Student Debt Loans and Labor Market Outcomes: A Lesson in Unintended Consequences

Sun-Ki Choi Queens University of Charlotte

Hyungjo Hur Dankook University

The student loan policy was initiated to improve the equality of educational opportunities and help lowincome families provide higher education opportunities for their children. However, with the average student loan amount increasing, recipients experience problems and restrictions in their early-career choices. This study examines the early-career labor market choices of college graduates who obtained student loans to finance their higher education. We used the National Survey of College Graduates data to estimate the effects of student loans on the employment status and current wages of college graduates. In this research, we compared two groups of workers: those with student loans and those without loans. Using basic models and Mahalanobis distance matching, we found that graduates who rely on student loans are more likely to participate in the labor market than those who do not. Graduates with student loans tend to demonstrate risk-averse behaviors due to their financial restrictions. Thus, student loan debt creates inequity in the early-career labor market for college graduates.

Keywords: student loan, wage differential, unintended consequences, risk-aversion behavior, loan policy

INTRODUCTION

Students undertake college education to obtain better opportunities in the labor market and, therefore, a better quality of life. The student loan policy was introduced in the U.S. to improve the equality of educational opportunity and to allocate financial resources more efficiently, especially to help low-income families to provide their children with more opportunities for higher education. However, as of 2021, the total student loan debt has reached \$1.56 trillion and is expected to continue to rise (Hanson, 2021).¹ As the average student debt load increases, students who have undertaken loans experience more pressure to find a job immediately after graduation since they are eager to pay back their debts. This pressure drives them to have a myopic view when searching for early-career jobs.

Many scholars have emphasized the importance of continuing education after high school graduation to adapt to current and future jobs (NCES, 2001; Grubb, 1999). Carnevale, Smith, and Strohl (2013) anticipated that, by 2020, 65% of jobs will require post-secondary education and training beyond high school diploma. Blumenstyk (2020) predicted that, by 2027, only 30% of jobs will be available for people who do not have more than a high school education. Disregarding whether the figures these scholars presented are correct or wrong, it is evident that many scholars emphasize the need for post-secondary

education. In particular, President Biden is focused on improving the student loan policy and recognizes the importance of education beyond the high school level. In this way, students from low-income families will have more opportunities to receive education and thus increase their social mobility (Baum & Blagg, 2021).

According to the U.S. National Center for Education Statistics, in 2019, the percentage of high school graduates enrolled in colleges was 66.2%, up from 61.7% in 2000 (see Figure 1).² However, paying for a college education is a prevalent obstacle for high school students, with 43.2 million with an average student loan debt of \$39,351.³ However, in terms of the expected value of lifetime earnings, it is worth investing in a bachelor's degree for many students. In 2020, the unemployment rate of high school graduates was 9.0% and their median weekly earnings were \$781, while the unemployment rate of bachelor's degree holders was only 5.5% and they had a median weekly income of \$1,305.⁴

Owing to the increasing student debt load, many college students face problems and restrictions in the early-career labor market. Therefore, high school students must consider the costs and benefits of a college education carefully. Recently, the college enrollment rate has fluctuated (62% in 2001, 70 % in 2009, and 66% in 2019). Thus, student debt has become a major concern for low-income families. According to recent education data, the immediate college enrollment rate for students from high-income families was higher than that of low- and middle-income families (Hanson, 2021).⁵ Students from low- and middle-income families experience problems and restrictions with regards to their housing (Brown, Caldwell, & Sutherland, 2014), marriage (Gicheva, 2016), educational, and occupational choices (Perry & Buckwalter, 2010; Rothstein & Rouse, 2011). These problems often extend to students' families, especially if their parents continue to provide financial support to their children after they graduate college (Curan, 2015; Korkki, 2014). In particular, students with heavy debt loads tend to find that their job options are limited. In contrast, those with less debt (who may be from more fortunate backgrounds) can pursue better job conditions in terms of wage and fringe benefits, since they have enough time to search for a suitable job.

There has been increasing concern about whether and how debt burden negatively affects students' labor market decisions such as employment status, salary, and job quality. To provide a snapshot of young college graduates' employment status and job quality, the current study explores the early-career labor market for college graduates who utilized student loans to finance their higher education. Using National Survey of College Graduates (NSCG) data for 2017 and 2019, this study examines the impact of student debt on the employment status and the salary of college graduates with student loans. The analysis considers two groups of workers: those with student loans and those without student loans.

The remainder of this paper is organized as follows. Section 2 discusses previous literature that examined the impact of student loans on employment status and wages as well as scrutinizes the current educational debt burden and related policies. Section 3 describes the main dataset, the NSCG data, and presents summary statistics for the main variables. Section 4 presents the results obtained from the probit model for employment status and the ordinary least squares (OLS) wage equations. Section 5 discusses handling selection bias by reviewing and comparing existing matching methods for controlling selection bias. Lastly, Section 6 discusses the results and presents the study's conclusions.

LITERATURE REVIEW: POST-COLLEGE GRADUATION DECISIONS AND THEIR CURRENT STATUS

Post-College Graduation Decisions and Current Employment Status

The U.S. student loan policy was initiated to improve educational opportunity equality and allocate financial resources more efficiently. In particular, for students belonging to low-income families, student loans offer better educational opportunities (Woodhall, 1987). However, with the continuous increase in educational costs, students are daunted by the residual risk of educational debt and the resulting uncertainty, increasing their stress while hindering their independence (Perry & Buckwalter, 2010). In other words, students are less likely to spend sufficient searching time for suitable jobs due to their debt burden. This financial obligation significantly limits their life choices since they consider financial debt a risk to their future livelihood.

Their risk-averse behavior is better understood in the context of rational choice theory (Becker, 1976, 2009; Elster, 1986), which views life choices as a cost-benefit analysis process. This analysis considers various factors, their interrelatedness, and the desired outcomes (Dowd & Coury, 2006). For example, when high school graduates decide on whether to go to college or not, they should consider the benefits of college education, such as higher wages and better fringe benefits, as well as the costs associated with college tuition and fees until graduation, in addition to their opportunity costs. This behavior can be explained using a life-cycle model, wherein student debt takes the role of the effect of income on employment decisions, which is proportional to the ratio of educational debt to the current discounted value of total lifetime earnings (Rothstein & Rouse, 2011). Rational choice theory is also affected by psychological constructs such as students' emotions and motivations (Kaufman, 1999).

There has been considerable debate about whether education debt negatively affects students' decisionmaking regarding their choice of early-career labor market participation. Some researchers have found that debt has no significant effect on the early employment of students (Rothstein & Rouse, 2011; Saks, 2017), while other studies observed significant effects (Halbesleben & Buckley, 2004; Hobfoll & Freedy, 1993). Therefore, since both lines of reasoning offer strong arguments, further research is required using recent data to analyze the effect of student loan debt on employment (Choi, 2014). Students tend to search for jobs immediately after graduation since starting full-time work after graduation will allow them to repay their debt. Another hypothesis is that students with debt tend to spend longer searching for a job because they expect that receiving higher income from better-matched jobs (jobs with relatively higher salaries) would reduce the long-term financial strain of loan repayment. Considering these factors, it is important to examine whether students' decision-making behaviors after college graduation differ based on their status of student debt or not. Overall, this study hypothesizes that students with educational debt are more likely to be employed.

Post-College Graduation Decisions and Wages

Job and career choices are considered among the most important post-college decisions. Students make these choices by comparing their current debt status to their expected lifetime earnings. Zhang (2013) found that education debt did not significantly affect graduates' career choices; however, other studies found that education debt motivated students to pursue high-paying jobs (Minicozzi, 2005; Field, 2009). Specifically, the latter argued that college graduates with student debt are more likely to find jobs with high initial wages but low wage growth rates. Specifically, Rothstein and Rouse (2011) noted that college graduates with student loan debt are less likely to choose low-paying public sector jobs. Daniels and Smythe (2018) found that college graduates with student loan debt seek to work more hours to earn more income to repay their debt. Therefore, when undertaking their job search, the financial burdens of student loans affect the behavior of college graduates (Ennis et al., 2000; Sinclair & Cheung, 2016). Based on these conflicting findings in existing literature, this study hypothesizes that students with educational debt are more likely to be employed in high-paying jobs.

Context: The Current Educational Debt Burden

The current fluctuations in college enrollment rates (Figure 1) can be partly attributed to increasing student debt burdens. High school students decide whether to go to college or not based on current college students' income and lifestyle after graduation, and many high school students decide not to go to college because of their fear of accruing massive debt. Figure 2 shows the recent increase in tuition and fees at both public and private colleges. The average costs for studying at public four-year colleges and universities increased by 72% from 1989–90 to 2009–10, and by 20% from 2009-10 to 2019-20 (in 2019 dollars). Similarly, the average costs for studying at private colleges and universities increased by 140% from 1989-90 to 2019-20 (in 2019 dollars).

Furthermore, the percentage of people with student debt is increasing (Figure 3) and many graduates struggle to repay their student loans promptly. According to the NSCG, 62% of college graduates had student debt in 2000, while 36% of the overall graduate population still had debt in 2019. College graduates of the 2018, 68% graduated with debt, while 49% of the overall graduate population still had debt in 2019.

