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ECONOMICS OF TERTIARY EDUCATION: ANALYSIS OF STUDENTS' DECISIONS AND OUTCOMES

DOCTORAL DISSERTATION

Ljubljana, 2015

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The undersigned Tjaša Bartolj, a student at the University of Ljubljana, Faculty of Economics, (hereafter: FELU), declare that I am the author of the doctoral dissertation entitled Economics of Tertiary Education: Analysis of Students' Decisions and Outcomes, written under supervision of Sašo Polanec, PhD.

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ZAHVALE

Posebej se želim zahvaliti mentorju, dr. Sašu Polancu, za strokovne nasvete, vodenje, pomoč pri pridobivanju podatkov in številne ure namenjene spoznavanju in urejanju podatkovnih baz. Neprecenljive so tudi vse razprave o teh in bodočih raziskavah, pa tudi tiste o trenutni situaciji v mikro in makro okolju.

Za podporo v času študija se zahvaljujem Tomažu, staršema ter Katji.

Zahvaljujem se vsem, ki so mi omogočili dostop do podatkov, brez katerih moje delo ne bi bilo mogoče – Domnu Jakusu, mag. Tilnu Balonu, dr. Andreji Cirman, Statističnemu uradu Republike Slovenije, dr. Darku Zupancu, dr. Gašperju Cankarju, Sebastjanu Česniku in Petru Šraju.

Hvala tudi vsem sodelavcem na Inštitutu za ekonomska raziskovanja za delovno, a hkrati sproščeno okolje.

EKONOMIKA TERCIARNEGA IZOBRAŽEVANJA: ANALIZA ŠTUDENTSKIH ODLOČITEV IN REZULTATOV

Povzetek

Niz člankov analizira dejavnike, ki vplivajo na dve odločitvi študentov terciarnega izobraževanja, ter učinke teh odločitev na rezultate posameznikov na trgu dela oziroma na njihov študijski uspeh. Natančneje, analiziramo kako se študentje odločajo za smer študija in kaj vpliva na njihovo odločitev za študentsko delo. Poleg tega ocenimo vpliv teh izbir na rezultate, kot so zasebni donosi izobraževanja, učnih uspeh, višina plače oziroma verjetnost zaposlitve. Najprej se osredotočimo na dejavnike, ki vplivajo na odločitev o smeri študija, s posebnim poudarkom na razlikovanju vpliva splošne sposobnosti in sposobnosti specifične za določeno študijsko smer. Izbira študijske smeri pa med drugim vpliva na zaposlitvene možnosti in plačo. Ena od možnosti merjenja tega učinka je ocena stopenj donosov izobraževanja, zato nadaljujemo z analizo evolucije donosov različnih stopenj in smeri terciarnega izobraževanja v obdobju tranzicije v Sloveniji. Toda povpraševanje po delavcih, ki sooblikuje te donose, ni odvisno zgolj od njihove smeri študija, pač pa je odvisno tudi od pridobljenega znanja in delovnih izkušenj. Slednje določa za iskalce prve zaposlitve njihova izbira alokacije časa namenjenega študiju in delu. Doktorsko delo zato nadaljuje z analizo stiliziranega dejstva o študentskem delu, ki pravi, da so glavni vzrok za študentko delo nizki družinski dohodki. Sledi ocena vpliva študentskega dela na študijske rezultate. Zaključimo pa z analizo učinkov študijskega uspeha in študentskega dela na rezultate na trgu dela. Disertacija je sestavljena iz petih člankov, njihove glavne ugotovitve opisuje spodnje besedilo.

V prvem članku proučujemo vpliv kognitivne sposobnosti na izbiro študijske smeri. Za ta namen uporabimo administrativno podatkovno bazo, ki vsebuje zapise o vseh redno vpisanih študentih štiriletnega študija ekonomskih in poslovnih smeri, ki jih ponuja največja slovenska univerza. V nasprotju z obstoječimi študijami nam podatki omogočajo razlikovanje med splošno sposobnostjo, merjeno s povprečno srednješolsko oceno, in sposobnostjo specifično za določeno smer, ki temelji na ocenah predmetov povezanih s to smerjo. Članek pokaže, da imajo študentje z višjo splošno sposobnostjo večjo verjetnost, da se bodo vpisali na ekonomske smeri, višja specifična sposobnost za neko smer (npr. višja ocena pri predmetu računovodstvo) pa povečuje verjetnost vpisa na to smer (računovodstvo). Poleg tega ugotovimo, da sta oba spola bolj odzivna na specifične sposobnosti za smeri, ki so tradicionalno bolj značilne za določen spol (npr. poslovna informatika za moške). Ti rezultati kažejo, da bi morali oblikovalci politik, ki želijo spremeniti strukturo ponudbe delovne sile, poskušati vplivati na specifične sposobnosti posameznikov za določene smeri študija.

Drugi članek analizira evolucijo zasebnih donosov terciarnega izobraževanja v obdobju tranzicije iz socialističnega v tržno gospodarstvo z uporabo dohodninskih podatkov vseh aktivnih slovenskih prebivalcev med leti 1994 in 2008. Članek dokumentira bogato medsebojno vplivanje ponudbe in povpraševanja na trgu dela srednješolsko in univerzitetno izobraženih delavcev. Pokažemo, da je kljub pomembnemu povečanju ponudbe delovne sile povpraševanje po univerzitetno izobraženih delavcih dominiralo in povečalo donose izobraževanje v začetnem obdobju tranzicije (1994–2001),

medtem ko je v kasnejšem obdobju (2001–2008) veljalo obratno. Odkrijemo tudi znatno heterogenost donosov med spoloma, med stopnjami in med smermi izobrazbe. Posebej veliki (nizki) donosi so značilni za smeri, ki so bile v času socializma zatirane (spodbujane).

Tretji članek proučuje povezavo med nedelovnim dohodkom in študentskim delom. Povezava, ki jo opazimo v podatkih, ima obliko narobe obrnjene črke U, kar kaže, da (v nasprotju s pričakovanji) študentje z nizkimi družinskimi dohodki, ki navadno prejmejo manj denarja od svojih staršev, opravijo manj študentskega dela kot študentje iz premožnejših družin. V članku razvijemo teoretični model, ki poleg našega empiričnega dognanja, da študentje z najnižjimi družinskimi dohodki z največjo verjetnostjo opustijo študij (med študenti, ki niso opravili letnika), predpostavlja, da absolutna nenaklonjenost tveganju staršev pada s premoženjem. Model napove, da študentje iz družin z nizkimi dohodki zmanjšajo študentsko delo, da bi se izognili verjetni prihodnji finančni omejitvi. Slednja je rezultat nepripravljenosti staršev za nadaljnje financiranje študija otrok, ki niso opravili letnika. Menimo, da to povzroči naraščajoči del povezave med nedelovnim dohodkom in študentskim delom.

Četrti članek raziskuje vzročne učinke študentskega dela na študijski uspeh z uporabo metode paritve enake verjetnosti (angl. *propensity score matching*). Ta metoda nam dovoljuje ocenitev vzročnih učinkov ločeno po letnikih študija, kar pa ni mogoče, če so zaradi endogenosti študentskega dela uporabljeni notranji instrumenti. Ugotovimo, da ima študentsko delo ničen ali majhen negativen učinek na študijski uspeh, ki ga merimo s petimi spremenljivkami. K obstoječi literaturi, ki ne razlikuje vplivov študentskega dela po letnikih študija, prispevamo tudi z ugotovitvijo, da študentsko delo škoduje študijskemu uspehu predvsem v prvem letniku, saj študentje takrat težje najdejo pravo ravnovesje med študijem in delom.

Zadnji članek analizira premalo raziskan vpliv študentskega dela na rezultate na trgu dela. Odkrijemo, da ima študentsko delo (še posebej strokovno zahtevno študentsko delo, ki je povezano z izbrano študijsko smerjo) statistično značilen pozitiven učinek na zaposlenost, urno postavko in verjetnost zaposlitve za nedoločen čas. Študentsko delo najbolj koristi tistim, ki med štiriletnim dodiplomskim študijem delajo več kot 10 mesecev, a manj kot 2 leti. Medtem ko pozitivni učinki naraščajo z dodatnimi leti izkušenj, pa dodatne koristi niso statistično značilne. Poleg tega odkrijemo, da ima na poklicno kariero po končanem študiju večji vpliv študijski uspeh kot študentsko delo.

Ključne besede: človeški kapital, izbira študijske smeri, donosi izobraževanja, študentsko delo, družinski dohodek, finančne omejitve, študijski uspeh, zaposlitev

ECONOMICS OF TERTIARY EDUCATION: ANALYSIS OF STUDENTS' DECISIONS AND OUTCOMES

Summary

This series of papers analyzes factors influencing two separate decisions of individuals during their tertiary education and the effects of these decisions on students' outcomes. Specifically, we analyze how students select college majors and what influences their decision on labor supply during study. Furthermore, we estimate the effect of these choices on outcomes such as private returns to education, academic performance, wages, or probability of employment. We first concentrate on the factors that determine college major choice, with special attention on the distinction between general and major-specific ability. Students' selection of field of study, among other things, influences their employment opportunities and wages. One way to capture this impact is to estimate the rates of return to their education, so we continue with the analysis of evolution of returns to different levels and fields of tertiary education during transition in Slovenia. However, the demand for specific workers that co-shapes these returns does not depend only on the field of education but also on the acquired knowledge and the work experience. The latter are determined by the allocation of time between study and work for the first-time entrants on the labor market. We therefore proceed with the analysis of the stylized fact of student labor supply that the low family income is the main driving force behind the student's decision to work. Next, we estimate the effect of student employment on academic performance. We conclude with the analysis of relative impacts of academic performance and student work on post-college professional career. The thesis consists of five papers, with their main findings described below.

In the first paper we study the impact of cognitive ability on college major choices using an administrative data set for full-time students enrolled in four-year business and economics programs offered by the largest Slovenian university. In contrast to existing studies, we are able to distinguish between general ability, measured with high school GPA, and major-specific ability, measured with grades achieved in major-specific courses. We show that students with higher general ability are more likely to enroll in Economics majors, while higher major-specific ability (e.g., higher grade in Accounting) increases the likelihood of choosing that major (Accounting). We also find that both genders are more responsive to measured major-specific ability in majors that are traditionally more popular among them (e.g., Business Informatics for males). These results suggest that policy makers aiming to change the structure of the labor supply should attempt to change the major-specific abilities of students.

The second paper analyses the evolution of private returns to tertiary education during the period of transition from a socialist to a market economy using the personal income tax data of all Slovenian workers employed between 1994 and 2008. We document a rich interplay between supply and demand in the labor markets of high school and university graduates. We show that in spite of significant increases in the labor supply, the demand for university graduates dominated and increased the rates of return in the early period of transition (1994–2001), while in the later period

(2001–2008) the opposite was the case. We also provide evidence on considerable heterogeneity in the rates of return between genders, levels, and fields of study, with particularly large (low) returns to the fields that were suppressed (favored) during socialism. These initial differences in returns have, however, gradually declined.

The third paper explores a relationship between non-labor income and labor supply of students. We find an inverse U-shaped relationship, which implies—counterintuitively—that students from poorer families, who typically receive lower transfers from their parents, tend to supply less work than students from more affluent families. We develop a theoretical model which builds on assumed DARA preferences of parents and on our empirical observation that students with the lowest non-labor income exhibit the highest drop-out rates (among students who failed to pass a study year). The model predicts that students from low-income families cut back work efforts in order to avoid probable future financial constraints. The latter arise from parents' unwillingness to make additional risky investments in children's education if they fail to pass a study year. We suggest that the positive relationship between non-labor income and labor supply for lower levels of income may be driven by these considerations.

The fourth article studies the causal effects of student work on academic performance using propensity score matching technique. This estimation approach allows us to estimate the causal effects separately for different years of study, which is not possible when inside instruments are used to deal with endogeneity of student work. We use five distinct measures of academic performance and find that student work has either no effect or a small negative effect. Supplementing existing studies that do not differentiate between study years, we show that student work harms academic success mostly in the first year of study, when students are less likely to find the right balance between work and study.

The last paper analyzes the effects of student work during college studies on subsequent labor market outcomes. We find that work experience gained during studies increases probability of employment, hourly wage, and probability of signing indefinite employment contract, especially when it is high-skilled work in occupations related to college major. Individuals benefit most by increasing their student work experience up to 2 years, whereas additional experience generally has statistically insignificant effects. We compare these effects of student work experience to the effects of superior academic performance and find that students may enjoy greater returns by putting more effort to studies rather than work experience.

Keywords: Human capital, School choice, Returns to education, Student work, Family income, Financial constraints, Academic performance, Employment

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

The proportion of students obtaining tertiary education has increased recently. For example, the percentage of a 25–64-year-old population with tertiary education increased from 34, 23, and 21 percent in 1997 to 42, 41, and 35 percent in 2012 in the United States, United Kingdom, and Sweden, respectively. Similar trends can also be observed in Slovenia, where the percentage increased from 15 percent in 2002 to 26 percent in 2012. The estimated probability that a young person from Slovenia will enter tertiary education of type A, if current age-specific entry rates continue, increased from 40 percent in 2005 to 76 percent in 2012. However, the tertiary graduation rates did not follow the same pattern. Slovenian graduation rates (the estimated percentage of age cohort that will complete tertiary education) were low—45 percent in 2012—and comparable to the graduation rates in other countries (OECD, 2014). Moreover, Slovenia is facing increasing unemployment rates among individuals with tertiary education. Data for the Slovenian labor market show that the percentage of unemployed individuals with tertiary education among all unemployed persons increased from 4.9 percent in January 2005 to 15.5 percent in January 2014 (Employment Service of Slovenia, 2015).

In addition, studies show that students take longer than required to complete their studies. Brunello and Winter-Ebmer (2002) analyzed 3000 Economics and Business college students from 10 European countries and found that there is a significant percentage of students expecting to graduate at least one year later than the required time—31.2 percent in Sweden, 30.8 percent in Italy, 17.1 percent in France, and 10 percent in Germany. Similarly, Bound et al. (2007) show that time to completion of a BA degree in the United States increased significantly in the last three decades. In Slovenia, the average duration of studies (roughly 7 years for old university programs and almost 4 years for the first cycle of the new programs), according to Slovenian Statistical Office data (SORS, 2015), also substantially exceeds the average required time (5 years for old and 3 for new programs).

Low graduation rates, prolonged time of studies, and high unemployment rates of graduates show that there is a need for a better understanding of factors that influence outcomes in tertiary education. The importance of such research is even more crucial in countries such as Slovenia, where public organizations without tuition fees for full-time undergraduate students with domestic residence predominate. As Hanushek and Woessmann (2008) pointed out, there is a difference between school attainment and knowledge. If schools are not efficient, the effect of increased schooling on economic growth is small. Thus, the governments that concentrate on a share of population enrolled in tertiary programs are not necessarily improving the country's growth prospects. More important is the provision of a labor supply with a quality knowledge that matches the demand on the market. Therefore, governments should be able to set appropriate incentives. However, this is not possible without being acquainted with the factors that influence the behavior of students and the situation on the labor markets.

The aim of this doctoral dissertation is to contribute to the understanding of students' decisions and outcomes during tertiary education. The most important decision that students make is their choice of college major, as it not only determines their future job opportunities, but has also an important implication for the structure of the labor force and labor market outcomes. The first paper thus concentrates on the impact of different types of ability on college major choice and argues that the mixed evidence regarding the impact of ability on this decision in existing literature may be due to inability to distinguish between different types of ability. We differentiate between 'general' ability, which is measured with high school average grades and points achieved on a standardized national exam at the end of high school, and 'major-specific ability', which is a unique feature of our data, measured with grades achieved in major-specific courses. The importance of both ability measures is estimated with mixed and nested logit models using an administrative data set for full-time economics and business students enrolled in four-year undergraduate programs at the Faculty of Economics, University of Ljubljana.

As already mentioned above, college major choice determines the structure of labor supply, which together with the labor demand, forms returns to education. During socialism direct wage setting that maintained low income inequality caused low private rates of return and consequently, a low proportion of university graduates in the labor force. Furthermore, government's setting of entry quotas for different educational programs and direct allocation of capital to specific industries led to a relatively high supply of graduates in technical fields of study and manufacturing, and a relatively low supply of graduates in social sciences, law, and business studies. Several papers showed that liberalization of wage determination at the end of the socialist era caused an increase in returns to education, however they concentrated only on the early transition period and did not explore the differences across levels and fields of tertiary education. The second paper of this dissertation aims to fill this gap in the literature and shows the evolution of private rates of return to different levels and fields of tertiary education, using Slovenian data on all economically active workers between 1994 and 2008. In order to reduce the cognitive ability bias, we augment the Mincerian earnings equation with our measure of general cognitive ability based on high school Matura examination. Additionally, we check the robustness of our results by estimating the returns to education separately for workers employed in the private sector. As the net wage does not capture all monetary rewards of education, the rates of return based on it do not necessarily capture the full effects of educational attainment. Therefore we also estimate the returns as reflected in the total reported labor income.

The second paper shows that the field of study influences the demand for workers' services and thus their labor market outcomes. However, labor demand depends also on the acquired knowledge and the work experience. For graduates entering the labor market, work experience is obtained through student labor supply, which increased for decades, and nowadays the employment rates of students are around 40 percent in US and 70 percent in EU countries. Although a commonly cited stylized fact of student labor supply explains this with poor economic background and high college costs, our data on full-time undergraduate students at University of Ljubljana reject a monotonically decreasing relation between student work and family income. This is shown in the third paper, which argues that the differences in the observed shape of this relationship may be attributed to two effects that work in the opposite directions. One of them is the income effect of non-labor income described by the standard neoclassical theory of labor supply, which predicts a negative effect of non-wage income on student work. And the second one is a probable future financial constraint for students with low family income, which is caused by decreasing absolute risk aversion of their parents. The paper shows empirical results that motivate our theoretical model, which explains this effect of family income on student work that was so-far neglected.

Student work can, however, either increase or decrease human capital, as students acquire new skills, abilities, and knowledge but potentially devote less time to studying. We examine the casual effects of student work on academic performance in the fourth paper. Our analysis uses five distinct measures of academic performance—number of attempts to pass an exam, number of passed exams, average grade, average passing grade, and probability of passing a year—each of them measuring a different aspect of academic success. Unlike many existing studies, we allow for non-linear effects of student work and analyze these effects for each year of study separately. The innovation lies also in the first attempt to measure the effects of student work on academic performance with propensity score matching technique.

In the fifth paper we continue with the focus on student work, but concentrate on the impact of student-work experience on post-college labor-market outcomes, which we measure with probability of employment, hourly wages, and probability of signing an employment contract with indefinite duration. These effects are relatively underexplored, since the results of studies analyzing the effects of student work during high school cannot be generalized to work performed by college students. We also examine whether different types of student work have a diverse impact on post-college outcomes. Our research further contributes to the literature not only with the comparison of the relative impacts of academic results and student work on labor-market outcomes, but also by being the first to use propensity score matching in such analysis.

The remainder of the thesis is organized as follows. The next five chapters are presented in the format of scientific papers that can be read individually, which results in some repetition, especially in the sections describing institutional framework, data sources, and methods. The conclusion summarizes the key findings, points out the contribution of the thesis to the literature, and explains possible limitations of the five papers. The thesis ends with a longer summary in the Slovenian language.

1 COLLEGE MAJOR CHOICE AND ABILITY: WHY IS GENERAL ABILITY NOT ENOUGH?[1]

Abstract

In this paper we study the impact of cognitive ability on college major choices using an administrative data set for full-time students enrolled in four-year business and economics programs offered by the largest Slovenian university. In contrast to existing studies, we are able to distinguish between general ability, measured with high school GPA, and major-specific ability, measured with grades achieved in major-specific courses. We show that students with higher general ability are more likely to enroll in Economics majors, while higher major-specific ability (e.g. higher grade in Accounting) increases the likelihood of choosing that major (Accounting). We also find that both genders are more responsive to measured major-specific ability in majors that are traditionally more popular among them (e.g. Business Informatics for males). These results suggest that policy makers aiming to change the structure of the labor supply should attempt to change the major-specific abilities of students.

Keywords: Educational economics, Human capital, Salary wage differentials, School choice
JEL classification: I23

[1]This paper is coauthored with Sašo Polanec and has been published as Bartolj and Polanec (2012).

1.1 Introduction

One of the most important economic decisions students make are college major choices. These not only determine graduates' future job opportunities (see e.g. Daymont and Andrisani, 1984; Brown and Corcoran, 1997), but also have important implications for the structure of the labor force and labor market outcomes, such as equilibrium wages and unemployment rates. Understanding how these choices are made and which factors determine them will enable policy makers to change the entry quotas (in state-dominated tertiary education systems) and set appropriate incentives for adjustment of labor supply according to the needs of the labor market and other developmental goals. Such will also help universities and their faculties understand why some majors are crowded and why others are struggling for students.

Empirical and theoretical research has identified several factors that determine college major choice. The most important of these are gender, ability, peer effects, and expected future income. While the authors agree on the effects of gender and expected future income, mixed evidence is found regarding the impact of ability and choices of peers on major choice. In this paper we study the impact of ability on major choices by Slovenian students and argue that the mixed evidence may be due to inability to distinguish between different types of ability. We use an administrative dataset for full-time economics and business students enrolled in four-year undergraduate programs at the Faculty of Economics, University of Ljubljana (hereafter FELU). Unlike the existing studies that use limited information on student ability, approximated by some measure of general ability (e.g. SAT score), our data allow us to distinguish between two types of ability measures. The first captures 'general' ability and is measured with high school average grades and points achieved on a standardized national exam at the end of high school. It typically reflects problem-solving ability and language proficiency. The second type consists of measures of 'major-specific abilities', which are a unique feature of our data. Since the coursework in the first two years is common for all students at the FELU and their major choice is made when enrolling to the third year, we are able to measure these abilities with grades achieved in compulsory first- and second-year courses common to all business and economics students. In particular, we allocate courses to majors based on the premise that the first two years' courses are similar to the courses of chosen majors (in the last two years) in terms of topics covered, and that the methodological tools used require similar abilities. For example, the grade achieved in the first-year Accounting course is a measure of the major-specific ability for the Accounting major for all students independent of their subsequent major choice, while the average grade achieved in two Business Information Systems courses reflects the major-specific ability for the Business Informatics major.

We estimate mixed logit and nested logit models, and show that both types of ability measures explain part of the variation in major choices. We find that students with higher general ability are more likely to choose Economics majors. More importantly, we show that higher major-specific ability measures imply higher probability of choosing the corresponding major and lower probability of choosing other majors. For example, students achieving higher grade in Accounting course are more likely to major in Accounting, while students with a higher grade in Business Information

Systems are more likely to choose the Business Informatics major. Our results are hence complementary to those of Arcidiacono et al. (2012), who find evidence on the importance of subjective (survey) measures of major-specific ability for major choices. We also observe an interaction between ability and preferences of students, as both genders tend to exhibit greater responsiveness to major-specific ability in the fields that are also generally preferred by that gender. For example, while a higher average grade in Business Information Systems courses increases the likelihood of choosing the Business Informatics major, which is more popular among males, the marginal effect is significantly higher for males than for females. These results contribute to the literature that shows gender differences in their preferences and expectations (see e.g. Zafar, 2009; Turner and Bowen, 1999; Montmarquette et al., 2002).

The rest of the paper is organized as follows. In Section 1.2, we review the existing literature on college major choice. The institutional framework that is necessary for understanding the empirical analysis is provided in Section 1.3. We summarize the data in Section 1.4 and present and discuss the results in Section 1.5. In the last section we present our conclusions.

1.2 Related Literature

College major choice has been the subject of research interest for quite some time. The literature has identified a large set of factors that determine these choices. Here we briefly review recent evidence on the impact of the determinants that are also featured in our empirical analysis, such as expected future earnings and personal characteristics (e.g. gender, ability, and preferences).

The key market determinant of the choice of major is the difference in the expected future earnings across majors. Berger (1988) and Boudarbat (2008) show that students are more likely to choose majors with higher streams of future earnings. While Montmarquette et al. (2002) confirm the importance of expected earnings on choice of major, they also report significant differences in the marginal effects of this variable by gender and race. Moreover, survey evidence by Arcidiacono et al. (2012) suggests that a substantial share of students would choose a different major if they made no forecast error of future earnings.

The differences in college major choices between males and females are not related only to the differences in responses to expected incomes. The literature has found significant differences in preferences, in sharp contrast to only modest differences in ability. In particular, Turner and Bowen (1999) find that differences in pre-collegiate preparation only partly explain gender gaps in major choices. The main part of the gap is explained by the differences in preferences, expectations, and gender-specific effects of college experience. In a more recent study that uses survey information on subjective expectations about choice-specific outcomes of students at Northwestern University, Zafar (2009) distinguishes between the effects of preferences and beliefs on differences in college major choice between genders. The author confirms the role of preferences and finds that differences in beliefs play only a minor role. He shows that females care more about non-pecuniary outcomes, such as gaining approval of parents and enjoying work, while males are more focused on pecuniary outcomes, such as the social status of the job, the likelihood of finding a job, and the earnings associated with the job.

There is also a long tradition of research on the effects of cognitive ability on college major choices, which is also the focus of this article. Fiorito and Dauffenbach (1982) identify ability as one of the most important non-market factors affecting curriculum choice. Paglin and Rufolo (1990) find that mathematical ability has a great influence on field choice. Since these studies measure ability with scores achieved on verbal and mathematics tests, they do not sufficiently differentiate students' ability to perform in specific majors. Arcidiacono et al. (2012) and an early study by Arcidiacono (2004) deal with this problem by asking students to estimate their relative ability in specific majors, and show that choice of major is influenced by their ability to perform coursework in a particular major. However, these results are subject to measurement bias due to the discrepancy between actual and perceived ability. In this article we avoid this issue by using an administrative data set that contains actual grades students achieved in different courses, which allows us to measure major-specific ability appropriately.

Researchers studying college major choices face, from a methodological point of view, two main problems—data availability and computational capability. As a consequence, earlier literature on major choice mostly used multinomial logit models, while only recently some researchers used less restrictive methods that relax the assumption of independence of irrelevant alternatives (IIA). Some used the random parameters logit (e.g. Zafar, 2009) or the heteroscedastic extreme value model and the multinomial probit model (e.g. Montmarquette et al., 2002). However, some of these less restrictive models are widely used in other research fields. For example, the nested logit model is common in applied literature on transportation (e.g. Dissanayake and Morikawa, 2010; Hensher, 1998), marketing (e.g. Richards, 2007; Guadagni and Little, 1998) and in different fields of economics (e.g. Dubin, 2007; Rasciute and Pentecost, 2010). This study also extends the set of applications of the nested logit model to the college major choice.

1.3 Institutional Context of Empirical Analysis

Our study of college major choices uses a rich data set on students enrolled at the Faculty of Economics at the largest Slovenian university, the University of Ljubljana. To give the reader an overview of the context in which this study is conducted, Table 1.1 provides a comparison of some of the key tertiary education and labor market statistics between Slovenia, the United States, and the United Kingdom. These statistics reveal some similarities and highlight some important differences. First, Slovenia's student population (according to ISCED 1997, levels 5A, 5B, and 6) represents 5.23% of the total of approximately 2 million Slovenian residents, which is close to the 5.76% in the US, and significantly higher than 3.76% in the UK. Next, the share of female students is almost the same in all three countries, while the share of Business and Administration students is significantly higher in Slovenia. The latter may be a result of high private returns to Business majors in the 1990s and early 2000s (Bartolj et al., 2013). In contrast to the US and the UK,

Table 1.1: Tertiary Education and Labor Market Statistics for Slovenia, US and UK, 2004

	Slovenia	US	UK
Total number of students [thousand]	104	16,900	2,247
Share of total population [percent]	5.23	5.76	3.76
Female students [percent]	56.9	57.0	57.1
Enrolled in social sciences, business and law [percent]	43.2	47.5[a]	27.3
Enrolled in business and administration [percent]	29.8	12.8[a]	15.6
Graduation rate (first-time) [percent]	17.8	33.2	39.1
Population with tertiary education (age 25-64) [percent]	19.0	39.0	29.4
Mean annual gross earnings (age 25-64) [USD]	16,644	34,934	38,579
Relative earnings premium of tertiary education[b]			
Males	217	179	150
Females	190	166	178
Private rates of return to tertiary education (IRR)			
Males[c]	14.3/10.6	11.0	14.3
Females[c]	12.8/10.6	8.4	14.5

Notes: [a] The data refer to year 2005. [b] All levels of tertiary education. [c] For Slovenia internal rates of return (IRR) are calculated separately for ISCED level 5A and 5B, while for the US and the UK the returns are for all ISCED levels 5 and 6.

Sources: The statistics on the number of students, structure of students and population with tertiary education are from various tables available at the Eurostat online portal with Education and training indicators: http://epp.eurostat.ec.europa.eu/portal/page/portal/education/data/database. The graduation rates are obtained from OECD Education at Glance, 2006, Table A3.1. The average gross earnings for Slovenia are published by the national Statistical Office in the Statistical Yearbook, Table 13.2, while the values for the US and the UK are obtained from the OECD Comparison of Wages, available at http://www.oecd.org/dataoecd/33/28/34545117.pdf. The data on relative earnings premiums are from OECD Education at Glance, 2006 and 2008 (for Slovenia), Table A9.1. The data on private rates of return in the US and UK are from OECD Education at Glance, 2006, Table A10.1., and from Ahčan and Polanec (2006) for Slovenia.

Slovenia also exhibits rather low graduation rates and consequently a low share of employees with a tertiary education degree. The relative scarcity of tertiary education graduates in Slovenia is reflected in their higher wage premia and rather high private rates of return measured with internal rate of return (IRR), although a low level of development implies that the average wage in the economy is still significantly lower than those in the US and the UK.

The University of Ljubljana, located in the country's capital, is the largest of the three Slovenian universities. It consists of 26 faculties and academies, and in the academic year 2004/2005 enrolled about 58 thousand full- and part-time students. The Faculty of Economics is the largest department of the university, with eight thousand students enrolled in undergraduate and graduate programs. Like the majority of Slovenian higher education organizations, it is a public organization and does not charge tuition fees to full-time undergraduate students with domestic residence.[2]

The relevant period of our study is before the start of the Bologna reform process in Slovenian

[2]See HE Act (1993). At the FELU, part-time students pay tuition fee that amounts to 2,500 EUR per academic year.

tertiary education system (2007). During this period a high-school graduate could enroll in the programs offered by the University of Ljubljana after completing any general or vocational four-year high school study. The applicants were ranked nationally according to a weighted average grade, calculated from the grade percentage averages achieved in the third and fourth year of the high school study and a national exam called 'matura.' This is a Slovene equivalent of the SAT in the US, which is also taken by high-school students in other central European countries such as Austria, Switzerland, and Italy.[3] Note that the high-school grading system distinguishes between five grades, ranging between 1 (insufficient) and 5 (excellent), with 2 as the lowest passing grade. The matura consists of three compulsory (Slovene language, Mathematics, and one foreign language - usually English) and two elective subjects (e.g. Biology, History, Physics, etc.). At the FELU only the top 650 applicants were enrolled in the four-year business and economics programs.[4] This entry quota was binding for all cohorts included in our study.

In contrast to the typical distinction between Business (Harvard Business School, MIT Sloan School of Management, Yale School of Management, London Business School) and Economics programs (The University of Chicago Department of Economics, Harvard University Department of Economics, LSE Economics Department), the FELU offers both programs. Moreover, all undergraduate students at the FELU were obliged to attend the same set of courses during their first two years, regardless of their subsequent choice of major. Students enrolled in economics program also attend business courses and vice versa. For example, a student who obtains her diploma in Banking and Finance will have attended courses in Accounting, Management, Entrepreneurship, Commercial Law, and Business Information Systems, while a student majoring in Management has taken courses in Microeconomics, Macroeconomics, and Political Economics, in addition to rigorous courses in Mathematics. The list of first two years' courses is provided in Appendix (Table A.1).

The structure of the program enabled students to make an informed and completely free choice between five majors in business (Accounting and Auditing (Acc), Business Informatics (BI), Finance (Fin), Marketing (Mrk), and Management and Organization (Mng)) and three majors in economics (Banking and Finance (BF), International Economics (IE), and National Economics (NE)), before the start of the third year. The two programs differ in the emphasis they place on different types of skills. The business program aims to attract students who wish to start working in companies and focuses on the acquisition of practical skills, whereas the economics program is designed for students who intend to continue their studies in graduate programs in the fields of economics and work either in academia, the financial industry, or governmental organizations (compare the third and fourth year curricula in Tables A.2 and A.3 in Appendix). From Table A.2 it is evident that there is greater similarity between the majors in the Economics program than between the majors in the Business program, as the former have in common all third-year courses and share several fourth-year courses. In fact, although the Banking and Finance and the Finance major may share the word 'finance' in the title, the curricula of the two are very different.

[3] See Ministry of Education and Sport (2010) for details.

[4] Although the FELU also enrolls students in a 2-year program in business studies, these are not considered in our analysis.

The expected time to complete any four-year program at the FELU is five years, which includes an additional year for completion of the final thesis (diploma). However, the actual study time typically varies between four and six years, and can extend beyond ten years. The grading scheme for undergraduate studies operates on a 10-point scale, with 1 as the lowest and 10 as the highest grade. A minimum requirement to pass an exam is 6, which usually corresponds to at least 60 points out of 100. Students who fail an exam are allowed to retake it with no limit on the total number of attempts, although the number of exam dates for each course was limited to three per academic year. If they are to progress to the next year of study, students cannot receive a failing grade in more than one course.

1.4 Data, Measurement, and Summary Statistics

1.4.1 Data Description and Measurement

Our study of college major choices relies on data for all students who enrolled in the four-year undergraduate programs at the FELU between 1994 and 2004, and made their major choices between 1996 and 2006. In line with empirical work of Arcidiacono et al. (2012), we relate these choices to various measures of specific cognitive abilities, in addition to a set of control variables. However, while their study relies on survey data, which allows them to distinguish between students' own estimates of major-specific ability and preferences for different majors, we exploit administrative data with actual grades achieved in different courses. We interpret these grades as objective measures of ability, although we are aware of the possibility that preferences may act as confounding determinants for the study effort, which is reflected in grades and subsequent major choice.

In line with traditional psychological literature, we distinguish between general (the g factor) and major-specific cognitive abilities, although this distinction has recently been disputed. While psychometric literature conceptualized g as either a higher order factor or as a first order factor in principal components models on scores of different cognitive tasks (e.g. Carroll, 1993),[5] there is no unitary cause of general ability in either psychological or biological factors (e.g. Ackerman et al., 2005; Luciano et al., 2005).[6] As shown in a theoretical model of general intelligence by Van Der Maas et al. (2006), the positive correlations between scores of different cognitive tasks allow for an alternative explanation that does not rely on the existence of a g factor. They argue that specific abilities are endogenous and depend on interactions between specific abilities possessed in the past. The high school GPA may then be interpreted as an aggregate measure of specific abilities rather than a measure of general ability. Despite these advances in the theory of general intelligence, we refer to the high school GPA as a measure of general ability.

[5] Spearman (1904) introduced a notion of mental energy as an underlying cause of g.

[6] Studies have attempted to link general ability to an underlying cognitive factor, such as speed or efficiency of information processing, working memory, and the capacity to handle cognitive complexity. Among biological factors of general ability considered were brain size, neural efficiency or pruning, and neural plasticity (Detterman, 2002).

We construct our measure of general ability as an unweighted average of two variables: i) the average grade achieved at the matura examination, and ii) the average grade in the last two years of high school. The matura is a national exam with equal conditions for all candidates. The written part of the exam is prepared and assessed externally. This in combination with the fact that during the process of grading tests are anonymized, the matura examination is a more objective measure of ability, while average grade in the last two years is a measure of study results over a longer time span. The combined measure reduces the specific problems related to either of the two measures. For instance, the external examination is a one-off test, which may be influenced by idiosyncratic events ('the bad day effect'), while the high school average grade may not be entirely comparable due to variation in the grading policies across schools.

A unique feature of our data set is the possibility of measuring specific abilities of students using the grades achieved in the common first- and second-year college courses. Clearly, these grades may be used to construct measures of specific abilities in many different ways. One approach is to construct a set of measures of major-specific abilities based on the average grade achieved in a set of relevant courses and enter into the econometric models only one variable called 'major-specific ability'. While we use such an approach in an older working paper version of this article (see Logaj and Polanec, 2011), it suffers from two important limitations: the arbitrariness of the selection of courses for calculation of the major-specific GPAs, and the possibility that the estimated marginal effects of major-specific variable may be driven by a small number of courses that are good predictors of some major choices.[7]

To avoid these limitations and to gain a deeper insight in the role of ability for college major choices, we follow an alternative approach and relate these choices to grades achieved in the first- and second-year courses. In this alternative approach, however, we still need to determine major-specific courses. Our allocation of courses to majors, as shown in Table 1.2, relies on the premise that courses similar in terms of topics covered and methodological tools used require similar abilities. Then, the grades achieved in the corresponding courses are appropriate measures of major-specific abilities. Some allocations of courses to Business majors are straightforward, as the titles of courses coincide with the titles of majors (i.e. Accounting, Business Informatics and Management majors). It is also reasonable to allocate courses in Accounting, Enterprise Economics, Mathematics and Microeconomics to the Finance major, as these courses cover important methodological tools for the study of finance (e.g. calculation of present and future values, sums of geometric series, probability theory, models of individual and business decisions under risk and uncertainty, accounting tools).[8] Admittedly, the choice of courses for the Marketing major (Entrepreneurship and Commercial Law) is less than ideal. However, students of this major are obliged to pass a course in International Commercial Law (common with the International Economics major, see Table A.3 in Appendix). For the economics majors, the set of the first two years' courses that capture major-

[7]We would like to thank one of the referees for the suggestion to explore the predictive power of alternative specifications of major-specific ability. Although different approaches do not allow direct comparison of results, the key insight on the importance of specific ability for college major choice is the same.

[8]Enterprise Economics is one of the courses that is not part of the standard curricula of economics and business programs in the US. The origins of this course may be traced to Germany. It covers topics in Finance, Accounting, and Microeconomics.

specific abilities overlap, as students who choose these fields face very similar coursework in the last two years of study. In particular, the third-year courses are the same for all economics majors, while the fourth year curricula differ in only a few courses (see Tables A.2 and A.3). The common feature of the economics majors are courses that rely on mathematics, microeconomic theory (e.g. International Economics, Economics of EU, Theory of Corporate Finance), macroeconomic theory (Monetary Economics, History of Economic Thought, Development Economics), and statistical tools (Econometrics). Thus, all three economics majors are related to the following courses: Mathematics, Microeconomics, Macroeconomics, National Economics, Political Economy, Economic Statistics and Statistics. In addition, we allocate the Accounting course to the Banking and Finance major, and the first-year Organization course to the National Economics major, as it covers some of the topics that are relevant to the Labor Economics—a course that is exclusively part of the curriculum of the National Economics major.

Table 1.2: Allocation of First- and Second-Year Courses to Specific Majors

	Business Majors					Economics Majors		
Course	Acc	BI	Fin	Mng	Mrk	IE	BF	NE
Accounting	x		x				x	
Business Information Systems		x						
Enterprise Economics			x					
Mathematics			x			x	x	x
Microeconomics			x			x	x	x
Management				x				
Organization				x				x
Entrepreneurship					x			
Commercial Law					x			
Macroeconomics						x	x	x
Political Economics						x	x	x
National Economics						x	x	x
Economic Statistics						x	x	x
Statistics						x	x	x

In order to capture the effect of prospective income differences on the choice of major, we use personal income tax records data for all recently employed graduates of the FELU. The data are kindly provided by the Slovenian Tax Office and were analyzed in the safe room of the Slovenian Statistical Office. We extracted information on the average annual net wage for the period 1995–2005 and calculated the major-specific average net wage for each cohort of students, separately for males and females. In particular, we assume that students who enrolled in 1994 and made a major choice in 1996 based their decision on the most recent net wage of persons who graduated in 1994 and were employed in 1995. The advantage of this approach is that we can exploit not only income differences between majors and genders, but also income differences over time within majors. Its main disadvantage is that it is static and ignores the entire trajectories of future wages. This is due to the unavailability of wage data for graduates who completed one of the programs at the FELU after 2005, and the incomparability of courses and programs offered by the faculty before 1990.

Finally, we also relate the college major choices to a set of personal characteristics of students such as age, gender, and the distance between the students' home addresses and Ljubljana. The latter variable is used to capture local labor market conditions. Since Slovenia is a mono-centric country, we construct a step variable (*region*) for five regions: 0 for a distance below 10 km (residents of the capital), 1 for a distance between 10 and 40 km, 2 for a distance between 40 and 70 km, 3 for a distance between 70 and 110 km, and 4 for a distance above 110 km. In regression analysis we enter a set of dummy variables, which assume the value 1 for each specific distance interval (e.g. below 10 km) and 0 otherwise.

1.4.2 Summary Statistics

We estimate our empirical models of college major choice using the sample of full-time students enrolled in four-year business and economics programs, who attended (and passed) the same set of courses in the first two years of study.[9] For this sample of students we report the key summary statistics. In Table 1.3 we show their program/major choices. Evidently, both males and females choose the business program more frequently, with a slightly stronger preference by the latter. The Marketing and Finance majors are the most likely choices among the business majors, while the Banking and Finance major is the most popular choice among the economics students. Females in the business program also frequently select the Accounting major, whereas males tend to prefer the Organization and Management, and Business Informatics majors.

