women needed a longer time to finish their degree than men. Interesting, findings by Jacob et al, (2002) established that women over 25 have a harder time finishing their degree due to time constraints. Women are more likely to do household chores and look after the family. While our dataset is for a younger group, gender roles are less likely to not exist before the age of 24. We also found that time taken to finish degree when earning is not of significance between man and women. A possible explanation can be that earning, thereby working puts the same exertion on the students regardless of gender.

In our analysis with SES, we found that individuals from low SES are significantly detrimentally effected both when working and not working when we analyze how fast they complete the degree. Literature from Barbanchon et al. (2019) and Magda (2014) support this finding. Both the works had found that socio economic factors have a significant effect on study success. However, both the authors work was with school children who were mid to late teens unlike our model where we are working with university students who are over 20. This may be due to other problems that are associated with lower SES that may burden the students and hamper them from achieving higher educational outcomes.

Lastly, we find that immigration status has no statistically significant impact on time taken to finish education. This may be due to laws regarding work hours and work laws for students in Norway. Students, both native and non-native are likely to face similar working conditions. Also according to SSB(2018) , 40% of the students have work during the entire semester. So working part time is common regardless of immigration status.

Finally, we shall discuss a few potential problems in this analysis. First, there is always the problem of omitted variable bias in regressions of any type. This analysis could have been expanded to include other socio-economic background variables and income indicators. An example of this could be loan taken to during study.

Secondly, there could have been lack of homoscedasticity (in which the error term is same across all values of independent variables). The standard errors of the coefficients would then have been biased. This could also provide incorrect statistical significance. To correct for this, we used robust standard errors in our empirical analysis.

Lastly, If the dependent variable is a binary outcome, as in our analysis about completion of education, multiple linear regression may not be the best choice for analysis. Logistic regression could have been more appropriate. However, the data set is panel data set with multiple observations over time. Also, the other dependent variables (time taken to finish degree) is continuous. Due to these two reasons, linear regression models were used.

6. Conclusion

This paper examined the impact of engaging in part-time work whilst still pursuing full-time tertiary education. Study success was measured based on two outcomes: the time taken for the student to complete their graduation, and secondly a binary variable that coded for slow and fast completion of degree. As a secondary objective we also wanted to observe how the finding changes for different groups of people. For both the analysis we had the same independent variables. We used a fixed time effect for the education variable encoding fields of study as we did not want to see variation in findings due to variation within fields of study, we used three different groups to check for heterogeneity: Women vs Men, Individuals from low SES vs Individuals from high SES, and Native individual Vs Non-Native Individuals.

For the first part of the analysis with the dependent variable being time taken to complete degree, we find that except for the variable coding for no earnings when women relative to men, all the other interaction variables searching for heterogeneity provides us statistically insignificant results. In Model 1 of this analysis, we get a significant result which says that for the very simple regression with no interacting variables; here, both not earnings and earnings lead to decreased time needed to complete degree. However, we should remember that estimating the causal effect of part-time work is a difficult process and what we are getting are just statistically significant correlations.

For the second part of the analysis with the dependent variable taking binary form for duration of study, we again find that results are significant for the simplest model, Model1 with the independent variables being not earnings and earnings (in log) ; however this time the result is a increase in higher chance to finish the degree faster. This is in accordance with our analysis in the first part of analysis. Lastly, we find very strong evidence (p value is less than 0.001) that lower socio-economic status has negative effect on completion of degree in both the cases of the individual working or not. This is supported by all literature as well.

Our analysis provides mostly statistically insignificant result and thus, other then the results above we can not talk about trends due to heterogeneity.

Lastly, the results for study success could be more refined by making the dependent variable include some aspect of the students' grade. This would make the result more informative. Further research could also be done to see if working part time as students lead to jobs success as fresh graduate. As Norway introduced tuition fees in the year 2023, it would also be interesting to see if there is a demography shift in part time student workers.