While students finance their college education using various sources, loans from schools, banks, and the government are the main sources of college education finance (Baum & O'Malley, 2003; Baum & Saunders, 1998). The federal and state governments as well as private companies have undertaken various efforts to mitigate the financial strain of college graduates entering the workforce. First, there are different types of loan forgiveness programs to help mitigate students' financial burdens. These programs, such as the public service loan forgiveness program and the teacher loan forgiveness program, seek to attract people to work in specific types of jobs. Second, companies also help college graduates with student loan debt by covering their monthly loan repayments (Helhoski, 2019; Tanzi & Hagan, 2019). Recently, due to the impact of COVID-19 on the economy, many student loan borrowers face difficulties repaying their loans. Consequently, the Biden administration extended the freeze on student loan payments until January 2022. This shows that the student loan issue and its effects on the job-related decisions of college graduates are widely recognized in U.S. society. In line with these social needs, it is important to conduct research on student loans as well as college graduates' career-related decision-making process, their current employment status, and their performance.

DATA AND MEASUREMENT

This research data was obtained from the 2017 and 2019 NSCG, conducted by the National Science Foundation (NSF). This dataset is a nationally representative sample of college graduates of bachelor's, master's, doctoral, and professional degree programs living in the U.S. The data were anonymized and de-identified by the NSF and is available for research purposes upon request to the NSF. This study focused on the labor market decision, employment status, and wages of college graduates that were aged less than 40 years.

Given the observations made in this study, it is evident that educational debt is an important issue many college graduates face that significantly influences their transitional decision-making process. Therefore, the analysis focused on measuring the extent to which college graduates' educational debt characteristics affect their likelihood of employment and their annual salaries. For this purpose, two dependent variables were considered. First, respondents were asked to complete a survey related to their employment status. It was found that some graduates find jobs earlier after graduation than others. The respondents' employment status was represented as a dummy variable, indicating whether they were employed or not (1: employed; 0: not employed). The second response variable was the annual salary of these graduates, which the survey respondents provided.

Educational debt (the presence of educational debt) was a key independent variable used in this study to measure the impact of student loans on employment status and salary. A dummy variable was created to indicate whether a college graduate has educational debt or not. To examine the other factors affecting the dependent variables (employment status and wage), detailed demographic and socioeconomic variables, such as age, gender, race, marital status, children, father's education level, mother's education level, college major, and graduation year, were also controlled. Table 1 presents the summary statistics for the main variables. The employment rate and average annual salary increased between 2017 and 2019. From the sample, 64.2 % and 64.9 % of early-career stage workers utilized student loans to finance their college education in 2017 and 2019, respectively. This rate of receiving student loans is consistent with the national average shown in Figure 1.

Variables	Summar	y statistics		Domain
		2017	2019	
Fmployment	Yes	89.2%	90.1%	Are you employed?
Employment	No	10.8%	9.9%	Note: "Yes" is coded as 1.
Salary	M	68,357	71,007	What is your salary?
~ alal j	SD	62,858	46,806	
Log Salary	M	10.9	11.0	What is your salary?
0	SD	0.8	0.8	
Student debt load	Yes	64.2%	64.9%	Do you have educational debt?
	N0 Mala	53.8% 52.6%	53.1% 52.0%	Are you: Mala/Escoled as 1.
Male	Fomala	32.0%	52.9% 47.1%	Note: "Male" is coded as 1
	M	47.4%	47.1%	Note. Male is coded as 1.
Age		30.0	30.3 4.0	What is your age?
	Ves	51 3%	49 3%	Are you married?
Married	No	48 7%	49.370 50.7%	Note: "Married" is coded as 1
	Yes	36.3%	33.8%	Do you have children?
Child	No	63.7%	66.2%	Note: "Yes" is coded as 1.
	White	55.6%	54.6%	
	Black	7.8%	7.4%	
Race	Asian	17.8%	17.8%	What is your race?
	Hispanic	13.3%	14.6%	
	Other	5.5%	5.6%	
Work duration	М	42.1	42.2	How long do you work at your
(month)	SD	40.0	39.4	job?
	1-10 employees			
	11-24 employees	7.8%	7.5%	
	25-99 employees	5.0%	4.8%	
	100-499 employees	10.3%	11.0%	
Employer size	500-999 employees	14.3%	15.0%	How many people work for your
(company)	1,000-4,999	6.5%	7.4%	employer?
	employees	13.2%	14.5%	
	5,000-2,499	15.7%	16.5%	
	employees	27.2%	23.3%	
	2,500+ employees	51 60/	51 20/	To what extent is your current
Migmatch	Closely related	31.0% 20.1%	20.4%	North related to your educational
wiisillatell	Not related	29.1%	29.4% 10.3%	lovel?
	Ves	17.3%	17.3%	Did you receive any training?
Child	No	63 7%	55.070 66.7%	Note: "Has training" is coded as 1
	Computer & Math	9.3%	9.7%	
	Biology	11 5%	11.4%	
	Physical	3.9%	39%	
Major	Social Science	21.2%	20.5%	What is your major?
	Engineering	23.6%	24.2%	······································
	S & E Related Field	11.8%	12.5%	
	Non-S & E	18.7%	17.8%	

TABLE 1DESCRIPTIVE STATISTICS FOR VARIABLES

	Academia	13.9%	13.0%	
Job sector	Business	75.8%	77.2%	What is your job sector?
	Government	11.3%	9.8%	
	Northeast	19.2%	19.5%	
Employer location	Midwest	24.2%	24.1%	Where is your current employer
Employer location	South	29.7%	28.6%	located?
	West	26.9%	27.8%	
Father's education	Less than high school High school	7.0% 21.5% 21.1%	7.5% 21.7% 20.3%	What is your father's education
level	Vocational school Bachelor Over Bachelor	27.9% 22.5%	27.6% 22.9%	level?
Mother's	Less than high school High school	7.4% 21.9% 24.8%	7.6% 21.7% 23.6%	What is your mother's education
education level	Vocational school Bachelor Over Bachelor	28.5% 17.4%	29.3% 17.8%	level?

Tables 2 and 3 show the mean differences of key selected variables in our model between student loan recipients and non-recipients in 2017 and 2019, respectively. According to these tables, the proportion of male workers who graduated college without student loans is higher for non-recipients than recipients. This means a higher proportion of female college graduates have received student loans for their college education compared to non-recipients. The difference is significant in terms of race. We compare White to non-White college graduates; White college graduates received 3.3 percent fewer student loans than non-White college graduates. In addition, as parents receive more education (bachelors and above), their children are less likely to receive student loans. The impact of parents' education level can be explained in two potential ways. First, the positive correlation between education and wage implies that the group of college graduates whose parents received higher education are more likely to receive support to pay their tuition and fees from their parents. This will significantly lower the probability of receiving student loans to finance their higher education. Second, unobservable ability differences which is inherited from parents can affect the likelihood of receiving student loans. For students with a comparative advantage in college education, the marginal cost of schooling will be relatively lower, as a result, they do not need to borrow money to pay for their college education.

TABLE 2MEAN DIFFERENCES FOR KEY VARIABLES BY STUDENT LOAN RECIPIENT
STATUS (2017)

	2017						
		Young (Ag	e <30)	Old (30≤ Age ≤39)			
	Loan	No Loan	Difference	Loan	No Loan	Difference	
Gender: Male	0.4743	0.5245	0.0502***	0 5015	0.5635	0.0620***	
Gender. Male	0.4743	0.3243	(0.0117)	0.3013		(0.0108)	
Paca: White	0.4893	0.5218	0.0325***	0.5770	0.5992	0.0222**	
Kaee. winte			(0.0117)			(0.0107)	
Major: Social Science	0.2669	0.1999	-0.0670***	0.2341	0.1849	-0.0492***	
Major. Social Science			(0.0098)			(0.0087)	
Father's Edu: Over Bachelors	0 1507	0 2055	0.1548***	0 1/20	0 2422	0.0983***	
Father's Edu. Over Bachelors	0.1307	0.3055	(0.0100)	0.1439	0.2422	(0.0090)	
Mother's Edu: Over Pachalors	0.1410	0.2200	0.0890***	0.1196	0 1771	0.0585***	
Womer's Edu. Over Bachelors	0.1419	0.2309	(0.0093)	0.1180	0.1//1	(0.0080)	

Standard errors are given in parentheses *** p<0.01, ** p<0.05, * p<0.1

TABLE 3 MEAN DIFFERENCES FOR KEY VARIABLES BY STUDENT LOAN RECIPIENT STATUS (2019)