Next, we provide summary statistics on general and major-specific ability of students choosing different majors. Tables 1.4 and 1.5 show the relative mean grades by majors in addition to the overall averages of high school GPA and college grades. Note that for college courses that are taught both in the first and second year (Mathematics, Microeconomics, Macroeconomics, Statistics, and Business Information Systems), we calculate the unweighted mean values for each pair of grades.[10] The relative mean grades are calculated as ratios between the mean grade of students who choose a specific major and the overall average grade (second to the last column denoted Mean). They not only allow us to compare the average grades across majors, but also to make inference about the relative ability of students who choose specific majors. Looking at the relative means across majors reveals that students who enrolled in economics majors achieved significantly higher grades both in high school and the first two years of college. Among specific majors, students choosing the Banking and Finance and International Economics majors have the highest grades, while students selecting Marketing, Organization and Management, and Business Informatics have the lowest. Comparison between genders suggests that females tend to achieve higher grades in high school, while in college the rankings vary across courses.

Comparison of the relative means of grades achieved in the first- and second-year courses suggests that students choosing a specific major have a relatively higher grade in the corresponding major-specific courses. For example, the male (female) students majoring in Accounting have the relative mean in Accounting course equal to 1.046 (1.040), which is the highest relative mean between all courses. Similarly, for students choosing the Business Informatics major, the relative mean of the Business Information Systems courses is the highest among all courses. Although the students

[9] We drop data on 384 students who transferred from a two-year business program to one of the four-year programs, as their grades are not fully comparable to the grades of students who started in the four-year programs due to less demanding coursework.

[10] This assumption is, however, not critical for the results as they are robust to inclusion of the two sets of courses separately.

majoring in Management have higher relative means in the major-specific courses, particularly those in the Organization course, the relative means in the Management course are among the highest, but not exceptionally high. Also in line with expectations, for the field of Finance, we observe relatively high grades in Mathematics and Microeconomics, in addition to Enterprise Economics, while for the field of Marketing the highest relative grade is in Commercial Law. The students choosing one of the economics majors also appear to have relatively high grades in courses such as National Economics, Political Economy, Mathematics, Microeconomics, Macroeconomics, and Statistics. Moreover, those who choose Banking and Finance tend to have a higher relative grade in Accounting, while those who choose the National Economics major have relatively high grades in Organization.

As previously mentioned, we introduce the following control variables: i) a set of dummy variables for the distance between Ljubljana and the county of permanent residence, ii) age, and iii) the case-varying average net wage of graduates. We report the summary statistics for these variables in Table 1.6. While there is no evident correlation between age and chosen field of study, the distance from Ljubljana appears to be an important determinant of major choice. In particular, students who major in National Economics, Accounting, and Marketing have permanent residence further away from Ljubljana, while students who major in Organization and Management and International Economics have a permanent address closer to the capital. The mean of variable region does not differ between genders, with the exception of majors in Finance and Business Informatics. The mean is higher for females than for males majoring in Finance, but the opposite is the case for a Business Informatics or Banking and Finance majors. The expected net wage varies significantly across fields, with the highest values for graduates in Banking and Finance for both males and females and the lowest in Marketing for males and Accounting for females.

Table 1.3: Number of Students by Program and Major

	Males		Females		All	
Program / Major	Freq.	Share	Freq.	Share	Freq.	Share
Business	1,939	82.27	2,729	85.93	4,668	84.36
Accounting	140	5.94	387	12.19	527	9.52
Business Informatics	366	15.53	95	2.99	461	8.33
Finance	670	28.43	991	31.2	1,661	30.02
Marketing	383	16.25	827	26.04	1,210	21.87
Organization and Management	380	16.12	429	13.51	809	14.62
Economics	418	17.73	447	14.08	865	15.63
Banking and Finance	252	10.69	221	6.96	473	8.55
International Economics	109	4.62	175	5.51	284	5.13
National Economics	57	2.42	51	1.61	108	1.95
Total	2,357	100.0	3,176	100.0	5,533	100.0

Notes: The cohorts of students enrolled between 1994 and 2004 are considered. The sample consists of all full-time students enrolled in four-year business and economics programs who followed the same set of courses in their first two years of study and passed all the exams. The shares are given in percent of respective column total.

Table 1.4: Summary Statistics on High School GPA and College Grades by Major, Males

	Relative Mean by Majors								All Majors	
	Acc	BI	Fin	Mng	Mrk	BF	IE	NE	Mean	St. Dev.
High School GPA	0.992	0.962	0.994	0.982	0.972	1.095	1.076	1.077	3.772	0.684
Accounting	1.046	0.967	1.009	0.966	0.975	1.077	1.005	1.039	6.803	1.048
Business Inf. Sys.	1.020	1.013	0.994	0.982	0.972	1.045	1.025	0.997	7.561	1.096
Enterprise Economics	1.016	0.957	1.004	0.981	0.988	1.064	1.034	1.046	7.077	1.061
Mathematics	1.007	0.993	1.009	0.980	0.991	1.031	0.998	0.989	6.430	0.842
Microeconomics	1.032	0.961	1.010	0.967	0.976	1.070	1.056	1.016	7.322	1.063
Management	0.995	0.930	1.008	0.990	0.998	1.059	1.074	1.044	7.373	1.249
Organization	0.991	0.972	0.995	0.992	0.993	1.057	1.039	1.030	7.282	1.241
Commercial Law	1.009	0.977	0.997	0.985	0.997	1.056	1.018	1.003	6.874	1.103
Entrepreneurship	1.017	1.007	0.993	0.990	0.987	1.028	1.026	0.981	7.972	0.952
Macroeconomics	1.000	0.971	0.994	0.989	0.978	1.077	1.042	1.066	6.490	0.978
Political Economy	1.013	0.966	0.995	0.968	0.971	1.101	1.079	1.052	7.138	1.126
National Economics	1.019	0.960	1.009	0.976	0.972	1.067	1.060	1.037	7.519	1.257
Statistics	0.994	0.975	0.999	0.974	0.991	1.072	1.037	1.026	6.931	1.151
Economic Statistics	1.010	0.977	0.993	0.977	0.994	1.066	1.041	1.026	6.825	0.917

Notes: Allocation of first- and second-year courses to specific majors is represented by the shaded values. High school GPA is the average of grade achieved in “matura” exam and the mean grade of the third and fourth year of high school study. The relative mean values of high school GPA and grades achieved in first two years are calculated as a ratio between the average grade of person selecting a major and an overall mean. The standard deviations are calculated for all students.

Table 1.5: Summary Statistics on High School GPA and College Grades by Major, Females

	Relative Mean by Majors								All Majors	
	Acc	BI	Fin	Mng	Mrk	BF	IE	NE	Mean	St. Dev.
High School GPA	0.998	0.969	1.002	0.974	0.984	1.068	1.070	0.972	3.863	0.678
Accounting	1.040	0.966	1.006	0.964	0.979	1.053	1.010	1.021	6.750	1.028
Business Inf. Sys.	1.008	1.005	1.009	0.980	0.980	1.038	1.016	1.021	7.487	1.061
Enterprise Economics	1.012	0.966	1.018	0.960	0.986	1.038	1.000	1.017	7.060	1.025
Mathematics	0.995	0.984	1.011	0.990	0.988	1.028	0.998	1.018	6.414	0.795
Microeconomics	1.005	0.952	1.013	0.977	0.976	1.061	1.031	1.016	7.356	1.056
Management	1.001	0.912	1.009	0.986	0.994	1.045	0.999	1.015	7.600	0.887
Organization	1.000	0.981	0.997	1.003	0.990	1.023	1.022	1.056	7.509	1.184
Commercial Law	0.999	0.961	0.996	0.987	0.997	1.050	1.027	1.008	6.985	1.084
Entrepreneurship	1.010	0.995	1.004	0.997	0.986	1.019	1.007	0.991	8.050	1.061
Macroeconomics	0.997	0.986	1.002	0.979	0.984	1.060	1.036	1.049	6.486	0.995
Political Economy	1.005	0.944	1.008	0.974	0.974	1.087	1.045	1.022	7.169	1.172
National Economics	1.005	0.965	1.007	0.971	0.988	1.048	1.020	1.051	7.346	1.308
Statistics	1.005	0.968	1.013	0.983	0.972	1.058	1.033	1.016	6.925	1.162
Economic Statistics	1.002	0.954	1.006	0.983	0.995	1.039	1.006	0.991	6.881	0.880

Notes: Allocation of first- and second-year courses to specific majors is represented by the shaded values. High school GPA is the average of grade achieved in "matura" exam and the mean grade of the third and fourth year of high school study. The relative mean values of high school GPA and grades achieved in first two years are calculated as a ratio between the average grade of person selecting a major and an overall mean. The standard deviations are calculated for all students.

Table 1.6: Summary Statistics for Control Variables, by Major and Gender

	Males		Females	
Major	Mean	St. Dev.	Mean	St. Dev.
A. Region[(a)]				
Accounting	1.636	1.259	1.693	1.213
Business Informatics	1.451	1.308	1.347	1.183
Finance	1.457	1.274	1.585	1.215
Management and Organization	1.347	1.298	1.361	1.222
Marketing	1.525	1.334	1.557	1.290
Banking and Finance	1.401	1.334	1.588	1.331
International Economics	1.376	1.275	1.389	1.249
National Economics	1.579	1.349	1.784	1.270
B. Age				
Accounting	19.029	0.587	18.979	0.635
Business Informatics	19.014	0.510	18.905	0.485
Finance	18.940	0.628	18.918	0.513
Marketing	18.961	0.676	18.917	0.515
Organization and Management	18.982	0.551	18.930	0.615
Banking and Finance	18.956	0.675	18.964	0.563
International Economics	18.835	0.569	18.920	0.519
National Economics	18.860	0.611	19.157	0.703
C. Expected Net Annual Wage[(b)]				
Accounting	10,609	3,411	8,971	1,598
Business Informatics	11,579	1,814	9,405	851
Finance	10,497	1,951	9,527	1,141
Marketing	10,277	807	9,409	814
Organization and Management	10,527	1,353	10,107	731
Banking and Finance	12,423	1,152	10,663	1,689
International Economics	10,378	1,102	9,986	1,119
National Economics	10,538	2,274	10,067	1,555

Notes: [(a)] There are five regions based on the distance between student's home address and FELU (Ljubljana). Student is in region 0 if the distance is less than 10 km; in region 1 if the distance is at least 10 km, but less than 40 km; in region 2 if the distance is at least 40 km, but less than 70 km; in region 3 if the distance is at least 70 km, but less than 110 km; and in region 4 otherwise. [(b)] For each major the expected net annual wage is calculated as the average net annual wage of first-time graduates. Wages are in constant (2004) Euros. The exchange rate in 2004 was 1 EUR = 1.24 USD.

1.5 Econometric Modeling of College Major Choice

Our econometric modeling relies on the standard premise of rational agents who maximize expected utility. This assumption implies that each of N students chooses a major by comparing utility levels of m distinct majors. Each option may give her a different utility level and these utilities may vary between students. In particular, student i choosing major j enjoys the following utility:

$$u_{ij} = \mathbf{z}'_{ij}\boldsymbol{\alpha} + \mathbf{w}'_i\gamma_{\boldsymbol{j}} + \varepsilon_{ij}, \qquad j = 1, 2, ..., m, \tag{1.1}$$

where $\mathbf{z}_{ij}$ are alternative-varying regressors, $\mathbf{w}_i$ are alternative-invariant or case-specific regressors, $\boldsymbol{\alpha_j}$'s and $\boldsymbol{\gamma_j}$'s are the corresponding parameters, and ε_{ij} is the random component of utility. As students are assumed to be rational, $\boldsymbol{\alpha_j}$'s are the same for all majors ($\boldsymbol{\alpha_j} = \boldsymbol{\alpha}$). Since students choose the major with the highest utility, the probability that student i chooses major j is:

$$\begin{aligned}\Pr[y_i = j|\mathbf{x}_{i1}, ..., \mathbf{x}_{im}] &= \Pr[u_{ij} \geq u_{ik},\ \text{for all k}] \\ &= \Pr[u_{ik} - u_{ij} \leq 0, \text{for all k}] \\ &= \Pr[\varepsilon_{ik} - \varepsilon_{ij} \leq (\mathbf{x}_{ij} - \mathbf{x}_{ik})'\boldsymbol{\beta},\ \text{for all k}].\end{aligned} \tag{1.2}$$

where $\mathbf{x}_{ij}$ is a vector that contains both alternative-varying and case-specific regressors, and $\boldsymbol{\beta}$ is a vector that contains both $\boldsymbol{\alpha}$ and all $\boldsymbol{\gamma_j}$'s.

Different assumptions regarding the joint distribution of error terms are associated with different types of multinomial models. In principle, we could consider both ordered and unordered choice models. However, there is no obvious ordering of college majors in our data. Arcidiacono et al. (2012), who use an ordered choice model, have information on students' preferences that can be used for ordering of options. Since this is not the case for our data, we apply unordered multinomial models.

The dependent variable, y, is equal to j if major j is selected. Thus, the probability that major j is chosen by student i, conditional on the regressors $\mathbf{x}_i$, is defined as:

$$p_{ij} = \Pr[y_i = j] = F_j(\mathbf{x}_i, \boldsymbol{\beta}), \qquad j = 1, ..., m, \quad i = 1, ..., N. \tag{1.3}$$

By introducing m indicator variables $y_1, y_2, ..., y_m$, so that y_j assumes the value 1 if major j is chosen and 0 otherwise, the multinomial density for student i can be written as:

$$f(y_i) = p_{i1}^{y_{i1}} \cdot p_{i2}^{y_{i2}} \cdot ... \cdot p_{im}^{y_{im}} = \prod_{j=1}^{m} p_{ij}^{y_{ij}}, \tag{1.4}$$

where functional form $F_j(.)$ corresponds to a specific multinomial model. The maximum likelihood estimator (MLE), that is used for the multinomial models, maximizes the log-likelihood function $\mathcal{L} = \sum_{i=1}^{N}\sum_{j=1}^{m} y_{ij} \ln p_{ij}$, that follows from multinomial density defined in (1.4).

In what follows, we estimate two econometric models for college major choices of Slovenian business and economics students. The first is the mixed logit model with an assumption of independence of irrelevant alternatives (IIA) and the second is the nested logit model that relaxes this assumption.

1.5.1 The Mixed Logit Model

For the mixed logit model,[11] the probability that student i selects major j is:

$$p_{ij} = \frac{e^{\mathbf{z}'_{ij}\boldsymbol{\alpha}+\mathbf{w}'_i\boldsymbol{\gamma_j}}}{\sum_{l=1}^{m} e^{\mathbf{z}'_{il}\boldsymbol{\alpha}+\mathbf{w}'_i\boldsymbol{\gamma_l}}}, \qquad j = 1, ..., m. \tag{1.5}$$

The error term ε_{ij} is assumed to be identically and independently distributed according to the Type I extreme value distribution with density $f(\varepsilon_{ij}) = e^{-\varepsilon_{ij}} \exp(-e^{-\varepsilon_{ij}})$, which ensures that the choice probability in (1.2) has a closed form presented in the equation above. Since the coefficients or taste weights are uninformative, we present the marginal effects. For the alternative-varying regressors, these are:

$$\begin{aligned}\frac{\partial p_{ij}}{\partial \mathbf{z}_{ij}} &= p_{ij}(1 - p_{ij})\boldsymbol{\alpha} \text{ if } j = k \\ \frac{\partial p_{ij}}{\partial \mathbf{z}_{ik}} &= - p_{ij}p_{ik}\boldsymbol{\alpha} \text{ if } j \neq k,\end{aligned}$$

For the only alternative-varying regressor in our empirical model, the net wage, these expressions imply that the probability of choosing major j increases with an increase in net wage of major j and decreases with an increase in net wage of all other majors if $\alpha_{netwage} > 0$, while the opposite is true if $\alpha_{netwage} < 0$. The marginal effects for alternative-invariant regressors are:

$$\frac{\partial p_{ij}}{\partial \mathbf{w}_{ij}} = p_{ij}(\boldsymbol{\gamma_j} - \overline{\boldsymbol{\gamma}}_{\boldsymbol{i}}),$$

where $\overline{\boldsymbol{\gamma}}_{\boldsymbol{i}} = \sum_l p_{il}\boldsymbol{\gamma_i}$. Thus, for example, the marginal effect for high school GPA is positive for major j if the coefficients for that major are higher than the average of coefficients for the high school GPA of all other majors.

In the empirical estimation of the mixed logit model, the major-invariant regressors are high school GPA, average grades achieved in the first- and second-year courses, a dummy variable for females, age, and a set of dummy variables that represent different regions (a dummy for region = 0 is omitted to avoid multicollinearity), while the only major-specific regressor is the log of net wage. In all estimations, the National Economics major is used as a base alternative and all the coefficients should be interpreted with respect to this major. As shown above, the estimated coefficients of the mixed logit model cannot be interpreted as marginal effects, and the signs of the two may not be the same. Since we are interested in marginal effects, we report them in tables in the main text (see Tables 1.7, 1.8, 1.9, and 1.10) and summarize the estimated coefficients and specification tests in Appendix (see first two columns in Table A.4). Note that, while some of the coefficients are statistically insignificant (e.g. age, grades in Mathematics and Statistics), the Wald test for inclusion of all groups of variables is nevertheless statistically significant.

[11] The term mixed logit model is used here to refer to the model that is a combination of the multinomial and the conditional logit model and should not be confused with the random parameters logit model. See McFadden and Train (2000) for an extended discussion of the mixed logit model.

The marginal effects at the mean, shown in Tables 1.7 and 1.8, confirm our main hypothesis, which states that students base their college major choices on both general and major-specific abilities. Higher general ability, measured with high school GPA, increases the likelihood of selecting the Banking and Finance, and International Economics majors, two of the three economics majors, which suggests that more able students are more likely to choose methodologically more demanding majors. For example, for males, an increase in the high school GPA by 1 grade point increases the likelihood of choosing the Banking and Finance major by 3.22 percentage points, and reduces the likelihood of choosing the Finance major by 2.38 percentage points. More importantly, higher relative major-specific ability implies higher likelihood of choosing the corresponding major and lower likelihood of choosing all other majors. As already noted above, we approximate the major-specific abilities with grades achieved in the first- and second-year (college) courses that cover either similar topics or use similar methodological tools as the corresponding third- and fourth-year courses. We find, for example, that an increase in grade achieved in the first-year Accounting course by 1 grade point increases the probability of choosing the Accounting major by 1.91 percentage points for males and 3.64 percentage points for females, whereas an increase in the average grade achieved in the first- and second-year Business Information Systems courses increases the probability of choosing this major by 4.89 and 0.98 percentage points for males and females, respectively. These differences in the size of marginal effects between genders also suggest that preferences interact with major-specific ability in determining choice. The importance of major-specific ability is confirmed also for all other majors, although not all courses listed in Table 1.2 have positive and statistically significant marginal effects. For the Finance major, grades achieved in three out of four courses have significant marginal effects, and for the Marketing and Management majors the grade achieved in one out of two courses has a significant effect. For the economics majors, we find that an increase in four out of eight courses increases the likelihood of choosing at least one of them. In particular, an increase in the average grade achieved in Macroeconomics courses increases the likelihood of choosing each of the three economics majors, while a higher grade in Political Economy increases the probability of choosing the Banking and Finance, and International Economics majors. Our results also imply that a higher grade in the first-year Accounting course increases the probability of choosing Banking and Finance, while a higher grade achieved in the first-year Organization course increases the likelihood of choosing the National Economics major. The importance of major-specific ability for major choices in our data is also confirmed by the negative values of marginal effects for grades achieved in courses that are specific to other majors, which may be interpreted as the 'substitution effect'. For example, higher grades achieved in Enterprise Economics, Microeconomics, Management and Political Economy courses reduce the likelihood of choosing the Business Informatics major, while higher grades achieved in Business Information Systems, Microeconomics, Macroeconomics, Political Economy and Statistics reduce the probability of choosing the Marketing major.

In Table 1.9 we report the marginal effects at the mean for the major-specific wage. For the sake of brevity, we only present these marginal effects for both genders jointly. We confirm a well established result in the literature that an increase in the major-specific wage, ceteris paribus, increases the likelihood of individuals' choosing that field and decreases the probability of choosing other majors.[12] The marginal effects for the remaining alternative-invariant control variables are shown in Table 1.10. These suggest that being female increases the probability of choosing the Accounting, Finance, Marketing, and International Economics majors and decreases the probability of choosing the National Economics, Banking and Finance, Management, and Business Informatics majors. Further, older students are less likely to major in Finance, while all the other marginal effects for age are not statistically different from zero. Finally, the variable measuring distance between the home address and the capital, which aims to capture differences in socio-economic backgrounds of students and employment opportunities in different regions, seems to have some effect on major choice. Specifically, students from regions outside of Ljubljana are more likely to major in Accounting, Finance, and Marketing than are students with a permanent address in Ljubljana, while students living outside the capital are less likely to major in Banking and Finance, International Economics, and Management. This is not unexpected, since urban regions provide more possibilities for employment for such a labor force. An alternative interpretation for this result may be the competition of other management schools that are further away from the capital. Thus, some of the students interested in management and living in more distant regions might choose to study there. In the same way, it is reasonable to believe that students from the most remote regions are more likely to major in Marketing, given that these regions have tourism as one of the major industries and hence have a greater demand for such a workforce.

[12]Note that the marginal effects are similar for both males and females.

Table 1.7: Mixed Logit: Marginal Effects at the Mean for High School GPA and College Grades, Males

Change in Grade	Change in Pr[Acc]	Pr[BI]	Pr[Fin]	Pr[Mng]	Pr[Mrk]	Pr[BF]	Pr[IE]	Pr[NE]
High School GPA	−0.77	−0.59	−2.38**	−0.62	−1.22	3.22***	2.47***	−0.14
	(0.48)	(1.10)	(1.17)	(0.97)	(0.85)	(0.79)	(0.49)	(0.38)
Accounting	1.91***	−0.73	1.66**	−2.51***	−0.95*	0.96**	−0.55*	0.18
	(0.29)	(0.75)	(0.73)	(0.67)	(0.56)	(0.43)	(0.28)	(0.22)
Business Inf. Sys.	0.13	4.89***	−0.45	−0.59	−2.73***	−0.61	−0.51	−0.18
	(0.36)	(0.81)	(0.87)	(0.73)	(0.65)	(0.58)	(0.35)	(0.29)
Enterprise Economics	0.45	−1.85***	2.84***	−1.42**	0.07	0.04	−0.32	0.15
	(0.28)	(0.71)	(0.70)	(0.61)	(0.52)	(0.44)	(0.27)	(0.22)
Mathematics	−0.41	0.05	2.66***	−0.88	−0.57	0.00	−0.68**	−0.22
	(0.34)	(0.73)	(0.80)	(0.69)	(0.62)	(0.50)	(0.33)	(0.26)
Microeconomics	0.21	−1.58***	1.95***	−0.72	−0.78*	0.61	0.43*	−0.17
	(0.23)	(0.58)	(0.58)	(0.49)	(0.43)	(0.37)	(0.22)	(0.19)
Management	0.06	−4.03***	1.85	0.70	1.24	0.03	0.03	0.08
	(0.24)	(0.62)	(0.58)	(0.48)	(0.42)	(0.38)	(0.22)	(0.19)
Organization	−0.30	−0.10	−1.72***	1.64***	0.54	−0.41	−0.03	0.34*
	(0.25)	(0.62)	(0.63)	(0.51)	(0.45)	(0.41)	(0.24)	(0.20)
Commercial Law	0.02	−0.68	−1.21*	0.07	1.22**	0.81*	0.06	−0.34
	(0.29)	(0.73)	(0.72)	(0.61)	(0.52)	(0.44)	(0.27)	(0.23)
Entrepreneurship	0.22	0.56	−0.30	0.65	−0.09	−0.57	−0.10	−0.40*
	(0.28)	(0.68)	(0.68)	(0.57)	(0.49)	(0.44)	(0.26)	(0.22)
Macroeconomics	−0.46	−1.36	−0.50	0.10	−1.53**	1.96***	0.77**	0.99***
	(0.39)	(1.02)	(0.97)	(0.85)	(0.76)	(0.53)	(0.33)	(0.26)
Political Economy	0.06	−1.62**	0.06	−1.32**	−1.09**	2.64***	0.94***	0.29
	(0.25)	(0.64)	(0.64)	(0.55)	(0.48)	(0.40)	(0.24)	(0.20)
National Economics	−0.10	−0.86	0.70	−0.68	0.13	0.21	0.28	0.27
	(0.26)	(0.60)	(0.63)	(0.53)	(0.47)	(0.41)	(0.24)	(0.20)
Economic Statistics	−0.04	−1.17	−0.25	−0.79	0.94*	1.23***	0.12	−0.07
	(0.29)	(0.76)	(0.73)	(0.64)	(0.54)	(0.44)	(0.27)	(0.23)
Statistics	−0.15	0.03	0.55	−0.41	−1.01*	0.63	0.25	0.06
	(0.28)	(0.66)	(0.67)	(0.58)	(0.52)	(0.41)	(0.25)	(0.21)

Notes: Allocation of first- and second-year courses to specific majors is represented by the shaded values. Standard errors are reported in parentheses. Marginal effects and standard errors are given as a percentage. *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1.

Table 1.8: Mixed Logit: Marginal Effects at the Mean for High School GPA and College Grades, Females

Change in Grade	Change in Pr[Acc]	Pr[BI]	Pr[Fin]	Pr[Mng]	Pr[Mrk]	Pr[BF]	Pr[IE]	Pr[NE]
High School GPA	−1.35	−0.06	−1.97	−0.26	−1.45	2.15***	2.97***	−0.07
	(0.91)	(0.22)	(1.21)	(0.81)	(1.18)	(0.52)	(0.55)	(0.25)
Accounting	3.64***	−0.18	1.07	−2.31***	−2.06***	0.48*	−0.76**	0.08
	(0.52)	(0.15)	(0.74)	(0.56)	(0.77)	(0.28)	(0.33)	(0.14)
Business Inf. Sys.	0.91	0.98***	1.23	0.22	−2.91***	−0.08	−0.34	−0.04
	(0.68)	(0.17)	(0.91)	(0.61)	(0.90)	(0.38)	(0.40)	(0.19)
Enterprise Economics	0.63	−0.39***	2.25***	−1.47***	−0.53	−0.12	−0.49	0.06
	(0.54)	(0.14)	(0.72)	(0.51)	(0.72)	(0.29)	(0.31)	(0.14)
Mathematics	−0.77	0.02	3.01***	−0.64	−0.77	0.02	−0.77**	−0.14
	(0.65)	(0.14)	(0.84)	(0.59)	(0.87)	(0.33)	(0.38)	(0.17)
Microeconomics	0.28	−0.31***	1.68***	−0.75*	−1.56***	0.31	0.44*	−0.13
	(0.45)	(0.11)	(0.59)	(0.41)	(0.60)	(0.25)	(0.26)	(0.12)
Management	−0.36	−0.81***	0.64	0.02	0.87	−0.22	−0.17	−0.01
	(0.45)	(0.13)	(0.59)	(0.40)	(0.58)	(0.25)	(0.26)	(0.12)
Organization	−0.57	−0.01	−1.74***	1.36***	0.95	−0.24	−0.01	0.23*
	(0.49)	(0.12)	(0.65)	(0.43)	(0.63)	(0.27)	(0.28)	(0.13)
Commercial Law	−0.07	−0.15	−1.63**	−0.08	1.65**	0.45	0.02	−0.24
	(0.55)	(0.14)	(0.74)	(0.51)	(0.72)	(0.29)	(0.31)	(0.15)
Entrepreneurship	0.46	0.10	−0.29	0.54	−0.11	−0.36	−0.11	−0.26*
	(0.54)	(0.13)	(0.70)	(0.48)	(0.68)	(0.29)	(0.30)	(0.14)
Macroeconomics	−0.79	−0.21	−0.14	0.24	−2.07**	1.32***	0.96**	0.66***
	(0.75)	(0.20)	(1.00)	(0.71)	(1.05)	(0.35)	(0.39)	(0.18)
Political Economy	0.11	−0.29**	0.03	−1.08**	−1.75***	1.67***	1.09***	0.18
	(0.49)	(0.13)	(0.65)	(0.46)	(0.66)	(0.26)	(0.27)	(0.13)
National Economics	−0.29	−0.17	0.51	−0.65	0.01	0.09	0.30	0.17
	(0.49)	(0.12)	(0.65)	(0.44)	(0.65)	(0.27)	(0.28)	(0.13)
Economic Statistics	−0.23	−0.24	−0.66	−0.80	1.16	0.71**	0.08	−0.07
	(0.56)	(0.15)	(0.75)	(0.53)	(0.75)	(0.29)	(0.32)	(0.15)
Statistics	−0.20	0.02	0.87	−0.21	−1.36*	0.45*	0.34	0.05
	(0.53)	(0.13)	(0.70)	(0.49)	(0.72)	(0.27)	(0.29)	(0.14)

Notes: Allocation of first- and second-year courses to specific majors is represented by the shaded values. Standard errors are reported in parentheses. Marginal effects and standard errors are given as a percentage. *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1.

Table 1.9: Mixed logit: Marginal Effects at the Mean for Net Wage, All Students

Change in Net Wage	Change in Pr[Acc]	Pr[BI]	Pr[Fin]	Pr[Mng]	Pr[Mrk]	Pr[BF]	Pr[IE]	Pr[NE]
Acc	5.42***	−0.32***	−1.99***	−0.92***	−1.37***	−0.45***	−0.30***	−0.11***
	(1.76)	(0.10)	(0.64)	(0.29)	(0.44)	(0.14)	(0.09)	(0.03)
BI	−0.32***	3.21***	−1.13***	−0.52***	−0.78***	−0.26***	−0.17***	−0.07***
	(0.10)	(1.06)	(0.37)	(0.17)	(0.25)	(0.08)	(0.05)	(0.02)
Fin	−1.99***	−1.13***	14.17***	−3.24***	−4.83***	−1.59***	−1.04***	−0.39***
	(0.64)	(0.37)	(4.60)	(1.05)	(1.57)	(0.52)	(0.34)	(0.13)
Mng	−0.92***	−0.52***	−3.24***	8.25***	−2.22***	−0.73***	−0.48***	−0.18***
	(0.29)	(0.17)	(1.05)	(2.68)	(0.72)	(0.24)	(0.15)	(0.06)
Mrk	−1.37***	−0.78***	−4.83***	−2.22***	11.22***	−1.09***	−0.72***	−0.27***
	(0.44)	(0.25)	(1.57)	(0.72)	(3.64)	(0.35)	(0.23)	(0.08)
BF	−0.45***	−0.26***	−1.59***	−0.73***	−1.09***	4.42***	−0.24***	−0.09***
	(0.14)	(0.08)	(0.52)	(0.24)	(0.35)	(1.44)	(0.07)	(0.02)
IE	−0.30***	−0.17***	−1.04***	−0.48***	−0.72***	−0.24***	2.97***	−0.06***
	(0.09)	(0.05)	(0.34)	(0.15)	(0.23)	(0.07)	(0.98)	(0.01)
NE	−0.11***	−0.07***	−0.39***	−0.18***	−0.27***	−0.09***	−0.06***	1.13***
	(0.03)	(0.02)	(0.13)	(0.06)	(0.08)	(0.02)	(0.01)	(0.38)

Notes: Marginal effects of a change in the major-specific average net wage are represented by the shaded values. Standard errors are reported in parentheses. Marginal effects and standard errors are given as a percentage.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1.

Table 1.10: Mixed Logit: Marginal Effects at the Mean for Case-Specific Control Variables, All Students

Change in Variable	Change in Pr[Acc]	Pr[BI]	Pr[Fin]	Pr[Mng]	Pr[Mrk]	Pr[BF]	Pr[IE]	Pr[NE]
Female	6.29***	−10.16***	2.59*	−4.37***	9.07***	−3.14***	0.43	−0.76**
	(0.78)	(0.79)	(1.33)	(1.05)	(1.16)	(0.74)	(0.57)	(0.36)
Age	0.93	0.42	−2.29*	0.66	−0.42	0.79	−0.43	0.31
	(0.66)	(0.44)	(1.18)	(0.87)	(1.05)	(0.58)	(0.53)	(0.27)
Region 1	2.80**	0.10	2.13	−2.48**	−0.07	−2.41***	−0.62	0.50
	(1.31)	(0.70)	(1.86)	(1.24)	(1.61)	(0.82)	(0.71)	(0.55)
Region 2	5.13***	−0.43	4.02**	−3.48***	−1.58	−1.89**	−1.44**	−0.36
	(1.48)	(0.73)	(1.98)	(1.28)	(1.67)	(0.86)	(0.70)	(0.51)
Region 3	2.83**	−0.23	3.08	−3.25**	−0.68	−1.51*	−1.21*	0.92
	(1.38)	(0.72)	(1.95)	(1.27)	(1.67)	(0.87)	(0.71)	(0.63)
Region 4	4.80**	−0.53	−4.02	−5.63***	7.31**	−0.72	−1.88**	0.62
	(2.37)	(1.07)	(2.91)	(1.74)	(2.89)	(1.30)	(0.93)	(0.94)

Notes: Standard errors are reported in parentheses. Marginal effects and standard errors are given as a percentage. There are five regions that are based on the distance between student's home address and FELU (Ljubljana). Student is in region 0 if the distance is less than 10 km; in region 1 if the distance is at least 10 km, but less than 40 km; in region 2 if the distance is at least 40 km, but less than 70 km; in region 3 if the distance is at least 70 km, but less than 110 km; and in region 4 otherwise. For each region we construct a dummy variable that assumes the value 1 if the student is from the corresponding region and 0 otherwise. *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1.

1.5.2 The Nested Logit Model

The results for the mixed logit rely on the restrictive assumption of independence of error terms, which implies that all the unobserved factors that affect major choice are independent. Since majors share a large set of courses, this assumption, known also as the independence of irrelevant alternatives (IIA), is likely to be violated. In the nested logit model (henceforth NL) (McFadden, 1978) that breaks alternatives into groups (nests), this assumption is relaxed as it allows the error terms to be correlated within the nests, but not between the nests. This model is convenient for the choice of major among students at FELU, as the economics and business programs represent natural nests due to a large number of common third- and fourth-year courses. It is therefore reasonable to assume that an addition of a new major in, say, an economics program will affect the probability of choosing other majors in this program, while there will be little influence on majors in the business program. Applying the nested logit model to our data permits the correlation of errors within economics and within a business program, but not between them.

We denote the nests with B_k ($k = economics, business$) and using the same notation as above, we can write the assumed generalized extreme value joint cumulative distribution function for the errors:

$$F(\varepsilon) = \exp\left(-\sum_{k=1}^{K}\left(\sum_{j\in B_k} e^{-\varepsilon_{ij}/\tau_k}\right)^{\tau_k}\right), \tag{1.6}$$

where τ_k stands for the scaling or dissimilarity parameter equal to $\sqrt{1-\rho_k}$, with ρ_k representing the correlation coefficient between error terms for majors within nest k. Assuming the rationality of students, we assume that an individual chooses the nest that gives her the highest utility. This utility is called an inclusive value and is defined as:

$$I_{ik} = \ln\left(\sum_{j\in B_k} e^{\mathbf{x}'_{ij}\boldsymbol{\beta}/\tau_k}\right), \tag{1.7}$$

where $\mathbf{x}_{ij}$ denotes (for simplicity) the set of alternative-specific variables, although it is straightforward to extend this model to case-specific variables. By denoting the nest specific variables with $\mathbf{q}_{ik}$, the probability of choosing nest k, can be written as:

$$p_{ik} = \frac{\exp(\mathbf{q}'_{ik}\boldsymbol{\delta} + \tau_k I_{ik})}{\sum_{k'=1}^{K}\exp(\mathbf{q}'_{ik'}\boldsymbol{\delta} + \tau_{k'} I_{ik'})}, \tag{1.8}$$

and the probability of choosing alternative j conditional on deciding for nest k as:

$$p_{ij|k} = \frac{\exp(\mathbf{x}'_{ij}\boldsymbol{\beta}/\tau_k)}{\sum_{j'\in B_k}\exp(\mathbf{x}'_{ij'}\boldsymbol{\beta}/\tau_k)}. \tag{1.9}$$

The probability of choosing alternative j from nest k is then a product of equations in (1.8) and (1.9). The estimates of the NL can be obtained by applying the full information maximum likelihood (FIML) estimator that maximizes log likelihood based on a sample of observations from density (for one observation):

$$f(y_i) = \prod_{k=1}^{K} \left((p_{ik})^{1\{y_i \in B_k\}} \prod_{j \in B_k} (p_{ij|k})^{1\{y_i = j\}} \right), \tag{1.10}$$

where $1\{y_i \in B_k)$ denotes an indicator function that assumes the value 1 if student chooses major that belongs to nest B_k, and $1\{y_i = j\}$ is an indicator that assumes the value 1 if student chooses major j.

The estimation results for the program and major choice of economics and business students are shown in Appendix (the last two columns of Table A.4) Again, a National Economics major is used as the base alternative. The log-likelihood and the information criteria are higher for this model than the corresponding values for the mixed logit model, and the coefficients differ between the two models. Moreover, the likelihood ratio statistic (χ^2) for the hypothesis that both $\tau_{economics}$ and $\tau_{business}$ are equal to 1 is 37.84, therefore rejecting the null hypothesis that the NL model reduces to the mixed logit model.[13] Both scaling parameters are larger than 1, indicating that the model is not consistent with the additive random utility model, although it is nevertheless mathematically correct.[14]

Tables 1.11, 1.12, 1.13, and 1.14 summarize the marginal effects calculated at the mean values of regressors, which are directly comparable to the marginal effects of the mixed logit model in Tables 1.7, 1.8, 1.9, and 1.10.[15] Despite significant differences between the coefficients of the two models, the differences in the marginal effects are relatively small for all key variables of interest. Namely, an increase in the high school GPA, a measure of general ability, increases the probability of choosing two of three economics majors and decreases the likelihood of choosing a major in Finance. More importantly, although some of the marginal effects are lower in value, increases in grades achieved in major-specific courses increase the likelihood of choosing corresponding majors in general, which confirms our main hypothesis that major-specific ability is important for understanding college major decisions. There is, however, an important difference in the marginal effects of wages as for the nested logit an increase in the major-specific net wage of any of the three economics majors increases the likelihood of choosing the other two economics majors (see Tables 1.9 and 1.13). This finding suggests that students who choose one of the economics majors take into account the possibility that they will be able to successfully compete for similar jobs as students of the other two majors, which is consistent with observed similarity of curricula of economics majors and low costs of mobility between major-specific jobs.

[13]The Hausman and McFadden (1984) test shows that the IIA is not violated. The contradicting results are in line with the findings of other authors, who suggest that this and other choice set partitioning tests of the IIA can be unreliable (see e.g. Cheng and Long, 2007; Fry and Harris, 1996).

[14]The choice probabilities lie between zero and one and sum over alternatives to one.

[15]Note that the standard errors of the marginal effects for the nested logit model cannot be computed.

1.6 Conclusions

In this paper we provide new evidence that shows that not only general, but also major-specific abilities play an important role in explaining college major choices of economics and business students. We show this by using objective measures of major-specific ability, based on the grades that students achieved in the relevant set of first- and second-year courses. Our results complement the evidence of Arcidiacono et al. (2012), who rely on subjective, i.e., students' own estimates of major-specific ability. We also find significant differences in preferences between genders, which is in line with existing studies by Turner and Bowen (1999), Montmarquette et al. (2002), and Zafar (2009). In our data, males prefer the Business Informatics, Management, and Banking and Finance majors, while females are more likely to major in Accounting, Finance, and Marketing. Finally, we find evidence of interaction between preferences and major-specific ability, as both genders tend to be more responsive to major-specific ability in fields that are also generally more popular among them (e.g. Business Informatics for males).

Although the results are based on data for a single institution in a small nation, there are two reasons to believe that the main result (stating that major-specific abilities are important in explaining college major choices) can be generalized to other institutional contexts. First, our results are in line with findings of other authors. And second, although the institutional framework is not entirely comparable to the United States, the behavior of students is influenced by similar factors.

Our conclusions are, however, subject to a caveat. While college grades are objective measures of major-specific ability, they may reflect not only major-specific ability, but also preferences of students regarding majors. For example, a student with a strong preference for Accounting may put greater effort into studying for the first-year Accounting course and subsequently choose the Accounting major. As a consequence, the estimated marginal effects of major-specific ability on major choice may be upward biased. While psychological studies find that people tend to prefer what they are good at, which may suggest that this bias is small, we cannot be certain of its size. Nevertheless, we believe that the positive marginal effects of our major-specific ability measures on the likelihood of choice for both males and females even in the least popular majors confirm the importance of our ability measures for college major choices.

Table 1.11: Nested Logit: Marginal Effects at Mean for High School GPA and College Grades, Males

Change in Grade	Pr[Acc]	Pr[BI]	Pr[Fin]	Change in Pr[Mng]	Pr[Mrk]	Pr[BF]	Pr[IE]	Pr[NE]
High School GPA	−0.76	−0.36	−2.11	−0.32	−0.85	2.62	1.62	0.16
Accounting	2.13	−0.69	1.72	−2.52	−1.09	0.70	−0.34	0.10
Business Inf. Sys.	0.22	4.75	−0.20	−0.59	−2.76	−0.58	−0.60	−0.24
Enterprise Economics	0.53	−1.85	2.74	−1.61	−0.09	0.13	0.02	0.13
Mathematics	−0.89	0.00	−0.50	0.20	2.85	−0.54	−0.76	−0.26
Microeconomics	0.20	−1.47	2.01	−0.67	−0.82	0.50	0.34	−0.08
Management	0.09	−4.09	1.67	0.54	1.06	0.31	0.24	0.17
Organization	−0.36	0.02	−1.88	1.70	0.53	−0.06	−0.16	0.21
Commercial Law	−0.03	−0.37	−1.09	0.17	1.11	0.22	0.14	−0.15
Entreprenurship	0.28	0.41	−0.34	0.65	−0.11	−0.40	−0.27	−0.22
Macroeconomics	−0.42	−1.28	−0.07	0.28	−1.29	1.51	0.81	0.46
Political Economy	0.16	−1.77	0.53	−1.29	−0.88	1.95	0.99	0.32
National Economics	−0.14	−0.88	0.84	−0.69	0.19	0.20	0.30	0.18
Statistics	−0.15	0.20	0.72	−0.35	−0.99	0.28	0.19	0.11
Economic Statistics	0.00	−1.00	−0.21	−0.81	1.08	0.98	−0.05	0.03

Note: Allocation of first- and second-year courses to specific majors is represented by the shaded values. Marginal effects are given as a percentage. High school GPA is calculated as an average of the matura examination results and the high school average grade.