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Appendix

Log file for making the dataset

```
      name:  <unnamed>
       log:  /ess/p836/data/durable/projects/p23msswapno/log/credu.smcl
  log type:  smcl
 opened on:   6 Oct 2023, 15:31:29

. 
. // education type
. local KURS /ess/p836/data/durable/pop1/edu/W19_0977_F_UTD_KURS_POP1

. use  w19 hoved kode tilgdato nus2000 hskode if kode=="1" & hoved=="3" using `KURS', clear

. g u = runiform()

. bysort w19_0977_lopenr_person tilgdato nus2000 hskode : keep if _n==1
(502,211 observations deleted)

. bysort w19_0977_lopenr_person tilgdato (u): g nenroll = _N

. bysort w19_0977_lopenr_person tilgdato (u): keep if _n==1
(457,216 observations deleted)

. g year = int(tilgdato / 100)

. ta year

       year |      Freq.     Percent        Cum.
------------+-----------------------------------
       1970 |      1,214        0.01        0.01
       1971 |     10,613        0.07        0.08
       1972 |     11,989        0.08        0.16
       1973 |     13,659        0.09        0.25
       1974 |     29,634        0.19        0.44
       1975 |     57,865        0.38        0.82
       1976 |     53,404        0.35        1.17
       1977 |     52,580        0.35        1.52
       1978 |     55,173        0.36        1.88
       1979 |     57,764        0.38        2.26
       1980 |     78,459        0.51        2.77
       1981 |     64,757        0.42        3.20
       1982 |     61,587        0.40        3.60
       1983 |     64,467        0.42        4.02
       1984 |     66,563        0.44        4.46
       1985 |     71,449        0.47        4.93
```

```
      1986 |     75,931        0.50        5.43
      1987 |     81,620        0.54        5.96
      1988 |     89,864        0.59        6.55
      1989 |    104,943        0.69        7.24
      1990 |    115,380        0.76        8.00
      1991 |    121,234        0.80        8.80
      1992 |    131,537        0.86        9.66
      1993 |    138,273        0.91       10.57
      1994 |    142,105        0.93       11.50
      1995 |    154,210        1.01       12.51
      1996 |    146,640        0.96       13.47
      1997 |    162,536        1.07       14.54
      1998 |    230,127        1.51       16.05
      1999 |    372,529        2.44       18.49
      2000 |    384,717        2.52       21.02
      2001 |    387,167        2.54       23.56
      2002 |    454,609        2.98       26.54
      2003 |    591,559        3.88       30.43
      2004 |    581,970        3.82       34.25
      2005 |    578,550        3.80       38.04
      2006 |    588,351        3.86       41.90
      2007 |    569,947        3.74       45.64
      2008 |    569,242        3.74       49.38
      2009 |    558,858        3.67       53.05
      2010 |    554,993        3.64       56.69
      2011 |    622,231        4.08       60.77
      2012 |    570,137        3.74       64.52
      2013 |    591,926        3.88       68.40
      2014 |    597,647        3.92       72.32
      2015 |    633,200        4.16       76.48
      2016 |    622,559        4.09       80.56
      2017 |    642,803        4.22       84.78
      2018 |    626,166        4.11       88.89
      2019 |    638,781        4.19       93.08
      2020 |    659,023        4.33       97.41
      2021 |    394,690        2.59      100.00
------------+-----------------------------------
      Total | 15,237,232      100.00

. drop year

. rename tilgdato aar_forste_reg_uh

. drop kode hoved

. rename w19  w19_0977_lopenr_person_p1

. tempfile nus

. save `nus'
```

```
file /tsd/p836/data/durable/tmp/St33923.000001 saved as .dta format

.
. // first enrollment
. use "/ess/p836/data/durable/pop1/edu/tab_utd_person_w19_0977_pop1.dta", clear
(TAB_UTD_PERSON_W19_0977_POP1    )

.
. g ystart = aar_forste_reg_uh
(5,212,385 missing values generated)

. label var ystart "first year enrolled in higer education"

.
. keep if ystart<. // only keep people who started higher ed.
(5,212,385 observations deleted)

. g y = int(ystart/100) // extract year only

. g mstart = ystart - 100 * y // extract month of start

. replace ystart = y
(2,066,488 real changes made)

.
. merge 1:1 w19_0977_lopenr_person aar_forste_reg_uh using `nus', keep(1 3)  // nus2000
(variable aar_forste_reg_uh was long, now double to accommodate using data's values)

    Result                           # of obs.
    -----------------------------------------
    Not matched                       263,824
        from master                   263,824  (_merge==1)
        from using                          0  (_merge==2)

    Matched                         1,802,664  (_merge==3)
    -----------------------------------------

. tab y _merge

           | Matching result from
           |        merge
         y | Master on  Matched ( |     Total
-----------+----------------------+----------
      1900 |        18          0 |        18
      1901 |         2          0 |         2
      1902 |         1          0 |         1
      1923 |         1          0 |         1
      1924 |         1          0 |         1
      1929 |         2          0 |         2
      1930 |         1          0 |         1
```