	2017					
		Young (Ag	e <30)	Old $(30 \le Age \le 39)$		
	Loan	No Loan	Difference	Loan	No Loan	Difference
Gondor: Mala	0 4573	0 5371	0.0798***	0.4003	0.5724	0.0822***
Gender. Male	0.4373	0.3371	(0.0102)	0.4905		(0.0097)
Page: White	0.4840	0.5132	0.0291***	0.5522	0.5926	0.0404***
Kace. willte			(0.0102)			(0.0096)
Major: Social Science	0.2564	0.1942	-0.0622***	0.2278	0.1811	-0.0467***
Wajor. Social Science			(0.0084)			(0.0077)
Eather's Educ Over Pachalors	0 1500	0.3100	0.1512***	0 1240	0.2440	0.1109***
Famer's Edu: Over Bachelors	0.1300		(0.0088)	0.1340	0.2449	(0.0080)
Mother's Edu: Over Pachalors	0 1 4 7 9	0.2259	0.0880***	0 1 1 2 9	0 1706	0.0658***
Moulei's Edu. Over Bachelors	0.1478	0.2558	(0.0082)	0.1138	0.1790	(0.0072)

Standard errors are given in parentheses *** p<0.01, ** p<0.05, * p<0.1

BASIC ESTIMATIONS

This section examined the effects of student loans on the employment status and salary of college graduates. In particular, two groups, i.e., college graduates with and without student loans, were compared. The first dependent variable is the probability of being employed. To analyze the binary choice of whether or not college graduates are employed, the following probit model⁶ was used:

$$P(Y_{it}=1) = \Phi(k'_{it} \rho + \beta Debt_{it}), \qquad (1)$$

where *i* indexes individuals and *t* indexes time. In this estimation, Y_{it} represents an individual *i*'s employment status at time *t* (1 = employed, 0 = not employed), while Φ (·) is the distribution function for the standard normal. Here, the dummy variable $Debt_{it}$ equals one if a worker utilized student loans to finance

his/her college education, and 0, otherwise. The variable k_{it} is a vector of demographic and socioeconomic characteristics (i.e., age, race, marriage, children, father's education level, mother's education level, and graduation year). Additionally, the sample was narrowed down to full-time workers only. Thus, workers who worked less than 35 hours per week were excluded from the sample. Moreover, the age range of the college graduates included in the sample was 20–39 years.

Second, the wage equation used to estimate the OLS wage model is below.

$Y_{it} = \alpha + \beta Debt_{it} + \rho k_{it} + \varepsilon_{it}$

(2)

where Y_{it} is an individual *i*'s logged annual salary at time *t*. The vector of observable characteristics k_{it} was the same as in the probit model, including additional variables related to employer information and posthiring variables as well as ε_{it} , the disturbance term. The additional variables included were work duration (and its square), employer size, horizontal mismatch, etc. These variables could not be included in Equation 1 because they are missing values for college graduates who are not employed yet.

Table 4 shows the marginal effect of student loan debt on employment status in the 2017 and 2019 dataset. The results show that college graduates with student loans have a significantly higher probability of employment than those without student loans. The employment status differential was larger for younger age group workers, i.e., aged less than 30 years, as compared to older age group workers (i.e., aged between 30 and 39 years). The employment rate for graduates with student loans for the younger group was more than 3% compared to those without student loans in both 2017 and 2019, showing an increasing trend. Regarding the older workers group, about 2% more student loan recipients were employed than non-recipients; however, the magnitude of this differential decreased between 2017 and 2019.

Table 5 shows the basic OLS wage equation results. The OLS results indicate that, surprisingly, there was no statistically significant difference between student loan recipients and non-recipients regarding wages at the 10% significance level. Moreover, the estimated values for the impact of student debt load on wages varied from -1.12% to 1.35%. These findings suggest that the impact of student loans on wage was insignificant and inconsistent for workers in both age groups.

	2017		2019	
	(1)	(2)	(3)	(4)
Employed	Age <30	30≤ Age ≤39	Age <30	30≤ Age ≤39
Student debt load	0.0312***	0.0225***	0.0394***	0.0218***
	(0.00785)	(0.00619)	(0.00682)	(0.00526)
Age	0.0388	0.0297	0.0505	0.0147
-	(0.0553)	(0.0258)	(0.0482)	(0.0218)
Age squared	-0.000481	-0.000386	-0.000803	-0.000178
	(0.00105)	(0.000378)	(0.000914)	(0.000320)
Male	0.0522***	0.0964***	0.0297***	0.0886***
	(0.00759)	(0.00654)	(0.00647)	(0.00558)
Race: Black	-0.0228	0.00865	-0.0409***	-0.0106
(ref: White)	(0.0154)	(0.0111)	(0.0141)	(0.0105)
Asian	-0.120***	-0.0548***	-0.0780***	-0.0465***
	(0.0128)	(0.0102)	(0.0107)	(0.00820)
Hispanic	-0.0134	-0.0147	-0.0465***	-0.00648
	(0.0121)	(0.00965)	(0.0108)	(0.00757)
Other	-0.0632***	0.00501	-0.0346**	-0.00238
	(0.0190)	(0.0128)	(0.0150)	(0.0110)

TABLE 4 PROBIT REGRESSION: MARGINAL EFFECTS OF STUDENT DEBT LOAD ON EMPLOYMENT STATUS

Married	-0.00788	0.00147	-0.00937	0.00453
	(0.00919)	(0.00737)	(0.00783)	(0.00608)
Child	-0.0971***	-0.0371***	-0.0852***	-0.0385***
	(0.0151)	(0.00696)	(0.0131)	(0.00584)
Major: Biological	-0.119***	-0.00442	-0.0943***	0.0149
(Ref: Computer & Math)	(0.0238)	(0.0128)	(0.0183)	(0.00922)
Physical	-0.0137	-0.00442	-0.0420*	0.0301***
	(0.0238)	(0.0176)	(0.0220)	(0.0107)
Social Science	-0.0328*	-0.0161	-0.0272**	-0.00541
	(0.0169)	(0.0118)	(0.0134)	(0.00942)
Engineering	0.0187	0.0212**	0.0397***	0.0263***
	(0.0143)	(0.0100)	(0.0106)	(0.00799)
S & E Related Field	-0.0432**	0.0157	-0.0201	0.00359
	(0.0197)	(0.0109)	(0.0145)	(0.00957)
Non–S & E	-0.00647	-0.00615	0.00337	-0.0128
	(0.0168)	(0.0113)	(0.0131)	(0.00973)
Father's education level				
High school	-0.0206	-0.00175	-0.0321*	-0.00277
(Ref: Less than high school)	(0.0183)	(0.0133)	(0.0166)	(0.0103)
Vocational school	0.0109	-0.00552	-0.0334*	0.00237
	(0.0166)	(0.0138)	(0.0172)	(0.0104)
Bachelor	-0.0146	-0.0245*	-0.0471***	-0.00187
	(0.0181)	(0.0148)	(0.0172)	(0.0107)
Over Bachelor	-0.0280	-0.0259	-0.0598***	-0.00751
	(0.0196)	(0.0159)	(0.0186)	(0.0116)
Mother's education level				
High school	0.0355***	0.0140	0.0272**	0.00401
(Ref: Less than high school)	(0.0136)	(0.0114)	(0.0123)	(0.00957)
Vocational school	0.0406***	0.0164	0.0297**	0.0113
	(0.0138)	(0.0116)	(0.0125)	(0.00954)
Bachelor	0.0341**	0.0149	0.0366***	0.00615
	(0.0150)	(0.0119)	(0.0130)	(0.00999)
Over Bachelor	0.0259*	0.0143	0.0311**	0.0149
	(0.0155)	(0.0126)	(0.0131)	(0.0101)
Observations	7,360	9,432	9,690	12,294
Pseudo R-squared	0.0969	0.0814	0.0671	0.0837

Standard errors are given in parentheses *** p<0.01, ** p<0.05, * p<0.1The coefficients presented are the marginal effects from probit regressions Pseudo R2 values are presented for the probit regression analyses.