Table 1.12: Nested Logit: Marginal Effects at Mean for High School GPA and College Grades, Females

Change in Grade	Change in Pr[Acc]	Pr[BI]	Pr[Fin]	Pr[Mng]	Pr[Mrk]	Pr[BF]	Pr[IE]	Pr[NE]
High School GPA	−1.31	−0.04	−1.86	−0.11	−1.04	2.28	1.87	0.20
Accounting	3.95	−0.15	1.54	−2.04	−1.89	−0.30	−1.00	−0.13
Business Inf. Sys.	0.98	1.00	1.21	0.10	−3.11	0.08	−0.21	−0.06
Enterprise Economics	0.78	−0.39	2.26	−1.48	−0.63	−0.28	−0.27	0.01
Mathematics	−0.54	0.00	−0.81	0.07	3.33	−0.68	−0.88	−0.36
Microeconomics	0.25	−0.30	1.76	−0.65	−1.54	0.29	0.28	−0.09
Management	−0.25	−0.85	0.70	0.01	0.80	−0.27	−0.15	0.01
Organization	−0.59	0.02	−1.72	1.41	1.02	−0.09	−0.20	0.16
Commercial Law	−0.15	−0.09	−1.37	0.04	1.52	0.10	0.09	−0.14
Entreprenurship	0.54	0.08	−0.31	0.52	−0.14	−0.27	−0.24	−0.17
Macroeconomics	−0.71	−0.22	0.15	0.31	−1.81	1.12	0.79	0.36
Political Economy	0.25	−0.34	0.40	−1.06	−1.49	1.24	0.81	0.20
National Economics	−0.38	−0.19	0.58	−0.65	0.06	0.14	0.29	0.14
Statistics	−0.20	0.05	0.96	−0.18	−1.36	0.32	0.28	0.12
Economic Statistics	−0.02	−0.19	−0.27	−0.65	1.62	0.15	−0.52	−0.13

Note: Allocation of first- and second-year courses to specific majors is represented by the shaded values. Marginal effects are given as a percentage. High school GPA is calculated as an average of the matura examination results and the high school average grade.

Table 1.13: Nested Logit: Marginal Effects at the Mean for Major-Specific Net Wage, All Students

Change in Net Wage	Change in Pr[Acc]	Pr[BI]	Pr[Fin]	Pr[Mng]	Pr[Mrk]	Pr[BF]	Pr[IE]	Pr[NE]
Acc	5.75	−0.27	−1.63	−0.73	−1.11	−1.03	−0.71	−0.26
BI	−0.41	3.25	−0.88	−0.41	−0.59	−0.56	−0.39	−0.14
Fin	−1.63	−0.89	15.29	−2.43	−3.69	−3.42	−2.36	−0.85
Mng	−0.73	−0.40	−1.66	8.19	−1.66	−1.53	−1.06	−0.38
Mrk	−1.12	−0.61	−3.69	−1.67	11.64	−2.34	−1.62	−0.58
BF	−1.03	−0.56	−3.42	−1.53	−2.34	5.06	2.81	1.01
IE	−0.71	−0.39	−2.35	−1.06	−1.61	2.81	2.62	0.70
NE	−0.26	−0.14	−0.85	−0.38	−0.58	1.01	0.70	0.50

Notes: Marginal effects of a change in the major-specific average net wage are represented by the shaded values. Marginal effects are given as a percentage.

Table 1.14: Nested Logit: Marginal Effects at the Mean for Case-Specific Control Variables

Change in Variable	Change in Pr[Acc]	Pr[BI]	Pr[Fin]	Pr[Mng]	Pr[Mrk]	Pr[BF]	Pr[IE]	Pr[NE]
Female	6.40	−10.84	1.88	−4.44	9.06	−1.68	−0.05	−0.32
Age	0.92	0.58	−2.19	0.81	−0.51	0.35	−0.13	0.17
Region 1	2.64	0.06	1.35	−2.55	−0.41	−1.16	−0.44	0.51
Region 2	5.24	−0.66	3.47	−3.74	−1.78	−1.58	−0.85	−0.10
Region 3	2.68	−0.26	2.38	−3.34	−1.02	−0.54	−0.64	0.74
Region 4	4.73	−0.30	−3.72	−5.59	6.61	−0.85	−0.99	0.11

Notes: Marginal effects are given as a percentage. There are five regions that are based on the distance between student's home address and FELU (Ljubljana). Student is in region 0 if the distance is less than 10 km; in region 1 if the distance is at least 10 km, but less than 40 km; in region 2 if the distance is at least 40 km, but less than 70 km; in region 3 if the distance is at least 70 km, but less than 110 km; and in region 4 otherwise. For each region we construct a dummy variable that assumes the value 1 if student is from the corresponding region and 0 otherwise.

2 EVOLUTION OF PRIVATE RETURNS TO TERTIARY EDUCATION DURING TRANSITION: EVIDENCE FROM SLOVENIA[16]

Abstract

This paper analyses the evolution of private returns to tertiary education during the period of transition from a socialist to a market economy using the personal income tax data of all Slovenian workers employed between 1994 and 2008. We document a rich interplay between supply and demand in the labor markets of high school and university graduates. We show, that in spite of significant increases in the labor supply, the demand for university graduates dominated and increased the rates of return in the early period of transition (1994–2001), while in the later period (2001–2008) the opposite was the case. We also provide evidence on considerable heterogeneity in the rates of return between genders, levels, and fields of study, with particularly large (low) returns to the fields that were suppressed (favored) during socialism. These initial differences in returns have, however, gradually declined.

Keywords: Economic transition, Labor economics, Returns to education, Tertiary education, Mincerian regressions
JEL classification: J24

[16]This paper is coauthored with Aleš Ahčan, Aljoša Feldin, and Sašo Polanec and has been published as Bartolj et al. (2013).

2.1 Introduction

The functioning of labor markets during socialism was heavily affected by various government interventions. One of the key measures that governments used was direct wage-setting with the aim of maintaining low income inequality, which resulted in low private returns to tertiary education and, in turn, a low proportion of university graduates in the labor force. The governments also affected educational choices by determining the entry quotas of different educational programs, and demand for graduates of different fields of study through direct allocation of capital to specific industries. The preference for technical fields of study and manufacturing led to a relatively high supply of graduates in these fields and a relatively low supply of graduates in social sciences, law, and business studies.

The end of the socialist era[17] was marked by a set of reforms, amongst which was a liberalization of wage determination. Several studies analysed the labor market outcomes in transition countries. Authors have, for instance, analysed labor markets in Slovenia (Orazem and Vodopivec, 1995, 1997; Stanovnik, 1997; Bevc, 1993), Czech Republic and Slovakia (Chase, 1998; Münich et al., 2005), Poland (Strawinski), Belarus (Pastore and Verashchagina, 2006), Russia (Brainerd, 1998), Vietnam (Moock et al., 2003), China (Li, 2003; Fey and Zimmerman, 2005) and a set of transition countries (Flabbi et al., 2008). These papers have two conclusions in common—the socialist era was followed by a period of increasing returns to education and increased wage inequality, although Flabbi et al. (2008) suggest that the evidence of a rising trend in returns to education in transition countries is rather weak, with significant differences across countries.

These studies typically focus on the dynamics of private returns to education in the early transition period and do not explore the differences across levels and fields of tertiary education.[18] The aim of this paper is to fill the gap in the literature and show the evolution of private rates of return to different levels of tertiary education and fields of study using Slovenian data on all economically active workers during the period of fifteen years between 1994 and 2008. While the Münich et al. (2005) study also examines returns to different fields of education in 1996, their analysis is limited to 2,284 men from a stratified random sample of households in the Czech Republic. In order to reduce the cognitive ability bias, we augment the Mincerian earnings equation with our measure of general cognitive ability based on points achieved at high school matura examination.[19] In addition, due

[17] See Bueno (2010) for a description and an analysis of the objectives of transition.

[18] The literature on returns to different fields of study is also relatively scarce for established market economies. Authors find large and consistent differences in the rates of return for 4-year college graduates (Arcidiacono, 2004), M.A. programs (Weiss, 1971), and for Canadian graduates (Finnie and Frenette, 2003; Stark, 2007). Non-American studies of rates of return to education by fields of study are similarly limited. The exceptions are Livanos and Pouliakas (2008) studying the Greek labor market, Blundell et al. (2000), O'Leary and Sloane (2005), and Walker and Zhu (2011) studying returns to higher education in Britain, Kelly et al. (2010) studying returns in Ireland, and Buonanno and Pozzoli (2009) studying the Italian labor market.

[19] To avoid the ability bias if using ordinary least squares estimator without some measure of ability, researchers have for example used (i) some proxy of ability (Griliches, 1977; Nordin, 2008), (ii) instrumental variables estimator (Angrist and Krueger, 1991, 1992; Card, 1995; Denny and Harmon, 2000; Harmon and Walker, 1995, 2000), or (iii) data on siblings or twins (Ashenfelter and Krueger, 1994). For a more comprehensive review see Harmon et al. (2000), Meghir and Rivkin (2011).

to the differences in the determination of wages in the public and private sector, we also check the robustness of our results by estimating the returns to education separately for workers employed in the private sector. Moreover, we do not study only returns to education as reflected in the wages of employees, but also total reported labor income.

We find that the private annual (monetary) rates of return, calculated with the Mincerian earnings function, follow an inverse U-shaped trend. During the 1994–2001 period, the returns to all levels, except for PhD, rose in spite of the increasing shares of workers with a 4-year undergraduate degree or higher. This finding suggests that the demand for university graduates grew at faster rate than their supply. A drop in the rates of return followed in the 2001–2008 period. In addition to variations of returns in time, we observe considerable heterogeneity in rates of return between genders, educational levels, and fields of study, with especially large returns in the beginning of the period analysed to the fields that were neglected during socialism, such as social studies, law, and business studies; and relatively low returns to the technical fields that were favoured by socialist leaders. Over time, these differences decreased with relative increases in the labor supply of graduates in the fields of social studies, law, and business. The differences in the returns between levels of tertiary education provide evidence that contrasts Card's 1999 result of constant return to all levels of education. On the basis of results from a sub-sample of workers with a measure of ability, we confirm the existence of a positive ability bias. We are able to proxy ability with a score achieved in a high school external examination for a sub-sample of workers and gain information on the ability bias in the analysed context. Moreover, we find that, in more homogeneous groups, males usually have higher rates of return than females. Lastly, the returns based on total reported labor income show that alternative income sources represent a non-negligible part of private rates of return. Differences between returns based on net wage and those based on net labor income increase with the level of education and are unequal between fields of study.

In the next section, the determination of wages in Slovenia is described, with the data sources and descriptive statistics in Section 2.3. In Section 2.4, the estimated returns and the robustness checks are presented. The paper finishes with the conclusion.

2.2 Determination of Wages in Slovenia

The wages in Slovenia are affected by collective bargaining and the minimum wage, promoted by law since 1990 and 1995, respectively. The collective bargaining process takes place at a national, industry, and firm level. At the national level, it is a process of negotiations between four main trade union associations and the employers' association over the key components of two national collective contracts, separate for private and public sector. The wage floors for different types of jobs, depending on difficulty of the job and educational requirements, apply to all employees of the covered employers and are determined in the industry-level collective contracts. The firm-level wages are set in firm-level bargaining between the union representatives and the firm management. Although these wages typically exceed the industry-level wage floors, they can be lower if a firm exhibits poor economic performance, reflected in operating losses and declining sales.

While trade union labor coverage is around 50 percent at the national level, a law on union representation stipulates that a trade union is representative at the national level and in sectors and occupations if membership exceeds the thresholds 10 and 15 percent of all employees, respectively. Hence, the coverage of collective contracts is significantly higher than the union density and may be up to 90 percent. It is also important to note that trade union representation is obligatory only in firms with at least 50 employees, which implies that gross wages in smaller firms may exhibit different wage premiums for job difficulty and educational attainment than the industry-level contracts.

Furthermore, according to the Employment Relationships Act, employees are eligible for a bonus for working the night shifts, on Sundays, on holidays, and for overtime work. Employers have to cover employees' costs for food during work time and travel costs to work. Employees also receive a seniority bonus: a relation between wage and overall tenure (in all firms) in addition to the holiday period, which also increases with overall tenure (from 20 days at the start of career and 30 days after 20 years of tenure). This affects also re-hiring prospects of older workers and could explain the rather high unemployment rates among them.

2.3 Data Description and Summary Statistics

2.3.1 Data Description

The analysis is based on the data on all employees that were economically active in Slovenia between 1994 and 2008, and have completed at least 4-year high school. The sample was created in a secure room at the Statistical Office of the Republic of Slovenia (SORS) by merging four distinct data sets. The first source of data is the Slovenian Employment Registry (SER) maintained by SORS, which contains information on age, gender, educational attainment, field of study, employment status, periods of employment, and working hours. The second source of data is the personal income tax returns from the Tax Administration of the Republic of Slovenia (TARS) with information on annual gross wages and related social contributions, wages earned by workers on short-term contracts, other types of work related compensation (e.g. taxable bonuses, perks), copyrights, and patent rights income. Finally, the data on the score achieved on the Matura examination and the sector of employment (public, private) are from the National Examination Center and Agency of the Republic of Slovenia for Public Legal Records and Related Services, respectively.

We exclude sole proprietors from the sample, as their income reflects contributions of both human and physical capital. We also exclude employees with incomplete information on all relevant characteristics. The data set does, however, include information on many unemployed persons. Unfortunately, the data for these persons are incomplete due to lack of information on educational attainment. Since the probability of unemployment is higher among less educated persons, the estimates of returns are likely to be downward biased.[20] Nevertheless, this bias should be small as we restrict the sample to only those persons that finished at least four years of high school. All in all, we have 5,194,050 observations.

We use two measures of net labor earnings. The first is net annual wage, which is equal to the gross wage without social contributions (22.1 percent of the gross wage) and the labor income tax. The special tax treatments (e.g. special child deductions) are disregarded. The second measure is net labor income. It is calculated in the same way as net wage, but also includes taxable bonuses, perks, wages earned on the basis of short-term labor contracts, copy and patent rights income. Both measures of net labor earnings are expressed in 2007 constant prices (EUR)[21] with no adjustment for part-time employment.

Since we are not able to measure the actual experience of workers, we use the potential experience. We calculate potential experience according to the following formula: *experience = age – years of education – school entry age*, where the school entry age is typically seven in Slovenia.

For a sub-sample of employees, who finished high school in 1995 or later, we are able to measure ability with the score achieved in the Matura examination. This is an equivalent of the Scholastic Aptitude Test (SAT), common also in some other European countries (e.g. Austria, Italy, Switzerland). The Matura examination in Slovenia consists of three mandatory subjects (the Slovene language, Mathematics and one foreign language—usually English, with grading from 1 to 8) and two elective subjects, such as Biology, History, or Physics with a grading from 1 to 5. In order to pass, student must obtain at least 10 out of 34 points.[22] We use a normalized score, thus the ability ranges between 0 and 1.[23]

2.3.2 Descriptive Statistics

As a transition country, Slovenia underwent significant dynamics in the labor markets. In the early transition period, after wage liberalization took place, the returns to education increased considerably. However, in comparison with the returns in Western economies, they were still rather low (Stanovnik 1997, Orazem and Vodopivec 1995). Nevertheless, increases in returns to education increased the demand for education and improved the level of education attained. Figure 2.1 shows the dynamics of the number of employees by level of education in the entire period of analysis, while Table 2.1 shows the employment structure in percentages in 1994, 2001, and 2008. Over the entire period of analysis, 1994–2008, the number of male (female) employees who completed high school

[20] A person is unemployed if she or he is registered at the local employment office. This definition is less strict than the standard ILO definition. Hence Slovenian unemployment rates based on registry exceeded survey unemployment rates by as much as 6 percentage points.

[21] The exchange rate in 2007 was 1 EUR = 1.37 USD.

[22] Note that the grading scale is changed every year so that the achieved points in each cohort are Gaussian distributed.

[23] We used also the non-normalized points, but the results are qualitatively similar.

increased from 78,319 (96,961) to 121,859 (122,729).[24] The largest change occurred in the number of female workers with a 4-year undergraduate (UG) degree, which increased from 20,924 in 1994 to 75,046 in 2008. While there was also a significant increase in the number of male workers with a four year undergraduate degree (from 23,479 to 50,707), the corresponding relative change was significantly smaller than for females. Similarly, the number of workers with graduate diplomas also increased significantly. The number of male and female workers with a Master's degree increased from 2,470 to 5,147 and from 1,387 to 5,140, respectively. Following a similar trend, the number of PhDs increased from 301 to 1,837 for females and from 1,395 to 3,131 for males.

The preference of socialist governments for technical fields of study, such as Engineering and Manufacturing, and Sciences and Mathematics, has caused an imbalance between the relative supply and demand of different groups of graduates. After wage liberalization, these imbalances led to divergence of wage premia and consequently of returns to different fields of study. This led to an increase in the number of employees with a four year UG degree in the fields of Social Sciences, Business and Law and Arts and Humanities (see Figure 2.2). The percentage of workers with a four year UG degree in Social Sciences, Business and Law among all workers within this category increased from 26.7 to 33.8 percent for males and from 34.6 to 43.3 percent for females. At the same time the share of male workers with a degree in Engineering and Manufacturing among all male workers with four year UG degree fell from 41.5 to 37.8 percent.

As expected, the average net wage increased during the analysed period for all levels of educational attainment (see Figure 2.3). In addition, the gender wage gap increased with the level of education, the highest being for the PhDs. Specifically, the mean net wage for males and females who had completed high school rose from 7,321 to 10,337 and from 6,447 to 8,585, respectively, while the net wage for PhDs grew from 22,050 to 28,782 for males, and from 18,786 to 23,337 for females. The discrepancy between male and female earnings is evident also in Figure 2.4, which presents the net wages by four year UG fields of study and gender. In 2008, the top-earning fields for males with a four year UG degree were Health and Welfare (24,456), Social Sciences, Business and Law (19,589), and Engineering and Manufacturing (19,059). The ranking of highest-earning fields for females was slightly different - Health and Welfare (16,366), Sciences and Mathematics (14,821), and Social Sciences, Business and Law (14,369).

Table 2.1: Employment Structure by Educational Attainment and Gender in Slovenia, 1994–2008

	Males			Females		
	1994	2001	2008	1994	2001	2008
High school	63.20	63.02	60.92	64.93	60.25	52.95
2-year UG	15.02	12.87	9.60	20.12	17.46	11.67
4-year UG	18.95	20.67	25.35	14.01	20.50	32.38
MSc/MA	1.71	2.09	2.57	0.73	1.34	2.22
PhD	1.12	1.35	1.56	0.21	0.45	0.78

Note: The employment shares are given in percentages.

[24] The total population in Slovenia is around 2 million; we exclude employees with less than completed 4-year high school and sole proprietors from analysis.

Figure 2.1: Dynamics of Employment by Educational Attainment and Gender

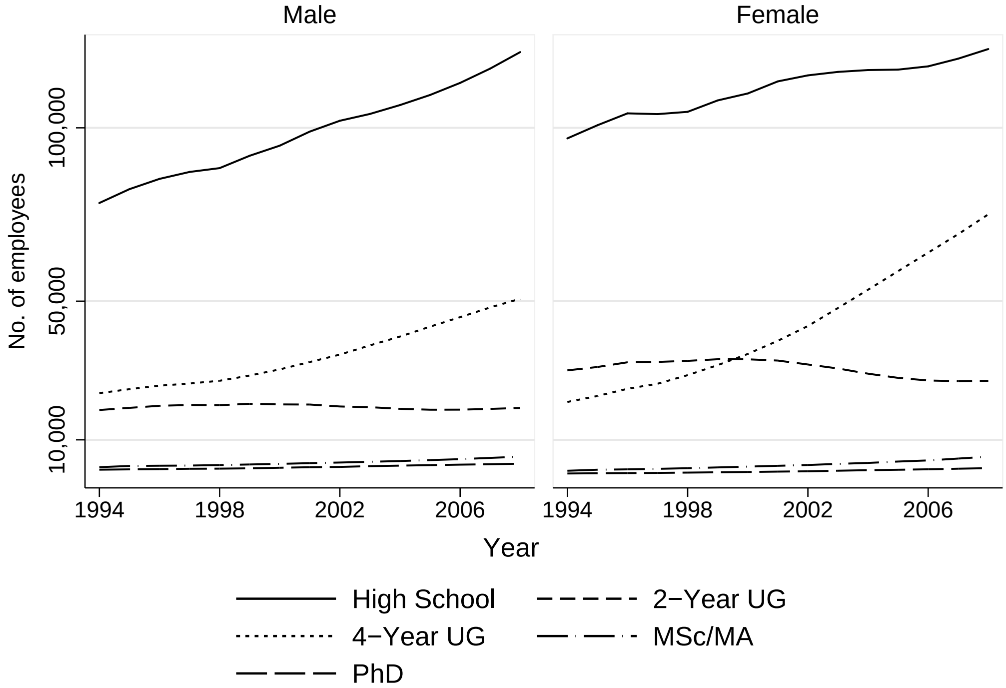
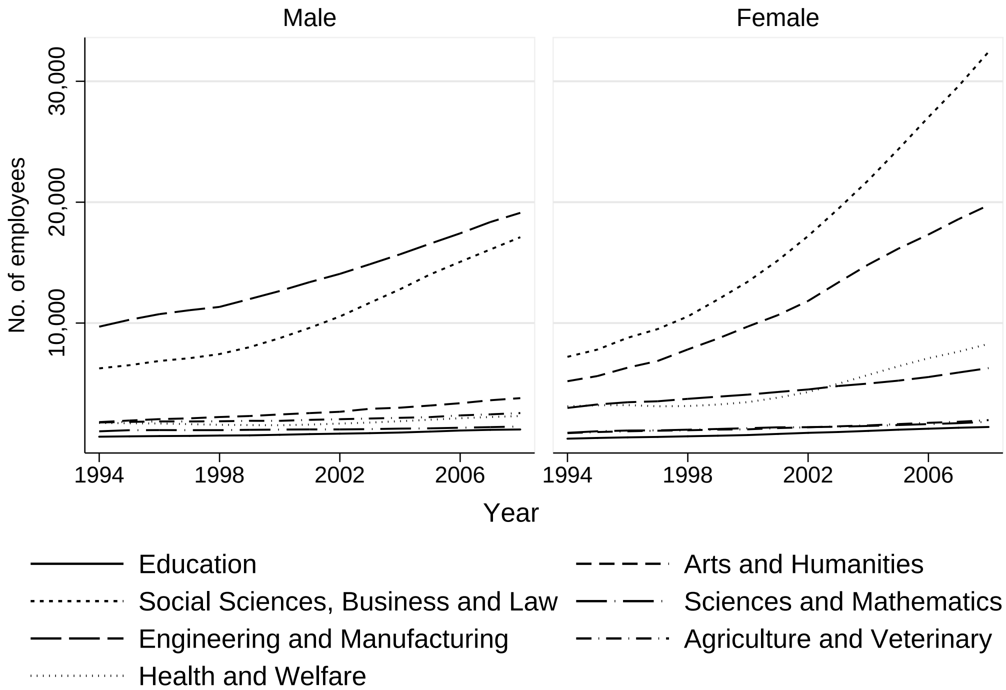


Figure 2.2: Dynamics of Employment by Fields of Study and Gender, 4-Year UG



The returns to tertiary education are estimated for three distinct samples: i) all employees, ii) sub-sample of employees with information on ability, and iii) sub-sample of employees in the private sector. The summary statistics for all three samples on key variables (female dummy, age, experience, net wage, net labor income, and measure of ability) are given in Table 2.2. The sub-sample

Figure 2.3: Dynamics of Average Net Wages by Educational Attainment and Gender

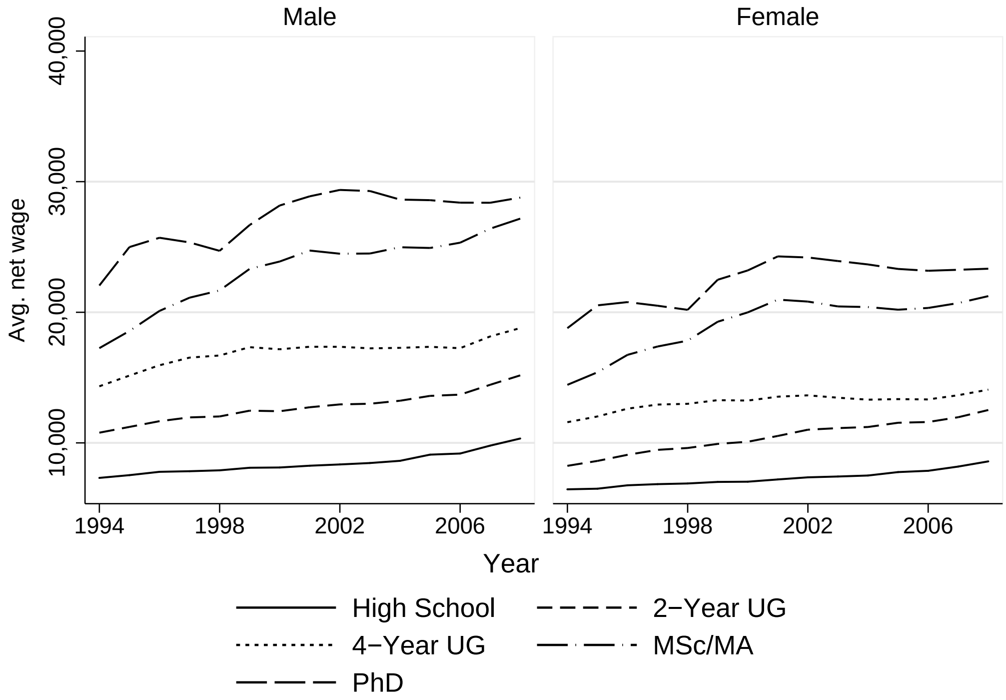
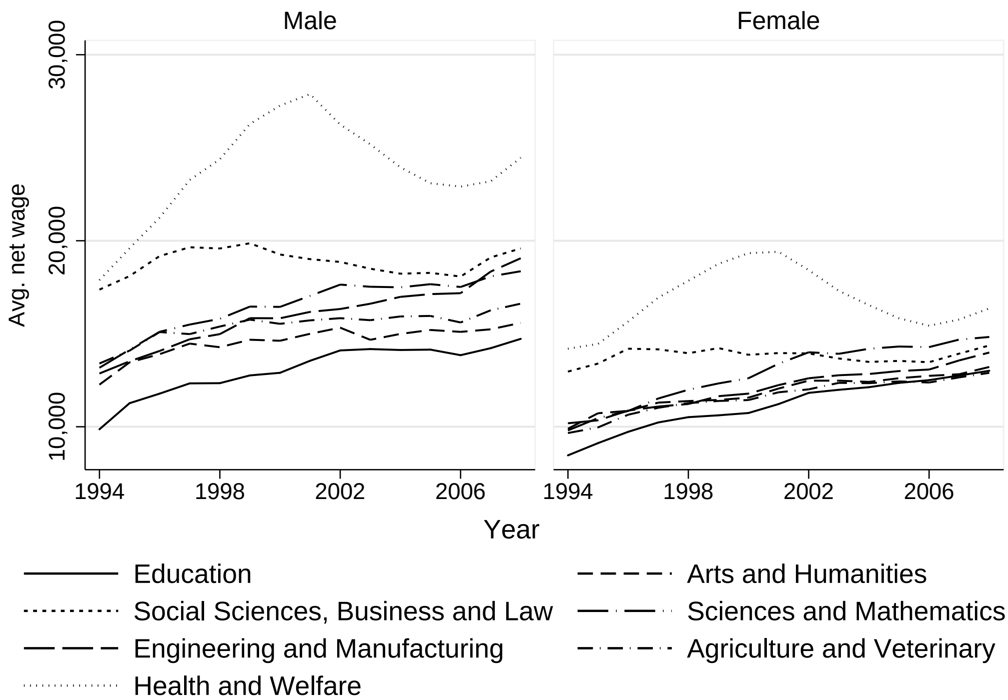


Figure 2.4: Dynamics of Average Net Wages by Fields of Study and Gender, 4-Year UG



of persons with ability is significantly smaller as this information is only available for younger employees who graduated from 1995 onwards, which is also reflected in lower mean age and experience than in the full sample and sample of private sector employees.

Table 2.2: Basic Characteristics of Workers in the Sample

	Full Sample	Ability sub-sample[(a)]	Private sector sub-sample[(b)]
Person-year observations	5,194,050	174,751	2,724,483
Females [percent]			
High School	52.95	51.22	45.23
2-Year UG	61.08	59.88	42.84
4-Year UG	55.29	65.69	40.98
Msc/MA	44.44	56.36	32.68
PhD	30.15	35.99	26.69
Mean age	38.43	27.56	38.34
Sd age	9.45	2.43	9.44
Mean experience	18.08	6.28	18.30
Sd experience	9.40	2.57	9.45
Mean net wage	10,406	9,289	10,066
Sd net wage	7,815	4,946	8,293
Mean net labor income	10,887	9,653	10,443
Sd net labor income	8,942	5,423	9,236
Mean ability		0.31	
Sd ability		0.20	

Notes: [(a)] Sub-sample of individuals for which ability is measured. [(b)] Sub-sample of individuals working in private sector.

2.4 Empirical Analysis

2.4.1 Methodology

Returns to education can be computed using many different estimation techniques and approaches (see Heckman et al., 2006, for a review). We follow the most frequently used approach, originally proposed by Mincer (1974). This approach relies on estimation of earnings equation using OLS and extraction of returns from regression coefficients on measures of schooling. Thus, in contrast to the methods based on calculation of internal rate of return (IRR), it neglects pecuniary and non-pecuniary costs of education as well as non-pecuniary benefits. This is, however, a small limitation for our data set as Slovenian students bear a small portion of costs of their studies. Most importantly, full time undergraduate students at public and government-dependent institutions, which enrolled 93 percent of all students in the first and second stage of tertiary education in 2008, do not have to pay tuition fees (Eurostat, 2012). Moreover, according to a Eurostudent (2008) survey, 49.4 percent of all students in tertiary education in the 2005–2008 period lived with their parents or relatives. Therefore, the Mincerian regression is an appropriate method for estimation of returns to education in Slovenia.

The returns are calculated by ordinary least squares estimation of Mincerian earnings function:

$$\ln y = \alpha + \sum_{j=1}^{J} \beta_j D_j + \gamma_1 z + \gamma_2 z^2 + \varepsilon, \tag{2.1}$$

where y are the individual earnings; D_j is a dummy variable indicating that a worker holds a degree of type j;[25] z represents the number of years an individual has worked since completed schooling, and ε is an error term. Equations for males and females are estimated separately. For a sub-sample of individuals with available information on score achieved at Matura examination, we estimate Equation (2.1) with this additional regressor measuring general cognitive ability (A):

$$\ln y = \alpha + \sum_{j=1}^{J} \beta_j D_j + \gamma_1 z + \gamma_2 z^2 + \delta A + \varepsilon. \tag{2.2}$$

The annual rate of return for each level of education, r_j, is then calculated as:

$$r_j = (1 + \beta_j - \beta_k)^{\frac{1}{T_j - T_k}} - 1, \tag{2.3}$$

where $T_j - T_k$ is the time needed to complete educational level j after level k was obtained (see Table 2.3) and $\beta_j - \beta_k$ is the difference in regression coefficients for the two levels of education. For example, the annual rate of return to PhD is calculated as:

$$r_{PhD} = (1 + \beta_{PhD} - \beta_{MSc})^{\frac{1}{2}} - 1.$$

Similarly, we calculate the return to four year UG degree in Education as

$$r_{4-yearUG,Educ.} = (1 + \beta_{4-yearUG,Educ.})^{\frac{1}{5}} - 1.$$

This gives us a rate of return for each additional year of a specific level of study. Note that we compare regression coefficient for a four year UG program with high school (omitted category) instead of a two year UG program, since the latter may not necessarily lead to four year UG programs due to mobility restrictions and direct enrolment of high school graduates in four year UG programs.

Table 2.3: Time Needed to Complete Educational Level j after Level k was Obtained

j	k	$T_j - T_k$
2-year UG	High school	$3^{(a)}$
4-year UG	High school	$5^{(a)(b)}$
MSc/MA	4-year UG	2
PhD	MSc/MA	2

Notes: $^{(a)}$ Since students typically have to write a theses it takes 3 years to complete 2-year UG program and 5 years to complete 4-year UG program. $^{(b)}$ The exceptions are Engineering and Manufacturing and Health and Welfare, that last 5.3 and 6 years, respectively.

[25] We separately estimate returns to levels of education and returns to fields of education. In the first case j is equal to a level of education (2-year UG, 4-year UG, MSc/MA, or Phd). In the second case j is equal to a degree in specific field (e.g. 4-year UG degree in Education). The omitted category is always high school.

2.4.2 Results and Discussion

Mincerian Earnings Function

The top panel of Table 2.4 presents annual returns to different levels of education for the full sample of persons in 1994, 2001, and 2008. The returns feature an inverse U-shaped dynamic for both males and females (see also Figure 2.5). This pattern suggests that labor demand for university graduates grew at a faster rate than their supply until 2001, which led to increases in the rates of return. However, after 2001, the continued increase in labor supply of graduates dominated increase in demand, which is reflected in declining rates of return for all levels of education with the exception of PhD level. Specifically, in the 1994–2001 period, the rate of return for males (females) with a four year UG degree increased from 9.78 (9.43) to 11.07 (11.25) percent, whereas in the 2001–2008 period, this rate decreased to 9.63 (9.94) percent.[26] At the same time, the percentage of males (females) with four year UG degrees among all male (female) workers who at least completed high school increased from 18.95 (14.01) to 20.67 (20.50) in the 1994–2001 period and then from 20.67 (20.50) to 25.35 (32.38) percent in the 2001–2008 period (see Table 2.1). This pattern of returns is consistent with a cobweb model of wage dynamics in labor markets with gestation lags and seems to have been observed also in other transition countries (see Carnoy et al., 2012 who depict a similar trend for Russia).

According to Card (1999), the results for the US imply that each additional year of education has the same proportional effect on earnings, ceteris paribus. In our case, this would imply equal rates of return for all levels of education. However, our results do not confirm that. For instance, while the rates of return for two year and four year UG degrees are similar—9.68 and 9.63 percent in 2008 for males, respectively—we find large differences between rates of return among four year UG, MSc and PhD degrees. In particular, in 2008, the returns to these degrees for females were 9.94 percent for a four year UG, 16.11 percent for MSc and only 6.28 percent for PhD degree.

In the lower panel of Table 2.4 and in Figure 2.6, we show the rates of return to different fields of study for four year UG programs.[27] We observe significant heterogeneity of returns across fields of study, particularly in 1994, which is in line with Farcnik and Domadenik (2012) who find considerable differences in the employment probabilities of Slovenian graduates by fields of study in the 2007–2009 period. While large differences in returns were also observed in developed countries (e.g. Stark, 2007), the differences observed in Slovenia were driven primarily by the distortions in the relative labor supply due to socialist government interventions. The highest returns were observed in the fields that were neglected during socialism (Social Sciences, Business and Law), while the returns were relatively low in the favoured technical fields of study (Engineering and Manufacturing; Science

[26]Other studies find the returns to schooling in range between 2 and 13 percent (e.g. Harmon et al., 2000; Boarini and Strauss, 2007, 2010). For example, Harmon et al. (2000) estimate the returns for males in 1995 to be 8.9 percent, 7.8 percent, and 13.0 percent for Slovenia, US, and Great Britain. However, direct comparison of these returns with our results may be problematic due to the differences in assumptions and estimation techniques.

[27]The results for other levels of tertiary education are omitted for the sake of brevity. They are, however, consistent with presented results.

and Mathematics). Again, the gestation lags in changing the structure of labor supply that would be consistent with labor demand took twenty years to reduce the extra returns in the fields of Social Sciences, Business and Law and bring them in line with returns in technical fields of study. Since choices of field of study are often driven by non-monetary factors such as preferences or ability, it is not surprising that differences in returns across fields continue to exist even in 2008.

Table 2.4: Private Rates of Return to Tertiary Education in Slovenia based on Net Wage, 1994–2008

	Males			Females		
	1994	2001	2008	1994	2001	2008
			Levels			
2-year UG	9.31	11.07	9.68	7.65	10.96	9.99
4-year UG	9.78	11.07	9.63	9.43	11.25	9.94
MSc/MA	10.82	17.40	14.82	11.26	18.20	16.11
PhD	11.92	8.94	6.62	9.29	8.33	6.28
Average[(a)]	9.70	11.35	9.87	8.45	11.32	10.18
			Fields (4-year UG)			
Education	5.88	8.70	6.70	6.45	9.49	9.26
Arts & Human.	8.27	9.85	7.56	7.60	10.25	9.49
Social Sci., Bus. & Law	11.61	11.68	9.79	10.82	11.77	10.18
Sci. & Math.	9.30	11.35	9.61	7.98	11.15	10.19
Eng. & Manufact.	8.06	9.89	9.46	7.25	8.92	8.67
Agricult. & Vet.	9.61	10.12	8.03	7.72	9.48	7.93
Health & Welfare	10.84	13.84	11.04	9.87	12.34	9.64

Notes: Estimated coefficients are presented in Table B.1. For the sake of brevity we present only results for levels of education. The returns are given in percentages. [(a)] Average return is calculated as a weighted average with employment shares as weights.

Ability Augmented Earnings Function

Since individuals with higher ability are more likely to enrol in tertiary education programs and choose more demanding fields that may yield higher returns, the estimates of regression coefficients for schooling (β's in Equation 2.1) might be biased. To reduce such biases, we augmented the Mincerian regression with our measure of general cognitive ability based on points achieved in the high school Matura examination. This measure is not without limitations; namely, the results achieved in the Matura examination may also reflect the effects of education, and thus may be picking up the productivity enhancing effect of education (e.g. Harmon et al., 2000). Also, it is not a perfect measure of the ability to earn money rather than a measure of ability in the IQ sense. In spite of these limitations, we believe that augmenting the Mincerian earnings function with this measure reduces the potential biases of estimated returns to education.

As already noted, the scores of the Matura examination are available only from 1995 onwards and since it takes eight years more for the first individuals with a PhD degree to enter the labor market, we can provide estimates of returns only for a sub-period between 2003 and 2008. The sample of individuals is further reduced as Matura is taken only by students of general secondary schools (excluding students of vocational secondary schools).

Figure 2.5: Private Annual Rates of Return to Tertiary Education in Slovenia by Educational Attainment and Gender [in percent]

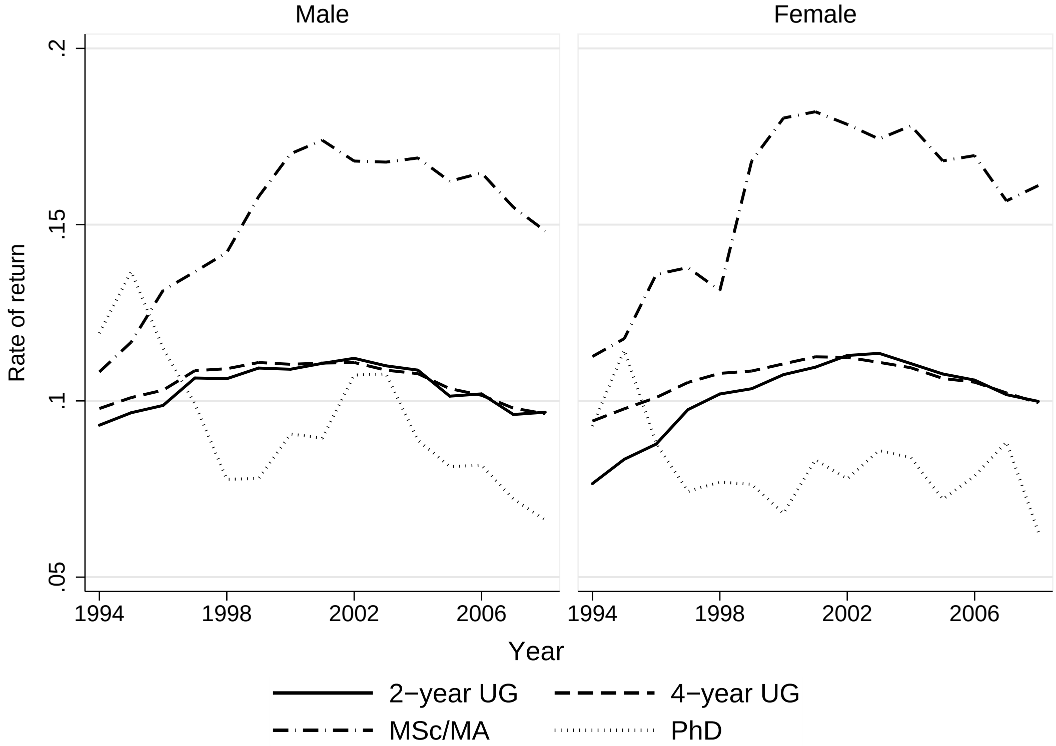


Figure 2.6: Private Annual Rates of Return to Tertiary Education in Slovenia by Fields of 4-year UG Study and Gender [in percent]

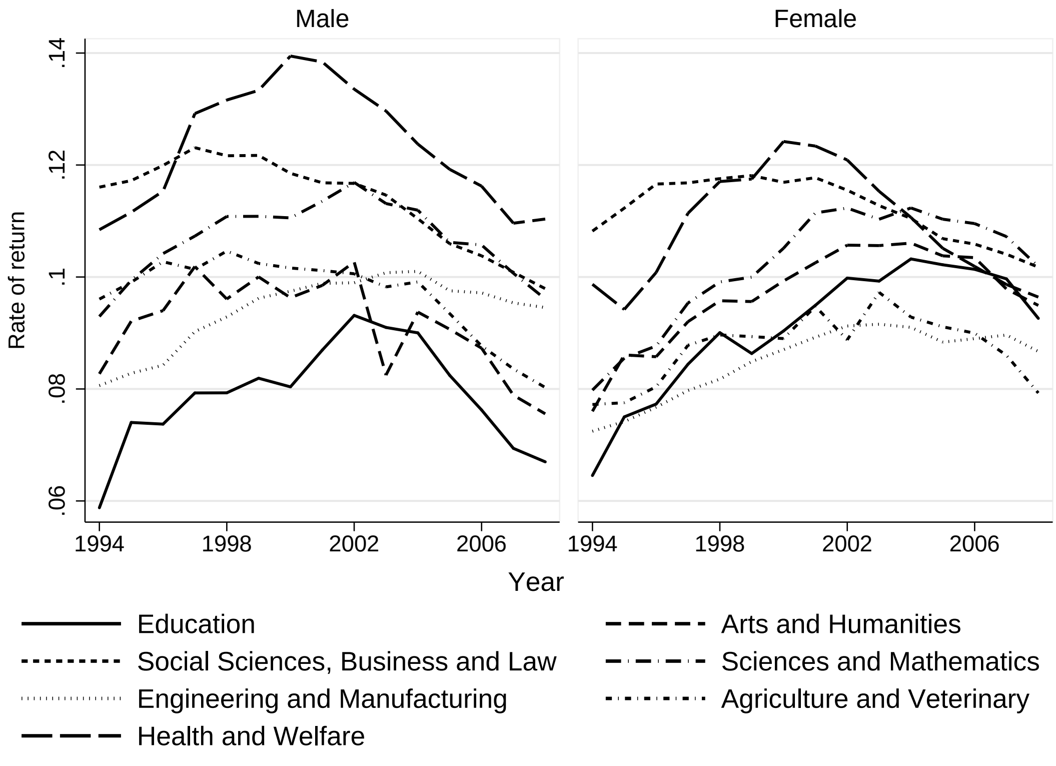


Table 2.5 presents the rates of return with and without (in parentheses) control of ability for individuals with results in the Matura examination. Comparison of these rates of return allows us to estimate the size of ability bias. We find a positive ability bias for all fields and levels of education, except for the two year UG degree.[28] However, its size is relatively small—usually less than one percentage point for different levels and fields of education. For example, the estimated return for males with a four year UG degree in 2008 was 8.84 percent when the ability measure was not included, and 8.47 percent after the inclusion of control variable, which suggests that ability bias concerns are less important in our data set.