1931	4	0	4
1932	3	0	3
1933	2	0	2
1934	3	0	3
1935	4	0	4
1936	7	0	7
1937	13	0	13
1938	8	0	8
1939	18	0	18
1940	20	0	20
1941	23	0	23
1942	34	0	34
1943	36	0	36
1944	52	0	52
1945	59	0	59
1946	67	0	67
1947	79	0	79
1948	95	0	95
1949	114	0	114
1950	131	0	131
1951	146	0	146
1952	188	0	188
1953	224	0	224
1954	268	0	268
1955	286	0	286
1956	340	0	340
1957	374	0	374
1958	383	0	383
1959	383	0	383
1960	454	0	454
1961	500	0	500
1962	548	0	548
1963	641	0	641
1964	651	0	651
1965	754	0	754
1966	560	0	560
1967	828	0	828
1968	937	0	937
1969	820	0	820
1970	203,510	609	204,119
1971	0	7,602	7,602
1972	0	8,671	8,671
1973	0	10,322	10,322
1974	49,892	18,433	68,325
1975	0	22,901	22,901
1976	0	18,883	18,883
1977	0	18,795	18,795
1978	0	20,309	20,309
1979	0	21,081	21,081
1980	0	35,454	35,454

```
      1981 |         0     22,882 |     22,882 
      1982 |         0     22,470 |     22,470 
      1983 |         1     23,322 |     23,323 
      1984 |         0     24,161 |     24,161 
      1985 |         0     23,984 |     23,984 
      1986 |         0     29,338 |     29,338 
      1987 |         0     29,677 |     29,677 
      1988 |         1     34,835 |     34,836 
      1989 |         0     37,342 |     37,342 
      1990 |         0     36,881 |     36,881 
      1991 |         0     37,252 |     37,252 
      1992 |         0     39,545 |     39,545 
      1993 |         0     39,189 |     39,189 
      1994 |         1     40,209 |     40,210 
      1995 |         0     42,223 |     42,223 
      1996 |         0     41,955 |     41,955 
      1997 |         1     40,783 |     40,784 
      1998 |         2     42,580 |     42,582 
      1999 |        21     43,191 |     43,212 
      2000 |       107     46,077 |     46,184 
      2001 |        97     45,372 |     45,469 
      2002 |        73     47,958 |     48,031 
      2003 |         0     48,172 |     48,172 
      2004 |         0     48,118 |     48,118 
      2005 |         1     48,896 |     48,897 
      2006 |         2     48,715 |     48,717 
      2007 |         0     48,771 |     48,771 
      2008 |         0     52,413 |     52,413 
      2009 |         2     53,781 |     53,783 
      2010 |         2     56,836 |     56,838 
      2011 |         0     55,679 |     55,679 
      2012 |         0     54,836 |     54,836 
      2013 |         4     57,128 |     57,132 
      2014 |         1     56,375 |     56,376 
      2015 |         3     55,627 |     55,630 
      2016 |        10     51,357 |     51,367 
      2017 |         6     47,765 |     47,771 
      2018 |         4     43,909 |     43,913 
-----------+----------------------+----------
     Total |   263,824  1,802,664 | 2,066,488 

. tab y _merge, row nof

           | Matching result from
           |         merge
         y | Master on  Matched ( |     Total
-----------+----------------------+----------
      1900 |    100.00       0.00 |    100.00 
      1901 |    100.00       0.00 |    100.00 
      1902 |    100.00       0.00 |    100.00 
```