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		2017		2019	
Ln (Salary) Age <30 $30 \le Åge \le 39$ Age <30 $30 \le Åge \le 39$ Student debt load 0.0135 0.00719 0.00729 -0.0112 Age 0.126 0.198*** -0.0110 0.189*** Age 0.0141 -0.00260*** 0.00111 -0.00235*** Age squared -0.0141 -0.00260*** 0.00127 (0.00239) Male 0.150*** 0.239*** 0.117*** 0.231*** (0.0180) (0.0153) (0.0147) (0.0129) Race: Black -0.139*** -0.195*** -0.195*** -0.027*** (0.0235) (0.0220) (0.0147) (0.0129) Race: Black -0.0117 0.0528** 0.0352* 0.0956*** (0.0235) (0.0220) (0.0178) (0.0178) 0.00169** Hispanic -0.0621** -0.0619*** -0.0619*** 0.02255 (0.0336) (0.0235) (0.0210) (0.0165) (0.0169) Other -0.0417 0.0177 -0.058** -0.019**		(1)	(2)	(3)	(4)
Student deb load 0.0135 0.00719 0.00729 -0.0112 Age (0.0179) (0.0153) (0.0146) (0.0128) Age (0.126) (0.0658) (0.117) (0.0559) Age squared -0.00141 -0.00260*** 0.00111 -0.00220) (0.000819) Male 0.150*** 0.239*** 0.117*** 0.231*** 0.231*** (Ref: White) (0.0325) (0.02090) (0.0271) (0.0278) 0.0178) Asian 0.0117 0.0528** 0.0158** 0.0198** 0.0178) Hispanic -0.0621** -0.0627*** -0.105*** 0.0019) Other -0.0417 0.0178) (0.0178) Hispanic -0.0621** -0.0598** 0.0255 Married 0.0718** 0.0179 (0.0188) 0.0178) Married 0.0718*** 0.0179 (0.0165) (0.0140) Obter -0.0417 -0.0793*** -0.0131 (0.00088** 0.00168** 0.00189**	Ln (Salary)	Age <30	30< Age <39	Age <30	30< Age <39
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Student debt load	0.0135	0.00719	0.00729	-0.0112
Age 0.126 0.198^{***} -0.0110 0.189^{***} Age squared (0.142) (0.0058) (0.117) (0.0559) Age squared (0.00269) (0.00220) (0.00235^{***}) Male 0.150^{***} 0.239^{***} 0.117^{***} 0.231^{***} Male 0.160^{***} 0.239^{***} 0.1177^{***} $0.0226)$ Race: Black -0.139^{***} -0.195^{***} -0.102^{***} -0.102^{***} (Bef: White) (0.0325) (0.0220) (0.0178) (0.0178) Hispanic -0.0621^{**} -0.0627^{***} -0.0598^{**} $0.00191)$ Other -0.0417 0.0177 -0.0598^{**} 0.0255 Married 0.0718^{***} 0.00333 (0.0227) (0.0144) Married 0.0709^{***} 0.00160^{***} -0.0131 (0.0266) (0.0175) (0.0227) (0.0144) Work duration 0.0079^{***} -0.0568^{***} $-3.98e^{-05***}$ $-8.02e^{-06***}$		(0.0179)	(0.0153)	(0.0146)	(0.0128)
Age(0.142)(0.0658)(0.117)(0.0559)Age squared-0.00141-0.00260***(0.00020)(0.000819)Male(0.150***(0.20026)**(0.000220)(0.000819)Male(0.150***(0.239***(0.117***(0.213***(0.180)(0.0153)(0.0147)(0.0129)Race: Black-0.139***-0.195***-0.102***(Ref: White)(0.0325)(0.0290)(0.0271)(0.0256)Asian0.0117(0.0220)(0.0198)(0.0178)Hispanic-0.0621**-0.0627***-0.105***-0.0619***(0.0263)(0.0235)(0.0210)(0.019)(0.019)Other-0.04170.0177-0.0598**0.0255(0.0356)(0.0333)(0.0288)(0.0276)Married0.0718***0.0709***0.00165(0.0146)Child-0.0857***0.00100-0.129***-0.0131(0.0266)(0.0175)(0.0227)(0.0144)Work duration0.00709***Work duration0.00709***0.00160***0.0058****0.00189***MismatchSomewhat related-0.0452**-0.053***-0.0519***-0.033***MismatchSomewhat related-0.0452**-0.0563***-0.0519***-0.033***Mot duration_squared-5.95e-05***-0.0519***-0.033***-0.333***Mot duration_squared-0.052***-0.259	Age	0.126	0.198***	-0.0110	0.189***
Age squared -0.00141 -0.00260^{***} 0.00111 -0.00235^{***} Male 0.150^{***} 0.239^{***} 0.00111 -0.00235^{***} Male 0.150^{***} 0.239^{***} 0.117^{***} 0.231^{***} (0.0180) 0.0153 0.0147 0.0129 Race: Black -0.139^{***} -0.195^{***} -0.195^{***} -0.102^{***} (Ref: White) (0.0325) $0.0220)$ (0.0271) (0.0256) Asian 0.0117 0.0528^{**} 0.0352^{*} 0.0956^{***} (0.0238) (0.0220) (0.0198) (0.0178) Hispanic -0.0621^{**} -0.0627^{***} -0.105^{***} (0.0263) (0.0235) (0.0210) (0.0191) Other -0.0417 0.0177 -0.0598^{**} 0.02255 Married 0.0718^{***} 0.0793^{***} 0.00100 -0.120^{***} (0.0202) (0.0179) (0.0165) (0.0146) Child -0.0857^{***} 0.00160^{***} 0.002277 (0.0146) (0.0202) (0.0175) (0.2277) (0.0146) (0.00035) (0.000353) (0.00276) Work duration 0.00709^{***} 0.00160^{***} 0.00568^{***} -0.0732^{***} (0.0213) (0.00459) (0.000814) (0.00385) Work duration $squared$ $-5.95e-05^{***}$ -0.0519^{***} -0.0732^{***} $(Ref: Closely related)$ -0.0452^{**} -0.0563^{***} -0.0519^{***} (0.0245) $(0.$	8-	(0.142)	(0.0658)	(0.117)	(0.0559)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Age squared	-0.00141	-0.00260***	0.00111	-0.00235***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	rige squared	(0.00111)	(0.00200)	(0.00220)	(0.00233)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Male	0.150***	0.239***	0.117***	0.231***
Race: Black (0.139^{***}) $(0.0125)^*$ $(0.0125)^*$ $(0.0125)^*$ (Ref: White) (0.0325) (0.0290) (0.0271) (0.0256) Asian 0.0117 0.0528^{**} 0.0352^* 0.0956^{***} (0.0238) (0.0220) (0.0198) (0.0178) Hispanic -0.0621^{**} -0.0627^{***} -0.105^{***} -0.0619^{***} (0.0263) (0.0235) (0.0210) (0.0191) Other -0.0417 0.0177 -0.0598^{**} 0.02255 (0.0356) (0.0333) (0.0288) (0.0276) Married 0.0718^{***} 0.00100^{*} -0.102^{***} (0.0202) (0.0179) (0.0165) (0.0146) Child -0.087^{***} 0.00100^{*} -0.0288^{**} (0.0266) (0.0175) (0.0227) (0.0144) Work duration 0.00709^{***} $-5.73e-06^{**}$ $-3.98e-05^{***}$ (0.00103) (0.000459) (0.000814) (0.000385) Work duration_squared $-5.95e-05^{***}$ $-5.73e-06^{**}$ $-3.98e-05^{***}$ Somewhat related -0.362^{***} -0.053^{***} -0.0732^{***} (Ref: Closely related) (0.0196) (0.0167) (0.0161) (0.0139) Not related -0.362^{***} -0.293^{***} -0.373^{***} (0.0245) (0.0199) (0.0140) (0.0122) Employer Size (0.0146) (0.0140) (0.0122) I1-24 employees 0.305^{***} 0.192^{***} 0.4	White	(0.0180)	(0.0153)	(0.0147)	(0.0129)
Nate: $(0.13)^{+}$ $(0.13)^{+}$ $(0.12)^{+}$ $(0.12)^{+}$ Asian (0.0325) (0.020) (0.0271) (0.0256) Asian $(0.017)^{+}$ (0.0223) (0.0198) (0.0178) Hispanic -0.0621^{**} -0.0627^{***} -0.105^{***} -0.0619^{***} (0.023) (0.0235) (0.0210) (0.0191) Other -0.0417 0.0177 -0.058^{***} 0.0225 (0.0356) (0.0333) (0.0288) (0.0276) Married (0.0718^{***}) 0.00100 -0.122^{***} (0.0202) (0.0179) (0.0165) (0.0146) Child -0.0857^{***} 0.00100 -0.122^{***} (0.00103) (0.000459) (0.00160^{***}) 0.00189^{***} (0.00103) (0.000459) (0.000814) (0.00385) Work duration_squared $-5.95e-05^{***}$ $-5.73e-06^{***}$ $-3.98e-05^{***}$ (0.00103) (0.00459) (0.00161) (0.0139) Not related -0.0452^{**} -0.053^{***} -0.0732^{***} (0.0245) (0.0199) (0.0170) (0.0170) Training 0.129^{***} 0.106^{***} 0.116^{***} $(1.24^{*}enployees)$ 0.305^{***} 0.198^{***} 0.259^{***} (0.449) (0.0473) (0.0403) (0.0400) (0.0145) (0.0199) (0.0122) Employees 0.305^{***} 0.198^{***} (0.449) (0.375) (0.3663) (0.327) (0.0278)	Race: Black	_0 139***	_0 105***	-0 105***	(0.012)
(Acian (0.0250) (0.0270) (0.0270) (0.0250) Asian (0.0238) (0.0220) (0.0198) (0.0178) Hispanic $-0.0621**$ $-0.0627***$ $-0.105***$ $-0.0619***$ (0.0263) (0.0235) (0.0210) (0.0191) Other -0.0417 0.0177 $-0.0598**$ 0.0255 Married $0.0718***$ $0.0793***$ $0.0808**$ $0.0776***$ (0.0202) (0.0179) (0.0165) (0.0146) Child $-0.0857***$ 0.00100 $-0.120***$ -0.0131 (0.0266) (0.0175) (0.0227) (0.0144) Work duration $0.00709***$ $0.00160***$ $-0.00519***$ $-8.02e-06***$ $(1.00e57)$ $(2.81e-06)$ $(9.41e-06)$ $(2.40e-06)$ Mismatch (0.0245) (0.0167) (0.00335) Work duration_squared $-5.95e-05***$ $-5.73e-06**$ $-3.98e-05***$ $-8.02e-06***$ $(1.20e-05)$ $(2.81e-06)$ $(9.41e-06)$ $(2.40e-06)$ Mismatch (0.0196) (0.167) (0.0161) (0.0139) Not related $-0.362***$ $-0.293***$ $-0.363***$ $-0.333***$ (0.0245) (0.0199) (0.0199) (0.0170) Training $0.129***$ $0.16***$ $0.16***$ $0.175***$ (0.0473) (0.0403) (0.0327) (0.0278) $10-499$ $0.365***$ $0.198***$ $0.259***$ $0.275***$ (0.0473) (0.0403) (0.0327) (0.0278) </td <td>(Raf: White)</td> <td>(0.0325)</td> <td>(0.0200)</td> <td>(0.0271)</td> <td>(0.0256)</td>	(Raf: White)	(0.0325)	(0.0200)	(0.0271)	(0.0256)