Another interesting result comes from comparison of the returns based on full sample and the returns from the sub-sample of individuals for which ability is measured, but not controlled for. While males in the ability sub-sample generally outperform females (with and without ability as a control variable), this does not hold for the full sample. Note that persons in the ability sub-sample completed general secondary schools which usually have higher entry requirements (based on the national exams at the end of primary school) than vocational schools, and are intended for those who wish to continue with the tertiary education. Thus, workers included in the ability sub-sample constitute a more homogeneous group in terms of discount rates, preferences, and ability than the workers in the full sample. This finding might therefore imply that estimated rates of return for females are lower than for males if we are able to control for the unobservables. Although we do not have empirical verification, we think that the described phenomenon might be attributed to employees with vocational secondary education in specific types of jobs who have high wages due to the adverse work conditions (e.g. miners, soldiers, and workers working at heights). Their premium reduces the returns to tertiary education for males to a greater extent than for females, since these are mainly male jobs. As the sample of employees who took Matura is less likely to include such workers, the returns for males exceed those of females.

[28]The difference in regression coefficients for 2-year UG is not statistically significant. See Table B.3.

Table 2.5: Private Rates of Return from Augmented and Original (in parentheses) Regressions for the Same Sub-sample

	Males			Females		
	2004	2006	2008	2004	2006	2008
			Levels			
2-year UG	10.53	10.30	5.94	4.52	5.74	4.52
	(10.07)	(10.04)	(6.08)	(4.97)	(5.87)	(4.32)
4-year UG	8.88	8.79	8.47	7.40	6.50	6.39
	(9.43)	(9.31)	(8.84)	(8.33)	(7.43)	(6.83)
MSc/MA	19.98	15.10	15.13	21.83	9.99	10.38
	(21.97)	(16.01)	(15.77)	(23.00)	(11.77)	(11.59)
PhD	8.55	3.63	3.24	-1.48[a]	11.97	3.07
	(9.32)	(4.65)	(4.57)	(-2.77)[a]	(12.39)	(3.87)
			Fields (4-year UG)			
Education	8.12	6.48	4.05	7.14	6.91	5.33
	(8.02)	(6.60)	(4.17)	(7.79)	(7.52)	(5.51)
Arts & Human.	7.71	7.26	6.03	7.92	6.24	5.60
	(8.30)	(7.78)	(6.43)	(8.71)	(7.07)	(5.93)
Social Sci., Bus. & Law	8.53	8.62	8.58	7.09	6.53	6.99
	(9.02)	(9.07)	(8.80)	(7.97)	(7.37)	(7.30)
Sci. & Math.	9.48	8.75	7.81	8.85	6.47	6.22
	(10.79)	(9.68)	(8.53)	(10.15)	(7.79)	(6.85)
Eng. & Manufact.	9.31	9.11	9.05	6.15	6.30	6.35
	(9.66)	(9.42)	(9.30)	(7.14)	(6.96)	(6.55)
Agricult. & Vet.	7.11	7.78	6.85	4.99	7.12	6.48
	(7.29)	(7.81)	(6.47)	(5.94)	(7.31)	(6.62)
Health & Welfare	9.53	9.79	10.02	7.92	6.96	7.02
	(10.35)	(10.56)	(10.62)	(9.01)	(8.26)	(7.79)

Note: [a] Coefficient in Mincerian regression is not statistically significant (see Table B.2).

2.4.3 Robustness checks

Private versus Public Sector

As mentioned in Section 2.2, Slovenian wages are mainly determined by collective bargaining. This process affects the wages of all employees in the public sector, while the private sector is unionised to a lesser extent, since representation of workers is not obligatory for firms with fewer than 50 employees. Unfortunately, the share of wages that are subject to collective contracts is not known. Furthermore, all employees in the Slovenian public sector (even the President, ministers, lower ranked public employees, etc.) have their wages set according to the fixed salary scheme. Their wage must reflect the difficulty of the job, an amount related to performance, and specific additional payments for overtime, night shifts, and work experience, but not necessarily their actual productivity. Due to the described differences in the determination of wages in the public and private sector, we conducted a robustness check by estimating the rates of return to education separately for the private sector.

Characteristics of the sub-sample of employees in private sector are presented in the last column of Table 2.2. Age and experience are approximately the same in both samples, while the share of females in private sector is smaller. The average earnings are lower in the private sector in terms of both the net wages and the net labor income, which is partly due to lower share of university graduates in this sector. At the same time the dispersion of incomes in the private sector is higher.

The estimates of rates of return for the private sector sub-sample are presented in Table 2.6. Overall, these are comparable to the rates observed in the full sample (Table 2.4), which is also reflected in comparable inverse U-shaped dynamics. There are, however, some important differences between the private and public sector returns to male MSc degrees, PhD degrees for both genders, and some specific fields of study, such as Education, and Arts and Humanities. These degrees and fields of study seem to be less productive in the private sector as the observed returns are much lower in the private sector than the returns of the full sample.

Net Wage versus Net Labor Income

The net wage does not capture all monetary rewards of education and thus the rates of return do not necessarily capture the full effects of educational attainment. While the net wage is the largest component of the total net labor income, it omits bonuses, perks, wages earned on the basis of short-term labor contracts, copyrights, and patent rights income. If the percent in the total labor income varies with educational attainment, the rates of return based on net wage may be biased.

The rates of return based on the full sample of observations and net labor income as a measure of income are presented in Table 2.7 and thus directly comparable to the rates of return reported in Table 2.4. A comparison reveals that the rates of return for net labor income exceed those based on the net wage for all levels of education and both genders. Moreover, these differences increase with the level of education, which may be a consequence of (i) the incentives created by the labor income taxation—the more educated individuals pay high marginal tax rates including high social contributions, thus they often resort to copyright contracts which allow workers to avoid the burden of social insurance, and/or (ii) better opportunities for higher educated workers to earn money. The differences are the highest in the field of Arts and Humanities for both genders, and the smallest in Agriculture and Veterinary Science for males and Social Sciences, Business and Law for females (except in the year 1994, when the lowest differences in returns for females where in Health and Welfare). However, the order of the fields with highest and the lowest returns remains the same. Furthermore, the returns for both genders again follow an inverse U-shaped pattern for all levels, except the PhD.

Table 2.6: Private Rates of Return to Tertiary Education in Slovenia, Private Sector

	Males			Females		
	1994	2001	2008	1994	2001	2008
				Levels		
2-year UG	10.32	10.83	10.00	8.67	10.17	8.91
4-year UG	9.85	10.52	9.53	9.62	10.95	9.73
MSc/MA	10.59	15.51	14.44	14.84	21.06	18.29
PhD	0.61	3.44	7.46	16.22	6.74	5.72
				Fields (4-year UG)		
Education	3.23	2.33	$1.28^{(a)}$	$1.65^{(a)}$	$1.67^{(a)}$	$0.10^{(a)}$
Arts & Human.	9.14	7.09	4.55	8.61	8.66	7.04
Social Sci., Bus. & Law	11.95	11.13	9.49	10.64	11.69	10.20
Sci. & Math.	8.98	11.54	9.90	6.94	11.40	10.22
Eng. & Manufact.	8.32	9.80	9.48	7.70	9.06	8.92
Agricult. & Vet.	9.79	10.49	8.29	8.09	9.63	7.48
Health & Welfare	11.75	10.98	9.50	11.70	12.72	10.60

Note: $^{(a)}$ Coefficient in Mincerian regression is not statistically significant (see Table B.4).

Table 2.7: Private Annual Rates of Return to Tertiary Education in Slovenia based on Net Labor Income, 1994–2008

	Males			Females		
	1994	2001	2008	1994	2001	2008
				Levels		
2-year UG	9.66	11.41	9.90	7.71	11.07	10.01
4-year UG	10.53	11.63	10.05	10.00	11.70	10.24
MSc/MA	14.36	19.78	16.91	13.16	20.30	17.72
PhD	16.37	12.98	11.32	14.24	10.53	9.87
				Fields (4-year UG)		
Educ.	5.98	9.03	7.39	6.94	9.73	9.55
Arts & Human.	10.52	11.36	8.95	8.85	11.08	9.97
Social Sci., Bus. & Law	12.09	12.05	10.12	11.15	12.00	10.37
Sci. & Math.	10.29	12.06	10.11	8.51	11.63	10.54
Eng. & Manufact.	8.87	10.40	9.77	7.87	9.44	9.01
Agricult. & Vet.	9.69	10.34	8.20	8.00	9.74	8.17
Health & Welfare	11.37	14.50	11.61	9.99	12.57	9.85

Note: Estimated coefficients are presented in Table B.5.

2.5 Conclusions

The analysis of dynamics of rates of returns during transition revealed many interesting features. The most important finding is the pattern of an inverse U-shaped trend of rates of return to all levels of education due to gestation lags in adjustment of labor supply to labor demand. In spite of the growing supply of university graduates over the entire period of analysis, the strong demand led to increases in the rates of return during the period 1994–2001. However, the continued growth of labor supply in the subsequent period (2001–2008) was not matched by comparable increases in the labor demand, which resulted in the decline of rates of return.

We also document large differences in the rates of return between different levels of education, which is inconsistent with evidence of constant rates of returns to schooling for all levels of education in the US (Card, 1999). Moreover, we observe considerable heterogeneity in the rates of return to different fields of study. In the early transition, the consequences of socialist government interventions were reflected in the higher (lower) relative supply of favoured (neglected) fields of studies and consequently in lower (higher) rates of return. However, over the course of transition, the supply of neglected fields of study increased relative to the favoured fields, which led to lower heterogeneity of returns across fields of study.

In order to deal with potential biases in the estimates of rates of return, we extended our empirical estimations with a measure of general cognitive ability. The rates of return calculated with and without the ability measure confirmed the existence of an upward bias of less than one percentage point.

Finally, we also provided two robustness tests. On one hand, we compared the rates of return in the private sector with those of all employees and found little difference. On the other hand, we estimated the returns using the wider measure of labor income—net labor income that includes net wage and other sources of income—and found that an important part of private rates of return to university graduates arises from alternative income sources, especially for workers with MSc and PhD degrees, or degrees in Arts and Humanities.

3 DOES LOW FAMILY INCOME DETER COLLEGE STUDENTS FROM SUPPLYING LABOR?[29]

Abstract

This paper explores a relationship between non-labor income and labor supply of students. We find an inverse U-shaped relationship, which implies—counterintuitively—that students from poorer families, who typically receive lower transfers from their parents, tend to supply less work than students from more affluent families. We develop a theoretical model which builds on assumed DARA preferences of parents and on our empirical observation that students with the lowest non-labor income exhibit the highest drop-out rates (among students who failed to pass a study year). The model predicts that students from low-income families cut back work efforts in order to avoid probable future financial constraints. The latter arise from parents' unwillingness to make additional risky investments in children's education if they fail to pass a study year. We suggest that the positive relationship between non-labor income and labor supply for lower levels of non-labor income may be driven by these considerations.

Keywords: Student work, Family income, Financial constraints
JEL classification: J22, I23, D1

[29]This paper is coauthored with Sašo Polanec and Aljoša Feldin.

3.1 Introduction

One of the most commonly cited stylized facts on student labor supply decisions states that students from low-income families work more than their peers from more affluent economic background. Several studies explore this relationship (Bachmann and Boes, 2014; Dustmann et al., 2009; Gong, 2009; Kalenkoski and Pabilonia, 2010; Pabilonia, 2001) and show that such behavior is consistent with a negative effect of non-wage income on work hours predicted by the standard neoclassical theory of labor supply.[30] Parental transfers that increase with family income and act as non-labor income play the key intermediary role in students' labor supply decisions.

However, in several studies another interesting phenomenon was found that was thus far largely ignored. Namely, the relationship between family income and student work hours is not monotonically decreasing over the entire family-income range. In fact, Pabilonia (2001) reports that the US high school students with parents in the middle-income quartiles are more likely to work than those with parents in the lowest income quartiles after controlling for allowances received. Similarly, Beerkens et al. (2011) show that Estonian college students from more privileged families are as likely to work as students from poor families, whereas Wolff (2006) does not find a significant influence of parental transfers on child's labor supply for French school children. Using our own data set we find an inverse U-shaped relationship between family income and student labor supply.

In this paper we argue that the differences in the shape of the observed relationship may be attributed to two effects that work in the opposite directions. As mentioned above, the basic static labor supply model predicts a negative relationship between work hours and non-labor income. Moreover, if the costs of study are high, students from low-income families may not be able to finance their studies with family transfers and have to increase their labor supply in order to study. Although this probably is not the main reason for student work, since a cross-country comparison reveals lower student employment rates in countries with high tuition fees and vice versa (e.g., 41 percent for US students and 70 percent for German students), it suggests a negative relationship between student work and family income. However, when dynamic aspects of the labor supply decision are considered and the current financial constraint is not binding, poorer students may work less in order to avoid a tougher sanction in the future—a greater likelihood of drop out. Consequently, student labor supply as a function of family income increases for low-income students. Fewer studies find this relation, since it cannot always be observed. If the costs of studies are high, students cannot lower student work below the threshold, which enables them to cover the basic costs of living and study. In an extreme case with high tuition fees, students from the low end of income distribution are not even observed, as they cannot enroll to college. The data we analyze in this paper exhibit an inverse U-shaped relationship, which suggests that the effect of current financial constraint is weaker than the effect of expected tougher sanction for students with low non-labor income. This gives us an opportunity to analyze the neglected relation between family income and student work.

[30] The effect is negative if leisure is a normal good. Mocan and Altindag (2011), Imbens et al. (2001), and Holtz-Eakin et al. (1993) provide empirical evidence supporting this assumption.

We contribute to the existing literature on student labor supply decisions in two important ways. First, we show that among students who fail a study year, those with low non-labor income are more likely to drop out after controlling for relevant characteristics.[31] Second, we develop an empirically-motivated theoretical model of student labor supply decisions, which in agreement with existing literature additionally assumes that (i) the probability of passing a year decreases with student work[32] and that (ii) parental absolute risk aversion declines with wealth (Guiso and Paiella, 2008). The model predicts lower labor supply for students with lower income (due to a higher probability of a binding financial constraint in the future) than for students with higher income and a probable option to repeat a study year. Therefore, we can explain the upward sloping part of the observed inverse U-shaped relationship between student work and family income. Lower labor supply of students from low-income families (in comparison to students from middle-income families) is a rational response to more credible threat by their parents to stop investing in the risky asset (student's education) after failed study year. In other words, students with low non-labor income self-restraint in order to increase the probability of advancing to the next year and decrease the probability of dropping out of program after failing to pass a year, since parents will no longer be willing to pay for their education. For students from more affluent families the threat is less credible, as they are aware of parental decreasing absolute risk aversion, so they expect they will be able to repeat a study year with greater likelihood. For these students the income effect of parental transfers dominates and the downward sloping part of the inverse U-shaped relation between student work and family income is observed.

The reminder of the paper is organized as follows. Section 3.2 explains institutional framework for our empirical analysis. Section 3.3 describes the sources of data and construction of variables used in empirical analysis. Section 3.4 outlines the estimation method and presents our key results. Section 3.5 provides the empirical evidence and theoretical rationale for the observed behavior of students and Section 3.6 concludes.

3.2 Institutional Framework

Our empirical analysis examines the decisions of full-time undergraduate students at University of Ljubljana, the largest of the three Slovenian universities. The university is a public organization and does not charge tuition fees to full-time undergraduate students with domestic residence (HE Act, 2012). High-school graduates can enroll in its programs after completing any general or vocational four-year high school program. If the number of applicants exceeds the number of enrollment places, applicants are ranked according to a weighted average grade, calculated from the grade percentage

[31] Higher attrition rates for students from poor families are evident also for US college students. See Ozdagli and Trachter (2011) and Stinebrickner and Stinebrickner (2003a).

[32] Evidence suggests that student work decreases credit completion (Darolia, 2014) and GPA (Beerkens et al., 2011; DeSimone, 2008; Callender, 2008; Kalenkoski and Pabilonia, 2010; Auers et al., 2007, and Stinebrickner and Stinebrickner, 2003b). The negative effect of student work on academic performance is confirmed also in a separate paper analyzing a subsample of data presented here (Bartolj and Polanec, 2015). Darolia (2014) and Ehrenberg and Sherman (1987), however, do not find a negative effect of student work on GPA.

averages achieved in the third and fourth year of the high school study and a national exam called 'matura'.[33] Some programs also rank students based on examination of specific talents/abilities, grades from a specific subject achieved in the third and fourth year of the high school study, and/or grades from particular part of matura examination into the weighted average grade.

Students are entitled to free health care, subsidized meals, and traveling expenses. Those who live outside of Ljubljana have an option to live in subsidized housing, but due to the limited number of placements they have to fulfill certain criteria based on academic achievement, financial situation, and traveling distance to the university. In addition to generous subsidies, students are also eligible for an additional tax deduction and can work under different regulations than other employees.

Student work in Slovenia can be performed by students aged 15–26 years and are enrolled in any state-approved primary, vocational, high school, or undergraduate programs. Their work must be temporary and on a part-time basis. Each job is based on a referral, i.e. a student employment contract, from student employment agencies—organizations authorized to provide job placement services for students. These agencies charge concession fee defined as a percentage of students' earnings, which has to be paid by employers that hire students on top of students' salary.[34] The concession fee was rising over the years and was set to 14% of students' earnings at the end of the analyzed period (EIAU Act, 2006). In addition employers have to pay 20% value added tax on the concession fee. Therefore the total costs of student work for the employer in 2008 (the end of analyzed period) were 116.8% of student's earnings, but were lower in the previous years.

On the other hand, regular employment contracts are subject to social contributions[35] amounting to as much as 38.2 percent of gross wage. Employer also has to pay a bonus for working the night shifts, on Sundays, on holidays, for overtime work, seniority bonus, and bonus for job performance. In addition, employer has to cover employees' costs for meals during work and transportation costs (SSC Act, 2001). During the period of analysis gross wages were also subject to a progressive payroll tax. Furthermore, if an employer terminates the employment contract due to business reasons or due to employee's incompetence, the employee is entitled to severance pay.

The rigid regulations governing regular employment contracts and loose regulations for student employment contracts made student work extremely competitive. Consequently, the demand for student labor is strong. In 2008, when there were 114,391 students in all types of tertiary education, 927,809 student employment contracts and 54,363,336 hours of student work were realized.[36] The amount of student work was therefore equivalent to approximately 26,000 full-time employments, while there were roughly 871,000 employed and 67,000 unemployed persons in the same year.

[33]This is a Slovene equivalent of the SAT in the US, which is also taken by high-school students in other central European countries, such as Austria, Switzerland, and Italy. The matura consists of three compulsory (Slovene language, Mathematics, and one foreign language—usually English) and two elective subjects (e.g. Biology, History, Physics, etc.).

[34]The concession fee is used to cover the costs of job placement organization, students' scholarships, student organizations (unions), and renovation and building of student dormitories (EIAU Act, 2006, Act RACD, 2003).

[35]We distinguish four different types of contributions: retirement, health, unemployment, and maternity leave.

[36]In addition, there were 463,391 high school student employment contracts with 29,895,280 hours of work.

Another important aspect of Slovenian institutional context that could be relevant for students labor supply decisions are social transfers. Unconditional transfers could in principle have negative effect due to pure income effect, whereas conditional transfers could exhibit high effective taxation and reduce labor supply due to low net income related to student work. During the period of analysis a person could have been entitled to three types of social transfers that could affect student work choices: (i) child benefit, (ii) social assistance, and (iii) state scholarship. Below we describe in turn each one of them and explain how student work income affects their eligibility and family income per member. It should be noted that our analysis includes only students with income per family member above 1,800 EUR per year in 2004 constant prices.

The amount of child benefit depends on the ratio of income per family member to the average wage of Slovenian worker and the number of children in the family. The smaller is the share and the more children there are in the family, the higher is the child benefit. The family income is constructed as a sum of incomes received by all family members, including those earned by students. However, even for those with the lowest incomes in our sample, it pays to earn at least the amount equal to additional student tax deduction, since an increase in the family income per capita offsets the reduction in child benefit.[37] This additional tax deduction amounts to as much as 51 percent of the average annual gross wage and could affect behavior of only small proportion of students, who earned annual incomes exceeding 5,600 EUR.

Social assistance is also contingent on the level of income per family member, which in addition to other types of income also includes student earnings. However, our sample restriction to include only students with income per family member above 1,800 EUR drops the families eligible for financial social assistance. In contrast to the other two mentioned transfers, family income (which is a basis for means test) for state scholarship does not include student earnings below the value of additional student tax deduction. In summary, the rules governing the payments of social transfers were such that the vast majority of students was not affected. Hence, as we show below and discuss in more detail, these rules could not have affected students' labor supply decisions to feature the inverse U-shaped relationship between the family income per family member and student work.

3.3 Data

3.3.1 Data Sources

We study labor supply decisions of a sample of students who were enrolled in the undergraduate programs at University of Ljubljana between 1997 and 2008. For this purpose we merged individual-level data from several sources. The key source that permits our analysis is the Slovenian Tax

[37]For example, in 2007 a family with one child and annual family income per member equal to 1,800 EUR (without this benefit) gets 2,094 EUR per family member when child benefit is taken into account. However, if this child earns 2,800 EUR with student work, this additional work does not increase taxes and raises family income per member to 2,985 EUR despite the drop in child benefit.

Administration (henceforth TARS). It provides information on personal incomes earned by students and their parents. While students with sufficiently low earnings are typically not obliged to fill an income tax report, the student employment agencies have a legal obligation to report the total income received by all working students. In addition to student incomes, TARS is also the source of data for incomes of students' families. Tax fillings for personal income tax include both labor and capital incomes. Labor incomes comprise wages and salaries, bonuses, perks, wages earned on the basis of short-term labor contracts, and royalties. Capital incomes include interest, dividends, rents, and incomes of sole proprietors.

The second source of data are application sheets for all enrolled students in the undergraduate programs at University of Ljubljana. From this source we use information on age, gender, location of permanent residence, chosen major, and study year of students. Based on enrollment history of each student, we also construct a variable indicating if student passed a year from observing repeated enrollment, and a variable indicating if student dropped out of program when student is not enrolled in program in a following years.

The third source of data is the National Examination Center (henceforth NEC), which collects the data on students' high-school performance. From this source of data we use information on the third- and fourth-year average grades and the average GPA from the final (external) examination called *matura*.[38] The matura is a national exam with the same rules for all candidates. The written part of the exam is prepared and assessed externally. As the matura examination is anonymized, it may be considered as an objective measure of ability, whereas the average grade in the last two years of high-school study is a measure of performance/ability over a longer time span. The combined measure reduces the specific problems related to either of the two measures. For instance, the external examination is a one-off test, which may be influenced by idiosyncratic events ('the bad day effect'), while the high school average grade may not be entirely comparable due to variation in the grading policies across schools.

The fourth source of data is the Slovenian Statistical Office (henceforth SORS). From SORS we obtained the data from Central Registry of Population, which allows us to establish links between parents and students using unique personal identifiers. These links allow us to determine family incomes and parental educational attainment. Finally, SORS provided information on all scholarships received by students, ranging from social scholarships targeted to students with low-income families, scholarships for talented individuals (Zois scholarships), and firms' scholarships. All these data sets were merged in a safe room at SORS using aforementioned unique personal identifiers.

[38]We have data on high school performance of students that passed general matura, which enables enrollment in all programs of tertiary education. We do not use data on vocational matura, which is by itself not sufficient for enrollment to university courses, as student have to additionally pass one subject of general matura in order to be able to enroll to university courses.

3.3.2 Description of Variables and Summary Statistics

In this subsection we provide the definitions of variables that are considered in the empirical model of student labor supply choices and key summary statistics. Before we turn to these, we provide some information on the sample used in the analysis.

Our sample consists of students who were enrolled in programs with different duration of studies. In particular, the majority of programs have a statutory five years of study, while others may last longer. In order to have representative sample of students that covers all faculties, we omitted only the data for students in the fifth year (if this was not the final year of study that is intended for writing bachelor thesis) and the sixth year of study. The number of observations in our final sample is presented in Table 3.1. While attrition rates are not negligible, the total difference between the number of observations in the first year of study (63,503) and the final year of study (35,676) should not be attributed solely to attrition, as we do not observe all students in all years of study, but only students enrolled during the period 1997–2008.[39] The share of females is 59.2, 63.6, and 67.1 percent in the first, second to fourth, and final year of study, respectively.

Table 3.1: Sample Size by Year of Study and Gender

	1st Year	2nd to 4th Year	Final Year
Number of observations	63,503	111,624	35,676
Males	25,891	40,635	11,723
Females	37,612	70,989	23,953

Let us now turn to the variables in our empirical model of student work. We use two measures of student work: (i) an indicator variable for student work and (ii) a continuous variable that measures the amount of work. Unfortunately, we cannot measure the number of working hours as TARS collects only information on the total annual income earned by students. Looking at the summary statistics for the indicator variable (see Table 3.2), we can observe that Slovenian students are highly likely to supply labor. Already in the first year of study as much as 82.5 percent of students work and yet this share increases with year of study. In the final year of study only 5 percent of them abstain from the labor market. The amount of work performed by these students is also high and like the share of working students, their earnings are increasing with year of study. Due to the high personal income tax deduction for student workers, the majority of students pay no labor income tax, which results in very similar averages of gross and net incomes (1,452 and 1,450 in the first year of study, respectively). The difference in earnings between the first and the final year of study is comparable to an average monthly net wage of full-time employees. Such behavior of students may be attributed to two likely explanations—students in higher years of study need less time for studying/study more efficiently and have therefore more time for work or, alternatively, students believe that work experiences in the last years of study are more important for finding a future employer and devote more time to work.[40]

[39] Some students were still enrolled in undergraduate program by the end of the analyzed period.

[40] Another possible explanation could be that hourly wage increases with years of study. We investigated this possibility using the data provided by one of the student employment agencies (e-Študentski servis) that

Further insights on the distributions of labor incomes of students by year of study and gender can be found in Figure C.1. First note that males are slightly less likely to work, although for those who do, the distribution is shifted to the right of that for females. According to empirical evidence that females are more risk averse than males (see, for example, Jianakoplos and Bernasek, 1998; Watson and McNaughton, 2007; Borghans et al., 2009), one might expect that females would be less likely to work and conditional on working earn lower income. However, since additional risk associated with a modest amount of work is negligible and additional work experience might help a person to find a job, one may interpret such labor supply decisions of females as less risk averse. Figure C.1 further reveals that the share of those who are working increases with the year of study and that the participation rate not only increases with the years of study, but also with school years (see Figure C.2), although the 2008 financial crisis significantly affected earnings of students, shifting their distribution to the left.

As our aim is to explore the relationship between student non-labor income and different margins of student labor supply, we start the description of explanatory variables with different measures of income. Non-labor income consists of all types of incomes received by students that are not related to work, among which parental transfers are typically the most important category. Calculation of student non-labor income can be problematic as our administrative sources of data do not contain information on actual parental transfers to students. On the other hand, survey data usually fail to include some parts of non-labor income and focus on parental transfers. Existing survey-based empirical analyses find that parental income has a positive effect on parental transfers (see, for example, Kalenkoski and Pabilonia, 2010; Dustmann et al., 2009). Therefore, as long as we can rely on empirical evidence that transfers are a monotonic function of family income and do not depend on students' earnings (as also shown by Kalenkoski and Pabilonia, 2010 and Dustmann et al., 2009), we can use family income per family member as a proxy for parental transfers. So, we calculate non-labor income as a sum of (i) net family income per family member, which is constructed as the sum of parental net income divided by the number of family members,[41] and serves as a proxy for parental transfer, (ii) scholarships, and (iii) pension received after deceased parents.

Table 3.2 shows the average values of non-labor income of students by year of study. It is evident that the average non-labor income increases with year of study, which may be partly attributed to growth of average labor incomes in the economy during the period of analysis and partly to higher attrition rates among low-income families. Since students might supply different amounts of work if their non-labor income depends on academic success, we construct a variable conditional-income share that measures a share of scholarships and pensions in their non-labor income.[42] The shares

allows us to distinguish between hourly wages and working hours. The data indeed reveal that hourly wages of students in the final year of study were higher than those in the earlier years of study. For example, in 2005 students in the final year earned on average 13 percent higher hourly wage than those enrolled in the first year of study, whereas in 2007 this difference declined to only 6 percent. These differences are, however, too small to account for the entire increase of an average student's earnings between the first and the final year of study.

[41]Family members comprise parents and children under the age of 27 to be consistent with the definition in the Income Tax Act that defines a dependent family member every person up to the age of 26.

[42]Children have a right to receive a pension after their deceased parent until the end of their schooling or until they are 26 years old. Therefore students who are not enrolled in a program lose pension. Similarly,

of income contingent on academic results are 14.3, 18.2, and 14.5 percent in the first, second to fourth, and final year of study, respectively. Another important dimension of non-labor incomes of students is how uncertain they are. Labor and capital incomes differ in terms of uncertainty—the latter tend to be less persistent and more volatile. High share of incomes that arise from capital thus imply that parental transfers may be more uncertain and rational students who are aware of the source of income might decide to work more in order to self-insure against the risk. We define stochastic income as a sum of incomes derived from self-employment (sole proprietorship), profits from ownership of shares and other holdings, investment coupons, incomes from rents, and other irregular incomes such as bonuses, one-off solidarity assistance etc. These incomes represent around 3 percent of non-labor income in all years of study, which suggests that for an average student this is not an important source of financing.

The final measure in the group of variables measuring incomes is the expected net income after graduation. Students enrolled in programs that may expect lower income after graduation may be more inclined to risk not passing a year or even not graduate. Thus, higher expected net wage works as an incentive to finish studies as soon as possible and supply less work. A comparison between expected net wage and net student work income shows, that students on average earn 9.9 percent of their expected net wage in the first year of study, while this percentage increases to 17.3 in the final year of study.

The third set of statistics in Table 3.2 shows average age, an indicator variable for students who are themselves parents, and a measure of ability based on grades achieved in high school. The average age for each study year reflects for how many years students prolonged their studies. For example, students prolong their studies by one year as the average age in the final year (24) exceeds the age of a student, who would start her studies as a 19-year-old (which is the average age in the first year of study) and continue her studies without interruptions, by approximately one year. Student parent is a binary variable indicating if a student has a child. Although the percentage of parents among students is low (3 percent in the final year of study), we include this variable in our empirical analysis, since having a child significantly affects the time and budget constraints. The high school GPA variable in a group of personal characteristics is a proxy for general ability. We construct it as a normalized unweighted average of (i) the average grade achieved at matura examination, and (ii) the average grade in the last two years of high school. The average high school GPA in the second to fourth year of study (0.518) exceeds its average in the first year of study (0.457), suggesting that students with lower ability are more likely to drop out of college.

Next set of variables measures different aspects of students' family characteristics such as parental educational attainment, presence of step parents, and ownership of family business. For parental educational attainment we construct a binary indicator variable that assumes value 1 if a parent has completed university degree or higher and 0 otherwise. The average values of these variables (Table 3.2) show that the share of parents who completed university degree is roughly 20 percent, with slightly lower share for mothers and higher shares for students in senior years. We also construct indicator variables for students who have at least one step parent and students whose parents own

the amount and eligibility for scholarships depend on academic performance.

a family business. In our sample the share of students with step parents is around 25 percent, although it appears that students with step parents are slightly less frequent in senior years of study. The share of students with at least one parent with family business is around 15.5 percent in the first year and 13.9 percent in the final year. These numbers also suggest that students with family business are less likely to complete studies. The last variable in the fourth set of variables is the number of siblings who are below 27-years of age. We observe that number of siblings declines with years of study.

The last set of variables used in the analysis are indicator variables that capture history of study performance and the average additional years of study above the standard 5 statutory years of study. The measures of study performance are the indicator variables that assume value 1 if students repeat current or past year of study. These measures capture the effect of less time needed for studies by students who repeat current year of study as they may have less remaining exams to pass in order to pass a year and thus could supply more labor. Similarly, students who repeated previous year of study could decide to pass some of the exams for the current year of study and thus reduce the number of exams needed to pass a year, so they could also supply more labor. It is evident from Table 3.2 that the share of students who repeat a given year of study exhibits a U-shaped pattern. The share of students who repeat the first year is 12.9 percent, the share of students who repeat the second to fourth years of study is 7.2 percent, whereas the share of repetitions among the final year students is as high as 28.3 percent. The variable additional years of study measures the average number of years to completion of study minus the statutory remaining years of study.[43] Students enrolled in programs with longer duration may supply less work as they face greater risks of not completing studies. The average numbers suggests that students with longer studies represent an important fraction of all students.

The structures of sample by region and faculty are presented in Table C.1 and Table C.2, respectively. The majority of students comes from Osrednjeslovenska region, which is not only the biggest region, but also the region in which University of Ljubljana is located. The largest number of students enrolled at University of Ljubljana[44] study at the Faculty of Arts and Humanities. Although only 7[45] out of 19 faculties are from the (wider) social science field, they enroll more than half of students.

[43]For example, students whose studies take 5 years plus an additional year for writing thesis, have additional years variable equal to 1.

[44]We exclude academies, Faculty of maritime studies and transport, which is not located in Ljubljana, and faculties that did not exist in the present form throughout the entire analyzed period, such as Faculty of social work.

[45]Faculty of Arts of Humanities, Faculty of Economics, Faculty of Law, Faculty of Social Sciences, Faculty of Sports, Faculty of Education, and Faculty of Theology.

Table 3.2: Summary Statistics

	1st Year		2nd to 4th Year		Final Year	
	Mean	Sd	Mean	Sd	Mean	Sd
Probability of working	0.825	0.380	0.895	0.306	0.945	0.228
Gross student work income	1,452	1,600	1,824	1,757	2,562	2,169
Net student work income	1,450	1,589	1,820	1,738	2,545	2,119
Non-labor income	6,223	3,558	7,093	4,238	7,364	4,920
Conditional-income share	0.143	0.234	0.182	0.249	0.145	0.237
Stochastic-income share	0.028	0.070	0.031	0.074	0.036	0.078
Expected net wage	14,637	2,987	14,862	3,071	14,693	2,615
Age	19.203	0.728	21.344	1.293	24.028	1.167
Student parent	0.002	0.049	0.007	0.101	0.030	0.218
High school GPA	0.457	0.219	0.518	0.210	0.513	0.199
University or higher—mum	0.188	0.391	0.210	0.407	0.200	0.400
University or higher—dad	0.203	0.403	0.223	0.416	0.215	0.411
Step parent	0.270	0.444	0.257	0.437	0.262	0.440
Family business	0.155	0.362	0.152	0.359	0.139	0.346
No. of siblings	1.092	0.832	1.001	0.858	0.788	0.826
Repeating a year	0.129	0.335	0.072	0.258	0.283	0.450
Repeated previous year	0.007	0.083	0.158	0.364	0.028	0.164
Additional years	0.180	0.384	0.197	0.398	0.000	0.000
School year	2,001.9	3.0	2,003.5	2.8	2,005.1	2.1

Notes: All income-related variables are in constant (2004) Euros. The exchange rate in 2004 was 1 EUR = 1.24 USD. High school GPA is the average grade achieved in 'matura' exam and the mean grade of the third and fourth year of high school study. Additional years indicate if student has more than 4 years of regular study.

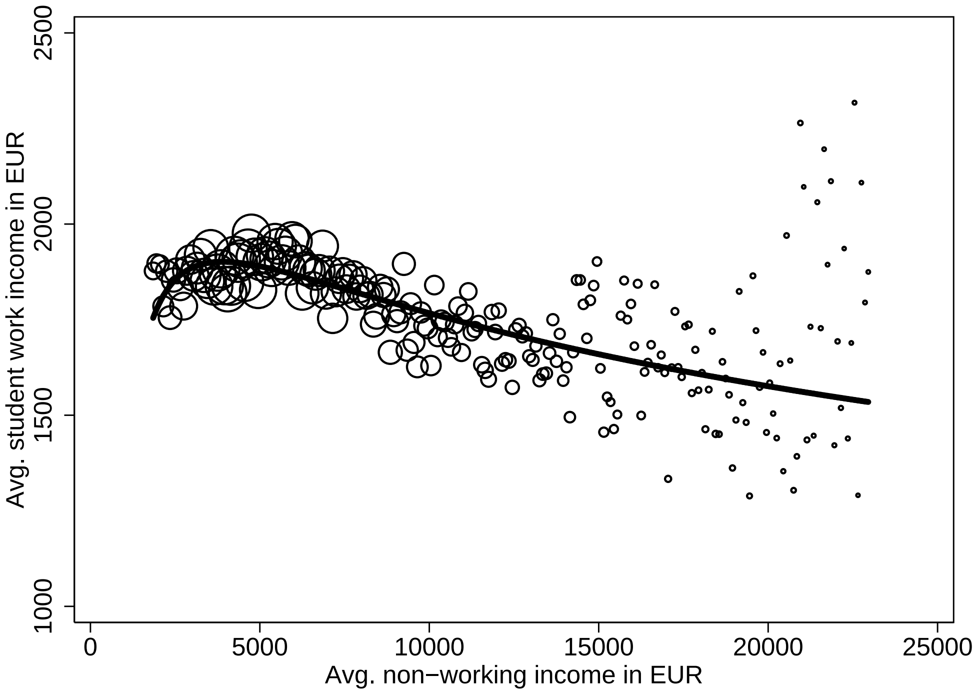
3.4 Empirical Analysis

3.4.1 Unconditional Relationship between Labor Supply and Non-Working Income

Figure 3.1 shows the inverse U-shaped relationship between average student income and average non-labor income. Note that the areas of symbols are proportional to the frequency of students with specific values of non-labor income. Contrary to what is usually observed in the literature, students with the lowest non-labor income are not the ones who work the most—at low values of non-labor income, the average student earnings increase with the amount of non-labor income, whereas at high values additional non-working income reduces the average student earnings. In fact, we observe surprisingly small differences in earnings among students with different economic backgrounds as the average labor income of students with different values of family income ranges between 1,500 and 2,000 EUR, which suggests that the effects of financial constraints and income effect are not very large and tend to be either dominated or off-set by alternative effects that are also at work.

The average earnings of students shown in Figure 3.1 reflect two decisions made by students: (i) decision to work and (ii) decision on the amount of work. Figure 3.2 decomposes the average earnings in the probability work and the average income conditional on working. Figure shows that the observed positive relationship is mainly driven by the differences in the probability of work among students with different non-labor incomes. For example, in the first year of study the probability of work of those with non-labor incomes below 3,000 EUR is around 80 percent, whereas the probability of work of those with income between 5,000 and 6,000 EUR is 85 percent. In more senior years of study the range with positive relationship is still observed, although the size of this effect appears to be much weaker. The relationship between average income, conditional on working, is flat over a large range of values.