1923	100.00	0.00	100.00
1924	100.00	0.00	100.00
1929	100.00	0.00	100.00
1930	100.00	0.00	100.00
1931	100.00	0.00	100.00
1932	100.00	0.00	100.00
1933	100.00	0.00	100.00
1934	100.00	0.00	100.00
1935	100.00	0.00	100.00
1936	100.00	0.00	100.00
1937	100.00	0.00	100.00
1938	100.00	0.00	100.00
1939	100.00	0.00	100.00
1940	100.00	0.00	100.00
1941	100.00	0.00	100.00
1942	100.00	0.00	100.00
1943	100.00	0.00	100.00
1944	100.00	0.00	100.00
1945	100.00	0.00	100.00
1946	100.00	0.00	100.00
1947	100.00	0.00	100.00
1948	100.00	0.00	100.00
1949	100.00	0.00	100.00
1950	100.00	0.00	100.00
1951	100.00	0.00	100.00
1952	100.00	0.00	100.00
1953	100.00	0.00	100.00
1954	100.00	0.00	100.00
1955	100.00	0.00	100.00
1956	100.00	0.00	100.00
1957	100.00	0.00	100.00
1958	100.00	0.00	100.00
1959	100.00	0.00	100.00
1960	100.00	0.00	100.00
1961	100.00	0.00	100.00
1962	100.00	0.00	100.00
1963	100.00	0.00	100.00
1964	100.00	0.00	100.00
1965	100.00	0.00	100.00
1966	100.00	0.00	100.00
1967	100.00	0.00	100.00
1968	100.00	0.00	100.00
1969	100.00	0.00	100.00
1970	99.70	0.30	100.00
1971	0.00	100.00	100.00
1972	0.00	100.00	100.00
1973	0.00	100.00	100.00
1974	73.02	26.98	100.00
1975	0.00	100.00	100.00
1976	0.00	100.00	100.00

1977	0.00	100.00	100.00
1978	0.00	100.00	100.00
1979	0.00	100.00	100.00
1980	0.00	100.00	100.00
1981	0.00	100.00	100.00
1982	0.00	100.00	100.00
1983	0.00	100.00	100.00
1984	0.00	100.00	100.00
1985	0.00	100.00	100.00
1986	0.00	100.00	100.00
1987	0.00	100.00	100.00
1988	0.00	100.00	100.00
1989	0.00	100.00	100.00
1990	0.00	100.00	100.00
1991	0.00	100.00	100.00
1992	0.00	100.00	100.00
1993	0.00	100.00	100.00
1994	0.00	100.00	100.00
1995	0.00	100.00	100.00
1996	0.00	100.00	100.00
1997	0.00	100.00	100.00
1998	0.00	100.00	100.00
1999	0.05	99.95	100.00
2000	0.23	99.77	100.00
2001	0.21	99.79	100.00
2002	0.15	99.85	100.00
2003	0.00	100.00	100.00
2004	0.00	100.00	100.00
2005	0.00	100.00	100.00
2006	0.00	100.00	100.00
2007	0.00	100.00	100.00
2008	0.00	100.00	100.00
2009	0.00	100.00	100.00
2010	0.00	100.00	100.00
2011	0.00	100.00	100.00
2012	0.00	100.00	100.00
2013	0.01	99.99	100.00
2014	0.00	100.00	100.00
2015	0.01	99.99	100.00
2016	0.02	99.98	100.00
2017	0.01	99.99	100.00
2018	0.01	99.99	100.00
Total	12.77	87.23	100.00

. drop _merge

.

. merge 1:1 w19_0977_faste_oppl_pop1 using /ess/p836/data/durable/pop1/edu/sesjonsdata_avidentifisert, keepusing(milscore) keep(1 3) nogen
variable w19_0977_faste_oppl_pop1 not found
r(111);

end of do-file

r(111);

.