Astan 0.0117 0.0028^{-1} 0.0022^{-1} 0.0020^{-1} Hispanic -0.0621^{**} -0.0627^{***} -0.105^{***} -0.0619^{***} (0.0238) (0.0235) (0.0210) (0.0191) Other -0.0417 0.0177 -0.0598^{**} 0.0255 Married 0.0718^{***} 0.0793^{***} 0.0808^{***} 0.0276 Married 0.0718^{***} 0.0793^{***} 0.0808^{***} 0.0776^{***} (0.0202) (0.0179) (0.0165) (0.0146) Child -0.0857^{***} 0.00100 -0.120^{***} -0.0131 (0.0266) (0.0175) (0.0227) (0.0144) Work duration 0.00709^{***} 0.00160^{***} 0.000843^{***} (0.00103) (0.000459) (0.000844) (0.000385) Work duration_squared $-5.95e-05^{***}$ $-5.73e-06^{***}$ $-3.98e-05^{***}$ $-8.02e-06^{***}$ Somewhat related -0.0452^{**} -0.0563^{***} -0.0519^{***} $-8.02e-06^{***}$ Somewhat related -0.0452^{**} -0.293^{***} -0.333^{***} -0.333^{***} (0.0245) (0.0167) (0.01161) (0.0139) Not related -0.362^{***} -0.293^{***} -0.363^{***} -0.333^{***} (0.0245) (0.017) (0.0146) (0.0170) Training 0.129^{***} 0.106^{***} 0.114^{***} (0.0171) (0.0143) (0.0278) $(0.275^{***}$ (0.0473) (0.0403) (0.4000)	A sign	(0.0323)	(0.0290)	(0.0271)	0.0056***
Hispanic (0.0236) (0.02236) $(0.027***$ (0.0178) Hispanic (0.0263) (0.0235) (0.0210) $(0.019**)$ Other (0.0263) (0.0235) (0.0210) $(0.019**)$ Other (0.0417) (0.0177) $(0.059***)$ (0.0276) Married $(0.0718***)$ $(0.0793***)$ (0.0288) (0.0276) Married (0.0702) (0.0179) (0.0165) (0.0146) Child (0.0202) (0.0179) (0.0165) (0.0146) Child (0.0202) (0.0179) (0.0165) (0.0144) Work duration (0.0206) (0.0175) (0.0227) (0.0144) Work duration_squared $-5.95e-05***$ $-5.73e-06**$ $-3.98e-05***$ $-8.02e-06***$ (1.20e-05) $(2.81e-06)$ $(9.41e-06)$ $(2.40e-06)$ Mismatch (0.0245) (0.0167) (0.0161) (0.0139) Not related $-0.362***$ $-0.293***$ $-0.363***$ $-0.333***$ (0.0245) (0.0167) (0.0170) (0.0170) Training $0.129***$ $0.106***$ $0.116***$ $0.117***$ (0.0171) (0.0143) (0.0400) (0.0322) In-24 employees $0.305***$ $0.198***$ $0.259***$ $0.275***$ (0.499) $0.383***$ $0.392**$ $0.404***$ $0.452***$ (0.0473) (0.0403) (0.0400) (0.0321) (0.0499) 0.329 (0.327) (0.278) (0.0499) 0.329 </td <td>Asian</td> <td>(0.0117)</td> <td>$(0.0328)^{\circ}$</td> <td>(0.0332)</td> <td>(0.0930^{-11})</td>	Asian	(0.0117)	$(0.0328)^{\circ}$	(0.0332)	(0.0930^{-11})
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Hispania	(0.0256)	(0.0220)	(0.0196)	(0.0176)
Other (0.0203) (0.0213) (0.0213) (0.0213) Other -0.0417 0.0177 -0.0598^{**} 0.0255 Married 0.0718^{***} 0.0793^{***} 0.0808^{***} 0.0276^{***} (0.0202) (0.0179) (0.0165) (0.0146) Child -0.0857^{***} 0.00100 -0.120^{***} -0.0131 (0.0266) (0.0175) (0.0227) (0.0144) Work duration 0.00709^{***} 0.00160^{***} 0.00568^{***} 0.00189^{***} (0.00103) (0.000459) (0.000814) (0.000385) Work duration_squared $-5.95e+05^{***}$ $-5.73e-06^{**}$ $-3.98e-05^{***}$ $-8.02e-06^{***}$ $(1.20e-05)$ $(2.81e-06)$ $(9.41e-06)$ $(2.40e-06)$ Mismatch (0.0125) (0.0167) (0.0161) (0.0139) Not related -0.0452^{**} -0.093^{***} -0.0732^{***} (0.0245) (0.0199) (0.0170) (0.0170) Training 0.129^{***} 0.106^{***} 0.116^{***} (0.0171) (0.0403) (0.0400) (0.0342) $25-99$ 0.333^{***} 0.392^{***} 0.404^{***} 0.452^{***} (0.0499) 0.480^{***} 0.481^{***} 0.490^{***} 0.514^{***} (0.0499) $0.388)$ (0.0310) (0.0321) (0.0261) $500-999$ 0.499^{***} 0.566^{***} 0.513^{***} 0.603^{***} (0.0398) (0.0314) (0.0318) (0.0264) <td>Hispanic</td> <td>-0.0021</td> <td>-0.0027</td> <td>-0.103^{-11}</td> <td>-0.0019^{+++}</td>	Hispanic	-0.0021	-0.0027	-0.103^{-11}	-0.0019^{+++}
Other -0.0417 0.0177 -0.0598^{**} 0.0255 Married (0.0356) (0.0333) (0.0288) (0.0276) Married 0.0718^{***} 0.0793^{***} 0.0808^{***} 0.0776^{***} (0.0202) (0.0179) (0.0165) (0.0146) Child -0.0857^{***} 0.00100 -0.120^{***} -0.0131 (0.0266) (0.0175) (0.0227) (0.0144) Work duration 0.00709^{***} 0.00160^{***} 0.000814 (0.00103) (0.000459) (0.000814) (0.000385) Work duration_squared $-5.95e \cdot 05^{***}$ $-5.73e \cdot 06^{**}$ $-3.98e \cdot 05^{***}$ $-8.02e \cdot 06^{***}$ $(1.20e \cdot 05)$ $(2.81e \cdot 06)$ $(9.41e \cdot 06)$ $(2.40e \cdot 06)$ Mismatch $(0.0125)^{**}$ -0.0563^{***} -0.0519^{***} -0.0732^{***} Somewhat related -0.0452^{**} -0.0563^{***} -0.0519^{***} -0.0732^{***} (Ref: Closely related) (0.0196) (0.0167) (0.0161) (0.0139) Not related -0.362^{***} -0.293^{***} -0.363^{***} -0.333^{***} (0.0245) (0.0199) (0.0170) (0.0170) Training 0.129^{***} 0.106^{***} 0.114^{***} $(1-24 employees$ 0.305^{***} 0.198^{***} 0.259^{***} 0.275^{***} (0.4409) (0.0329) (0.0327) (0.0278) $100-499$ 0.480^{***} 0.481^{***} 0.490^{***} 0.514^{****} $(0.049$	Other	(0.0203)	(0.0233)	(0.0210)	(0.0191)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Other	-0.0417	0.0177	-0.0598**	0.0255
$\begin{array}{llllllllllllllllllllllllllllllllllll$		(0.0356)	(0.0333)	(0.0288)	(0.02/6)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Married	0.0/18***	0.0/93***	0.0808***	0.0776***
$\begin{array}{cccc} {\rm Child} & -0.085 / *** & 0.00100 & -0.120 *** & -0.0131 \\ & (0.0266) & (0.0175) & (0.0227) & (0.0144) \\ {\rm Work \ duration} & 0.00709 *** & 0.00160 *** & 0.00568 *** & 0.00189 *** \\ & (0.00103) & (0.000459) & (0.000814) & (0.000385) \\ {\rm Work \ duration_squared} & -5.95 e \cdot 05 *** & -5.73 e \cdot 06 ** & -3.98 e \cdot 05 *** & -8.02 e \cdot 06 *** \\ & (1.20 e \cdot 05) & (2.81 e \cdot 06) & (9.41 e \cdot 06) & (2.40 e \cdot 06) \\ {\rm Mismatch} & & & & & & & & & & & & & & & & & & &$		(0.0202)	(0.0179)	(0.0165)	(0.0146)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Child	-0.0857***	0.00100	-0.120***	-0.0131
Work duration 0.00709^{**} 0.00160^{***} 0.00568^{***} 0.00189^{***} (0.00103) (0.000459) (0.000814) (0.000385) Work duration_squared $-5.95e \cdot 05^{***}$ $-5.73e \cdot 06^{***}$ $-3.98e \cdot 05^{***}$ $-8.02e \cdot 06^{***}$ $(1.20e \cdot 05)$ $(2.81e \cdot 06)$ $(9.41e \cdot 06)$ $(2.40e \cdot 06)$ Mismatch (0.0196) (0.0167) (0.0161) (0.0139) Not related -0.0452^{***} -0.293^{***} -0.363^{***} -0.333^{***} (0.0245) (0.0199) (0.0199) (0.0170) Training 0.129^{***} 0.106^{***} 0.116^{***} (0.0171) (0.0146) (0.0140) (0.0122) Employer Size $11-24$ employees 0.305^{***} 0.198^{***} 0.259^{***} $(1-24 employees)$ 0.305^{***} 0.198^{***} 0.404^{***} 0.452^{***} (0.0409) (0.0329) (0.0400) (0.0327) (0.0278) $100-499$ 0.480^{***} 0.481^{***} 0.490^{***} 0.514^{***} (0.0453) (0.0375) (0.0363) (0.0302) $1,000-4,999$ 0.579^{***} 0.566^{***} 0.513^{***} 0.634^{***} $0.0398)$ (0.0314) (0.0313) (0.0258) $2500+$ 0.690^{***} 0.586^{***} 0.512^{***} 0.690^{***}		(0.0266)	(0.0175)	(0.0227)	(0.0144)