Figure 3.1: Unconditional Relationship Between Student Earnings and Non-labor Income

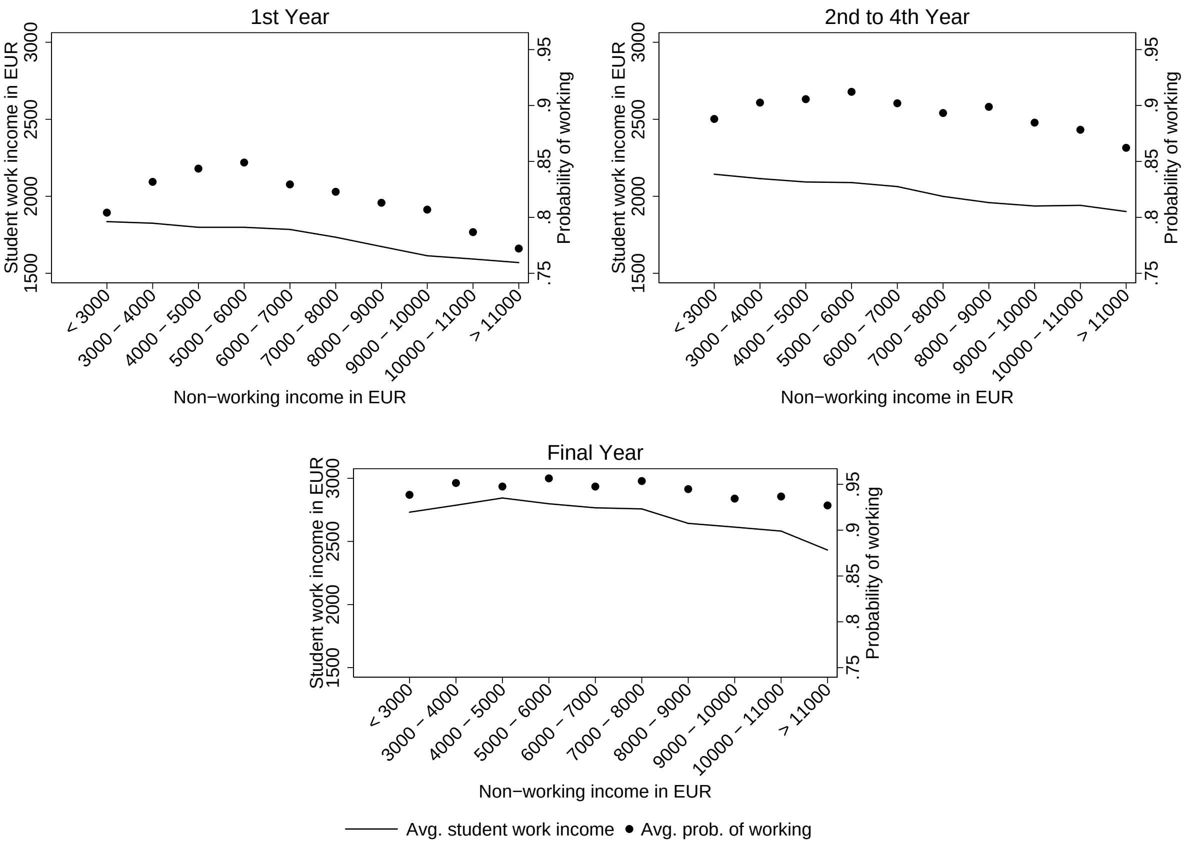


Notes: Students without earnings are included by setting their income to zero. Areas of symbols are proportional to frequency of students with a specific value of non-working income. Symbols with frequency lower than 10 were deleted. Values are in constant (2004) Euros.

3.4.2 Estimation Method and Results

The evidence on the inverse U-shaped relationship between student work and non-labor income presented thus far was unconditional. Hence one could easily argue that it is driven by other variables that may also determine students decisions. Hence we proceed with estimation of an empirical model for two joint decisions: (i) decision to work and (ii) decision on the amount of work. These two decisions are likely to be correlated and as a consequences the error terms of two modeling equations may be correlated as well. A method that allows for such correlation between the error terms is the Heckman's selection model (Heckman, 1979). The estimates of this model can be obtained using the two-stage estimation procedure. In the first stage we estimate the equation

Figure 3.2: Probability of Work and Earnings Conditional on Working, by Non-labor Income and Year of Study



Note: Values are in constant (2004) Euros.

for self-selection into work:

$$Pr(y_{1i} = 1) = Pr(x'_{1i}\beta_1 + \epsilon_{1i} > 0) \tag{3.1}$$

where y_1 is an indicator variable that assumes value 1 if student works and 0 otherwise, x'_{1i} denotes a set of explanatory variables (that are discussed above in the description of variables) and indicator variables for faculties, school years, and regions, and β_1 is a vector of corresponding regression coefficients. We estimate this equation using the standard probit regression, which assumes that the probability function is the cumulative distribution function of the standard normal distribution, i.e. $\Pr(.) = \Phi(.)$. In the second stage, we estimate the equation for student earnings in logs (y_2):

$$y_{2i} = x'_{2i}\beta_2 + \sigma_{12}\lambda(x'_{1i}\hat{\beta}_1) + \epsilon_{2i} \tag{3.2}$$

where x'_{2i} is the same set of explanatory variables as in vector x'_{1i} with corresponding coefficients β_2, $\hat{\beta}_1$ denotes the vector of estimated coefficients from the first stage probit regression, and $\lambda(x'_{1i}\hat{\beta}_1) = \frac{\phi(x'_{1i}\hat{\beta}_1)}{\Phi(x'_{1i}\hat{\beta}_1)}$ is the estimated inverse Mills ratio. Equation (3.2) is estimated with OLS using only positive values of y_2.

The Heckman selection model is a non-linear model and consequently the estimates of coefficients differ from the estimates of marginal effects. As we are primarily interested in the marginal effects, we omit the estimated coefficients from presentation. Tables 3.3 and C.3 show the marginal effects for key explanatory variables on the probability of work and log of student earnings. Note that we introduce the non-labor income in equations (3.1) and (3.2) in a discretized form, i.e. an indicator variable for each income bracket. However, in order to avoid perfect multicollinearity, one of the indicator variables cannot be included in estimations—we eliminate the indicator variable for the lowest non-labor income. Hence the interpretation of the estimated marginal effects for higher income groups is relative to these lowest levels of income. The results show (Table 3.3) that after controlling for other relevant variables, such as ability, age, and family characteristics, students with the worst economic background have the lowest probability of work. In fact, the relationship between probability of work and non-working income is still inversely U-shaped for all years of study. For example, students in the first year of study with non-working income between 3,000 and 4,000 EUR have 2.8 percentage points higher probability of work (ceteris paribus) than those with a non-labor income below 3,000 EUR. The marginal effects then increase with non-labor income and peak for those with non-labor income between 5,000 and 6,000 EUR. While for students with non-labor income up to 10,000 EUR the likelihood of work is 4 to 5 percentage points higher than that for those with lowest non-labor income, the probability of work for the wealthiest students exceeds the likelihood of the worse-off students by 2.6 percentage points. Comparison of marginal effects between study years shows that the importance of non-working income for determination of decision to work diminishes. Marginal effects for every non-working income bracket are the highest in the first year and the smallest in the final year of study.

Marginal effects of non-labor income on the logarithm of earnings are mainly statistically insignificant with couple of exceptions. First-year working students with non-labor between 5,000 and 6,000 EUR earn 5.3 percent higher income than those with the non-labor income below 3,000 EUR, whereas students with non-labor income exceeding 11,000 EUR had 13.3 percent lower earnings. Moreover, although insignificant, the estimates of marginal effects suggest an inverse U-shaped relationship. Thus, based on overall results we can clearly reject the widely-held belief that the students with low non-labor income work more.

Although these effects of non-labor income on student labor supply appear relatively small in size, we should point out that we measure the net effects of different effects that link the two variables. Namely, if the effect that works in the opposite direction to pure-income effect—the effect of future financial constraints—would not be present, students from low-income families could have worked much more than the student from medium income families. This suggests that the total effect related to the alternative mechanism we discuss below could be much larger than the measured net effect.

Before we turn to discussion of marginal effects of other variables, we should address some additional concerns regarding our explanation of the observed relationship between non-labor income and student work. One of the possible explanations for observed behavior is that demand for labor varies with family income per capita. In other words, if demand for student labor was not perfectly elastic, one of the possible selection mechanisms could be through parental social networks. We provide two reasons why we believe this is not the case. Our estimates of marginal effects are conditional on several variables that could control for better social networks and greater demand such as location of permanent residence, parental educational attainment, and ownership of firms. For example, students from Ljubljana could have better information about labor demand in Ljubljana than commuting students. The fact that the size of marginal effects is comparable to the unconditional differences in, say, probability of work, suggest that observed variation is not driven by heterogeneity of demand for labor of students with different non-labor incomes. Moreover, the data show that in 2008 there were 114,391 students enrolled in all types of tertiary education and 927,809 student-employment contracts issued on the basis of which payments were made to students.[46] In other words, there were approximately 8.1 employment contracts per student. Although one student can have more than one employment contract, we believe that it is reasonable to assume that students could work if they choose so.

Another concern regarding our findings is related to the fact that we discuss labor supply decisions based on total earnings rather than on hours of work. If students with the lowest non-working income are less likely to get a well-paid job than those who are better-off, they might still be working more, but the observed earnings would not differ or would even be lower for those with lower non-labor income. In Table C.4 we show that only students with non-working income above 11,000 EUR earn statistically significantly higher hourly wages than those with the lowest non-labor income. This evidence suggests that the observed inverse U-shaped relationship between non-labor income and earnings is also valid for the relationship between hours of work and non-labor income. We turn to the explanation of these results in Section 3.5.

Table C.3 presents the marginal effects for other variables included in our empirical model. Students in our sample seem to respond strongly to incomes that are contingent upon academic performance (conditional-income share). Students, who do not pass a study year successfully may not be entitled to receive non-labor incomes such as state scholarships and pensions. The higher is the share of these incomes, the lower are the probability of work and the average income of working students. For example, if the share of these incomes increases from 0 to 50 percent, first-year students are 5 percentage points less likely to supply labor and are expected to earn roughly 15 percent lower income. These effects are stronger in the earlier years of study, which is consistent with the fact that students face lower risks due to better time management (greater ability to prepare for exams) and smaller number of years of lost benefits towards the end of study. Such behavior suggests that students make their labor supply choices in a manner that is consistent with the proposed mechanism of our theoretical explanation for the inversely U-shaped relationship between non-labor income and student labor supply.

The results also suggest that more able students, measured with high school GPA and parental educational attainment (university degree or higher), supply less labor. Although high-ability students could, in principle, afford to study less and supply more labor, students in our sample appear more interested in coursework, may better understand risks regarding passing a year, and may not

[46] The data on the number of student employment contracts are attained from Ministry of labor, family, social affairs and equal opportunities. The source of information on total number of students is SORS.

be willing to risk not completing studies. The importance of time constraint for determination of student work is also apparent. Students who are themselves parents may be engaged in nursing children and thus have less time to supply labor. On the other hand, students who repeat a year may have less tight time constraint as they may have passed some of the exams already. Both variables related to failing a year of study suggest that students indeed respond in this way. We also find that family business positively affects labor supply of students, which is an indication that these students may be better positioned in the labor market and can work greater number of hours.[47] As in Figure C.1, we observe that females work with higher probability, but those who work earn as much as males. The share of stochastic income in non-labor income decreases the likelihood of working, but those who do work, earn more. The opposite pattern is observed for the effect of number of student's siblings as more siblings leads to higher likelihood of labor supply and smaller earnings among the working students. The effect of expected net wage on student labor supply is positive, although small or even statistically insignificant. The effect of age varies between study years: older students tend to supply more labor in the first year of studies, whereas those in the final year supply less labor.

[47] An alternative explanation for such behavior is that parents with family business used student employment contracts to avoid taxes.

Table 3.3: Marginal Effects for Heckman Selection Model: Non-labor Income

	1st Year		2nd to 4th Year		Final Year	
Non-labor income	Pr[Employed]	Log Income	Pr[Employed]	Log Income	Pr[Employed]	Log Income
3,000–4,000	0.028**	0.033	0.011*	0.004	0.012*	0.010
	(0.006)	(0.022)	(0.005)	(0.017)	(0.005)	(0.031)
4,000–5,000	0.043**	0.036	0.016**	0.003	0.008	0.028
	(0.006)	(0.021)	(0.005)	(0.017)	(0.005)	(0.031)
5,000–6,000	0.052**	0.053*	0.026**	0.009	0.020**	0.042
	(0.006)	(0.022)	(0.005)	(0.017)	(0.005)	(0.030)
6,000–7,000	0.041**	0.034	0.023**	0.002	0.013*	0.035
	(0.007)	(0.025)	(0.005)	(0.019)	(0.006)	(0.033)
7,000-8,000	0.042**	0.038	0.021**	−0.007	0.020**	0.057
	(0.007)	(0.027)	(0.005)	(0.020)	(0.006)	(0.034)
8,000–9,000	0.044**	0.009	0.030**	−0.005	0.015*	−0.001
	(0.008)	(0.031)	(0.005)	(0.021)	(0.006)	(0.035)
9,000–10,000	0.046**	−0.014	0.022**	−0.001	0.008	−0.021
	(0.009)	(0.036)	(0.006)	(0.024)	(0.007)	(0.037)
10,000–11,000	0.031**	−0.028	0.020**	−0.002	0.010	0.033
	(0.010)	(0.043)	(0.006)	(0.026)	(0.007)	(0.045)
above 11,000	0.026**	−0.133**	0.015**	−0.061**	0.010	−0.052
	(0.008)	(0.033)	(0.005)	(0.021)	(0.006)	(0.034)

Notes: Standard errors are reported in parentheses. Dummy variable for non-working income below 3000 is omitted. ** p-value $<$ 0.01, * p-value $<$ 0.05.

3.4.3 Robustness Test: Incomes Supplemented with Social Transfers

Social transfers in Slovenia can represent an important part of family income and thus student's non-labor income. A first concern regarding social transfers is their potential to discourage students from working in order to retain state aid. Since students with low non-working income are more likely to receive social transfers, this could explain the observed relation between student work and non-labor income. But as explained in Section 3.2 this cannot be the case as (i) students' families included in our sample are not eligible for a transfer, (ii) student work does not affect the requirements for acquisition of a transfer, or (iii) the construction of a transfer encourages at least some work. Social transfers therefore cannot justify the inverse U-shaped pattern of probability of work.

Nevertheless, in the extreme case, social transfers might move student to a higher non-working income bracket. This would distort the interpretation of the results presented in the previous section, which due to data limitations do not take social transfers into account. In this section, we present estimation results with and without social transfers, but pooled over all years of study to preserve space. The subsample which includes social transfers, is available for period from 2002 to 2004 and has 44,734 observations (16,550 males and 28,184 females). The summary statistics are presented in Table C.5. When social transfers are included, the average non-working income increases from 6,372 to 6,469 EUR, whereas conditional- and stochastic-income share drop from 0.161 and 0.029 to 0.155 and 0.028, respectively.

The estimated marginal effects of the Heckman selection model with and without social transfers are compared in Table C.6. The differences in the estimated marginal effects are minimal, which suggests the results shown in previous section are not sensitive to inclusion of social transfers. Moreover, we can observe that in the results pooled over the study years, the inverse U-shaped relationship between labor supply and non-working income becomes evident also in the equation for earnings.

3.5 An Explanation of Observed Behavior of Students

In this section we provide an explanation for the observed labor supply decisions made by Slovenian students. We start this section by laying out empirical evidence that shows that among students who fail a study year, the probability of dropping out of college decreases with non-labor income. We argue that such behavior may be a consequence of parental unwillingness to provide additional transfers to their children in order to continue studying. Such behavior of parents is consistent with the empirically observed shape of utility functions, which exhibit a decreasing absolute risk aversion (DARA) (see Guiso and Paiella, 2008 and Chiappori and Paiella, 2011). DARA preferences imply that willingness to bear risk in terms of absolute value of wealth decline with wealth.

Our empirical findings motivate a simple theoretical model of student's decisions, which assumes DARA parental utility and an increasing relationship between probability of failing a year and student work. Theoretical results show, that the optimal level of student work increases with non-labor income, as long as the threat of no further investment in education for poorer students is credible. In other words, students cut back work efforts in order to avoid future financial constraints and inability to complete studies. The credibility of the threat declines with family income per capita as students are aware of greater willingness to bear risk by their parents. This dynamic mechanism thus predicts a positive relationship between non-labor income and labor supply—the observed upward-sloping part of the relationship between student work and non-labor income. When this effect is combined with the static model of labor supply, which predicts a negative relationship between non-labor income and labor supply, we get an inverse U-shaped relationship. In what follows we only provide theoretical explanation for an upward-sloping part of the relationship as the downward-sloping part is well understood.

3.5.1 Empirical Evidence

In order to analyze the relationship between dropping out of college and non-labor income, we construct a subsample of individuals who failed to pass a study year. As Table C.7 shows, there were 19,896 (10,981) students who failed to pass the first (second to fourth) year of study. While there are roughly 60 percent of females in the full sample, among those who fail a study year, females present approximately 50 percent, suggesting that males have higher probability of failing a year than females. Students in subsample have on average a bit higher probability of working and student work income in the first year of study than those in the full sample. The averages are approximately the same in the second to fourth year of study (see Table C.8). In addition, we observe lower high school GPA and conditional income share for students who fail a study year compared to all students.

The variable of interest is an indicator variable equal to 1 if student dropped out of program after failing to pass a year and 0 if student enrolled again in the same year of study. A descriptive relationship between drop-out rate and non-labor income is presented in Figure C.3, where a sharp drop in average probability of dropping out is observed as the average non-working income increases from its lowest points. In order to control for student characteristics, we also estimate a logit model for the probability of dropping out for the sample of students who failed to pass a year. Tables 3.4 and C.9 present the marginal effects (evaluated at the mean values for continuous variables). These estimates confirm the descriptive evidence, as the probability of dropping out decreases with non-labor income by as much as 10 percentage points.

3.5.2 A Theoretical Model

Let $x \in [0, \overline{x}]$ denote student's yearly earnings from work with $\overline{x}$ being the upper bound on the amount. We assume that the probability that student fails a year is positively correlated with

Table 3.4: Marginal Effects for Probability of Dropping Out for Students Who Failed to Pass a Year: Non-labor income

Non-labor income	1st Year	2nd to 4th Year
3,000–4,000	−0.043**	−0.025
	(0.012)	(0.017)
4,000–5,000	−0.064**	−0.067**
	(0.012)	(0.016)
5,000–6,000	−0.067**	−0.081**
	(0.013)	(0.017)
6,000–7,000	−0.059**	−0.049**
	(0.014)	(0.017)
7,000–8,000	−0.064**	−0.076**
	(0.016)	(0.019)
8,000–9,000	−0.055**	−0.101**
	(0.018)	(0.021)
9,000–10,000	−0.089**	−0.095**
	(0.021)	(0.024)
10,000–11,000	−0.027	−0.097**
	(0.025)	(0.026)
above 11,000	−0.055**	−0.089**
	(0.020)	(0.022)

Notes: Standard errors are reported in parentheses. Dummy variable for non-working income below 3000 is omitted. ** p-value < 0.01, * p-value < 0.05.

the amount of time spent working and, hence, with the money earned. Specifically, we define this probability as $p(x) = a + (1-a)\,(x/\overline{x})^{\alpha}$. For $\alpha > 1$, the probability of failing a year is convex in the amount of student work, which embodies the idea that increments of time devoted to work should not be as costly at lower amounts of work as they should be at higher amounts. This is also consistent with empirical evidence for Slovenian students (Bartolj and Polanec, 2015). By $a \in (0,1)$ we assume there is a positive probability of failing a year even when students are not working.

Let the student's family income be $w \in [L, H]$ with L and H being respective lower and upper bounds to it and let $\gamma \in (0,1)$ be its share transferred to the student. Given our evidence on the relationship between college drop-out rate and non-labor income (see Figure C.3), we assume that the wealthier parents are more likely to give their student-child a second chance if she fails a year at college. Specifically, we model the probability of dropping out of college after failing a year as $r(w) = b + (1-b)\left(\dfrac{H-w}{H-L}\right)^{\beta}$. For $\beta > 1$, the decreasing and convex $r(w)$ resembles the dropout frequency in Figure C.3.

Rational students are aware that the more time they devote to work the more likely they are to fail a year and, consequently, the more likely they are to drop out of college. We assume that students are risk averse and share a common von Neumann-Morgenstern utility function $u(W)$ for present values of wealth W. We model a student's decision making process in a very simple way. Given her non-labor income and income from work, there are three cases that student considers. First, student may fail a year and be forced to drop out of college. Second, after failing a year, she might be given another chance and she stays in the college. We assume that in this case she does not do any more student work in the future and finishes college successfully.[48] Third, she finishes without

[48]This is a simplifying assumption as it is evidently at odds with our evidence on work performed by

failing a year. We then write her expected utility as:

$$\begin{aligned} u(x,w) &= p(x)\Bigg[r(w)u\left(\gamma w + x + \frac{\delta\left(\phi L + (1-\phi)\,w\right)}{2\,(1-\delta)}\right) \\ &\qquad + (1-r(w))\,u\left(\gamma w + x + \frac{\delta\left((1-\phi)\,w + \phi H\right)}{2\,(1-\delta)}\right)\Bigg], \\ &+ (1-p(x))\,u\left(\gamma w + x + \frac{\delta\left((1-\psi)\,w + \psi H\right)}{2\,(1-\delta)}\right) \end{aligned} \tag{3.3}$$

where $\delta \in [0,1]$ is a student's discount factor for future income flows, while $\phi \in [0,1]$ and $\psi \in (\phi, 1]$ are used to weigh the role of respective incomes in her future wealth. Her current wealth is a sum of her respective non-labor and labor incomes, while she also cares about her future income. We assume that in the case of failure, shown in the first part of utility function on the right-hand side of Equation (3.3), her per-period income is reduced from a half of her current family's income to a linear combination of the latter and the half of family income lower bound L. If, after failing a year, she is given a second chance, she will successfully finish and her future per-period income rises towards the half of the upper bond H. If she is successful without failing a year her future wealth is increased even more than in the last case, since $\psi > \phi$.

Students maximize their expected utility in Equation (3.3) with respect to their earnings from student work x. We are interested in the relationship between their optimal decision and their family income, described by $x^* = x^*(w)$. Even with using a simple utility for wealth $u(W) = \sqrt{W}$ this relationship is quite complicated, therefore we avoid solving the problem analytically and rather present its numerical examination in the following subsection.

3.5.3 Numerical Analysis

Table 3.5 collects the parameter values we use in our illustrative example. Values for $\overline{x}$, L, and H are chosen so that the maximum income that a student can earn is a half of the lower-bound for family income. By $\gamma = 0.25$ we implicitly assume that student comes from a four-member family that splits its income evenly among them. Probability that a student fails a year irrespective of amount of student work is $a = 0.2$, while the probability that she has to leave college is $b = 0.5$ (irrespective of her family income). Her discount factor is 0.8.

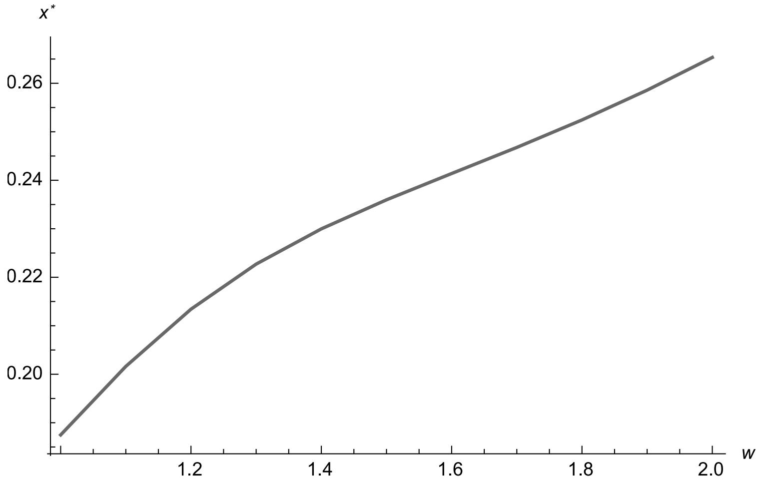
Table 3.5: Parameter Values

$\overline{x}$	L	H	a	α	b	β	γ	δ	ϕ	ψ	$u(W)$
0.5	1	2	0.2	4	0.5	6	0.25	0.8	0.5	0.7	$\sqrt{W}$

Figure 3.3 shows that, under the assumptions of our model, student willingness to work increases with their family income. Even though working more increases the probability of failing and consequently the possibility of worse future income this is more than off-set by the fact that wealthier families are more likely to support their student-children even if they fail a year at college.

repeating students.

Figure 3.3: Optimal Amount of Student Work given Family Income



This result offers a simple explanation for our empirical observation that for lower values of non-working income the average amount of student work is increasing (see Figure 3.1). The constraint of having to leave the college in case of failing a year being imposed by her parents makes a student to perform better in college and hence lowers the amount of time she devotes to work. Figure 3.1 reveals another effect of non-working income that we do not attempt to describe in our model. Above some level of non-working income its income effect kicks in and the students' labor supply starts decreasing.[49]

3.6 Conclusions

This paper presents evidence on an inverse U-shaped relationship between non-labor income and student work. Although previous studies found similar behavior of students (e.g. Pabilonia, 2001 and Beerkens et al., 2011), no explanation has been put forward to reconcile the evidence with theoretical models of labor supply. In fact, the standard neoclassical theory predicts that higher non-labor income should reduce supply of labor by students, which is only consistent with a declining part of the observed relationship. Moreover, financial constraints faced by students should only reinforce the observed negative part of the relationship.

We provide empirical evidence suggesting that students from low-income families, who receive lower transfers, are also more likely to drop out of studies if they fail to pass a study year, which suggests that engaging in labor market poses greater risk of not being able to continue with studies. We develop a theoretical model that relies on this relationship and predicts an increasing relationship between non-labor income and student labor supply. The key assumption for our results is that parents' preferences are described by a utility function that features a decreasing absolute risk aversion. This utility function implies that poorer parents are more risk averse and are less willing

[49]In a simple static model of utility maximization with respect to consumption of a consumption good and leisure the latter is linearly increasing in non-working income when preferences are described with Cobb-Douglas function.

to make additional investments in a risky asset in the form of children's human capital. Students from poor families, who are aware of such parental preferences, respond to this credible threat and supply less labor in order to reduce the risk of not being able to pass a year or even studies. In other words, risk-averse students reduce labor supply in order to avoid future financial constraints. It is important to note that such responses to credible threats are also observed for incomes that students receive from other sources than parents. Our results show that scholarships and pensions (after deceased parents) that are paid to students depending on academic performance also reduce labor supply of students.

We believe that the relationship between non-labor income and labor supply of students reflects the impact of three mentioned mechanisms. First, as the basic static labor supply model predicts, income effect decreases student work as the non-working income increases. Second, current financial constraints increase student labor supply. And third, low non-working with future financial constraint decreases labor supply. The absence of the second and the presence of the third factor in our data, cause the observed inverse U-shaped relation between labor supply and non-working income.

It is important to note that we rule out the possibility that the reason for observed behavior are differences in social transfers and differences in labor demand. However, there might still be additional explanations of why low family income deters student work, besides the expected future financial constraint. For example, students from low-income families might be more eager to finish their studies early in order to become independent of their parents or may be more modest due to lower reference income levels. Since our data do not enable us to explore such psychological aspects of student behavior, we leave this issue to future research.

4 DOES WORK HARM ACADEMIC PERFORMANCE OF STUDENTS? EVIDENCE USING PROPENSITY SCORE MATCHING[50]

Abstract

This article studies the causal effects of student work on academic performance using propensity score matching technique. This estimation approach allows us to estimate the causal effects separately for different years of study, which is not possible when inside instruments are used to deal with endogeneity of student work. We use five distinct measures of academic performance and find that student work has either no effect or a small negative effect. Supplementing existing studies that do not differentiate between study years, we show that student work harms academic success mostly in the first year of study when students are less likely to find the right balance between work and study.

Keywords: Student work, Academic performance, Propensity score matching
JEL classification: I21, J24, I23

[50]This paper is coauthored with Sašo Polanec.

4.1 Introduction

The human capital theory predicts that student work can either increase or decrease the stock of accumulated knowledge and consequently improve or worsen individual productivity. Student work increases human capital through acquisition of new skills, abilities, and knowledge, which may all contribute to academic success and more importantly to the post-college labor market success. At the same time student work might crowd out time for studying and therefore impair academic performance, resulting in a lower accumulation of human capital. In this paper we study empirically the effects of student work on academic performance.

A large body of existing empirical literature concentrated on the impact of student work on high-school grades. The conclusions of this line of research are, however, mixed. They report (i) *negative effect* (Rothstein, 2007; Tyler, 2003; Singh, 1998; Eckstein and Wolpin, 1999; Dustmann and Soest, 2007—only for females and Lillydahl, 1990—only for sizable levels of student work), (ii) *curvilinear effect* (DeSimone, 2006; Oettinger, 1999; Post and Pong, 2009 and Quirk et al., 2001), and (iii) *no effect* (Lee and Orazem, 2010). Papers that analyzed student work during high school also found that it decreases educational time (Kalenkoski and Pabilonia, 2012 and DeSimone, 2006), but positively affects graduation rates (Ruhm, 1997 and Lee and Orazem, 2010).

These results may not be applicable to the post-secondary studies due to important differences between high-school and college studies. The latter are usually less structured and have fewer weekly hours in class, and thus permit more hours of work even for students enrolled in full-time programs. But at the same time, college students are supposed to take full responsibility for their decisions and are not guided by their teachers and/or parents. Therefore college students may more likely worsen their academic performance by taking too much paid work. Nevertheless, the empirical evidence on the effects of student work on academic performance for college students is similarly inconclusive. Using GPA as a measure of academic performance, Darolia (2014) and Ehrenberg and Sherman (1987) found no evidence that student work affects GPA, while others found a negative effect (Beerkens et al., 2011; DeSimone, 2008; Callender, 2008; Kalenkoski and Pabilonia, 2010; Auers et al., 2007; Stinebrickner and Stinebrickner, 2003a). Besides GPA, authors observed also 'graduation-on-time' (Ehrenberg and Sherman, 1987; Beerkens et al., 2011), number of credits per term (Darolia, 2014), and drop-out probabilities (Ehrenberg and Sherman, 1987). All these measures of academic performance were adversely affected by student work.[51]

In this paper we contribute to the literature in two ways. First, we analyze the impact of student work on various aspects of academic performance using a rich collection of control variables, separately for each year of study. We estimate the effect of student work on five related measures of academic performance—number of attempts to pass an exam, number of passed exams, average grade, average passing grade, and probability of passing a year—each of them measuring a different aspect of academic success. While all these measures reflect the effect of student work on time allocated to studies, they show whether they adjust more along extensive margins (number of attempts

[51] Ehrenberg and Sherman (1987) find that only off-campus work negatively affected graduation-on-time and drop-out probabilities in the third and fourth year of study.

to pass exams) or intensive margins (average grades). The likelihood of passing is a combined measure that aims to capture an overall effect of student work on studying. Unlike many existing studies we also allow for non-linear effects of student work and analyze the effects for each year of study separately. These effects are measured while controlling for a rich set of personal, economic, family characteristics, and even past academic performance. Second, we estimate the average treatment effects on the treated (ATET) using propensity score matching. Although researchers used this method in other fields of labor economics, this is the first attempt to measure the effects of student work on academic performance. Since our measure of student work is continuous, we considered estimation of propensity score matching with continuous treatment. Unfortunately our sample did not satisfy the balancing property between all levels of student work, thus we use the standard propensity score matching for dichotomous variables by discretizing the treatment variable.

We calculate the ATET of student work on academic performance by comparing three levels of student work: 0–2 months, 2–7 months of work and more than 7 months. We find that student work indeed harms academic performance. However, such negative effects are typically small in size and found mostly for the first year students. The negative effect of work on the number of exam attempts and the number of passed exams in the first year of study does not exceed 10 percent of all required exams when students worked 2 to 7 months in comparison to those who worked up to 2 months. Similarly, the likelihood of passing the first year of study for students who worked 2–7 months is 4.7 percentage points lower when compared to those who worked less. However, we do not find a statistically significant difference in academic outcomes between students who worked 2 to 7 months and those who worked more than 7 months during the first year of study. In addition, estimates reveal lower average grade, average passing grade, number of exam attempts, and number of passed exams for fourth-year students with the most student work experience compared to those that work 2–7 months, although the two groups of students do not differ in the probability of passing a year.

The rest of the paper is organized as follows. Section 4.2 describes the relevant institutional framework. Section 4.3 presents data sources and summary statistics. Section 4.4 specifies the estimation method and discusses findings. Section 4.5 concludes.

4.2 Insitutional Framework

Our empirical analysis uses the data on Slovenian students enrolled in 4-year undergraduate programs at the Faculty of Economics, University of Ljubljana (henceforth FELU), which is one of the largest public schools in Slovenia with 8 thousand students enrolled in full- and part-time undergraduate and graduate studies. It is a part of the University of Ljubljana, which is located in country's capital.[52] The university is public and does not charge tuition fees to students with Slovene residence. Students can enroll in the programs offered by the FELU after completing any

[52]University of Ljubljana consists of 26 faculties and academies with more than 60 thousand students in peak years.

four-year high school program. The applicants are ranked nationally according to a weighted average grade, calculated from the grade percentage averages achieved in the third and fourth year of the high school study and a national exam called 'matura', a Slovene equivalent of the SAT in the US.[53]

The FELU offers five business majors (Accounting and Auditing, Business Informatics, Finance, Marketing, and Management and Organization) and three economics majors (Banking and Finance, International Economics, and National Economics). In the analyzed period, the majority of students majored in business studies such as Finance, Management and Organization, and Marketing. The expected time to complete any four-year program at the Faculty of Economics was five years, which includes the additional year for completion of the final thesis. However, the actual study time typically varied between 4 and 6 years, and could extend beyond 10 years. The grading scheme for undergraduate studies operates on a ten point scale with 1 as the lowest and 10 as the highest grade. The lowest passing grade was 6. Students who failed to pass an exam were allowed to retake it with no limit on the total number of attempts, although the number of exam dates for each course was limited to three per academic year. Due to a large number of students, each lecture and class session was generally given more than once, especially in the first two years of study, and students could usually freely choose when they will attend a lecture in a given course, which made their time schedule very flexible.

All full-time students in Slovenia are entitled to generous subsidies (e.g. free-health care, subsidized meals, and traveling expenses) and can work under different regulations than other employees. While regular-employment contracts are subject to high social contributions, which amount to 38.2 percent of gross wages, student-employment contracts—referrals—were not subject to any such tax in the analyzed period. Employers must also pay a bonus for working the night shifts, on Sundays, on holidays, for overtime work, seniority bonus, and bonus for job performance to regular employees (but not to student workers). In addition, employer has to cover regular employees' costs for meals during working hours and daily commuting costs (SSC Act, 2001). During the period of analysis gross wages were also subject to a progressive payroll tax, which was abolished in 2009. All these factors contributed to rather high demand for student work with total value reaching around 1.5% of GDP in the peak years.

Student work can be performed by full-time students between 15 and 26 years of age, who are enrolled in state-approved primary, vocational, high school, or undergraduate programs. Each job was based on a referral from an institution or organization authorized to provide job placement services for students—student employment agencies. These agencies charged concession fees, which partly cover the costs of their operations and partly finance students' scholarships, student organizations (unions) of universities, and renovation and building of student dormitories (EIAU Act, 2006; Act RACD, 2003).

Despite preferential tax treatment, student work was not completely tax free. It was subject to a

[53]The high-school grades range between 1 (insufficient) and 5 (excellent); 2 is the lowest passing grade. The matura consists of three compulsory (Slovene language, Mathematics, and one foreign language - usually English) and two elective subjects, such as Biology, History, Physics, etc.).

concession fee, value-added tax on concession fee, and personal-income tax. The concession fee was rising over the analyzed period, starting at 10 percent of students' gross earnings from 1997 to 2003. From 2003 until 2006 it equaled 12 percent and afterwards 14 percent of students' gross earnings. The concession fees were paid by employers on top of students' gross earnings. In addition, employers had to pay value added tax on the concession fee. Therefore the total costs of student work for the employer in 2008 were 116.8 percent of student's gross earnings. Gross earnings of students were also subject to a progressive personal-income tax. While the tax rates are the same for all recipients of different types of personal income, students incomes tax deduction was typically double that of regular employees. As a consequence, net earnings were the same as gross earnings for almost all students, even those who worked full-time entire year and received average (student) hourly wage. Since we are using data on gross earnings, we do not describe details of personal-income taxation.

4.3 Data

4.3.1 Data Sources

Our empirical analysis is based on information on all persons who were first enrolled in any of the 4-year undergraduate programs offered by the FELU between 1997 and 2004. The FELU application sheets data on all enrolled students in 4-year undergraduate programs, in addition to the data on all attempts to pass exams and grades achieved, were the sources for information on age, gender, location of permanent residence, chosen major, and study year of students. Based on enrollment history of each student, we also construct variables that indicate if a student passed a year, repeated a year, or dropped out of a program. Exam results were used to construct variables on study performance of students. Using unique person-specific identifiers, we merged this data set with other data sets in a secure room at the Slovenian Statistical Office.

The second source of data is the Slovenian Tax Authority (henceforth TARS), which received information on all personal incomes earned. The data on student earnings were reported to TARS by student employment agencies. While students with sufficiently low earnings were not obliged to fill an income tax report, the student employment agencies had a legal obligation to report earnings received by each working high-school or college student. Unfortunately, these data do not enable us to observe the month in which student work was performed, so we do not know how much student worked during semesters and how much during the breaks.

In addition, TARS is also the source of data for incomes of students' families. A standard procedure for data collection by tax authorities is reporting of own incomes by employees, which was also the case in Slovenia during the period of our analysis. However, the data we use are collected for inspection purposes and are reported by employers. Tax fillings for personal income tax include both labor and capital incomes, which are used to calculate per capita family incomes. Moreover, labor incomes of families include not only wages and salaries, but also bonuses, perks, wages earned on the basis of short-term labor contracts, and royalties. Capital incomes include interest, dividends, rents, and incomes of sole proprietors.

The third source of data is the National Examination Center, which collects the data on students' high-school performance. We extracted information on the third- and forth-year average grades and the grades from final (external) examination called matura. We used these grades to construct measure of high school GPA.

The last source of data is the Slovenian Statistical Office (henceforth SORS). From SORS we obtained the data from Central Registry of Population, which allows us to establish parent-child links through unique identifiers of parents for each student and thus to calculate family incomes and transfers for each student. Having an identity of parents allows us also to determine their educational attainment, which is collected from the Statistical Registry of Employment. Lastly, SORS provided information on all scholarships received by students, ranging from social scholarships targeted to students with low-income families, scholarships for talented individuals (Zois scholarships), and scholarships granted by prospective employers.

4.3.2 Construction of Variables and Summary Statistics

This paper analyzes the effects of student work on academic success of students who enrolled in the first year of undergraduate university (4-year) programs at FELU in the period 1997–2004. We limit the dataset to those aged between 18 and 20 years when enrolled in the first year of study and exclude persons who finished high school with vocational instead of general matura.[54] This gives us 3,707, 3,293, 3,201, and 3,103 observations in the first, second, third, and fourth year, respectively. The sample size and its structure by gender are presented in Table 4.1.

Table 4.1: Sample Size by Gender

	1st Year	2nd Year	3rd Year	4th Year
Number of observations	3,707	3,293	3,201	3,103
Males	1,619	1,402	1,337	1,302
Females	2,088	1,891	1,864	1,801

As mentioned above, we construct five different measures of academic performance in order to capture as many aspects of it as possible. In the top panel of Table 4.2 we show the means and standard deviations of these measures. The average grade is a variable that captures the differences in the intensive margin of students' study efforts. The average grade is calculated as an unweighted average of all exams taken in a specific year of study. All negative grades are set to 5, as the differences in negative grades do not exhibit the true variation in knowledge.[55] In the first year

[54]We have data on high school performance of students that passed general matura, which enables enrollment in all programs of tertiary education. We do not collect data on vocational matura, which is by itself not sufficient for enrollment to university courses, as student have to additionally pass one subject of general matura in order to be able to enroll to university courses.

[55]Grades are given on a scale ranging between 1 and 10, where 10 is the top grade. Although the negative grades range from 1 to 5, grades 1 to 4 are rarely used by some examiners and instead 5 is given to all students that do not pass the required threshold.

average grade is just above the minimum passing grade, but it increases with study years to 7.6 in the last year of study. This is expected, as the less able students drop out of program and the remaining students get more familiar with academic process. In addition we are interested in the impact of student work on grades conditional on passing, so we also look at the average of all passed exams, which equals 6.9 and 8.0 in the first and the last year of study, respectively.

The next two measures of academic performance capture the extensive margins of study efforts. These are the number of all attempts to pass exams and the number of exams passed. The number of required exams was 10 in the first and second year of study, between 8 and 9 in the third year, and between 8 and 10 in the fourth year of study, depending on a chosen major. Students might, however, retake an exam in order to get a passing grade at previously failed exam, or to improve a grade in a course, which they already passed. In the first years of study, the average number of exam attempts highly exceeds the number of required exams, while in the subsequent years the difference decreases. Similarly, the difference between the average number of passed exams and exam attempts diminishes with year of study. On average, students passed 8.0, 8.3, 7.1, and 7.7 exams in the first, second, third, and fourth year of study, respectively.

Our final measure of academic performance, which captures an overall effect of study efforts, is a binary variable which equals one for students that pass a study year and zero otherwise. Summary statistics reveal that a high percentage of students fails to proceed from the first to the second year of study (33.8 percent), but the vast majority pass the last two years of study. It should, however, be noted that students were not required to pass all exams in order to proceed to a subsequent year of study.[56]

The second set of summary statistics in Table 4.2 reflects the extent of student work. We can observe that a large share of students work and that this share of working students increases with years of study. Specifically, in the first and the last year of study the likelihood of working equals 81.5 and 95.1 percent, respectively. The average gross student earnings also increase with the year of study, causing a difference in earnings between the first and the last study year comparable to an average monthly net wage of regular employees. The last variable describing student work, which is also used in our estimations, are months of student work. Unfortunately, we do not have information on actual hours of work, hence we use average hourly gross wage to calculate the experience in months.[57] On average students worked 2.2, 2.7, 3.3, and 3.8 months in the first, second, third, and fourth year of study, respectively.