Log file for data description

```
      name:  <unnamed>
       log:  N:\durable\projects\p23msswapno\log/datadescrption.smcl
  log type:  smcl
 opened on:   8 Nov 2023, 14:09:22

. use "/ess/p836/data/durable/projects/p23msswapno/data/edu.dta" , clear
file /ess/p836/data/durable/projects/p23msswapno/data/edu.dta not found
r(601);

end of do-file

r(601);

. do "C:\Users\P836-O~1\AppData\Local\Temp\7\STD31e8_000000.tmp"

. g logearnings0 = log(earnings0)
variable logearnings0 already defined
r(110);

end of do-file

r(110);

. do "C:\Users\P836-O~1\AppData\Local\Temp\7\STD31e8_000000.tmp"

. g logearnings0 = log(earnings0)
variable logearnings0 already defined
r(110);

end of do-file

r(110);

. do "C:\Users\P836-O~1\AppData\Local\Temp\7\STD31e8_000000.tmp"

. hist logearnings0 if logearnings0 >5
```

```
(bin=55, start=5.0304379, width=.17195259)

.
end of do-file

. do "C:\Users\P836-O~1\AppData\Local\Temp\7\STD31e8_000000.tmp"

. hist logearnings0 if logearnings0 >5
(bin=55, start=5.0304379, width=.17195259)

.
end of do-file

. graph export "N:\durable\projects\p23msswapno\fig\Distribution of Earning with correct labels.png", as(png) name("Graph")
file N:\durable\projects\p23msswapno\fig\Distribution of Earning with correct labels.png saved as PNG format
do "C:\Users\P836-O~1\AppData\Local\Temp\7\STD31e8_000000.tmp"

. qui foreach y of var complete timetodegree {
variable lowses not found
r(111);

end of do-file

r(111);

. exit, clear
```

Code for regression analysis

```
clear all
use ./data/edu
capture log close
log using 2.log, append

destring nus2000, replace

g d1nus = int(nus2000 / 100000) // 1st nus digit
g d2nus = int(nus2000 / 10000)  // 2nd nus digit
g d3nus = int(nus2000 / 1000)   // 3rd nus digit

g timetodegree = ycomplete - ystart
g complete = timetodegree < .
g female = kjoenn - 1
g logearnings0 = log(earnings0)
g noearnings0 = earnings0 <= 0
replace logearnings0 = 0 if noearnings0
```

```
foreach v of var *wealth0 fearnings0 mearnings0 {
	g log`v' = log(`v')
	g no`v' = `v'==0
	replace log`v' = 0 if no`v'
}


encode invkat, gen(migrant)
g native = migrant==1
g lowses = sosbak>2

// analysis
qui foreach y of var complete timetodegree {
	regress `y' noearnings0 logearnings0 i.agestart i.ystart, robust
	est sto `y'

	xtreg `y' noearnings0 logearnings0 i.agestart i.ystart, fe i(d3nus)  vce(robust)
	est sto `y'3

	xtreg `y' noearnings0 logearnings0 i.agestart i.ystart female i.migrant i.sosbak *wealth0 
*fearn* *mearn*, fe i(d3nus) vce(robust)
	est sto `y'5

	xtreg `y' noearnings0 logearnings0 1.female#c.(noearnings0 logearnings0) i.agestart 
i.ystart female i.migrant i.sosbak *wealth0 *fearn* *mearn*, fe i(d3nus) vce(robust)
	est sto `y'6

	xtreg `y' noearnings0 logearnings0 1.lowses#c.(noearnings0 logearnings0) i.agestart 
i.ystart female i.migrant i.sosbak *wealth0 *fearn* *mearn*, fe i(d3nus) vce(robust)
	est sto `y'7

	xtreg `y' noearnings0 logearnings0 1.native#c.(noearnings0 logearnings0) i.agestart 
i.ystart female i.migrant i.sosbak *wealth0 *fearn* *mearn*, fe i(d3nus) vce(robust)
	est sto `y'8

	noi esttab `y'*, b(3) se title("`y'") keep(*noearnings0 *logearnings0) varwidth(30)
	noi esttab `y'* using log/`y'.rtf, b(3) se title("`y'") keep(*noearnings0 *logearnings0) 
varwidth(30) replace
}

exit

twoway (scatter timetodegree logearnings0 if logearnings0 > 0) ///
	(lfit timetodegree logearnings0 if logearnings0 > 0), ///
	title("Time to Degree vs Earnings") ///
	xtitle("Earnings During Study Start") ///
	ytitle("Time to Degree(years)")

log close
```