(0.00103) (0.000459) (0.000814) (0.000385) Work duration_squared-5.95e-05***-5.73e-06**-3.98e-05***-8.02e-06*** $(1.20e-05)$ $(2.81e-06)$ $(9.41e-06)$ $(2.40e-06)$ Mismatch(0.0152** $-0.0563***$ $-0.0519***$ $-0.0732***$ Somewhat related $-0.0452**$ $-0.0563***$ $-0.0519***$ $-0.0732***$ (Ref: Closely related) (0.0196) (0.0167) (0.0161) (0.0139) Not related $-0.362***$ $-0.293***$ $-0.363***$ $-0.333***$ (0.0245) (0.0199) (0.0199) (0.0170) Training $0.129***$ $0.106***$ $0.116***$ $0.114***$ (0.0171) (0.0473) (0.0403) (0.0400) (0.0342) Employer Size $11-24$ employees $0.305***$ $0.198***$ $0.259***$ $0.275***$ $(Ref: 1-10)$ (0.0473) (0.0403) (0.0400) (0.0342) $25-99$ $0.383***$ $0.392***$ $0.404***$ $0.452***$ (0.0499) (0.388) (0.0310) (0.0327) (0.0278) $100-499$ $0.480***$ $0.481***$ $0.400***$ $0.557***$ (0.0398) (0.0310) (0.0316) (0.0264) $5,000-2,499$ $0.536***$ $0.536***$ $0.535***$ $0.634***$ (0.0390) (0.0304) (0.0313) (0.0258) $2500+$ $0.602***$ $0.602***$ $0.612***$ $0.602***$	Work duration	0.00709***	0.00160^{***}	0.00568***	0.00189***
Work duration_squared $-5.95e-05^{***}$ $-5.73e-06^{**}$ $-3.98e-05^{***}$ $-8.02e-06^{***}$ Mismatch(1.20e-05)(2.81e-06)(9.41e-06)(2.40e-06)Mismatch(0.0196)(0.0167)(0.0161)(0.0139)Not related -0.362^{***} -0.293^{***} -0.363^{***} -0.333^{***} (0.0245)(0.0199)(0.0199)(0.0170)Training 0.129^{***} 0.106^{***} 0.116^{***} 0.114^{***} (0.0171)(0.0146)(0.0140)(0.0122)Employer Size11-24 employees 0.305^{***} 0.198^{***} 0.259^{***} 0.275^{***} (Ref: 1-10)(0.0473)(0.0403)(0.0400)(0.0342)25-99 0.383^{***} 0.392^{***} 0.404^{***} 0.452^{***} 100-499 0.480^{***} 0.481^{***} 0.490^{***} 0.514^{***} (0.0388)(0.0310)(0.0316)(0.0261)500-999 0.579^{***} 0.566^{***} 0.513^{***} 0.603^{***} (0.0398)(0.0314)(0.0318)(0.0264)5,000-2,499 0.536^{***} 0.586^{***} 0.535^{***} 0.634^{***} 2500+ 0.602^{***} 0.646^{***} 0.612^{***} 0.690^{***}		(0.00103)	(0.000459)	(0.000814)	(0.000385)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Work duration_squared	-5.95e-05***	-5.73e-06**	-3.98e-05***	-8.02e-06***
MismatchSomewhat related -0.0452^{**} -0.0563^{***} -0.0519^{***} -0.0732^{***} (Ref: Closely related) (0.0196) (0.0167) (0.0161) (0.0139) Not related -0.362^{***} -0.293^{***} -0.363^{***} -0.333^{***} (0.0245) (0.0199) (0.0199) (0.0170) Training 0.129^{***} 0.106^{***} 0.116^{***} 0.114^{***} (0.0171) (0.0146) (0.0140) (0.0122) Employer Size $11-24$ employees 0.305^{***} 0.198^{***} 0.259^{***} 0.275^{***} $(Ref: 1-10)$ (0.0473) (0.0403) (0.0400) (0.0342) $25-99$ 0.383^{***} 0.392^{***} 0.404^{***} 0.452^{***} (0.0409) (0.0329) (0.0327) (0.0278) $100-499$ 0.480^{***} 0.481^{***} 0.490^{***} 0.514^{***} (0.0388) (0.0310) (0.0316) (0.0326) $1,000-4,999$ 0.579^{***} 0.566^{***} 0.513^{***} 0.603^{***} $1,000-4,999$ 0.579^{***} 0.566^{***} 0.513^{***} 0.603^{***} $1,000-4,999$ 0.579^{***} 0.566^{***} 0.513^{***} 0.603^{***} $1,000-4,999$ 0.579^{***} 0.566^{***} 0.513^{***} 0.603^{***} $1,000-4,999$ 0.579^{***} 0.566^{***} 0.513^{***} 0.603^{***} $1,000-4,999$ 0.579^{***} 0.566^{***} 0.513^{***} 0.603^{***} </td <td></td> <td>(1.20e-05)</td> <td>(2.81e-06)</td> <td>(9.41e-06)</td> <td>(2.40e-06)</td>		(1.20e-05)	(2.81e-06)	(9.41e-06)	(2.40e-06)
Somewhat related -0.0452^{**} -0.0563^{***} -0.0519^{***} -0.0732^{***} (Ref: Closely related)(0.0196)(0.0167)(0.0161)(0.0139)Not related -0.362^{***} -0.293^{***} -0.363^{***} -0.333^{***} (0.0245)(0.0199)(0.0199)(0.0170)Training 0.129^{***} 0.106^{***} 0.116^{***} 0.114^{***} (0.0171)(0.0146)(0.0140)(0.0122)Employer Size 11^{-24} employees 0.305^{***} 0.198^{***} 0.259^{***} 0.275^{***} (Ref: 1-10)(0.0473)(0.0403)(0.0400)(0.0342)25-99 0.383^{***} 0.392^{***} 0.404^{***} 0.452^{***} (0.0409)(0.0329)(0.0327)(0.0278)100-499 0.480^{***} 0.481^{***} 0.490^{***} 0.514^{***} (0.0388)(0.0310)(0.0316)(0.0261)500-999 0.499^{***} 0.526^{***} 0.440^{***} 0.557^{***} (0.0398)(0.0314)(0.0318)(0.0302)1,000-4,999 0.579^{***} 0.566^{***} 0.513^{***} 0.634^{***} 0.0390 (0.0304)(0.0313)(0.0264)5,000-2,499 0.536^{***} 0.546^{***} 0.612^{***} 0.690^{***}	Mismatch				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Somewhat related	-0.0452**	-0.0563***	-0.0519***	-0.0732***
Not related -0.362^{***} -0.293^{***} -0.363^{***} -0.333^{***} (0.0245)(0.0199)(0.0199)(0.0170)Training 0.129^{***} 0.106^{***} 0.116^{***} 0.114^{***} (0.0171)(0.0146)(0.0140)(0.0122)Employer Size $11-24$ employees 0.305^{***} 0.198^{***} 0.259^{***} 0.275^{***} (Ref: 1-10)(0.0473)(0.0403)(0.0400)(0.0342)25-99 0.383^{***} 0.392^{***} 0.404^{***} 0.452^{***} (0.0499)(0.0329)(0.0327)(0.0278)100-499 0.480^{***} 0.481^{***} 0.490^{***} 0.514^{***} (0.0388)(0.0310)(0.0316)(0.0261)500-999 0.499^{***} 0.526^{***} 0.440^{***} 0.557^{***} (0.0453)(0.0375)(0.0363)(0.0302)1,000-4,999 0.579^{***} 0.566^{***} 0.513^{***} 0.603^{***} (0.0398)(0.0314)(0.0318)(0.0264)5,000-2,499 0.536^{***} 0.586^{***} 0.535^{***} 0.634^{***} 2 500+ 0.602^{***} 0.646^{***} 0.612^{***} 0.690^{***}	(Ref: Closely related)	(0.0196)	(0.0167)	(0.0161)	(0.0139)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Not related	-0.362***	-0.293***	-0.363***	-0.333***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.0245)	(0.0199)	(0.0199)	(0.0170)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Training	0.129***	0.106***	0.116***	0.114***
Employer Size 0.305^{***} 0.198^{***} 0.259^{***} 0.275^{***} (Ref: 1-10) (0.0473) (0.0403) (0.0400) (0.0342) 25-99 0.383^{***} 0.392^{***} 0.404^{***} 0.452^{***} (0.0409) (0.0329) (0.0327) (0.0278) $100-499$ 0.480^{***} 0.481^{***} 0.490^{***} 0.514^{***} (0.0388) (0.0310) (0.0316) (0.0261) $500-999$ 0.499^{***} 0.526^{***} 0.440^{***} 0.557^{***} (0.0453) (0.0375) (0.0363) (0.0302) $1,000-4,999$ 0.579^{***} 0.566^{***} 0.513^{***} 0.603^{***} (0.0398) (0.0314) (0.0318) (0.0264) $5,000-2,499$ 0.536^{***} 0.586^{***} 0.535^{***} 0.634^{***} (0.0390) (0.0304) (0.0313) (0.0258)		(0.0171)	(0.0146)	(0.0140)	(0.0122)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Employer Size				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	11-24 employees	0.305***	0.198***	0.259***	0.275***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	(Ref: 1-10)	(0.0473)	(0.0403)	(0.0400)	(0.0342)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	25-99	0.383***	0.392***	0.404***	0.452***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.0409)	(0.0329)	(0.0327)	(0.0278)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	100-499	0.480***	0.481***	0.490***	0.514***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.0388)	(0.0310)	(0.0316)	(0.0261)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	500-999	0.499***	0.526***	0.440***	0.557***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.0453)	(0.0375)	(0.0363)	(0.0302)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1.000-4.999	0.579***	0.566***	0.513***	0.603***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	-,	(0.0398)	(0.0314)	(0.0318)	(0.0264)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	5.000-2.499	0.536***	0.586***	0.535***	0.634***
2500+ 0.602*** 0.646*** 0.612*** 0.690***	-,~~~ -,	(0.0390)	(0.0304)	(0.0313)	(0.0258)
	2.500+	0.602***	0.646***	0.612***	0.690***