Students' characteristics are described with gender, age, and high school GPA. The latter is our measure of general ability, calculated as a normalized unweighted average of (i) the average grade achieved at matura examination, and (ii) the average grade in the last two years of high school. In the fourth year of study it exceeds its first year's value, suggesting that less able students are more likely to drop out of the program. The observed students' family characteristics include a binary variable for parental university degree or higher, a variable indicating if student has a child,

[56]For example, students could pass a year when passing 9 out of 10 exams in the first two years of study.
[57]The source of hourly gross wages is e-Študentski servis, the largest student employment agency in Slovenia.

Table 4.2: Summary Statistics

	1st Year		2nd Year		3rd Year		4th Year	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Avg. grade	6.230	0.783	6.671	0.813	6.811	0.918	7.618	0.983
Avg. passing grade	6.897	0.588	7.379	0.603	7.343	0.714	7.977	0.777
No. of exam attempts	13.888	3.658	12.920	3.190	10.015	2.828	9.091	2.595
No. of exams passed	7.961	2.482	8.277	2.045	7.085	1.958	7.689	2.326
Passed a year	0.662	0.473	0.750	0.433	0.925	0.263	0.993	0.084
Working during study	0.815	0.389	0.881	0.324	0.915	0.279	0.951	0.217
Gross student work income	1,473	1,663	1,791	1,788	2,161	1,867	2,614	1,968
Months of student work	2.245	2.535	2.730	2.725	3.264	2.831	3.841	2.920
Female	0.563	0.496	0.574	0.495	0.582	0.493	0.580	0.494
Age	18.910	0.418	20.186	0.656	21.405	0.852	22.436	0.881
High school GPA	0.492	0.157	0.506	0.155	0.507	0.155	0.508	0.155
University or higher—mum	0.185	0.388	0.193	0.395	0.197	0.398	0.207	0.405
University or higher—dad	0.219	0.414	0.227	0.419	0.227	0.419	0.230	0.421
Student parent	0.000	0.000	0.001	0.039	0.002	0.053	0.003	0.062
Step parent	0.237	0.425	0.231	0.422	0.235	0.424	0.235	0.424
No. of siblings	1.026	0.719	0.981	0.726	0.928	0.749	0.865	0.747
Non-labor income	6,369	3,774	6,776	4,204	7,228	4,647	7,663	5,161
Conditional-income share	0.127	0.216	0.138	0.228	0.154	0.240	0.160	0.242
Expected net wage	16,244	2,646	16,053	2,590	15,870	2,512	15,851	2,490
Repeated previous year			0.271	0.444	0.200	0.400	0.065	0.246
School year	2,000.3	2.2	2,001.6	2.2	2,002.8	2.2	2,003.9	2.2

Notes: All income-related variables are in constant (2004) Euros. The exchange rate in 2004 was 1 EUR = 1.24 USD.

a variable marking students with step parents and a variable measuring the number of siblings below the age of 27.

In order to capture student's economic background, we construct non-labor income variable. It is calculated as a sum of (i) net family income per family member, which equals the sum of parental net income divided by the number of family members,[58] (ii) scholarships, and (iii) pensions received after deceased parents. As student work supply and academic success might be further influenced by the non-working income which depends on academic performance, we define a variable—conditional-income share—that measures the share of scholarships and pensions in student's non-working income. We also include a measure of post-graduation expected net incomes. This measures captures the incentives that influence allocation of time between work and study. In constructing this measure we assume that students base their expectations of expected income on the most recent wage of persons of the same gender who graduated in their major.

Finally, our estimations also control for grade retention in the previous year of study, school year, chosen major, and region of permanent address. The grade retention reflects the time available for study and work as students have the opportunity to pass exams for the subsequent year during the repetition. In the table is presented the share of students that repeated the previous year of study. The last three variables attempt to capture the differences in labor market as well as study conditions. For example, chosen major affects the labor demand for students as well as the academic

[58] We count as family members parents and children under the age of 27, following the personal-income-tax act that defines as a dependent family member a person up to the age of 26 (in addition to other requirements).

requirements. Similarly, different regions offer diverse job opportunities, but at the same time affect the financial resources and time available for study and work, as those that live in regions located further away from the faculty have to travel daily or rent a room. We present the structure of sample by region in the Appendix (Table D.1). From the table it is evident that roughly 45% of all students originate in the Osrednjeslovenska region, where the FELU is located.

4.4 Empirical Analysis

4.4.1 Estimation Method

In order to estimate the effect of student work on academic performance we match students with different employment histories but similar predicted probabilities or propensity scores of student employment level. The advantages of propensity score matching are two-fold. First, it avoids the dimensionality problem of finding matched subjects when there are many control variables. And second, it imposes minimal structure on estimation. Another feature of matching approach, which we consider as an advantage, is putting an emphasis on observations with similar regressors. This means that observations at the margin might get no weight. In contrast, OLS tries to minimize squared errors, which may give observations at the margin large weights.

We estimate propensity scores using a logit regression for probability of working k hours during study year (SW_k), using personal characteristics (x) and academic performance in previous study year (A) as explanatory variables:

$$Pr[\mathrm{SW}_{ki} = 1] = \alpha_0 + \alpha_1 x_i + \alpha_2 A_i + u_i. \tag{4.1}$$

This conditional probability of receiving treatment (k hours of student work) given x and A is used to match treated observations to controls with similar values of the propensity score. The calculation of the average treatment effect on the treated (ATET) is then based on two assumptions: (i) conditional independence (also called selection on observables, unconfoundedness, or ignorability)[59] and (ii) overlap or matching assumption.[60]

The matching algorithm used in our analysis is radius matching with replacement and imposed common support. The radius matching is a variant of caliper matching that uses all control units within the caliper (or radius) and not only the nearest neighbor as it is done with caliper matching (Dehejia and Wahba, 2002). This feature of radius matching reduces bias of the estimates. Bias is further reduced by matching with replacement, since it allows a treatment unit to be matched to control unit even if control unit was already matched. As suggested by Austin (2011), we use

[59] Conditional on x, outcomes of treatment (y_1) and control group (y_0) are independent of treatment (D). Rosenbaum and Rubin (1983) showed that if the former holds, y_1 and y_0 are also independent of D for given value of propensity score.

[60] For every value of propensity score, there are observations in control and treatment group.

caliper equal to 0.2 of the standard deviation of the logit of the propensity score.[61]

Since we expect different levels of student work to have different impact on academic performance, we do not differentiate only between students who work and those who do not, but instead create three different binary treatment variables, which lead to estimation of three different ATETs. As shown in Table 4.3 we use those who have less than 2 months of work experience as control group for students with more than 2 but less than 7 months of student work experience (ATET_{11}) and for students with more than 7 months of student work experience in a given study year (ATET_{12}). Lastly, we use students with more than 2 but less than 7 months of student work experience as a control group for students with more than 7 months of student work experience in a given study year (ATET_{22}).

Another possibility would be to apply continuous matching as proposed by Hirano and Imbens (2004).[62] However, the estimation of dose-response function requires general propensity score to balance pre-treatment variables over all defined intervals at the same time, which is hard to achieve in general. This is also the case for our data and hence we estimate different propensity scores[63] for different treatment-control pairs, which makes it easier to achieve the balancing property. Another advantage of applied procedure is, that even though the balancing property is not achieved for some treatment-control pair, other ATETs are still valid. However, a downside of this is that ATETs cannot be directly compared. Namely, ATET_{22} is not equal to the difference between ATET_{12} and ATET_{11}, since control groups are, in general, not the same.

Table 4.3: Construction of Treatment and Control Groups based on Amount of Student Work experience

	TREATMENT	
Student work experience	2 – 7 months	more than 7 months
less than 2 months	ATET_{11}	ATET_{12}
2 – 7 months		ATET_{22}

In this manner we estimate the direct effect of student work on academic success, which is measured with average grade, average passing grade, number of exam attempts, number of passed exams, and probability to pass a study year. The indirect effect of student work on academic success in a subsequent period, through academic success in current period, is not accounted for. See also Figure D.1 for representation of causal chain and the estimated ATET.

Observed covariates x_i in Equation (4.1) include binary variables for different levels of non-working income, being female, having step parent, having children, university degrees of mother and father, regions of residence, school years, and majors. In addition, we control for a share of conditional

[61]We also considered other matching algorithms and other caliper values but obtained qualitatively similar ATETs. We chose this method in line with the recommendation to make a control group as locally comparable as possible to the treated, and baseline differences as little as possible in order to estimate the causal effects using comparable subjects (Lee, 2005).

[62]Estimation procedure proposed by Cattaneo (2010) cannot be used as all our outcome variables are not continuous.

[63]We estimate the same equation, but allow for different values of regression coefficients.

income in non-working income, expected net wage, age, high school GPA, and number of siblings under the age of 27. Furthermore, we add number of passed exams in previous year, average grade in previous year, and a binary variable that is equal to 1 if student was repeating previous study year and 0 otherwise in equations for second to fourth year of study. These variables measure academic success in previous period. We do not control for student work in previous period, as it does not induce imbalance across treatment and control group once we control for past academic success.

One of the reasons for observed differences in measured effects of student work on academic performance across different studies may be endogeneity of student work, which could occur due to omitted variable bias. This arises if there is a variable which affects academic success as well as student work, but is not controlled for in the estimation procedure. The most debated variable in this context is motivation, since it cannot be measured, but the authors usually agree that it might increase both variables of interest.

Although some studies ignore the fact that student work might be endogenous, others try to deal with it using different techniques. For example, Darolia (2014) uses fixed effects and system GMM estimator to account for time invariant unobserved variables and possibly dynamic relationship between student work and academic performance. DeSimone (2008) and Stinebrickner and Stinebrickner (2003a) use instrumental variable estimation and find a negative effect of student work on GPA. Although instrumental variables estimation solves the potential endogeneity and omitted variable bias problem, it estimates the so called local average treatment effect (LATE)—the effect of treatment on the population of compliers—which is usually not the same as the average treatment effect on the treated (Angrist and Pischke, 2008).

We used a binary variable indicating if either of student's parents owns a family business and a variable measuring the share of transitory income in student's non-working income as instruments to test the null hypothesis of exogeneity. The two variables were used, because they impact the labor supply of students, while they do not directly influence academic performance. Specifically, if parents own a family business, student is more likely to work, whereas students with a large share of transitory non-labor income work more in order to reduce the effects of financial uncertainty. We could not reject the null hypothesis, which is in line with Ehrenberg and Sherman (1987), and allows us to treat student work as exogenous.

4.4.2 Unconditional Effects of Student Work

Prior to the presentation of the estimated treatment effects, we provide some descriptive evidence on the relationship between student work experience and the five measures of academic performance. In Figures D.2 to D.5 are shown scatter plots with frequency-weighted markers. These plots reveal a rather strong negative relationship between the extent of student work and our measures of academic performance, which suggests that student work harms study success. More work is reflected in lower average grade, lower number of passed exams, lower number of all attempts to pass exams, and lower probability to pass a year. That is, students who work more hours are putting less effort in each exam (lower average grade) and prepare for smaller number of exams, which culminates in the lower likelihood to pass a year.[64]

The negative relationship between student work and our measures of academic success are stronger in the early years of study. For example, the overall measure of study success—the probability to pass a year—declines by roughly 20 percentage points between 0 and 7 months of work for students who were enrolled in the first year of study, while in the fourth year of study this difference in probability is less than 5 percentage points. These differences between study years suggest that student work is riskier in the early years of study as students face greater uncertainty about the expected effort required to pass exams. Moreover, the sample of students enrolled in the higher years of studies were selected to those who were able to pass, which makes these groups less heterogeneous in terms of ability. It is also interesting to observe an inverse U-shaped relationship between student work and academic performance for students in the fourth year with a peak at 3 months. This suggests that in the final year the trade-off between student work and academic performance only kicks in for those that work more than 3 months.

The scatter plots reveal a rather peculiar feature of more dispersed and even improved academic success for students who worked more than 7 months a year. This is observed for four measures of study (exception being the number of all attempts to pass exam) in the first year of study. This is partly due to smaller samples of students, but also due to possibility that some of the students participated in tax evasion. Since student work was taxed with the lowest tax rates, students could earn money for helping firms extract cash from businesses for some minor compensation. In fact, our estimates may suffer from attenuation bias due to tax evasion. The harmful effects of actual student work on study results could be even greater than the effects based on measured student work.

4.4.3 Causal Effects of Student Work

Descriptive evidence on the negative effects of student work on academic performance shown in Figures D.2 to D.5 is not causal as student work is endogenous. In Table 4.4 we show the estimates of average treatment effects on the treated, which can be interpreted as causal effects. As already mentioned above, the propensity score estimations control for previous academic success, student's and family characteristics, economic background, expected net wage, school year, major, and region. The propensity score balances variables in all estimations, hence we truly compare only students with similar characteristics that chose different levels of student work.

Overall, the estimated causal effects (ATETs) are in line with descriptive statistics shown above—student work indeed harms study outcomes—although they are often statistically insignificant. Let us start with description of the effects of student work on the average grades. We find no effect of

[64] Note that the total number of attempts to exams does not have an a priori negative relationship with student work. Students who work more are less likely to pass and consequently may exhibit more attempts to pass exams.

student work on average grade in the first and third year of study. The two significant effects are for those students who work 2–7 months in the second year of study and over 7 months in the fourth year of study. Specifically, we find that students who work 2–7 months in the second year have on average 0.072 lower average grade than they would have with less than 2 months of experience. In relative terms, this effect amounts to roughly 1 percent lower average grade. The effect is similar in size even if we compare average grades of students who worked less than 2 months with average grades of students who worked more than 7 months, although these are not statistically significant due to smaller sample size. A bit larger effect is observed in the fourth year of study for students with over 7 months of experience, when compared to those with 2–7 months of student work. The estimated ATETs for average passing grade are similar not only in significance but also in size. The only notable difference is the statistically significant negative ATET for students with over 7 months of work when those with less than 2 months of work are used as a control group.

Next we consider the ATETs for the number of exam attempts and the number of exams passed. Students might have a high number of exam attempts because they put more effort into studies and try to pass as many exams as possible or because they fail to pass some exams and have to retake them. As already mentioned above, the effect of student work on the number of exam attempts is not necessarily negative. Nevertheless, we find that students with 2–7 months and over 7 months of work have on average 0.418 and 0.644 less attempts to pass exams in the first year of study than they would have with less than 2 months of work, respectively. Also, students with over 7 months of student work experience have 0.378 less attempts than they would have with more than 2 but less than 7 months of work in the fourth year of study. In addition, we find a negative effect of work on the number of passed exams. Specifically, 2–7 months of work during the first, second, and third year of study decrease the number of passed exams compared to students with less than 2 months of student work by 0.263, 0.202, and 0.229, respectively. In relative terms, this is roughly 3 percent of the average number of exams passed. Furthermore, students with over 7 months of experience have 0.492 less passed exams in the first year than they would have if they had worked less than 2 months, and 0.469 less passed exams in the last year than they would have if they had had 2–7 months of experience. These results suggest, that students with more hours of student work do not only pass less exams, but also attempt to do so to a lesser extent, especially in the first year of study. However, the size of these effects is small, as it does not exceed 1 in any of the cases. In other words, the difference in passed exams and number of exam attempts between students with different student employment histories is less than 10 percent of required exams.

Perhaps the most important effect of student work is that on the probability of passing a year, as it captures the overall effect of work on study efforts. In line with findings on the number of passed exams, we discover a negative effect of student work on the likelihood of passing the first year of study. Students pass the first year of study with 4.7 and 6.8 percentage points lower probability if they work 2–7 months or more than 7 months instead of less than 2 months, respectively. Again, although these effects are statistically significant they are small in size.

In a nutshell, we find a somewhat surprising result that out of sixty estimated ATETs less than a third are statistically significant and even these are economically insignificant. The student work seems to be most harmful in the first year of study, although the effects are not linear. In particular, we find a significantly negative effect on the number of exam attempts, number of passed exams, and the probability to pass a year for an increase of student work above 2 months, but students that work over 7 months do not differ in these aspects of academic success from students with 2–7 months of experience when we control for relevant characteristics. In addition, we find that fourth-year students who work the most have lower average grade, average passing grade, number of exam attempts, and number of passed exams than they would have if they had worked 2–7 months, but the probability of passing a year is not different.

One of the possible reasons for insignificant results is above-mentioned attenuation bias related to our imperfect measurement of student work. As we estimate working hours using a fixed average wage in each given year, variation in hours worked does not reflect only actual hours worked, but also differences in hourly wages. Hence the insignificant effect of student work on the average passing grade in the first year for students who had 2–7 months instead of less than 2 months of implied experience can reflect the fact that students with 2–7 months of implied experience actually worked less, but had a better paying job. At same time, some students that were used as controls with less than 2 months of implied student work experience, could in fact had more than 2 months of work experience in the lowest paying jobs. While this may indeed be a problem, our matching approach controlled for many characteristics, among which is gender that might be correlated with performance of certain highly-paying jobs (e.g. hostess). Moreover, the data from one of the student agencies for the period 2006–2010 suggests that students performed very similar jobs and did not earn very different hourly wages. The correlation coefficient between hours of student work and average hourly wage for these students was -0.02, implying that the differences in hourly wages between different levels of student work do not cause an important bias in our estimates. The second reason for attenuation bias is the possibility that students engaged in tax evasion and reported earnings that were not at all related to actual work performed. While there was plenty of anecdotal evidence on tax evasion through student referrals in Slovenia, we believe that this phenomenon was relatively modest. One strong reason against these effects is the shape of the distribution of earnings. As it was rational for all students to engage in tax evasion, all that had a possibility to do so, should have exploited this possibility up to the amount of student tax deduction. This would lead to a distribution of earnings with a peak at the level of tax deduction, which is not observed in our data. Moreover, we should not observe any relationship between student work and academic performance if student work was mainly used as a mode for tax evasion. Thus, while we are aware that our measures of student work are not ideal, we believe, based on our results, that student work had rather modest negative effects on academic performance for the FELU students.

4.5 Conclusion

This paper analyzes the impact of student work on five different measures of academic performance, separately for each of the 4 years of undergraduate study. We find that student work has heterogeneous effects that vary with performance measures and study years. Our results suggest that mixed evidence on the adverse effects of student work on study outcomes cannot only be attributed to different estimation techniques accounting for potential omitted variable bias, but also a consequence of samples concentrating on dissimilar study years and outcome variables.

We find that student work harms academic performance mostly in the first year of study, although the size of effects is small. The observed negative effect of student work on the number of exam attempts and the number of passed exams in the first year of study for students that worked more than 2 months is smaller than 10 percent of all required exams. Similarly, the likelihood of passing the first year of study is lower by 6.8 percentage points for those who worked over 7 months in a year. The effects are also non-linear. For example, we do not find a statistically significant difference in academic outcomes between students who worked 2–7 months and those who worked more than 7 months during the first study year, conditional on observed characteristics. In addition, estimations reveal lower average grade, average passing grade, number of exam attempts, and number of passed exams for fourth-year students with the most student work experience compared to those that worked 2–7 months, however, they do not differ in the probability of passing a year.

In summary, we find that student work has either no effect or a small negative effect on different measures of academic performance. It should be, however, emphasized that these results are based on data for students that were enrolled in one faculty, which allows students to adjust study and work schedules quite easily due to repetition of classes. If other faculties have less flexible timetable, students may find it harder to balance work and study, and thus the negative effects of work might be larger.

Table 4.4: Estimates of Average Treatment Effects on the Treated

	Avg. grade		Avg. passing grade		No. of exam attempts	
	2–7 months	over 7 months	2–7 months	over 7 months	2–7 months	over 7 months
			1st Year			
less than 2 months	−0.001	0.007	0.004	0.021	−0.418**	−0.644*
	(0.028)	(0.056)	(0.021)	(0.042)	(0.134)	(0.261)
2–7 months		0.018		0.028		−0.239
		(0.056)		(0.041)		(0.266)
			2nd Year			
less than 2 months	−0.072*	−0.067	−0.051*	−0.058	−0.022	0.008
	(0.030)	(0.053)	(0.024)	(0.040)	(0.123)	(0.212)
2–7 months		0.040		0.028		−0.046
		(0.053)		(0.041)		(0.209)
			3rd Year			
less than 2 months	−0.053	−0.056	−0.033	−0.032	−0.163	−0.223
	(0.035)	(0.051)	(0.028)	(0.041)	(0.114)	(0.184)
2–7 months		−0.040		−0.022		0.133
		(0.052)		(0.041)		(0.171)
			4th Year			
less than 2 months	−0.051	−0.106	−0.055	−0.113*	0.010	−0.299
	(0.042)	(0.063)	(0.032)	(0.047)	(0.116)	(0.177)
2–7 months		−0.130**		−0.094*		−0.378**
		(0.050)		(0.041)		(0.144)

	No. of exams passed		Passed a year	
	2–7 months	over 7 months	2–7 months	over 7 months
		1st Year		
less than 2 months	−0.263**	−0.492**	−0.047**	−0.068*
	(0.094)	(0.184)	(0.018)	(0.033)
2–7 months		−0.198		−0.013
		(0.198)		(0.035)
		2nd Year		
less than 2 months	−0.202**	−0.167	−0.022	−0.032
	(0.077)	(0.139)	(0.016)	(0.030)
2–7 months		0.069		−0.000
		(0.137)		(0.030)
		3rd Year		
less than 2 months	−0.229**	−0.216	−0.012	−0.050*
	(0.080)	(0.126)	(0.010)	(0.020)
2–7 months		0.036		−0.038
		(0.121)		(0.020)
		4th Year		
less than 2 months	0.009	−0.287	−0.004	−0.005
	(0.106)	(0.163)	(0.003)	(0.005)
2 – 7 months		−0.469**		0.001
		(0.126)		(0.005)

Notes: * $p< 0.05$; ** $p < 0.01$. Standard errors are reported in parentheses.

5 THE EFFECTS OF STUDENT WORK AND ACADEMIC PERFORMANCE ON POST-COLLEGE LABOR MARKET OUTCOMES[65]

Abstract

This paper analyzes the effects of student work during college studies on subsequent labor market outcomes. We find that work experience gained during studies increases probability of employment, hourly wage, and probability of signing indefinite employment contract, especially when it is high-skilled work in occupations related to college major. Individuals benefit most by increasing their student work experience up to 2 years, whereas additional experience generally has statistically insignificant effects. We compare these effects of student work experience to the effects of superior academic performance and find that students may enjoy greater returns by putting more effort to studies rather than work experience.

Keywords: Student work experience, Wages, Employment
JEL classification: J24, J31, I21

[65]This paper is coauthored with Sašo Polanec.

5.1 Introduction

The percentage of students working during college increased for decades and nowadays a significant proportion of students work. Employment rate of US students in public (private) 4-year colleges was 41 (36.3) percent in 2011 (National Center for Educational Statistics), while the corresponding rates in EU countries were even higher. For example, the employment rates of German, Dutch, and Slovenian students not living (living) with their parents were 70 (72), 81.1 (88), and 79.7 (83) percent, respectively (Eurostudent, 2014).

The majority of papers, which analyzed the effects of student work, concentrated on its impact on academic success.[66] However, labor market economists are primarily interested in the effects of student work experience on post-college labor market outcomes. Although there are several studies that analyzed such effects for work experience gained during high-school studies (e.g. Light, 2001; Light, 1999; Ruhm, 1997), their results cannot be generalized to work performed by college students as the former are more likely to find student jobs that are related to their field of specialization. Since there are only a handful of studies using data for college students, these effects are relatively underexplored, a gap we attempt to fill in this paper.

From a theoretical point of view, we expect student work experience to have a positive effect on individual's productivity, and thus also a positive effect on the likelihood of worker being hired into regular employment and wage rates. Work during studies may also be used as a signal to prospective employers on individual's motivation to work and her abilities. Moreover, employers might rely on performance of student workers in selection process of regular workers. But on the other hand, labor market outcomes are also positively influenced by academic performance. Considering the evidence, which suggests a negative relation between student work and academic success,[67] it is important to asses their relative importance on employers decisions.

In this paper we study the effects of undergraduate student work experience and academic performance on probability of employment, hourly wages, and probability of signing an employment contract with indefinite duration. Our empirical analysis yields the following conclusions. First, complementing the results of Häkkinen (2006), Joensen, and Geel and Backes-Gellner (2012), who find a positive effect of student work on wages, we show that student work positively and significantly affects the likelihood of regular employment, gross hourly wage, and probability of signing indefinite contract. Students benefit the most by working 10–24 months during 4-year undergraduate studies. While positive effects generally increase with additional years of student work experience, these increases are not statistically significant.

[66]See, e.g., Ehrenberg and Sherman (1987), Eckstein and Wolpin (1999), Callender (2008), Kalenkoski and Pabilonia (2012), Rothstein (2007), Tyler (2003), DeSimone (2006), Dustmann and Soest (2007), Oettinger (1999), Stinebrickner and Stinebrickner (2003b).

[67]Beerkens et al. (2011), DeSimone (2008), Callender (2008), Kalenkoski and Pabilonia (2010), Auers et al. (2007), and Stinebrickner and Stinebrickner (2003b) find a negative effect of student work on GPA. In addition, Ehrenberg and Sherman (1987) and Beerkens et al. (2011) observe a negative effect of student work on 'graduation-on-time', while Darolia (2014) discovers a negative effect on number of credits per term. The negative effect of student work on academic performance is confirmed also in our separate paper analyzing similar data as presented here (Bartolj and Polanec, 2015).

Second, we show that different student jobs have different effects on post-college outcomes. In particular, the largest effects are obtained for jobs that may require a tertiary education degree, followed by jobs that require high-school degree but are related to the field of study, and low-skilled jobs unrelated to student's education. This finding is also consistent with Geel and Backes-Gellner (2012), who study Swiss graduates of tertiary education.[68] They find that only student employment with relation to study has a negative impact on duration of job search and a positive impact on wages, while related and unrelated student employment negatively affect unemployment after graduation.

And third, we study the impact of graduation and GPA in the top quartile of the distribution on previously described labor market outcomes. While there exists a considerable literature confirming the positive impact of academic performance on labor market outcomes,[69] to our knowledge only Ehrenberg and Sherman (1987) compared the relative impacts of academic results and student work. They found evidence that higher grade point averages led to higher earnings, but failed to find any relationship between student work and earnings. We contribute to this literature by showing that graduation increases probability of employment, gross hourly wage, and probability of signing indefinite contract more than an increase in student work experience from less than 10 months to more than 3 years during 4-year undergraduate study in the first and second year on the labor market. In addition, we find a greater positive effect of above average GPA on gross hourly wage than the effect of an increase in student work from less than 10 months to more than 3 years of student work experience in the first year on the labor market, while the effect is somewhat lower in the second year. The effect of having GPA in the top quartile of the distribution on probability of employment in the first year on the labor market is similar to the effect of an increase of student work from less than 10 months to 10–24 months of experience.

The distinguishing feature of our analysis is also the use of propensity score matching. Although it is an established method, it has not yet been used in this context. We consider its property to put emphasis on observations with similar regressors and thus giving less or no weight to observations at a margin as an advantage over methods that minimize squared errors and give such observations a lot of weight.

The remainder of this paper is organized as follows. Section 5.2 describes the institutional framework for student work and tertiary education system relevant for the analyzed data. Section 5.3 presents the key features of the data and summarize the variables used in empirical model. Section 5.4 shows the results of empirical models of post-college outcomes and Section 5.5 concludes.

[68] Joensen, on the other hand, does not find any evidence of differential effects of study-related jobs or jobs that require higher skill levels on wages for Danish population.

[69] For example, Jones and Jackson (1990) and Chia and Miller (2008) find a positive GPA–earnings relationship. Numerous studies find positive returns to tertiary education. The recent results for Slovenian data, which are used in this paper, can be found in Bartolj et al. (2013).

5.2 Institutional Context of Study

Our empirical analysis uses data on Slovenian students, who were enrolled in 4-year undergraduate programs at the Faculty of Economics, University of Ljubljana. As mentioned in introduction, the share of working students is relatively high in Slovenia, which is partly related to regulation of student work in Slovenia. Here we first provide a brief account of regulatory framework for student work, followed by a description of programs offered by the Faculty of Economics in the analyzed period.

5.2.1 Institutional Framework for Student Work

Student work in Slovenia has a long tradition dating back to 1970s when ex-socialist system was still in place. Traditionally the aim of student work was to help students to overcome potential financial constraints during studies, although it was more frequently performed by students from medium-income families.[70] Student work has a special tax treatment. While regular-employment contracts are subject to high social contributions, which amount to 38.2 percent of gross wages, student-employment contracts—referrals—were not subject to any such tax in the analyzed period.[71] Employers must also pay to regular employees (but not to student workers) a bonus for working the night shifts, on Sundays, on holidays, for overtime work, seniority bonus, and bonus for job performance. In addition, employer has to cover regular employees' costs for meals during working hours and daily commuting costs (SSC Act, 2001). During the period of analysis gross wages were also subject to a highly progressive payroll tax that was abolished in 2009.

Despite preferential tax treatment, student work is not completely tax free. Student work is subject to a concession fee, value-added tax on concession fee, and personal-income tax. The concession fee increased over the analyzed period, starting at 10 percent of students' gross earnings in the period 1997–2003. From 2003 until 2006 it was 12 percent and afterwards 14 percent of students' gross earnings. The concession fees are paid by employers on top of students' gross earnings. In addition employers have to pay a 20% value-added tax levied on the concession fee. Therefore the total costs of student work for the employer in 2008 were 116.8% of student gross earnings. As mentioned above, gross earnings of students are subject to a progressive personal-income tax. While the tax rates are the same for all recipients of different types of personal income, personal-income tax deduction applicable to students was typically double that of regular employees. As a consequence, net earnings for the majority of students were the same as gross earnings. Since we are using data on gross earnings, we do not describe details of personal-income taxation.

[70] Our own analysis, using the same Slovenian dataset as used in this study (see Bartolj et al., 2015), shows an inverse U-shaped relationship between family income per capita and student work, especially during early years of study.

[71] Social contributions offer retirement, disability, health, maternity leave, and unemployment insurance, in addition to parental protection insurance. The combined social contributions rates for regular employment contract are 22.1 and 16.1 percent of gross wage for employee and employer, respectively.

Student work cannot be performed by all students, as it is restricted to full-time students between 15 and 26 years of age, who are enrolled in any state-approved primary, vocational, high school, or undergraduate programs. Each job is based on a referral from an institution or organization authorized to provide job placement services for students—student employment agencies.[72]

5.2.2 Description of Slovenian Tertiary Education System

Our empirical analysis is restricted to a sample of full-time students majoring in business and economics programs, who first enrolled in 4-year programs offered by the Faculty of Economics (henceforth FELU) between 1997 and 2004, and entered the labor market between 2002 and 2010.[73] In order to fully understand the effects of academic success on labor market outcomes, we briefly describe the key features of educational system in Slovenia.

FELU is one of the largest public schools in Slovenia with 8 thousand students enrolled in full- and part-time undergraduate and graduate studies. It is a part of the University of Ljubljana, which is located in country's capital.[74] The university is public and does not charge tuition fees to students with Slovene residence. Students could enroll in the programs offered by the FELU after completing any four-year high school. The applicants were ranked nationally according to a weighted average grade, calculated from the grade percentage averages achieved in the third and fourth year of the high school study and a national exam called 'matura', an a Slovene equivalent of the SAT in the US.[75] A normalized version of these grades are used to calculate high school GPA, our measure of general ability.

The FELU offers five business majors (Accounting and Auditing, Business Informatics, Finance, Marketing, and Management and Organization) and three economics majors (Banking and Finance, International Economics, and National Economics). The majority of students were enrolled in business majors, such as Finance, Management and Organization, and Marketing. The expected time to complete any four-year program at the Faculty of Economics was five years, which includes the additional year for completion of the final thesis. However, the actual study time typically varies between 4 and 6 years, and can extend beyond 10 years. The grading scheme for undergraduate studies operates on a ten point scale with 1 as the lowest and 10 as the highest grade. A minimum requirement to pass an exam is 6. Students who fail to pass an exam were allowed to retake it with no limit on the total number of attempts, although the number of exam dates for each course was limited to three per academic year. Based on individual histories of academic results we construct measures that reflect study results such as the time required to reach the final year, the total number

[72] These agencies charge concession fee, which partly cover their costs of operations and partly finance students' scholarships, student organizations (unions) of universities, and renovation and building of student dormitories (EIAU Act, 2006; Act RACD, 2003).

[73] FELU also enrolls students to two-year undergraduate programs. These are not included in our study.

[74] University of Ljubljana consists of 26 faculties and academies with more than 60 thousand students in peak years.

[75] The high-school grades range between 1 (insufficient) and 5 (excellent); 2 is the lowest passing grade. The matura consists of three compulsory (Slovene language, Mathematics, and one foreign language - usually English) and two elective subjects, such as Biology, History, Physics, etc.).

of attempts to pass all exam, and the average grade of all exams.

The Slovenian students may receive different scholarships from prospective employers and government. The government pays two types of scholarship, based on merit (Zois scholarship) and family income (social scholarship). These scholarships may be temporarily lost if students do not successfully complete current year of studies. The amount of scholarship is conditional on the average grade.

5.3 Data

5.3.1 Data Sources

Our empirical analysis is based on information on persons who enrolled in the first year of 4-year university undergraduate programs at the FELU between 1997 and 2004, passed all exams and enrolled in the fifth year of study to write a final thesis. For this purpose we construct an individual-level panel data set with employment histories of these persons during and after studies. In particular, we use information on employment contracts of persons, their earnings, and personal characteristics, in addition to measures of performance during studies.

Using unique person-specific identifiers, we merged individual-level data from several different sources in a safe room at the Slovenian Statistical Office. The first source of data is the Slovenian Tax Authority (henceforth TARS), which collects information on all personal incomes earned. The data on student and regular-employee earnings are reported to TARS by student employment agencies and employers, respectively.[76] It provides information on labor incomes earned by persons during and after completion of studies. While students with sufficiently low earnings are typically not obliged to report personal incomes, student employment agencies have a legal obligation to report earnings received by each working high-school or college student. In addition, TARS is also the source of data for incomes of students' families and post-college earnings of students. Tax fillings for personal-income tax include both labor and capital incomes, which is important for construction of per-capita family income. Moreover, labor incomes of families include not only wages and salaries, but also bonuses, perks, wages earned on the basis of short-term labor contracts, and royalties. Capital incomes include interest, dividends, rents, and incomes of sole proprietors.

The second source of data on student earnings is a student employment agency, e-Študentski servis. This is an agency with a market share exceeding 50 percent in student work intermediation. Since this employment agency has more outlets in the central Slovenia, its market share in total student employment is even higher for FELU students. Their data contain not only information on incomes payable for each referral, but also information on earnings, number of working hours, identity of

[76] A standard procedure for data collection by tax authorities is reporting of own incomes by employees, which was also the case in Slovenia during the period of our analysis. However, the data we use are reported by employers or employment agencies and are usually used for inspection purposes.

employer, and types of jobs for all students who used their services. Unfortunately, this source of data has information regarding work only for referrals issued between January 2006 and December 2010, which reduces our sample to roughly half of all observations.

Next, we use the FELU application-sheet data on all enrolled students in 4-year undergraduate programs in addition to data on all attempts to pass exams and grades achieved. From this source of data we extract information on age, gender, location of permanent residence, chosen major, study year of students, and year of graduation. Based on enrollment history of each student, we also construct variables that indicate if student passed a year, repeated a year, or dropped out of a program. Exam results were used to construct variables on study performance of students.

The fourth source of data is National Examination Center, which collects the data on students' high-school performance. We have extracted information on the third- and forth-year average grades and the grades from final (external) examination called matura. We used these grades to construct a high school GPA.

The last source of data is the Slovenian Statistical Office (henceforth SORS). From SORS we obtained the data from Central Registry of Population, which allows us to establish identity of parents (a unique identifier) for each student and thus to attribute family incomes and transfers to students. Knowing the identity of parents, allows us to determine their educational attainment and family income. Finally, SORS also provided information on all scholarships received by students, ranging from social scholarships targeted to students with low-income families, scholarships for talented individuals (Zois scholarships) to scholarships granted by companies.

5.3.2 Construction of Variables and Summary Statistics

We are interested in the impact of student employment and academic performance on labor market outcomes. For this purpose we constructed a dataset of students, who enrolled in the first year at the FELU during the period 1997–2004 and sought regular employment between 2002 and 2010. The sample includes persons aged 18–20 years when enrolled in the first year of full-time undergraduate study. Due to data availability, we exclude persons who finished high school with vocational instead of general matura.[77] We analyze labor market outcomes in the first and second year on the labor market. Unfortunately, we do not have an actual information on entry on the labor market. Thus we assume the first year on the labor market to be two years after enrolling to the last year of study. The main reason is, that a lot of students extend their final year of study and/or need some time for job search. This gives us 2,616 and 2,347 observations in the first and second year on the labor market, respectively (see Table 5.1), among which approximately 60 percent are females.

The two variables that we attempt to explain in an empirical model are post-college employment

[77] We have access to data on high school performance of students that passed general matura, which enables enrollment in all programs of tertiary education. We do not collect data on vocational matura, which is by itself not sufficient for enrollment to university courses, as students have to additionally pass one subject of general matura in order to be able to enroll to university courses.

Table 5.1: Sample Size by Gender

	1st Year	2nd Year
Number of observations	2,616	2,347
Males	1,068	952
Females	1,548	1,395

status and post-college hourly gross wage. The former is an indicator variable that assumes value 1 if a person worked at least one hour and earned positive earnings in regular employment and value 0 otherwise. Table 5.2, which contains the summary statistics, reveals that 65.0 and 86.3 percent of persons were employed in the first and the second year, respectively. The hourly gross wage earned in regular employment is calculated as a ratio between annual gross earnings (as reported by TARS) and the total number of hours worked (as reported by SORS). In order to make it comparable over time, we deflate it using the Consumer Price Index. As expected, the average hourly gross wage is higher in the second year (6.75) than in the first year (4.37), as more people are employed and some regular work experience is gained.

One of the main explanatory variables is student work experience. It is constructed from annual earnings reported by student employment agencies for each person. As we do not have information on hours of work, we use average hourly gross wage rates reported by e-Študentski servis for regular university students to calculate the total number of working hours. Hence the observed differences in hours could reflect the differences in hourly wage rates. Since students perform a wide range of occupations, ranging from waitering tables to business analysis in consulting firms, the differences in wage rates could reflect also the differences in the type of experience students gained. In Table 5.2 it is shown that the average total student work experience in years (which is calculated by dividing hours worked by the total number of hours of a full-time employee per year) was roughly 1.8 years.

Among personal characteristics, Table 5.2 reports the average age when enrolled at university and a measure of general ability—high school GPA. As a result of the construction of our sample, the average age is almost 19 years. We base our measure of general ability on high school GPA (calculated from grades achieved in the third and fourth year of study and the final exam). We normalize this measure by subtracting 2—the minimum passing grade—and dividing by 3, which yields range between 0 and 1. The average GPA is around 0.5 in both periods.

Employers seeking regular workers are likely to select them based on their study results. We use several measures of study outcomes in order to capture these effects. In particular, as not all students actually defend their theses in the first year on the labor market, we construct an indicator variable that assumes value 1 if student graduated and 0 otherwise. This variable should capture the well-known 'sheep-skin' effect. Table 5.2 reveals that the FELU students rarely defend their thesis on time as the share of graduates in the first year is only 66.1 percent. In the second year this share is, however, much higher—80.9 percent. The other measures of study performance are: time needed to reach the final year, the total number of attempts to pass all exams, and the average grade of all exams. Table 5.2 shows that the average time to the final year was around 4.5 years, which implies that students needed roughly half a year more than it was expected. While the total

Table 5.2: Summary Statistics

	1st Year		2nd Year	
	Mean	Sd	Mean	Sd
Employed after college	0.650	0.477	0.863	0.344
Hourly gross wage after college	4.373	10.430	6.745	10.153
Student work experience in years	1.833	1.147	1.868	1.156
Age (at enrollment to faculty)	18.895	0.407	18.885	0.414
High school GPA	0.511	0.155	0.518	0.153
Graduated	0.661	0.473	0.809	0.393
Time to final year	4.522	0.749	4.521	0.741
No. of exam attempts	54.718	12.620	54.454	12.451
Avg. grade	6.801	0.750	6.808	0.744
University or higher—mum	0.208	0.406	0.206	0.404
University or higher—dad	0.235	0.424	0.235	0.424
Family business	0.162	0.369	0.156	0.363
Step parent	0.235	0.424	0.239	0.426
No. of sibling	0.790	0.750	0.804	0.746
Student parent	0.006	0.085	0.006	0.085
Non-labor income	8,005	5,794	7,920	5,682
Conditional-income share	0.147	0.232	0.153	0.237
Stochastic-income share	0.042	0.088	0.041	0.088
Expected net wage	15.852	2.484	15.749	2.452
Year	2,006.7	2.2	2,007.3	1.9

Notes: All income-related variables are in constant (2004) Euros. The exchange rate in 2004 was 1 EUR = 1.24 USD. Variables describing family characteristics and economic situation during studies are measured in the final year of study.

number of exams was 38, the average number of exam attempts was significantly higher—in both periods it was above 54. The average grade for all exams was around 6.8.

We also include family characteristics such as educational attainment of parents, ownership of family business by either of the two parents, having a step parent, number of siblings below the age of 27, and parental status before the entry to the labor market. The educational attainments of parents are measured with indicator variables that assume value 1 if they completed at least a 4-year undergraduate college degree.[78] Table 5.2 shows that around 20 percent of mothers and fathers had a college degree, while roughly 16 percent of parents owned a family business. On average, 24 percent of individuals had step parents and less than 1 percent had a child during their studies. When entering labor market, persons had on average less than one sibling under the age of 27.

The economic situation of person during the last year of study is described by non-labor income, conditional- and stochastic-income share. Non-labor income measures all incomes that are unrelated to student's work and includes (i) net family income per family member, which is constructed as the sum of parental net income divided by number of family members,[79] and serves as a proxy for parental transfers, (ii) scholarships, and (iii) pension received after deceased parents. The share of income that depends on academic success (conditional-income share) is calculated as a share of

[78]We also considered other measures of parental educational attainment such as the number of years of schooling. The results of the empirical model do not change qualitatively.

[79]We count as family members parents and children under the age of 27, following the income tax act that defines as a dependent family member a person up to the age of 26 (in addition to other requirements).

scholarships and pension benefit payments from a deceased parent[80] in their non-working income. Stochastic-income share, on the other hand, is a share of transitory incomes (such as capital incomes) in non-labor income. The average non-labor income in the final year of study for persons that just entered labor market was 8,005 EUR, 14.7 percent of which depended on the academic success and 4.2 percent of that income was transitory.

Lastly, Table 5.2 also contains summary statistics for the expected net wage, which is calculated separately for each year, major, and gender. We assume that students base their expectations on the most recent net wage of persons who graduated in their major. To capture differences in specific labor market conditions, our empirical model includes also dummies for year of observation on the labor market, major, and region of permanent residence of persons.

Table 5.3 shows there is a significant variation in popularity of different majors. The most popular are business majors, such as Finance, Marketing, and Management and Organization, while among the economics majors dominates Banking and Finance.[81] The regional structure (see Table 5.4) confirms the expected pattern that the students are most likely to originate from the region where FELU is located (Osrednjeslovenska region).

Table 5.3: Structure of Sample by Major

Major	1st Year	2nd Year
National Economy	1.22	1.24
International Economics	6.27	6.99
Banking and Finance	9.59	10.31
Marketing	19.07	18.07
Finance	31.65	31.23
Accounting	9.29	9.08
Management and Organization	13.38	13.98
Business Informatics	9.52	9.12

Note: Table presents shares in percent of respective column total.

Table 5.4: Structure of Sample by Region

Region	1st Year	2nd Year
Pomurska	1.45	1.62
Podravska	1.26	1.24
Koroška	1.80	1.62
Savinjska	7.11	6.90
Zasavska	2.14	1.96
Spodnjeposavska	2.33	2.39
Jugovzhodna	9.25	9.76
Osrednjeslovenska	45.95	45.97
Gorenjska	13.38	12.82
Notranjsko - kraška	2.48	2.39
Goriška	7.19	7.37
Obalno - kraška	5.66	5.97

Note: Table presents shares in percent of respective column total.

[80] Children have a right to receive a pension after their deceased parent until the end of their schooling or until they are 26 years old. Therefore students who are not enrolled in a program lose pension.
[81] Note that Slovenian employers often require specific field of specialization in job advertisements.

5.4 Empirical Analysis

5.4.1 Estimation Method

In order to estimate the effect of student work (and academic performance) on labor market outcomes we match students with different employment histories (academic performance) during study but similar predicted probabilities or propensity scores of student employment level (academic performance). The advantages of propensity score matching are two-fold. First, it avoids the dimensionality problem of finding matched subjects if there are many control variables. And second, it imposes minimal structure on estimation. Another characteristic of matching, which we consider as an advantage, is the fact that it puts an emphasis on observations with similar regressors. This means that observations at margin might get no weight. In contrast, OLS tries to minimize squared errors, which gives observations at margin a lot of weight.

For the calculation of treatment effects of student work we estimate propensity scores with logit regression for the probability of working k hours during study (SW_k), using personal characteristics (x) and academic performance (A) as explanatory variables. In similar manner, we use personal characteristics and student work as explanatory variables in the estimation of propensity scores for academic performance:

$$Pr[SW_{ki} = 1] = \alpha_0 + \alpha_1 x_i + \alpha_2 A_i + u_i \tag{5.1}$$

$$Pr[A_{ji} = 1] = \beta_0 + \beta_1 x_i + \beta_2 SW_i + e_i. \tag{5.2}$$

This conditional probability of receiving treatment (k hours of student work or level j of academic performance) given explanatory variables is used to match treated observations to controls with similar values of the propensity score. The calculation of average treatment effect on the treated (ATET) is then based on two assumptions: (i) conditional independence assumption (also called selection on observables, unconfoundedness, or ignorability)[82] and (ii) overlap or matching assumption.[83]

Matching algorithm used in our analysis is radius matching with replacement and imposed common support. Radius matching is a variant of caliper matching that uses all control units within the caliper (or radius) and not only the nearest neighbor as it does caliper matching (Dehejia and Wahba, 2002). This feature of radius matching reduces the bias of the estimated treatment effects. Bias is further reduced by matching with replacement, as it allows a treatment unit to be matched to control unit even if control unit was already matched. As suggested by Austin (2011) we use caliper equal to 0.2 of the standard deviation of the logit of the propensity score.[84]

[82] Conditional on x, outcomes of treatment (y_1) and control group (y_0) are independent of treatment (D). Rosenbaum and Rubin (1983) showed that if the former holds, y_1 and y_0 are also independent of D given propensity score.

[83] For every value of propensity score, there are observations in control and treatment group.

[84] We have also tried other matching algorithms and other caliper values but obtained qualitatively similar

Since we expect different levels of student work to have different impacts on labor market outcomes, we do not differentiate only between students who work and those who do not, but instead create six different binary treatment variables, which lead to estimation of six different ATETs. As shown in Table 5.5 we use those who have less than 10 months of student work experience as a control group for students with 10–24 months of work experience (ATET_{11}), for students with 2–3 years of work experience (ATET_{12}) and for students with over 3 years of work experience (ATET_{13}). Similarly, we use students with 10–24 months of work experience as a control group for those with treatment equal to 2–3 years of student work experience (ATET_{22}) and so on.

An alternative approach to the estimation of treatment effects would be to apply continuous matching as proposed by Hirano and Imbens (2004).[85] However, the estimation of dose-response function requires general propensity score to balance pre-treatment variables over all defined intervals, which is hard to achieve. We, on the other hand, estimate different propensity scores[86] for different treatment-control pairs, which makes it easier to achieve the balancing property. Another advantage of this procedure is, that even though the balancing property is not achieved for some treatment-control pair, other ATETs are still valid. However, a downside of this is that ATETs cannot be directly compared.[87]

Table 5.5: Construction of Treatment and Control Groups Based on the Amount of Student Work Experience

	TREATMENT		
Student work experience	10–24 months	2 - 3 years	more than 3 years
less than 10 months	ATET_{11}	ATET_{12}	ATET_{13}
10–24 months		ATET_{22}	ATET_{23}
2 - 3 years			ATET_{33}

We estimate the effect of student work on two outcome variables that measure labor market outcomes—probability of employment and hourly wage. The causal chain is presented in Figure E.1. Observe that we allow the causal relationship between student work and academic success to run in both directions. Since we measure the academic success and student work experience at the end of studies, extensive student work could harm academic success in a certain year, but at the same time poor academic performance could lower student work in the next year. As we assume that academic success affects student work and outcome variables, we have to include it among control variables, otherwise academic success can be unbalanced across treatment and control groups. But because we do that, we are able to estimate only the direct effect of student work on probability of employment:

$$E(Pr[w > 0]|SW_k = 1, x, A) - E(Pr[w > 0]|SW_k = 0, x, A), \tag{5.3}$$

where w denotes hourly wage, SW_k is dummy variable for treatment k, x are personal characteristics,

ATETs. We chose this method in line with the recommendation to make a control group as locally as possible and baseline differences as little as possible in order to compare comparable subjects (Lee, 2005).

[85] Estimation procedure proposed by Cattaneo (2010) cannot be used as all our outcome variables are not continuous.

[86] We estimate the same equation, but allow for different values of regression coefficients.

[87] ATET_{22} is not equal to the difference between ATET_{12} and ATET_{11}, since control group is not the same.

and A is academic success. Similarly, we do not estimate the total effect of student work on hourly wage but the combination of direct effect and indirect effect through probability of employment (see appendix E.2 for structural form equation):

$$E(w|SW_k = 1, x, A) - E(w|SW_k = 0, x, A). \tag{5.4}$$

For a subsample of individuals (with information on type of employment contract) we also estimate the effect of student work on probability of signing an employment contract with indefinite duration. Similarly as above, we estimate the combination of direct effect and indirect effect through probability of employment.

In the estimation of ATETs of academic performance on labor market outcomes, we define two treatments: (i) having a cumulative grade point average (GPA) of all exams taken in college in the 75th percentile or higher, and (ii) graduation. Analogous to estimation of ATETs described with Equations (5.3) and (5.4), we have to control here for student work as it might be unbalanced between groups with high and low GPA or between those with and without diploma. Therefore, the estimated ATETs do not encompass the indirect effect of academic performance on labor market outcomes through student work.

All treatment effects are estimated for the first and second year on the labor market. It should be noted that we do not estimate the 'dynamic model' which would include the lagged employment in the estimation of propensity scores for the second year,[88] because we are interested in ATETs that reflect total effect of treatment, which includes the indirect effect of student work on labor market outcomes in the second year through the outcomes in the first year on the labor market.

5.4.2 Student Work and Labor Market Outcomes

We first analyze the impact of student work experience on probability of employment. Average treatment effects on the treated for the first and the second year on the labor market are presented in Table 5.6. The average causal effect of 10–24 months of student work experience (treatment) on those with 10–24 months of student work experience (treated) is 9.3 percentage points in the first year. In other words, if students with 10–24 months of work experience had had instead less than 10 months of student work experience (controls), they would have on average a 9.3 percentage points lower probability of being employed in the first year on the labor market.

Although we find a positive relationship between student work experience and probability of employment, all increases in student work do not result in statistically significant increases in likelihood of being employed after college. In particular, observing students in the second year on the labor market, we find that those who work 10–24 months, 2–3 years, and more than 3 years during their study have on average 5.6, 9.7, and 12.2 percentage points higher probability of being employed than they would have with less than 10 months of student work experience, respectively. However,

[88] Hotz et al. (2002) showed that estimated returns to working while in high school or college dramatically diminish when dynamic selection model is used.

the probability of employment would not be statistically significantly different for students with 2–3 years of student work experience if they had worked only 10–24 months during college instead. Similarly, the increase of student employment from 2–3 years to more than 3 years does not statistically significantly increase the probability of being employed for students with the most work experience.

Table 5.6: Average Treatment Effects on the Treated: Probability of Employment

	Student work experience		
CONTROLS \ TREATED	10–24 months	2–3 years	more than 3 years
		1st Year	
Student work experience			
less than 10 months	0.093**	0.059	0.103*
	(0.027)	(0.034)	(0.041)
10–24 months		−0.031	0.006
		(0.026)	(0.030)
2–3 years			0.038
			(0.032)
		2nd Year	
Student work experience			
less than 10 months	0.056**	0.097**	0.122**
	(0.022)	(0.029)	(0.033)
10–24 months		0.023	0.044*
		(0.019)	(0.021)
2–3 year			0.032
			(0.023)

Notes: * $p< 0.05$; ** $p < 0.01$. Standard errors are reported in parentheses.

ATETs for gross hourly wage are presented in Table 5.7. Again, we find positive returns to student work experience. In particular, students who work 10–24 months, 2–3 years, and more than 3 years during their studies have on average 1.0, 0.7, and 1.3 EUR higher hourly wage (an increase equivalent to roughly 15 percent of average hourly wage) in the first year on the labor market than they would have if they had had less than 10 months of work experience, respectively. We, however, do not find a statistically significant ATETs when control group has more than 10 months of student work experience.

The above described results suggest that it pays for students to work more than 10 months, meaning that it is reasonable for students to work also during the semester. However, students do not gain or loose in terms of employability and gross hourly wage by increasing their student work experience above 2 years.

A comparison of ATETs for gross hourly wage (and majority of ATETs for probability of employment) in the first and the second year on the labor market reveals, that the importance of student work experience increases with time at first. The reason for increase in ATETs from the first to the second year on the labor market might be the indirect effect of student work experience on gross hourly wage through regular-work experience. Although regular-work experience is more relevant for the determination of gross hourly wage and employability, as it is more wholly available to the employers, students' who enter the labor market lack this kind of experience. Because regular-work experience depends on the probability of being employed in previous years, student work has a considerable effect on it in the second year on the labor market. Over time other factors influencing regular-work experience, such as skills acquired at regular work or attitude to regular work, prevail over student work experience. Thus, we see a decrease in ATETs if we observe all years on the labor market. Although we calculate these results, they are not presented as the observed years on the labor market depend on the year in which persons exits faculty. The analysis of all years, which is in our case limited to the year 2010, thus puts more weight on the first years on the labor market, since we observe less persons in e.g. sixth year than in the first year. Therefore, we cannot conclude whether a significant ATET is a consequence of persistent effect of e.g. student work or it is just a result of higher weight of first years. Nevertheless, we observe a decrease in size of ATETs. This finding is consistent with Häkkinen (2006), who finds a transient effect of student work on labor market success.

Table 5.7: Average Treatment Effects on the Treated: Gross Hourly Wage (in EUR)

	Student work experience		
CONTROLS \ TREATED	10–24 months	2–3 years	more than 3 years
		1st Year	
Student work experience			
less than 10 months	1.037*	0.681*	1.326**
	(0.501)	(0.310)	(0.421)
10–24 months		−0.302	0.271
		(0.374)	(0.466)
2–3 years			0.584
			(0.381)
		2nd Year	
Student work experience			
less than 10 months	1.115*	2.159**	2.284**
	(0.435)	(0.561)	(0.574)
10–24 months		0.649	0.372
		(0.569)	(0.644)
2–3 years			0.100
			(0.779)

Notes: Values are in constant (2004) Euros. The exchange rate in 2004 was 1 EUR = 1.24 USD. Standard errors are reported in parentheses. * $p < 0.05$; ** $p < 0.01$.

Probability of Signing Employment Contract with Indefinite Duration

Unfortunately, we do not have information on the type of contract for all persons, so we estimate the effect of student work experience on probability of getting an indefinite contract on a subsample. As Table E.1 shows, the number of observations decreases to 2,279 and 2,007 for the first and the second year on the labor market, respectively, but the share of females in the subsample remains at roughly 60 percent. Persons in the subsample have on average lower probability of employment and lower hourly gross wage after college than those in the full sample (see Table E.2). The difference is a consequence of construction of the indicator outcome variable, which equals zero for all unemployed persons and for employed with definite contracts, and 1 for those who reported to have a contract with indefinite duration. As the subsample excludes only employed persons without information on the type of contract, the share of employed is lower than in the full sample. As hourly wage after college equals zero for the unemployed, its values are also lower for the subsample. Other observed variables have similar averages in both samples.

We find that additional student work increases probability of signing indefinite contract. For example, Table 5.8 reports that students with 10–24 months of student work experience have on average 9.5 percentage points higher probability of signing such contract than they would have with less than 10 months of work experience in the second year on the labor market. Again we can observe that students mostly increase the chances of having contract with indefinite duration by increasing their work experience over 10 months. In the first year on the labor market ATETs are, however, statistically insignificant, which may be due to the probation period of employees when they enter a labor market.

Table 5.8: Average Treatment Effects on the Treated: Probability of Signing an Indefinite Contract

	Student work experience		
CONTROLS \ TREATED	10–24 months	2–3 years	more than 3 years
		1st Year	
Student work experience			
less than 10 months	0.035[1]	0.019	0.065
	(0.025)	(0.033)	(0.039)
10–24 months		−0.008	0.025
		(0.026)	(0.031)
2–3 years			0.025
			(0.033)
		2nd Year	
Student work experience			
less than 10 months	0.095**	0.124**	0.170**
	(0.031)	(0.037)	(0.043)
10–24 months		0.009	0.068
		(0.029)	(0.035)
2–3 years			0.062
			(0.037)

Notes: [1] Number indicates how many of the 50 explanatory variables are not balanced between control and treatment group at $p < 0.01$. * $p < 0.05$; ** $p < 0.01$. Standard errors are reported in parentheses.

A potential concern regarding our findings is related to the measurement of student work experience, which is based on earnings and can thus reflect also the differences in hourly wages. The 9.5 percentage point increase in the probability of signing an indefinite contract in the second year on the labor market for students who had 10–24 months instead of less than 10 months of implied experience can therefore be a result of either more hours worked or better paying job, which usually requires workers with better skills. At same time, some students that were used as controls with less than 10 months of student work experience, can in fact have more than 10 months of student work experience in the lowest paying jobs. However, on average the student work experience are measured correctly unless some levels of student earnings are earned only with below average or only with above average hourly wages. This is highly unlikely. In addition, such hourly wages would depend on e.g. academic performance, ability, and/or some other control variable, thus we would not be able to achieve balancing property for such levels of student employment. Therefore, we believe that our results are valid.

Related versus Unrelated Student Work Experience

Next we examine whether different types of student work affect student labor market outcomes differently. The treatment effects are estimated on a subsample of students that used referrals issued by one of the student employment agencies (e-Študentski servis) during 2006–2010. As shown in Table E.1, the total number of observations is 1,186 and 983 in the first and the second year on the labor market, respectively. These observations include information on the actual type of work performed by students—e-Študentski servis distinguishes between more than 100 occupations and reclassifies them according to International Standard Classification of Occupations (1988). We have grouped these occupations into 3 groups: i) related high-skilled occupations (e.g. business analysts, accountants, programmers),[89] ii) related, but less-skilled occupations (e.g. office work, data preparation)[90] and iii) unrelated low-skilled occupations (e.g. serving tables).[91] Since we do not observe entire employment histories of students that used services of this agency, we cannot calculate the ATETs in the same manner as shown in Tables 5.6 to 5.8. Instead, we construct three binary treatment variables, that lead to three average treatment effects. Specifically, we use unrelated low-skilled work as a control group for related less-skilled work and related high-skilled work, and related less-skilled work as a control group for related high-skilled work. Student is defined to have e.g. high-skilled student work experience if she performed at least some hours of such work. In the estimation of propensity scores, we add student work experience as an additional control variable.

Summary statistics of the subsample in Table E.3 reveals that compared to the full sample, the average student work experience in years are lower. This can be attributed to the observation period, which puts more weight on the years during financial crisis, which decreased student work hours (see Bartolj et al., 2015). Furthermore, persons in the subsample have poorer academic results (lower graduation rates, higher number of exam attempts) and higher non-labor income. The last is a result of agency's branch network, which is concentrated in wealthier parts of the country.

We find (see Table 5.9) that related high-skilled student work increases probability of employment compared to unrelated low-skilled (related less-skilled) student work by 15.8 (10.7) percentage points in the first year on the labor market. In addition, the gross hourly wage (probability of signing indefinite contract) of persons that worked in related less-skilled or high-skilled jobs during study is on average 0.8 and 1.6 EUR (8.4 and 21.9 percentage points) higher than it would be if they had worked in unrelated low-skilled jobs, respectively. In the second year on the labor market, the only significant impacts are the effects of related high-skilled work on probability of signing an employment contract with indefinite duration, which suggests that the effects of different types of student jobs are temporary. Persons with related high-skilled work have 22.8 percentage points higher probability of signing such contract than they would have with unrelated, low skilled experience and 15.6 percentage points higher probability than they would have with related, but less

[89]ISCO broad categories 1 and 2.
[90]ISCO broad categories 3, 4, 5 and 6.
[91]ISCO broad categories 7, 8 and 9.

skilled experience.

Table 5.9: Average Treatment Effects on the Treated for Different Types of Student Work

	1st year		2nd year	
CONTROLS \ TREATED	Related, less-skilled	Related, high-skilled	Related, less-skilled	Related, high-skilled
		Pr[Employment]		
Unrelated, low-skilled	0.038	0.158**	−0.001	0.019
	(0.034)	(0.057)	(0.029)	(0.052)
Related, less-skilled		0.107*		0.006
		(0.049)		(0.039)
		Gross hourly wage		
Unrelated, low-skilled	0.806*	1.597*	−0.819	−1.292
	(0.363)	(0.660)	(1.121)	(1.203)
Related, less-skilled		0.192		−0.817
		(0.903)		(1.032)
		Pr[Indefinite contract]		
Unrelated, low-skilled	0.084**	0.219**	0.072	0.228**
	(0.033)	(0.068)	(0.049)	(0.079)
Related, less-skilled		0.097		0.156*
		(0.059)		(0.061)

Notes: * $p< 0.05$; ** $p < 0.01$. Standard errors are reported in parentheses.

5.4.3 Academic Performance and Labor Market Outcomes

The last set of results provides evidence on the impact of academic performance on labor market outcomes. In contrast to student work experience, there is no unique measure of students' academic achievements. In this paper we concentrate on two measures that we believe are most likely observed by employers in selection process of regular workers and may thus have the greatest impact on labor market outcomes. These measurements are graduation and GPA in the top quartile of distribution. ATETs for both treatments are presented in Table 5.10.

The results show that graduation increases probability of employment for those who graduate by 28.6 and 21.7 percentage points in the first and second year on the labor market, respectively. A corresponding increase in gross hourly wage equals 2.6 and 2.3 EUR in the two years. Furthermore, graduation causes an 11.5 and 17.1 percentage points increase in probability of signing indefinite employment contract in the first and second year on the labor market, respectively. The ATETs of GPA in the 75th percentile or higher are smaller in size. We find that persons with above average GPA have a 9.0 percentage points higher probability of employment in the first year and 11.1 percentage point higher probability of indefinite contract in the second year than they would have if their GPA had been below the 75th percentile. In addition, above average GPA increases gross hourly wage by 2.6 and 1.7 EUR in the first and second year, respectively.

As table shows, not all variables are balanced in the calculation of ATETs. However, we nevertheless

Table 5.10: Average Treatment Effects on the Treated for Academic Performance

	Pr[Employed]	Gross hourly wage	Pr[Indefinite contract]
		1st Year	
Graduated	$0.286^{**,2}$	$2.572^{**,2}$	$0.115^{**,4}$
	(0.022)	(0.335)	(0.019)
GPA in the 75th percentile or higher	$0.090^{**,1}$	$2.635^{**,1}$	0.047^{1}
	(0.025)	(0.776)	(0.027)
		2nd Year	
Graduated	$0.217^{**,6}$	$2.337^{**,6}$	$0.171^{**,4}$
	(0.025)	(0.380)	(0.028)
GPA in the 75th percentile or higher	0.028	1.669^{*}	0.111^{**}
	(0.019)	(0.694)	(0.031)

Notes: $^{1-6}$ Number indicates how many of the 48 explanatory variables are not balanced between control and treatment group at $p < 0.01$. * $p < 0.05$; ** $p < 0.01$. Standard errors are reported in parentheses.

significantly increase the balancing property. For example, in the estimation of average graduation effect on graduates there are 15 unbalanced variables in the unmatched sample and 2 unbalanced variables in the matched one.

The comparison of ATETs of academic success and student work show, that the impacts of academic success are generally higher in size than the effects of student work on labor market outcomes. Specifically, the graduation increases the employability, gross hourly wage, and probability of signing indefinite contract in the first and the second year on the labor market more than any increase in student work experience. In addition, GPA in the 75th percentile or higher increases gross hourly wage in the first year on the labor market more than ‘full time’ employment during study, while in the second year ATET exceeds treatment effect of 10–24 months of student work experience. Similarly, above average GPA affects probability of signing indefinite employment contract more than does the increase of student work experience from less than 10 months to 10–24 months.

5.5 Conclusions

This paper analyzes the underexplored effect of college student work and academic performance on labor market outcomes. We show that student work positively and significantly affects the probability of employment, gross hourly wage, and the probability of signing an employment contract with indefinite duration. Our results show that students benefit most by increasing their work experience during 4-year undergraduate study from less than 10 months to 10–24 months. Additional student work experience has positive treatment effects, but their size is small and often statistically insignificant. The comparison of different types of student jobs shows that the high-skilled jobs, which are related to the field of study, are the most advantageous.

However, academic success seems to have a greater effect on post-college professional career. We discover that graduation increases probability of employment, gross hourly wage, and probability of signing indefinite employment contract more than an increase in student work experience from less than 10 months to more than 3 years during 4-year undergraduate study. In addition, students with GPA in the top quartile of the distribution increase their hourly wages in comparison to lower achieving students more than students who increase student work from less than 10 months to more than 3 years of experience in the first year on the labor market, while the difference is somewhat lower in the second year. The effect of ranking in the top quartile of the GPA distribution on probability of employment in the first year on the labor market is similar to the effect of increasing student work experience from less than 10 months to 10–24 months.

These results suggest that both, student work and academic performance, are beneficial for students in terms of labor market outcomes. Unfortunately, our data do not enable us to measure the effort needed to graduate, pass an exam with above average score, or perform one hour of student work, therefore we can not make any judgments regarding optimality of time allocation between studying and working. Nevertheless, results suggest that student work, especially high-skilled work related to the field of study, should be encouraged but to a limited extent, since after a certain point additional experience does not result in higher post-college labor market outcomes. At the same, we can reject the notion of some students that acquired practical skills matter more than theoretical ones. It should however be noted, that these results are based on data from one faculty and should be generalized with caution, as employers in other fields might have different preferences regarding academic and professional skills.

CONCLUSION

This doctoral dissertation aims to give insights into factors influencing students' decisions during tertiary education and the outcomes of these choices. Specifically, we analyze how students select college majors and what influences their decisions on labor supply during study. Furthermore, we estimate the effect of these choices on outcomes such as private returns to education, academic performance, wages, or probability of employment.

We begin with the study of the impact of cognitive ability on college major choices. The construction of a unique and objective measure of major-specific abilities allows us to provide new evidence that shows that not only general, but also major-specific abilities play an important role in the explanation of college major choices of economics and business students. Specifically, we find that students with higher general ability are more likely to choose methodologically more demanding majors, and that higher relative major-specific ability implies higher likelihood of choosing the corresponding major and lower likelihood of choosing all other majors. In addition, we confirm the importance of gender, major-specific net wage, and labor market conditions on major choice.

Students' selection of field of study, among other things, influences their employment opportunities and wages. One way to capture this impact is to estimate the rates of return to their education. This thesis contributes to the literature by estimating the evolution of private returns to education not only at the beginning of the transition but over a period of 15 years. Unlike other studies on returns to education during transition, we estimate returns to different levels and fields of tertiary education and find an inverse U-shaped trend. We show that, in spite of significant increases in the labor supply, the demand for university graduates outweighed this and increased the rates of return in the early period of transition (1994–2001), while in the later period (2001–2008) the opposite was the case. We also observe considerable heterogeneity in rates of return between genders, educational levels, and fields of study, with particularly large returns at the beginning of the period analyzed to the fields that were neglected during socialism (e.g., social studies, law, and business studies) and relatively low returns to the technical fields that were favored by socialist leaders. Furthermore, the differences between returns based on net wage and those based on total labor income show that the alternative income sources represent a non-negligible part of private rates of return.

Another factor that influences the labor market outcomes as well as educational outcomes is student work. We first concentrate on the relationship between non-labor income and student work and find that it is inversely U-shaped. Although previous studies observed similar behavior of students, no explanation has been put forward to reconcile the evidence with theoretical models of labor supply. We provide empirical evidence suggesting that students from low-income families, who receive lower transfers, are also more likely to drop out of studies if they fail to pass a study year. This motivates our theoretical model, which predicts an increasing relationship between non-labor income and student labor supply. The key assumption for our results is DARA parental utility function, which implies that poorer parents are more risk averse and are less willing to make additional investments in a risky asset in the form of children's human capital. We argue that students from poor families, who are aware of such parental preferences, respond to this credible threat and supply less labor in order to avoid future financial constraints. For all other students the threat is not credible, so only the income effect of non-working income is observed for them. The result is an inverse U-shaped relation between student work and family income discovered in our data. These findings contribute to the literature by revealing the third factor—future financial constraint—that has to be taken into account, along with the income effect of non-wage income and current financial constraint, in the explanation of influence of non-working income on student labor supply.

The thesis continues with the study of causal effects of student work on five different measures of academic performance using propensity score matching technique, separately for each of the 4 years of undergraduate study. We find that student work has either no effect or a small negative effect. Supplementing existing studies that do not differentiate between study years, we show that student work harms academic success mostly in the first year of study, when students are less likely to find the right balance between work and study. Our results suggest that mixed evidence on the adverse effects of student work on academic performance might be a consequence of samples concentrating on dissimilar study years and outcome variables.

Finally, we assess the relative influence of student work experience and academic performance on post-college labor market outcomes. The analysis of the underexplored effects of college student work and academic performance on professional career reveals that it positively and significantly affects the probability of employment, gross hourly wage, and likelihood of signing an indefinite contract. Our results show that students benefit most by increasing their work experience during 4-year undergraduate study from less than 10 months to 10–24 months. Additional student work experience has positive treatment effects, but their size is small and often statistically insignificant. The comparison of different types of student jobs shows that the high-skilled jobs, which are related to the field of study, are the most advantageous. However, academic success seems to have a greater effect on post-college professional career. Specifically, graduation increases all three outcome variables more than 'full-time' student employment.

The findings of this doctoral dissertation contribute not only to the literature as described above, but are also important for policy makers. Our estimates show that returns to education differ by field of study. The higher the supply and/or the lower the demand, the lower are the equilibrium wages and also the returns to education. But the understanding of factors influencing the selection of college major allows policy makers to set incentives that will appropriately adjust the structure of labor supply to the needs of the labor market and other development goals. Specifically, although higher wages by themselves attract students to the fields with higher returns, policy makers should also attempt to change major-specific abilities and in such way try to stimulate a faster adjustment of supply and demand in the labor market. In addition, our results suggest that student work, especially the high-skilled work related to the field of study, should be encouraged in the last years of study, but to a limited extent.

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APPENDICES

LIST OF APPENDICES

Appendix A: Chapter 1

Table A.1: 1st and 2nd Year Courses

1st year	2nd year
Accounting	Business Information Systems 2
Business Information Systems 1	Economic Statistics
Commercial Law	Entrepreneurship
Enterprise Economics	Foreign Language 1
Introduction to National Economics	Political Economy
Mathematics 1	Management
Organization of the Enterprise	Mathematics 2
Introductory Microeconomics	Intermediate Microeconomics
Introductory Macroeconomics	Intermediate Macroeconomics
Statistics 1	Statistics 2

Table A.2: 3rd Year Courses

	Economics Program			Business Program				
	NE	BF	IE	Mrk	Fin	Acc	Mng	BI
History of Economic Thought	x	x	x					
International Economics	x	x	x					
Monetary Economics	x	x	x	x	x	x	x	x
Industrial Organization	x	x	x					
Econometrics	x	x	x					
Theory of Economic Policy	x	x	x					
Public Finance	x	x	x		x	x		
Foreign Language 2	x	x	x	x	x	x	x	x
Principles of Marketing				x	x	x	x	x
Corporate Finance				x	x	x	x	x
Organization of Production				x	x	x	x	x
Managerial Accounting				x			x	
Methods of Marketing Research				x				
Consumer Behaviour				x				
Banking					x	x		
Financial Accounting					x			
Cost Accounting						x		
Principles of Management							x	
Human Resources and Management							x	
Decision Support Technology								x
Information Systems in the Economy								x
Databases								x
Elective				x			x	

Table A.3: 4th Year Courses by Major

	Economics program			Business program				
	NE	BF	IE	Mrk	Fin	Acc	Mng	BI
Development Economics	x	x	x					
Economics of European Union	x	x	x					
Corporate Finance	x		x					
Labor Economics	x							
Regional Economics	x							
National Accounting	x							
Philosophy of Economics	x							
Financial Economics		x						
Theory of Corporate Finance		x						
International Finance		x	x		x	x		
Financial Markets		x			x			
Banking		x						
Economics of Public Enterprises		x						
Economics and Politics of International Trade			x					
International Business			x	x			x	
International Marketing			x	x			x	
International Commercial Law			x	x				
Foreign Language 3			x					
International Economics				x	x	x	x	x
Strategic Management				x	x	x	x	x
Business Environment				x	x	x	x	x
Marketing Channels				x				
Marketing Communications				x				
Insurance					x			
Management Accounting					x	x		
Auditing						x		
Economics and Organization of Information Systems						x		
Orgranization Theory							x	
Analysis and Design of Organization							x	
Analysis and Planning of Organization							x	
Information Systems Development								x
Cost Accounting or Management Accounting								x
Object-oriented Methodology								x

(table continues)

(continued)

	Economics program			Business program				
	NE	BF	IE	Mrk	Fin	Acc	Mng	BI
Organizing and Decision Making								x
Elective	x	x	x	x	x	x	x	x
Elective	x			x				

Table A.4: Estimation Results: Mixed Logit and Nested Logit Model

			Mixed		NL	
Regressor	Type		Coeff.	St. Error	Coeff.	St. Error
Net Wage	Specific		0.639***	(0.207)	1.701***	(0.408)
Intercept	Invariant	Acc	3.693	(3.526)	14.972	(23.736)
		BI	10.871***	(3.644)	32.553	(23.820)
		Fin	8.683***	(3.310)	27.877	(23.581)
		Mng	10.270***	(3.440)	32.266	(23.657)
		Mrk	10.842***	(3.376)	34.889	(23.697)
		BF	−1.041	(3.544)	−1.613	(24.627)
		IE	5.305	(3.909)	49.365*	(29.800)
		NE	0.000		0.000	
High School GPA	Invariant	Acc	−0.065	(0.193)	2.178*	(1.251)
		BI	0.020	(0.196)	2.415*	(1.267)
		Fin	−0.015	(0.181)	2.302*	(1.244)
		Mng	0.025	(0.186)	2.434*	(1.253)
		Mrk	−0.010	(0.183)	2.351*	(1.243)
		BF	0.407**	(0.196)	3.101**	(1.479)
		IE	0.635***	(0.208)	3.353***	(1.514)
		NE	0.000		0.000	
Accounting	Invariant	Acc	0.238**	(0.111)	0.569	(0.793)
		BI	−0.133	(0.118)	−0.432	(0.784)
		Fin	−0.027	(0.105)	−0.148	(0.770)
		Mng	−0.232**	(0.111)	−0.708	(0.784)
		Mrk	0.041	(0.142)	−0.471	(0.775)
		BF	−0.085	(0.139)	0.450	(0.869)
		IE	0.012	(0.147)	−1.599	(1.057)
		NE	0.000		0.000	
Enterprise Economics	Invariant	Acc	0.006	(0.111)	−0.456	(0.710)
		BI	−0.203*	(0.116)	−1.036	(0.709)
		Fin	0.022	(0.104)	0.712	(1.561)
		Mng	−0.156	(0.109)	−0.265	(1.581)
		Mrk	−0.066	(0.106)	1.699	(1.577)
		BF	−0.066	(0.111)	−0.707	(1.778)
		IE	−0.143	(0.119)	2.195	(2.032)
		NE	0.000		0.000	
Business Informatics	Invariant	Acc	0.100	(0.146)	0.540	(0.967)
		BI	0.427***	(0.148)	1.385	(0.980)
		Fin	0.062	(0.137)	0.432	(0.957)
		Mng	0.041	(0.142)	0.353	(0.960)
		Mrk	−0.085	(0.139)	0.011	(0.964)
		BF	0.012	(0.147)	0.676	(1.107)
		IE	−0.041	(0.156)	−0.044	(1.174)
		NE	0.000		0.000	
Mathematics	Invariant	Acc	0.029	(0.134)	−0.268	(0.795)
		BI	0.100	(0.135)	−0.025	(0.787)
		Fin	0.183	(0.125)	0.183	(0.78)
		Mng	0.043	(0.130)	−0.210	(0.786)
		Mrk	0.062	(0.128)	−0.185	(0.783)
		BF	0.096	(0.133)	0.254	(0.888)
		IE	−0.061	(0.144)	−0.817	(0.959)
		NE	0.000		0.000	
Microeconomics	Invariant	Acc	0.109	(0.098)	1.209**	(0.579)
		BI	−0.040	(0.100)	0.838	(0.581)
		Fin	0.137	(0.092)	1.301**	(0.574)
		Mng	0.031	(0.095)	1.017*	(0.574)

(table continues)

(continued)

Regressor	Type		Mixed Coeff.	Mixed St. Error	NL Coeff.	NL St. Error
		Mrk	0.028	(0.093)	0.996*	(0.571)
		BF	0.140	(0.098)	1.304**	(0.651)
		IE	0.175*	(0.103)	1.441**	(0.695)
		NE	0.000		0.000	
Management	Invariant	Acc	−0.026	(0.095)	−0.493	(0.573)
		BI	−0.326***	(0.100)	−1.334**	(0.604)
		Fin	0.023	(0.089)	−0.383	(0.565)
		Mng	0.005	(0.092)	−0.439	(0.567)
		Mrk	0.036	(0.090)	−0.359	(0.565)
		BF	−0.034	(0.096)	−0.613	(0.656)
		IE	−0.030	(0.101)	−0.449	(0.703)
		NE	0.000		0.000	
Organization	Invariant	Acc	−0.206**	(0.101)	−1.540**	(0.650)
		BI	−0.164	(0.104)	−1.391**	(0.647)
		Fin	−0.212**	(0.095)	−1.558**	(0.644)
		Mng	−0.058	(0.098)	−1.117*	(0.641)
		Mrk	−0.124	(0.096)	−1.310**	(0.640)
		BF	−0.200*	(0.102)	−1.480*	(0.717)
		IE	−0.161	(0.108)	−1.823**	(0.831)
		NE	0.000		0.000	
Commercial Law	Invariant	Acc	0.154	(0.118)	1.165	(0.902)
		BI	0.101	(0.122)	1.105	(0.899)
		Fin	0.110	(0.111)	1.084	(0.892)
		Mng	0.154	(0.115)	1.206	(0.897)
		Mrk	0.221**	(0.113)	1.354	(0.899)
		BF	0.237	(0.118)	1.364	(0.998)
		IE	0.165	(0.125)	1.387	(1.106)
		NE	0.000		0.000	
Entrepreneurship	Invariant	Acc	0.216*	(0.110)	0.839	(0.616)
		BI	0.219*	(0.113)	0.807	(0.616)
		Fin	0.169	(0.103)	0.697	(0.604)
		Mng	0.218**	(0.106)	0.833	(0.609)
		Mrk	0.174*	(0.104)	0.709	(0.604)
		BF	0.118	(0.110)	0.803	(0.697)
		IE	0.157	(0.117)	0.714	(0.757)
		NE	0.000		0.000	
Macroeconomics	Invariant	Acc	−0.523***	(0.134)	−0.979	(0.795)
		BI	−0.544***	(0.142)	−1.060	(0.792)
		Fin	−0.463***	(0.121)	−0.814	(0.777)
		Mng	−0.440***	(0.129)	−0.762	(0.783)
		Mrk	−0.536***	(0.126)	−1.013	(0.782)
		BF	−0.236*	(0.128)	−0.640	(0.882)
		IE	−0.268*	(0.139)	−0.856	(0.984)
		NE	0.000		0.000	
Political Economics	Invariant	Acc	−0.120	(0.101)	0.560	(0.561)
		BI	−0.247**	(0.105)	0.146	(0.567)
		Fin	−0.129	(0.095)	0.541	(0.551)
		Mng	−0.210**	(0.099)	0.284	(0.555)
		Mrk	−0.195**	(0.097)	0.354	(0.551)
		BF	0.152	(0.101)	0.971	(0.648)
		IE	0.088	(0.107)	0.553	(0.649)
		NE	0.000		0.000	
National Economics	Invariant	Acc	−0.141	(0.103)	−0.717	(0.541)
		BI	−0.186*	(0.104)	−0.832	(0.542)
		Fin	−0.102	(0.096)	−0.587	(0.530)

(table continues)

(continued)

Regressor	Type		Mixed Coeff.	Mixed St. Error	NL Coeff.	NL St. Error
		Mng	−0.165*	(0.099)	−0.772	(0.534)
		Mrk	−0.117	(0.097)	−0.628	(0.530)
		BF	−0.102	(0.103)	−0.891	(0.623)
		IE	−0.057	(0.109)	−0.392	(0.646)
		NE	0.000		0.000	
Statistics	Invariant	Acc	−0.056	(0.108)	−0.355	(0.678)
		BI	−0.029	(0.110)	−0.255	(0.675)
		Fin	−0.013	(0.100)	−0.232	(0.669)
		Mng	−0.055	(0.104)	−0.351	(0.672)
		Mrk	−0.091	(0.102)	−0.452	(0.671)
		BF	0.037	(0.106)	−0.317	(0.764)
		IE	0.028	(0.113)	−0.255	(0.835)
		NE	0.000		0.000	
Economic Statistics	Invariant	Acc	0.025	(0.118)	0.592	(0.682)
		BI	−0.052	(0.123)	0.394	(0.685)
		Fin	0.023	(0.111)	0.573	(0.672)
		Mng	−0.016	(0.116)	0.459	(0.676)
		Mrk	0.087	(0.113)	0.762	(0.674)
		BF	0.163	(0.117)	1.388*	(0.778)
		IE	0.061	(0.125)	−0.331	(0.86)
		NE	0.000		0.000	
Female	Invariant	Acc	1.130***	(0.223)	2.405	(1.616)
		BI	−1.171***	(0.233)	−3.920**	(1.928)
		Fin	0.495**	(0.205)	0.712	(1.561)
		Mng	0.125	(0.212)	−0.265	(1.581)
		Mrk	0.836***	(0.208)	1.699	(1.577)
		BF	−0.004	(0.221)	−0.707	(1.778)
		IE	0.506**	(0.234)	2.195	(2.032)
		NE	0.000		0.000	
Age	Invariant	Acc	−0.074	(0.170)	−0.605	(0.873)
		BI	−0.094	(0.174)	−0.566	(0.878)
		Fin	−0.242	(0.160)	−1.037	(0.874)
		Mng	−0.130	(0.165)	−0.708	(0.864)
		Mrk	−0.192	(0.162)	−0.919	(0.868)
		BF	−0.067	(0.171)	−0.578	(1.023)
		IE	−0.260	(0.190)	−1.496	(1.096)
		NE	0.000		0.000	
Region 1	Invariant	Acc	0.017	(0.302)	−3.447	(2.197)
		BI	−0.241	(0.303)	−4.097*	(2.196)
		Fin	−0.198	(0.281)	−4.015*	(2.177)
		Mng	−0.431	(0.289)	−4.616**	(2.184)
		Mrk	−0.264	(0.285)	−4.175*	(2.176)
		BF	−0.612**	(0.302)	−5.297**	(2.485)
		IE	−0.391	(0.315)	−4.341*	(2.576)
		NE	0.000		0.000	
Region 2	Invariant	Acc	0.685*	(0.352)	−0.307	(2.310)
		BI	0.130	(0.358)	−1.897	(2.274)
		Fin	0.329	(0.334)	−1.275	(2.267)
		Mng	−0.034	(0.343)	−2.297	(2.265)
		Mrk	0.141	(0.338)	−1.773	(2.262)
		BF	−0.063	(0.353)	−2.309	(2.536)
		IE	−0.110	(0.371)	−1.589	(2.68)
		NE	0.000		0.000	
Region 3	Invariant	Acc	−0.170	(0.303)	−4.072*	(2.331)
		BI	−0.491	(0.305)	−4.888**	(2.333)

(table continues)

(continued)

Regressor	Type		Mixed Coeff.	Mixed St. Error	NL Coeff.	NL St. Error
		Fin	−0.358	(0.280)	−4.563**	(2.312)
		Mng	−0.676**	(0.290)	−5.414**	(2.326)
		Mrk	−0.479*	(0.285)	−4.881**	(2.312)
		BF	−0.663**	(0.301)	−5.338**	(2.609)
		IE	−0.713**	(0.321)	−6.030**	(2.842)
		NE	0.000		0.000	
Region 4	Invariant	Acc	0.121	(0.452)	−1.171	(3.217)
		BI	−0.407	(0.464)	−2.411	(3.206)
		Fin	−0.432	(0.425)	−4.563**	(2.312)
		Mng	−0.750*	(0.445)	−5.414**	(2.326)
		Mrk	−0.020	(0.426)	−4.881**	(2.312)
		BF	−0.404	(0.449)	−5.338**	(2.609)
		IE	−0.770	(0.500)	−6.030**	(2.842)
		NE	0.000		0.000	
Log-likelihood			-9553.8		-9534.8	
AIC			19417.5		19383.7	
BIC			20765.7		20749.2	
τ (economics)					10.175	(3.606)
τ (business)					2.809	(0.652)
LR test for IIA (p-value)					37.84	(0.000)

Notes: High school GPA is calculated as an average of the matura examination and high school average grade. Grades for courses in both first and second year are calculated as average grades. There are five regions that are based on the distance between student's home address and FELU (Ljubljana). Student is in region 0 if the distance is less than 10 km; in region 1 if the distance is at least 10 km, but less than 40 km; in region 2 if the distance is at least 40 km, but less than 70 km; in region 3 if the distance is at least 70 km, but less than 110 km; and in region 4 otherwise. For each region we construct a dummy variable that assumes the value 1 if student is from the corresponding region and 0 otherwise. Standard errors in parentheses. *** p-value< 0.01, ** p-value < 0.05, * p-value< 0.1.