TABLE 5WAGE REGRESSION: EFFECTS OF STUDENT DEBT LOAD ON SALARY

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	(0.0369)	(0.0289)	(0.0303)	(0.0247)
Major: Biological	-0.320***	-0.228***	-0.312***	-0.256***
(Ref: Computer & Math)	(0.0382)	(0.0317)	(0.0304)	(0.0266)
Physical	-0.251***	-0.173***	-0.256***	-0.195***
-	(0.0490)	(0.0422)	(0.0407)	(0.0349)
Social Science	-0.201***	-0.136***	-0.206***	-0.120***
	(0.0353)	(0.0285)	(0.0281)	(0.0242)
Engineering	0.0198	0.0269	0.0131	0.0163
6 6	(0.0331)	(0.0265)	(0.0260)	(0.0220)
S & E Related Field	-0.177***	-0.214***	-0.230***	-0.209***
	(0.0384)	(0.0311)	(0.0299)	(0.0259)
Non-S & E	-0.182***	-0.201***	-0.155***	-0.179***
	(0.0365)	(0.0276)	(0.0291)	(0.0234)
Job sector: Business	0.674***	0.541***	0.685***	0.520***
(Ref: Academia)	(0.0238)	(0.0233)	(0.0199)	(0.0194)
Government	0.508***	0.396***	0.536***	0.323***
	(0.0350)	(0.0294)	(0.0302)	(0.0255)
Employer location	()			(,
Midwest	-0.0939***	-0.158***	-0.0822***	-0.154***
(Ref: Northeast)	(0.0251)	(0.0220)	(0.0206)	(0.0182)
South	-0.0143	-0.0567***	-0.0398**	-0.0871***
	(0.0242)	(0.0211)	(0.0197)	(0.0176)
West	0.0339	-0.0142	0.0343*	-0.0106
	(0.0247)	(0.0215)	(0.0200)	(0.0177)
Father's education level				
High school	0.0514	-0.0104	0.00279	-0.0130
(Ref: Less than high school)	(0.0423)	(0.0344)	(0.0340)	(0.0281)
Vocational school	0.0452	0.0302	-0.00847	-0.00258
	(0.0428)	(0.0350)	(0.0346)	(0.0288)
Bachelor	0.0627	0.0366	0.00793	0.0284
	(0.0432)	(0.0355)	(0.0350)	(0.0290)
Over Bachelor	0.131***	0.0693*	0.0317	0.0808^{***}
	(0.0446)	(0.0370)	(0.0360)	(0.0302)
Mother's education level				
High school	0.0348	-0.0317	-0.0156	0.0449
(Ref: Less than high school)	(0.0434)	(0.0338)	(0.0354)	(0.0279)
Vocational school	-0.0208	-0.0186	-0.00511	0.0679**
	(0.0436)	(0.0345)	(0.0358)	(0.0286)
Bachelor	0.0342	0.0139	0.0334	0.0795***
	(0.0442)	(0.0353)	(0.0363)	(0.0290)
Over Bachelor	0.00459	0.0864 **	0.0362	0.116***
	(0.0465)	(0.0378)	(0.0380)	(0.0310)
Constant	7.190***	6.313***	9.260***	6.337***
	(1.879)	(1.120)	(1.538)	(0.948)
Observations	6,457	8,493	8,583	11,166
Adj R-squared	0.3022	0.2584	0.3258	0.2891

Augree0.50220.2384Standard errors are given in parentheses *** p<0.01, ** p<0.05, * p<0.1</td>

DEALING WITH SELECTION BIAS

In microeconomics, evaluation studies face the fundamental problem of selection bias. The problem arises in the current research since it seeks to estimate the difference in participant outcomes with and without the treatment (student loan). Both outcomes cannot be observed simultaneously for each individual. In other words, if one student receives student loans, he/she must be excluded from the sample of students that do not have loans. Considering the mean outcome of non-participants as an approximation is not advisable (Caliendo & Kopeinig, 2008). This problem is known as selection bias and is evident in the current research model, wherein students with student loans are motivated to pay back their debts as soon as possible and thus may have a higher probability of undertaking jobs impetuously. One solution to the selection problem is the matching approach, which has become popular for estimating causal treatment effects and has been widely used to evaluate labor market policy (Heckman, Ichimura, & Todd, 1997). The basic idea of the matching approach is to identify a large group of students without student loans who are similar to students with debts in all relevant pre-treatment observable covariates. Subsequently, the comparison of outcomes of this well-selected and thus acceptable group of students without loans with those of students with loans can be applied to the treatment (student loans). However, due to the "curse of dimensionality,"7 Rosenbaum and Rubin (1983) suggested utilizing balance scores to address selection bias. One such balancing score is the propensity score, which is used in an approach known as propensity score matching (PSM). However, King and Nielsen (2019) argued that PSM generates fragile and non-robust estimates that could vary widely depending on the outcome model. In particular, if researchers discard units distant from each other by imposing an increasingly tighter caliper, PSM will eventually worsen the balance even if units that are close together in terms of their propensity scores remain. This is known as the PSM paradox, which is why the use of PSM is discouraged in favor of potentially more robust methods that allow direct matching within the covariate space, such as the Mahalanobis distance, which is simply a measure of the distance between two data vectors (Rubin, 1980), given by the following equation:

$$M(X_1, X_2) = \sqrt{(X_1 - X_2)\Sigma^{-1}(X_1 - X_2)}$$
(3)

where Σ is the covariance matrix. If Σ is the identity matrix, then the Mahalanobis distance equals the Euclidean distance. If X_1 and X_2 are data vectors, a smaller M(X₁, X₂) means that the observations are more similar in terms of their covariate values, X. Thus, the Mahalanobis distance can be used as a measure of similarity and has the advantage of obtaining more closely matched observations that are not typically matched on average. Based on this advantage, Mahalanobis distance matching (MDM) was used as the matching method in this research.

This study focused on estimating the average treatment effects on treated (ATT), which can be defined as follows:

$$T_{ATT} = E(T | Debt_i = 1) = E[Y(1) / Debt_i = 1] - E[Y(0) / Debt_i = 0]$$
(4)

Since the counterfactual mean for students with debts, $E[Y(0) | Debt_i = 0]$, is not observable, the Mahalanobis distance was used as a balance metric to conduct matching for the missing counterparts. The MDM estimator for ATT is given as follows:

$$T_{MDM} = EM_{(X1,X2)|Debt=1} \{ E [Y(1) | Debt_i = 1, M(X_1, X_2)] - E [Y(0) | Debt_i = 0, M(X_1, X_2)] \},$$
(5)

where $M(X_1, X_2)$ is the Mahalanobis distance. Therefore, the above MDM estimator represents the mean difference between two groups based on pairing units that are close regarding the Mahalanobis distance to students with student loans. Thus, using the MDM method, the average treatment effects on the treated variables can be observed after controlling for selection bias.

Tables 6 and 7 summarize the comparison of the key variables' coefficients. First, regarding employment status, student loans had a positive and statistically significant effect in both models, with and without controlling for selection bias. The results showed that the employment rate differential between the two groups increased in 2019 as compared to the 2017 data. Among the younger age group, 3.01 % (2017) and 4.45 % (2019) more college graduates with student loans were employed. The estimation of 4.45 % in 2019 is approximately 14 % higher than the estimation obtained before controlling for selection bias. Among the older age group, 2.16% (2017) and 2.81% (2019) more college graduates were employed than their counterparts without student loan debt. Comparing the 2019 estimates for the older age workers, the estimation obtained from the MDM method was about 29% higher than that obtained from the basic probit model in Section 4.

Second, regarding the wage differential, clear evidence was obtained that it is important to consider selection bias when estimating the wage penalty faced by student loan recipients. The wage differentials between student loan recipients and non-recipients obtained from the basic OLS wage equation were not statistically significant for both the younger and older worker groups for all the sample years. However, the estimations of the wage differential using the matching model provide strong evidence of a wage penalty for college graduates with student loan debt. The wage penalties for the younger group of college graduates with student loans were 7.31% (2017) and 7.1% (2019), respectively. Moreover, student loan recipients among the older worker group also earned, on average, 6.67 % (2017) and 8.03% (2019) less than their nonrecipient counterparts. These findings from the wage equation indicate the shadowy side of the U.S. student loan policy, which many policy makers and researchers discussed. The recipients of student loans experience more stress to pay back their loans as soon as possible. This willingness to escape loan debt motivates these recipients to find jobs early and makes them more likely to be imprudent in their job search. Consequently, the recipients' careless job search increases the probability of vertical and/or horizontal job mismatch, which leads to a higher employment rate at a lower wage level for recipients.

These comparisons suggest that controlling for selection bias is important when examining the earlycareer labor market choices of college graduates who utilized student loans to finance their higher education. Selection bias arising from the missing comparison group generated misleading basic results regarding a smaller employment rate, especially in 2019, and an insignificant wage differential. The results obtained using the MDM method, which controls the fundamental evaluation problem arising from selection bias, provide more robust evidence of the effectiveness of measuring the effects of student loan debt on early-career labor market choices. College graduates with student loans are more motivated to find jobs earlier. However, after employment, loan recipients' debt status negatively impacts salary regardless of their age group (workers aged under 30 years and between 30 and 40 years).

 TABLE 6

 COMPARISON OF KEY VARIABLES' COEFFICIENTS: EMPLOYMENT STATUS

		2017		2019	
		Age <30	30≤ Age ≤39	Age <30	30≤ Age ≤39
Regression	Educational debt Load	0.0312***	0.0225***	0.0394***	0.0218***
		(0.0079)	(0.0062)	(0.0068)	(0.0053)
MDM	Educational debt Load	0.0301***	0.0216**	0.0448***	0.0281***
		(0.0104)	(0.0087)	(0.0095)	(0.0079)

Standard errors are given in parentheses *** p<0.01, ** p<0.05, * p<0.1

		2017		2019	
		Age <30	30≤ Age ≤39	Age <30	30≤ Age ≤39
Regression	Educational debt Load	0.0135	0.00719	0.00729	-0.0112
		(0.0179)	(0.0153)	(0.0146)	(0.0128)
MDM	Educational debt Load	-0.0732***	- 0.0667***	-0.071***	-0.0803***
		(0.02189)	(0.01834)	(0.01804)	(0.01483)
C 1 1	• • • • • • • • • • • • • • • • • • •	0.01 www. 0.0			

 TABLE 7

 COMPARISON OF KEY VARIABLES' COEFFICIENTS: LN(SALARY)

Standard errors are given in parentheses *** p<0.01, ** p<0.05, * p<0.1

DISCUSSION AND CONCLUSION

For decades, the U.S. has emphasized equal opportunity in education. Student loans are important in financing higher education opportunities, particularly for low-income families. In contrast to college students from low-income families, students from high-income families have more options to finance their college tuition and fees, such as financial support from their parents and/or relatives that do not need to be repaid. Students' loan burden is an unequal starting line when college students complete their education and search for jobs. This research examines how student loan debt was undertaken to finance college education affects early-career graduates' labor market decisions, employment probability, and annual salary choices.

The first finding of this study was that college graduates who rely on student loans are more likely to participate in the labor market than those who graduate college without it, which is consistent with the findings of previous studies (Halbesleben & Buckley, 2004; Hobfoll & Freedy, 1993). This result can be attributed to the fact that student loan recipients are eager to repay their debts, and thus tend to spend less time searching for better job matches. However, this shorter search time leads early-career college graduates to find jobs that are more likely to be vertically and/or horizontally mismatched for them. Previous studies found that both vertical and horizontal job mismatches hurt wages such that workers with mismatched jobs receive lower wages than those with matched jobs (Hur, Maurer, & Hawley, 2019; Robst, 2007). Therefore, this study further investigates the impact of student loans on wages.

The second finding of this research was that, for entry-level jobs, college graduates with student loans received lower annual salaries than those without student loans. The lower wages of college graduates with student loans indicate that they demonstrate risk-averse behavior due to their financial restrictions. If student loan recipients could search for jobs without any financial restrictions and thus spend enough time finding a more suitable job like non-recipients, the wage differential between student loan recipients and non-recipients would be narrower. The job decision of students with debt may seem acceptable in the short term, especially considering the financial restrictions arising from their need to repay their debts and reduce their financial stress. However, in the long term, this myopic selection of jobs that pay relatively lower wages to student loan recipients in their early career (less than 40 years of age) is not a rational lifetime choice for these graduates. Considering that student loan recipients tend to belong to mostly low- and middle-income families, the wage penalty faced by these recipients will increase income inequality in the U.S. and transmit income inequality from one generation to the next.

The main purpose of college education student loans is to provide everyone with an equal opportunity to receive higher education, which can help graduates have a better quality of life. However, the current research's results suggest that the distribution of student loans is not random. The findings indicate the existence of selection bias between student loan recipients and non-recipients, potentially arising from the non-recipients access to financial support from their family and relatives. Consequently, student loans, originally introduced to promote equity in society, have become an unintended hindrance to an egalitarian society.

While this study provides a useful snapshot of employment status and wage differentials, it has some limitations. First, the measures of labor market outcomes used in this study include employment status and salary. Although these are helpful measures, multiple additional measures, such as job satisfaction and turnover, can be used to evaluate these outcomes more accurately. Second, due to the limitations in obtaining detailed information regarding student loan amounts, it was only possible to investigate the impact of loan status in this study. Further studies can be conducted if detailed information regarding student loan amounts is available. Third, this study focused on early-career-stage college graduates aged less than 40 years. Thus, future studies can explore the long-term effects of student loan debt on labor maker outcomes.

Despite these limitations, this study provides meaningful insights into the current status of the labor market, focusing on college graduates. As the number of college graduates increases, obtaining more information about their situations and behaviors in the labor market is necessary. To fulfill these social needs, this study provides more information about the wage disadvantage faced by college graduates with student loans and their economically rational and irrational behaviors in the labor market. The findings of this research highlight the importance of the education policy in the U.S. in reducing income inequality.

ENDNOTES

- ^{1.} According to the Federal Reserve Bank of St. Louis, as of May 2022, the total amount of student loan debt has reached \$1.76 trillion.
- ^{2.} U.S. Bureau of Labor Statistics. (2017). College enrollment and work activity of high school graduates in 2016. Retrieved from https://www.bls.gov/news.release/hsgec.nr0.htm
- ^{3.} https://educationdata.org/student-loan-debt-statistics
- ^{4.} U.S. Bureau of Labor Statistics. (2020). Earnings and unemployment rates by educational attainment. Retrieved from https://www.bls.gov/emp/ep_chart_001.htm
- ^{5.} "Students in the highest quintile of socioeconomic status are 50% more likely to enroll in college than those in the lowest quintile."
- ^{6.} For this analysis, I estimate the probability of being employed with probit, logit, and LPM. They provide similar results.
- ^{7.} Conditioning on all relevant covariates is limited when there is a high dimensional vector of independent variables.

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APPENDIX

FIGURE 1 HIGH SCHOOL GRADUATES AND THEIR ENROLLMENT IN COLLEGE: 2000–2019



Source: National Center for Education Statistics

FIGURE 2 PUBLIC AND PRIVATE COLLEGE TUITION AND FEES: 1989–2020



Source: College Board, Annual Survey of Colleges; NCES, IPEDS Fall Enrollment data

FIGURE 3 EDUCATIONAL DEBT OF COLLEGE GRADUATES BY GRADUATION YEAR



Source: 2019 National Survey of College Graduates (NSCG)