Appendix B: Chapter 2

Table B.1: Estimation Results: Mincerian Wage Regression, Annual Net Wages

	Males			Females		
	1994	2001	2008	1994	2001	2008
$\beta_{2-yearUG}$	0.306***	0.370***	0.319***	0.248***	0.366***	0.330***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)
$\beta_{4-yearUG}$	0.595***	0.691***	0.584***	0.569***	0.704***	0.606***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
$\beta_{MSc/MA}$	0.823***	1.069***	0.902***	0.807***	1.101***	0.955***
	(0.014)	(0.011)	(0.009)	(0.016)	(0.012)	(0.009)
β_{PhD}	1.076***	1.256***	1.039***	1.001***	1.275***	1.084***
	(0.017)	(0.014)	(0.011)	(0.030)	(0.021)	(0.014)
z	0.037***	0.038***	0.041***	0.047***	0.055***	0.052***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
z^2	0.000***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$cons$	8.276***	8.421***	8.645***	8.152***	8.051***	8.192***
	(0.007)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.2: Estimation Results: Mincerian Wage Regression With and Without Ability, Annual Net Wages

	Males			Females		
	2004	2006	2008	2004	2006	2008
			With Ability			
$\beta_{2-yearUG}$	0.350***	0.342***	0.189***	0.142**	0.182***	0.142***
	(0.066)	(0.046)	(0.034)	(0.061)	(0.045)	(0.036)
$\beta_{4-yearUG}$	0.530***	0.524***	0.502***	0.429***	0.370***	0.363***
	(0.024)	(0.015)	(0.011)	(0.022)	(0.016)	(0.013)
$\beta_{MSc/MA}$	0.970***	0.849***	0.827***	0.913***	0.580***	0.582***
	(0.092)	(0.047)	(0.031)	(0.095)	(0.051)	(0.033)
β_{PhD}	1.148***	0.923***	0.893***	0.884	0.833***	0.644***
	(0.286)	(0.086)	(0.044)	(0.682)	(0.137)	(0.068)
z	0.082***	0.081***	0.085***	0.043***	0.011	0.004
	(0.015)	(0.010)	(0.007)	(0.012)	(0.008)	(0.007)
z^2	−0.003**	−0.003***	−0.003***	−0.002**	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
ability	0.287***	0.259***	0.211***	0.251***	0.314***	0.270***
	(0.047)	(0.031)	(0.024)	(0.039)	(0.029)	(0.024)
$cons$	8.263***	8.325***	8.433***	8.333***	8.501***	8.603***
	(0.056)	(0.040)	(0.030)	(0.048)	(0.036)	(0.029)
			Without Ability			
$\beta_{2-yearUG}$	0.334***	0.333***	0.194***	0.157***	0.187***	0.135***
	(0.058)	(0.042)	(0.032)	(0.056)	(0.042)	(0.033)
$\beta_{4-yearUG}$	0.569***	0.560***	0.528***	0.492***	0.431***	0.392***
	(0.021)	(0.014)	(0.010)	(0.020)	(0.015)	(0.011)
$\beta_{MSc/MA}$	1.057***	0.906***	0.868***	1.005***	0.680***	0.637***
	(0.088)	(0.046)	(0.031)	(0.096)	(0.051)	(0.032)
β_{PhD}	1.252***	1.002***	0.961***	0.950	0.943***	0.716***
	(0.282)	(0.086)	(0.044)	(0.699)	(0.141)	(0.068)
z	0.074***	0.068***	0.077***	0.035***	0.007	−0.006
	(0.014)	(0.009)	(0.007)	(0.010)	(0.008)	(0.006)
z^2	−0.002**	−0.002***	−0.002***	−0.001	0.000	0.001**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
$cons$	8.354***	8.422***	8.509***	8.371***	8.557***	8.707***
	(0.050)	(0.036)	(0.028)	(0.043)	(0.033)	(0.027)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.3: Differences in Coefficients Between Mincerian Wage Regression With and Without Ability

	Males			Females		
	2004	2006	2008	2004	2006	2008
2-year UG	−0.017	−0.009	0.005	0.015	0.004	−0.007
	(0.029)	(0.018)	(0.013)	(0.027)	(0.020)	(0.016)
4-year UG	0.039***	0.037***	0.026***	0.063***	0.061***	0.028***
	(0.011)	(0.006)	(0.004)	(0.011)	(0.007)	(0.005)
MSc/MA	0.087***	0.058***	0.040***	0.092***	0.100***	0.055***
	(0.025)	(0.010)	(0.007)	(0.014)	(0.011)	(0.008)
PhD	0.104***	0.079***	0.068***	0.067***	0.110***	0.072***
	(0.034)	(0.012)	(0.008)	(0.021)	(0.010)	(0.008)

Notes: The differences are calculated as $\beta_j^{baseline} - \beta_j^{ability}$, where $\beta_j^{baseline}$ and $\beta_j^{ability}$ are regression coefficients from Equation 2.1 and 2.2, respectively. Standard errors, reported in parentheses, are calculated as in Clogg et al. (1995). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.4: Estimation Results: Mincerian Wage Regression for Private Sector, Annual Net Wages

	Males			Females		
	1994	2001	2008	1994	2001	2008
$\beta_{2-yearUG}$	0.343***	0.361***	0.331***	0.283***	0.337***	0.292***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
$\beta_{4-yearUG}$	0.599***	0.649***	0.577***	0.583***	0.682***	0.591***
	(0.007)	(0.005)	(0.004)	(0.008)	(0.006)	(0.005)
$\beta_{MSc/MA}$	0.822***	0.984***	0.886***	0.901***	1.147***	0.991***
	(0.026)	(0.018)	(0.012)	(0.040)	(0.027)	(0.016)
β_{PhD}	0.834***	1.054***	1.041***	1.252***	1.286***	1.108***
	(0.068)	(0.040)	(0.026)	(0.156)	(0.077)	(0.040)
z	0.027***	0.038***	0.040***	0.034***	0.047***	0.051***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
z^2	0.000***	−0.001***	−0.001***	0.000***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$cons$	8.382***	8.431***	8.679***	8.249***	8.103***	8.226***
	(0.011)	(0.008)	(0.007)	(0.009)	(0.009)	(0.009)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

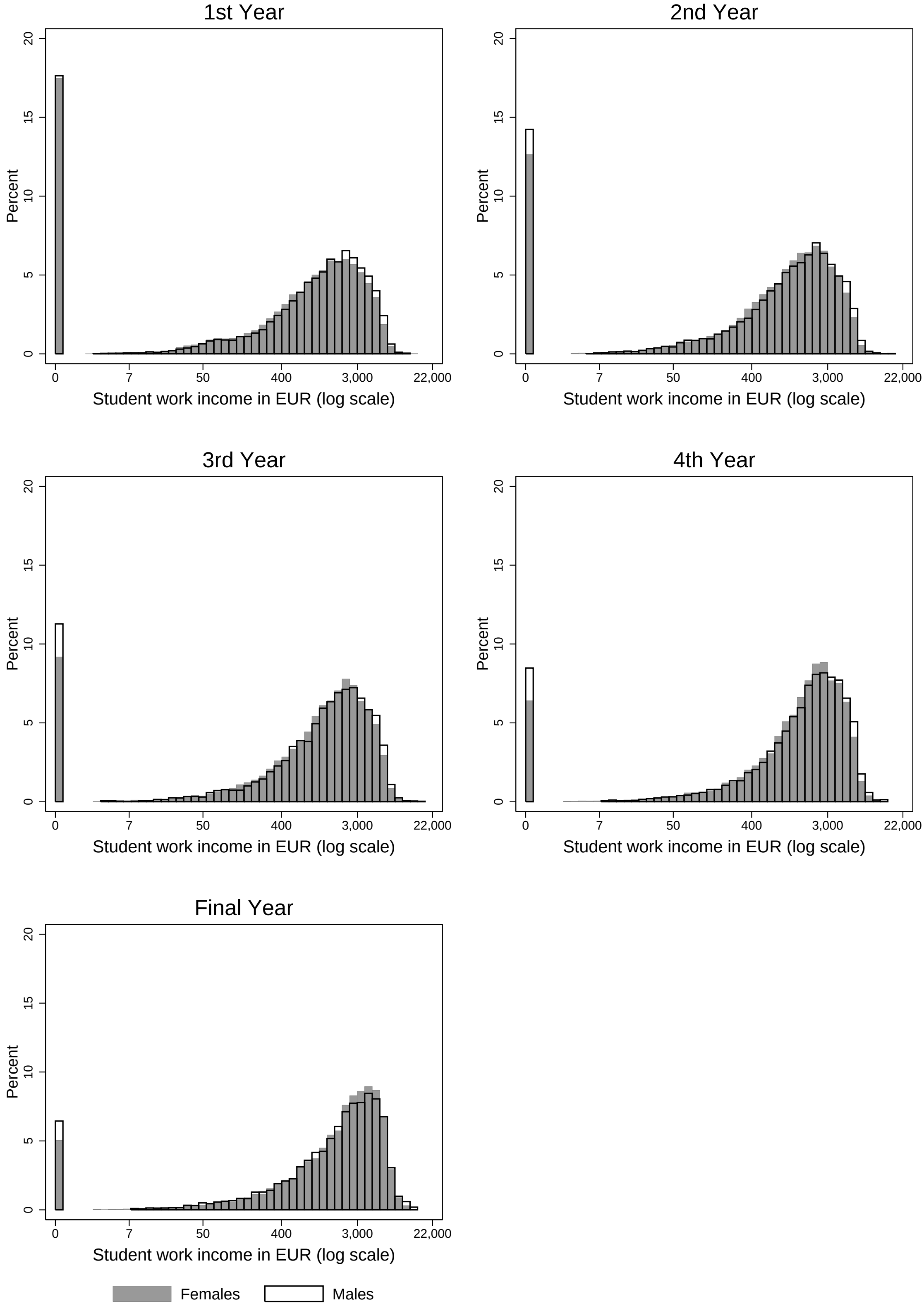
Table B.5: Estimation Results: Mincerian Wage Regression, Annual Net Labor Income

	Males			Females		
	1994	2001	2008	1994	2001	2008
$\beta_{2-yearUG}$	0.319***	0.383***	0.327***	0.250***	0.370***	0.331***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)
$\beta_{4-yearUG}$	0.650***	0.733***	0.614***	0.610***	0.739***	0.628***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
$\beta_{MSc/MA}$	0.958***	1.168***	0.981***	0.891***	1.186***	1.014***
	(0.014)	(0.011)	(0.009)	(0.016)	(0.012)	(0.009)
β_{PhD}	1.312***	1.444***	1.220***	1.196***	1.407***	1.221***
	(0.017)	(0.014)	(0.011)	(0.030)	(0.021)	(0.014)
z	0.037***	0.039***	0.042***	0.045***	0.055***	0.053***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
z^2	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$cons$	8.313***	8.428***	8.660***	8.184***	8.061***	8.203***
	(0.007)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

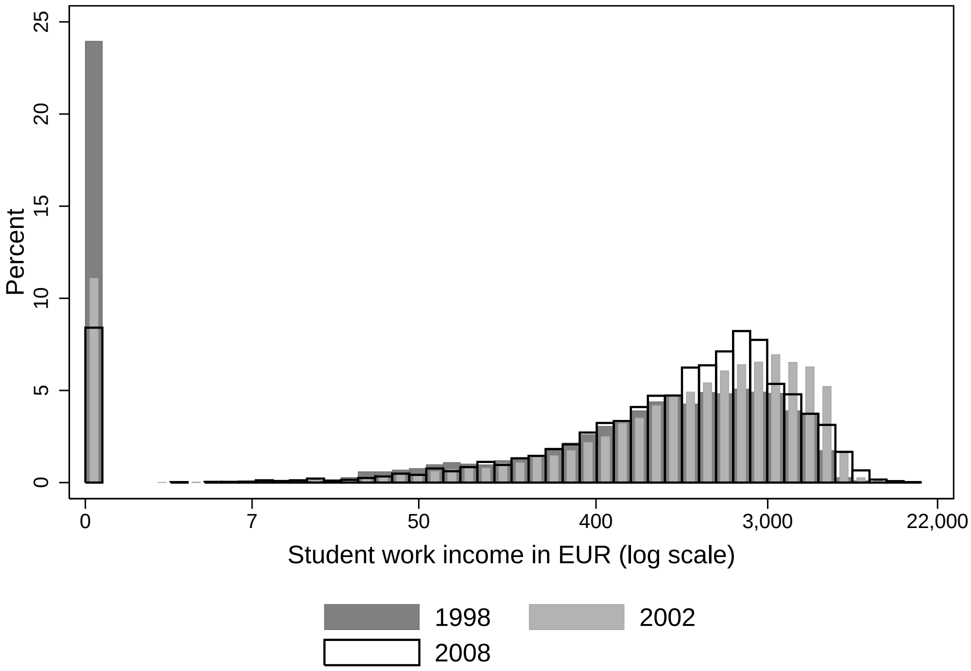
Appendix C: Chapter 3

Figure C.1: Distribution of Student Earnings by Study Year and Gender



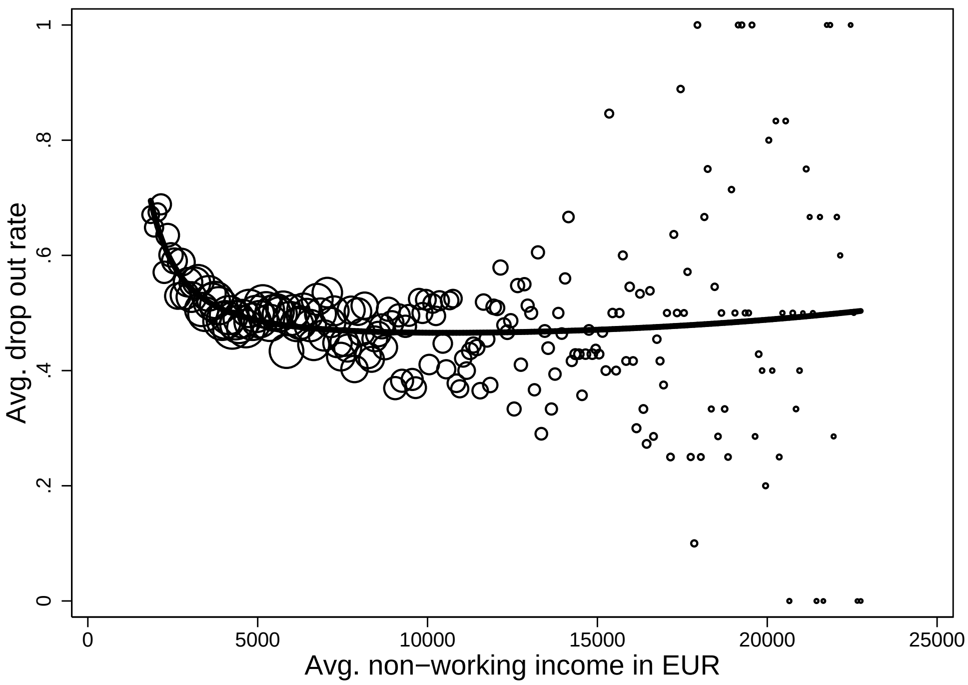
Notes: Bars with frequency lower than 3 were deleted. Values are in constant (2004) Euros.

Figure C.2: Distribution of Student Earnings by School Year



Notes: Bars with frequency lower than 3 were deleted. Values are in constant (2004) Euros.

Figure C.3: Average Drop-out Rate, by Average Non-labor Income



Notes: Areas of symbols are proportional to frequency of students with a specific value of non-working income. Symbols with frequency lower than 10 were deleted. Non working income is in constant (2004) Euros.

Table C.1: Structure of Sample by Region

	1st Year	2nd to 4th Year	Final Year
Pomurska	3.24	3.32	3.30
Podravska	6.08	6.82	6.94
Koroška	2.92	2.98	2.98
Savinjska	9.66	10.34	10.18
Zasavska	2.37	2.12	2.07
Spodnjeposavska	3.14	3.39	3.29
Jugovzhodna	8.36	8.51	8.15
Osrednjeslovenska	36.39	34.23	34.71
Gorenjska	12.74	12.74	12.67
Notranjsko - kraška	2.83	2.94	3.01
Goriška	7.41	7.83	7.81
Obalno - kraška	4.87	4.77	4.89

Note: Table presents shares in percent of respective column total.

Table C.2: Structure of Sample by Faculty

	1st Year	2nd to 4th Year	Final Year
Faculty of Arts and Humanities	23.75	22.39	25.60
Faculty of Economics	8.96	9.96	13.72
Faculty of Law	5.56	5.20	4.22
Faculty of Social Sciences	7.31	10.04	14.09
Faculty of Sports	2.84	3.34	2.66
Faculty of Education	7.63	7.76	7.59
Faculty of Theology	0.95	0.78	0.37
Faculty of Mechanical Engineering	3.25	2.42	0.94
Faculty of Electrical Engineering	4.23	3.75	2.70
Faculty of Architecture	1.80	2.47	2.12
Faculty of Civil Engineering and Geodesy	5.12	3.83	4.24
Faculty of Chemistry and Chemical Technology	3.66	2.75	2.23
Faculty of Mathematics and Physics	3.56	2.21	1.82
Faculty of Natural Sciences and Engineering	2.29	1.91	1.58
Faculty of Computer and Information Science	3.91	2.94	1.77
Biotechnical Faculty	7.39	7.95	8.19
Veterinary Faculty	1.18	1.37	1.51
Faculty of Medicine	4.08	5.54	2.84
Faculty of Pharmacy	2.51	3.39	1.81

Note: Table presents shares in percent of respective column total.

Table C.3: Marginal Effects for Heckman Selection Model: Control Variables

	1st Year		2nd to 4th Year		Final Year	
	Pr[Employed]	Log Income	Pr[Employed]	Log Income	Pr[Employed]	Log Income
Female	0.028**	−0.035	0.040**	−0.011	0.023**	0.004
	(0.007)	(0.028)	(0.004)	(0.020)	(0.007)	(0.043)
Conditional income share	−0.108**	−0.348**	−0.071**	−0.408**	−0.017**	−0.058
	(0.007)	(0.030)	(0.004)	(0.018)	(0.006)	(0.035)
Stochastic income share	−0.108**	0.630**	−0.078**	0.429**	−0.062**	0.202*
	(0.022)	(0.107)	(0.013)	(0.060)	(0.015)	(0.094)
Expected net wage (in 1000)	0.003	0.000	0.004**	0.002	0.003*	−0.011
	(0.001)	(0.006)	(0.001)	(0.004)	(0.001)	(0.010)
Age	0.018**	0.073**	−0.006**	0.033**	−0.017**	−0.121**
	(0.003)	(0.010)	(0.001)	(0.005)	(0.001)	(0.008)
Student parent	−0.121**	−0.271*	−0.080**	−0.656**	−0.051**	−0.481**
	(0.026)	(0.121)	(0.007)	(0.056)	(0.004)	(0.045)
Step parent	0.010**	0.054**	0.008**	0.026**	−0.001	−0.015
	(0.003)	(0.012)	(0.002)	(0.009)	(0.003)	(0.016)
High school GPA	−0.097**	−0.513**	−0.073**	−0.266**	−0.042**	−0.305**
	(0.008)	(0.032)	(0.005)	(0.024)	(0.007)	(0.042)
University or higher—mum	−0.035**	−0.098**	−0.020**	−0.081**	−0.007*	−0.091**
	(0.004)	(0.017)	(0.002)	(0.011)	(0.003)	(0.020)
University or higher—dad	−0.036**	−0.085**	−0.021**	−0.083**	−0.007*	−0.098**
	(0.004)	(0.016)	(0.003)	(0.011)	(0.003)	(0.019)
Family business	0.003	0.160**	0.013**	0.156**	0.003	0.069**
	(0.004)	(0.016)	(0.003)	(0.011)	(0.004)	(0.021)
No. of siblings	0.011**	−0.020**	0.007**	−0.011*	0.004**	−0.010
	(0.002)	(0.007)	(0.001)	(0.005)	(0.002)	(0.008)
Repeating a year	0.029**	0.235**	0.039**	0.279**	0.004	−0.018
	(0.006)	(0.017)	(0.004)	(0.014)	(0.003)	(0.017)
Repeated previous year	0.049*	0.132	0.020**	0.097**	−0.012	−0.112**
	(0.024)	(0.070)	(0.003)	(0.012)	(0.007)	(0.041)

Notes: Standard errors are reported in parentheses. Estimations also include a variable indicating if student has more than 4 years of regular study, dummy variables for schools, school years and regions of permanent address. ** p-value < 0.01, * p-value < 0.05.

Table C.4: OLS Estimates for Average Hourly Wage

	Log average hourly wage
Non-working income	
3,000–4,000	−0.021
	(0.012)
4,000–5,000	−0.020
	(0.011)
5,000–6,000	−0.007
	(0.011)
6,000–7,000	0.005
	(0.012)
7,000–8,000	0.017
	(0.012)
8,000–9,000	0.016
	(0.013)
9,000–10,000	0.013
	(0.014)
10,000–11,000	0.022
	(0.015)
above 11,000	0.040**
	(0.013)

Notes: Average hourly wage is calculated as a weighted average of student's gross hourly wages reported by e-Študentski servis in particular school year. Besides non-working income, estimated regression includes conditional- and stochastic-income share, expected net wage, age, high school GPA, number of siblings, dummies for students with children, parental education, family business, repeating this and previous study year, regions, school years, schools, and study years. ** p-value < 0.01, * p-value < 0.05.

Table C.5: Summary Statistics for Subsample with Social Transfers

	Without transfers		With transfers	
	Mean	Sd	Mean	Sd
Probability of working	0.896	0.305	0.896	0.305
Gross student work income	2,161	2,045	2,161	2,045
Net student work income	2,154	2,022	2,154	2,022
Non-working income	6,372	3,556	6,469	3,512
Conditional-income share	0.161	0.234	0.155	0.224
Stochastic-income share	0.029	0.077	0.028	0.076
Expected net wage	14.754	2.886	14.754	2.886
Female	0.630	0.483	0.630	0.483
Age	21.189	1.790	21.189	1.790
Student parent	0.008	0.116	0.008	0.116
High school GPA	0.496	0.210	0.496	0.210
University or higher—mum	0.190	0.393	0.190	0.393
University or higher—dad	0.211	0.408	0.211	0.408
Step parent	0.266	0.442	0.266	0.442
Family business	0.169	0.374	0.169	0.374
No. of sibling	0.986	0.840	0.986	0.840
Repeating a year	0.131	0.338	0.131	0.338
Repeated previous year	0.102	0.303	0.102	0.303
Additional years	0.148	0.355	0.148	0.355
School year	2,002.5	0.5	2,002.5	0.5
Study year	3.239	2.379	3.239	2.379

Notes: Data on social transfers are available only for years between 2002 and 2004. All income-related variables are in constant (2004) Euros. The exchange rate in 2004 was 1 EUR = 1.24 USD. Age is measured at enrollment in the first year of college. High school GPA is the average grade achieved in 'matura' exam and the mean grade of the third and fourth year of high school study. Additional years indicate if student has more than 4 years of regular study.

Table C.6: Estimation Results for Heckman Selection Model, With and Without Transfers

	With transfers		Without transfers	
	Pr[Employed]	Log Income	Pr[Employed]	Log Income
Non-working income				
3,000–4,000	0.015*	0.034	0.014*	0.034
	(0.007)	(0.031)	(0.007)	(0.027)
4,000–5,000	0.026**	0.020	0.025**	0.021
	(0.007)	(0.027)	(0.007)	(0.025)
5,000–6,000	0.040**	0.039	0.038**	0.041
	(0.007)	(0.030)	(0.007)	(0.027)
6,000–7,000	0.029**	0.051	0.028**	0.061*
	(0.007)	(0.034)	(0.007)	(0.029)
7,000–8,000	0.026**	0.106**	0.024**	0.095**
	(0.008)	(0.033)	(0.008)	(0.032)
8,000–9,000	0.031**	0.036	0.029**	0.037
	(0.008)	(0.036)	(0.008)	(0.037)
9,000–10,000	0.024**	0.054	0.022*	0.048
	(0.009)	(0.039)	(0.009)	(0.037)
10,000–11,000	0.029**	0.018	0.027**	0.017
	(0.010)	(0.046)	(0.010)	(0.043)
above 11,000	0.010	−0.071	0.008	−0.072
	(0.009)	(0.041)	(0.009)	(0.038)
Female	0.042**	0.050	0.042**	0.049
	(0.008)	(0.039)	(0.008)	(0.038)
Conditional income share	−0.074**	−0.347**	−0.071**	−0.339**
	(0.007)	(0.031)	(0.006)	(0.031)
Stochastic income share	−0.045*	0.536**	−0.045*	0.526**
	(0.020)	(0.095)	(0.020)	(0.094)
Expected net wage (in 1000)	0.004**	0.023*	0.004**	0.023**
	(0.002)	(0.009)	(0.002)	(0.009)
Age	0.006 * *	0.054**	0.006**	0.053**
	(0.002)	(0.009)	(0.002)	(0.008)
Student parent	−0.065**	−0.619**	−0.065**	−0.621**
	(0.010)	(0.067)	(0.010)	(0.066)
Step parent	0.004	0.037**	0.004	0.038**
	(0.003)	(0.014)	(0.003)	(0.014)
High school GPA	−0.091**	−0.406**	−0.092**	−0.407**
	(0.008)	(0.039)	(0.008)	(0.037)
University or higher - mum	−0.020**	−0.135**	−0.020**	−0.136**
	(0.004)	(0.019)	(0.004)	(0.019)
University or higher - dad	−0.021**	−0.068**	−0.021**	−0.068**
	(0.004)	(0.018)	(0.004)	(0.019)
Family business	0.008	0.154**	0.008	0.154**
	(0.004)	(0.017)	(0.004)	(0.018)
No. of siblings	0.009**	−0.019*	0.009**	−0.017*
	(0.002)	(0.008)	(0.002)	(0.008)
Repeating a year	0.018**	0.156**	0.018**	0.155**
	(0.005)	(0.020)	(0.005)	(0.019)
Repeated previous year	0.020**	0.087**	0.020**	0.087**
	(0.006)	(0.021)	(0.006)	(0.023)

Notes: Standard errors are reported in parentheses. Estimations also include a variable indicating if student has more than 4 years of regular study, dummy variables for schools, school years and regions of permanent address. ** p-value < 0.01, * p-value < 0.05.

Table C.7: Sample Size for Students Who Failed to Pass a Year, by Gender

	1st Year	2nd to 4th Year
Number of observations	19,896	10,981
Males	9,786	5,206
Females	10,110	5,775

Table C.8: Summary Statistics for Students who Failed to Pass a Year

	1st Year		2nd to 4th Year	
	Mean	Sd	Mean	Sd
Probability of working	0.842	0.365	0.887	0.317
Gross student work income	1,676	1,715	1,854	1,791
Net student work income	1,673	1,700	1,849	1,771
Non-labor income	5,745	3,180	6,577	3,775
Conditional income share	0.105	0.212	0.134	0.221
Stochastic income share	0.027	0.068	0.031	0.074
Expected net wage	14.705	2.663	15.165	3.070
Female	0.508	0.500	0.526	0.499
Age	19.256	0.771	21.004	1.273
Student parent	0.003	0.061	0.010	0.115
High school GPA	0.344	0.182	0.442	0.196
University or higher - mum	0.157	0.364	0.204	0.403
University or higher - dad	0.170	0.376	0.219	0.414
Step parent	0.293	0.455	0.282	0.450
Family business	0.150	0.357	0.147	0.354
No. of sibling	1.066	0.803	1.001	0.831
Repeating a year	0.105	0.306	0.070	0.256
Repeated previous year	0.007	0.081	0.211	0.408
Additional years	0.149	0.357	0.223	0.416
School year	2,002.0	3.1	2,003.1	2.8

Notes: All income-related variables are in constant (2004) Euros. The exchange rate in 2004 was 1 EUR = 1.24 USD. Age is measured at enrollment in the first year of college. High school GPA is the average grade achieved in 'matura' exam and the mean grade of the third and fourth year of high school study. Additional years indicate if student has more than 4 years of regular study.

Table C.9: Marginal Effects for Probability of Dropping Out for Students who Failed to Pass a Year: Control variables

	1st Year	2nd to 4th Year
Log working income	0.028**	0.007*
	(0.003)	(0.003)
High school GPA	−0.246**	0.049
	(0.022)	(0.026)
Female	−0.020	−0.094**
	(0.019)	(0.018)
Conditional income share	0.012	0.092**
	(0.017)	(0.019)
Stochastic income share	0.103	0.069
	(0.057)	(0.061)
Expected net wage (in 1000)	−0.007	−0.007
	(0.004)	(0.004)

(table continues)

(continued)

	1st Year	2nd to 4th Year
Age	0.158**	0.193**
	(0.005)	(0.004)
Student parent	−0.086	−0.140**
	(0.063)	(0.041)
Step parent	0.013	−0.008
	(0.007)	(0.009)
University or higher–mum	0.006	0.013
	(0.010)	(0.011)
University or higher–dad	−0.004	−0.010
	(0.010)	(0.011)
Family business	−0.002	0.009
	(0.010)	(0.011)
No. of siblings	0.003	0.003
	(0.004)	(0.005)
Additional years	0.021	0.097**
	(0.049)	(0.033)

Notes: Standard errors are reported in parentheses. Estimations also include a variable indicating if student has more than 4 years of regular study, dummy variables for schools, school years and regions of permanent address. ** p-value < 0.01, * p-value < 0.05.

Appendix D: Chapter 4

Table D.1: Structure of Sample by Region

Region	1st Year	2nd Year	3rd Year	4th Year
Pomurska	1.67	1.49	1.56	1.55
Podravska	1.32	1.31	1.28	1.32
Koroška	1.81	1.67	1.69	1.74
Savinjska	7.72	7.44	7.37	7.35
Zasavska	1.92	2.06	2.12	2.19
Spodnjeposavska	2.32	2.25	2.31	2.06
Jugovzhodna	8.96	9.20	9.53	9.38
Osrednjeslovenska	45.51	45.19	44.80	45.25
Gorenjska	13.33	13.54	13.59	13.44
Notranjsko - kraška	2.48	2.46	2.56	2.51
Goriška	7.09	7.29	7.31	7.32
Obalno - kraška	5.88	6.10	5.87	5.90

Note: Table presents shares in percent of respective column total.

Figure D.1: Representation of Causal Chain

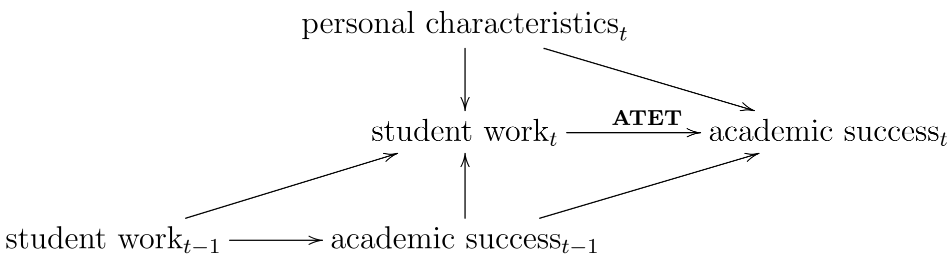
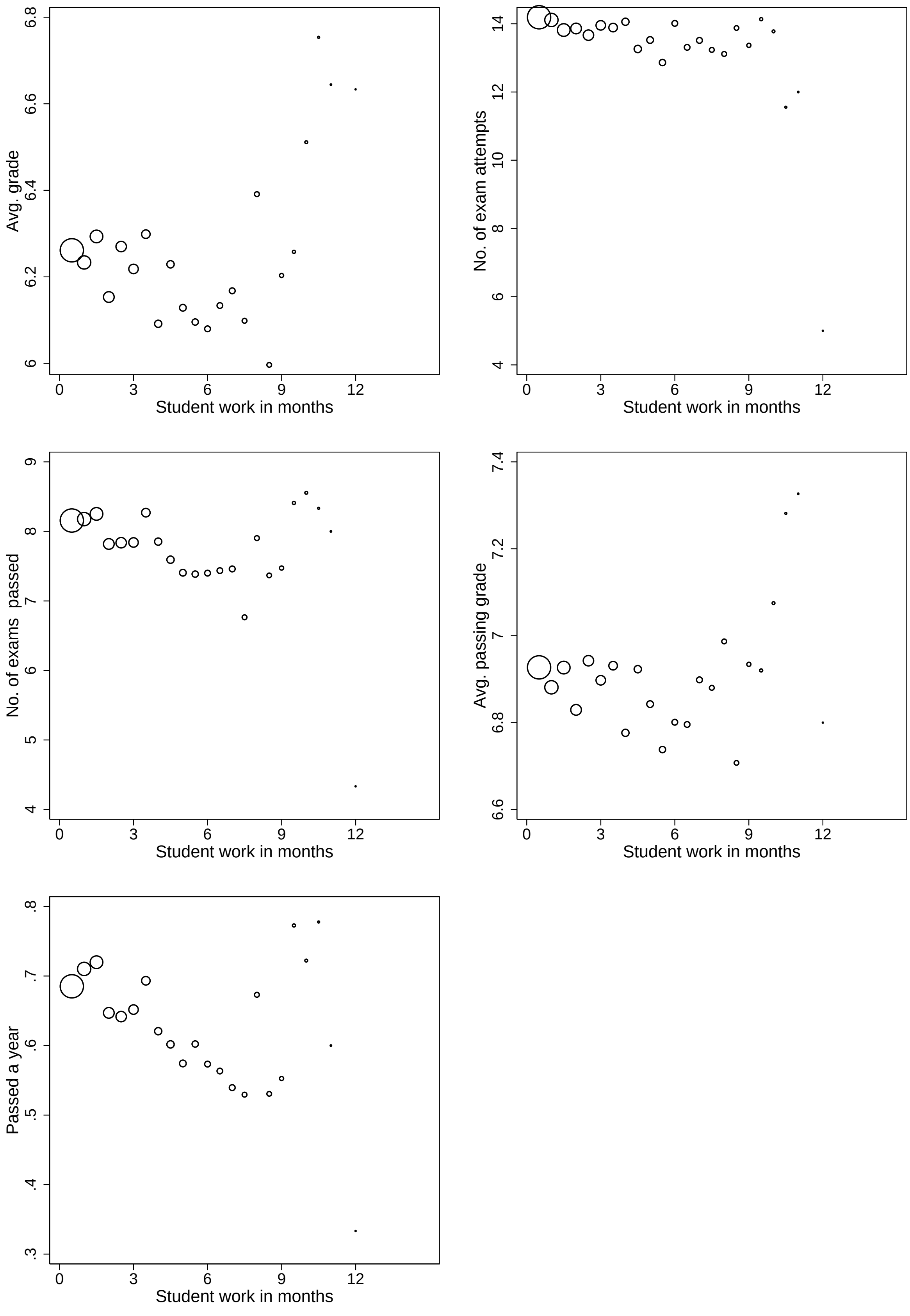
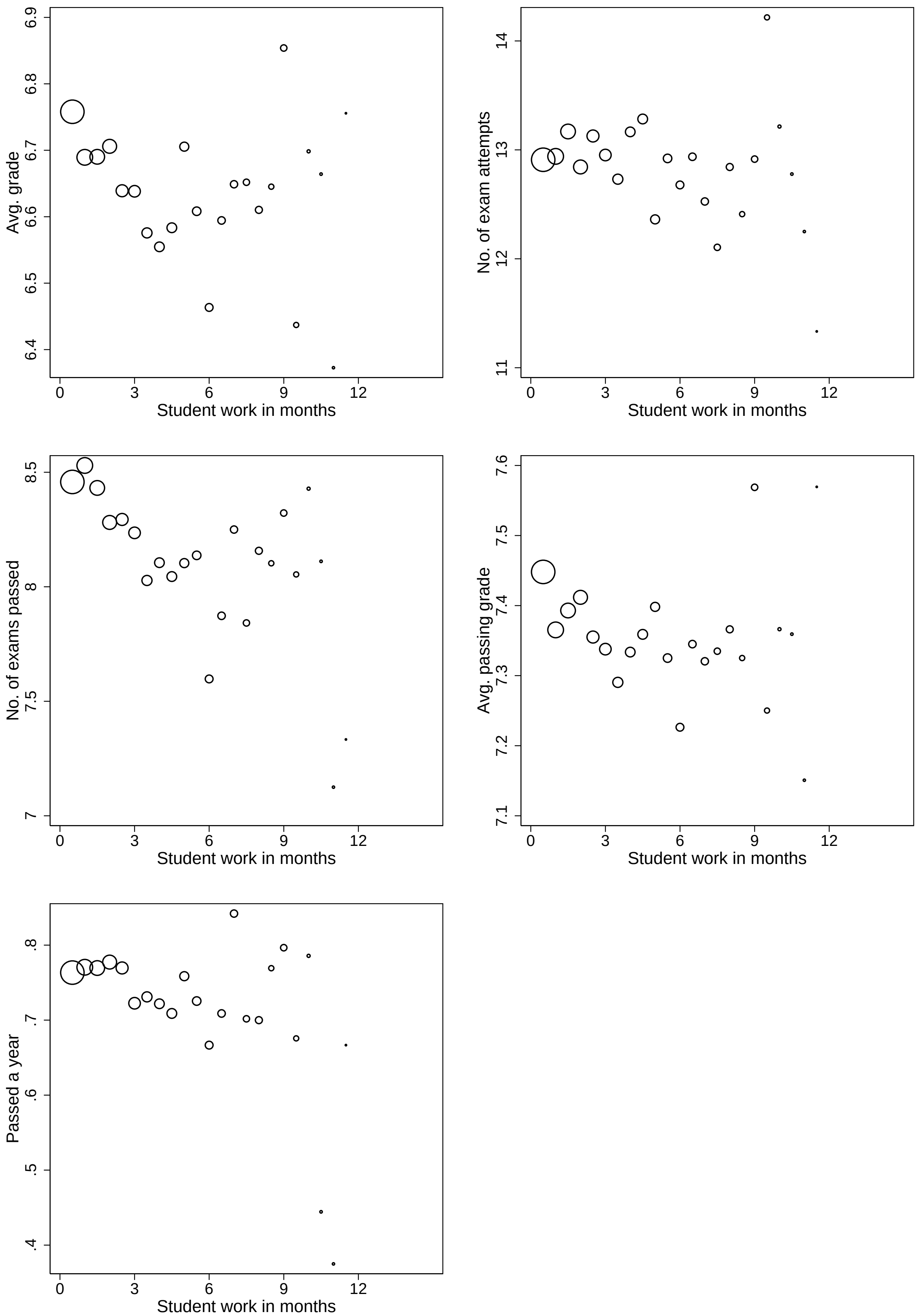


Figure D.2: Academic Performance by Student Work in the First Year of Study



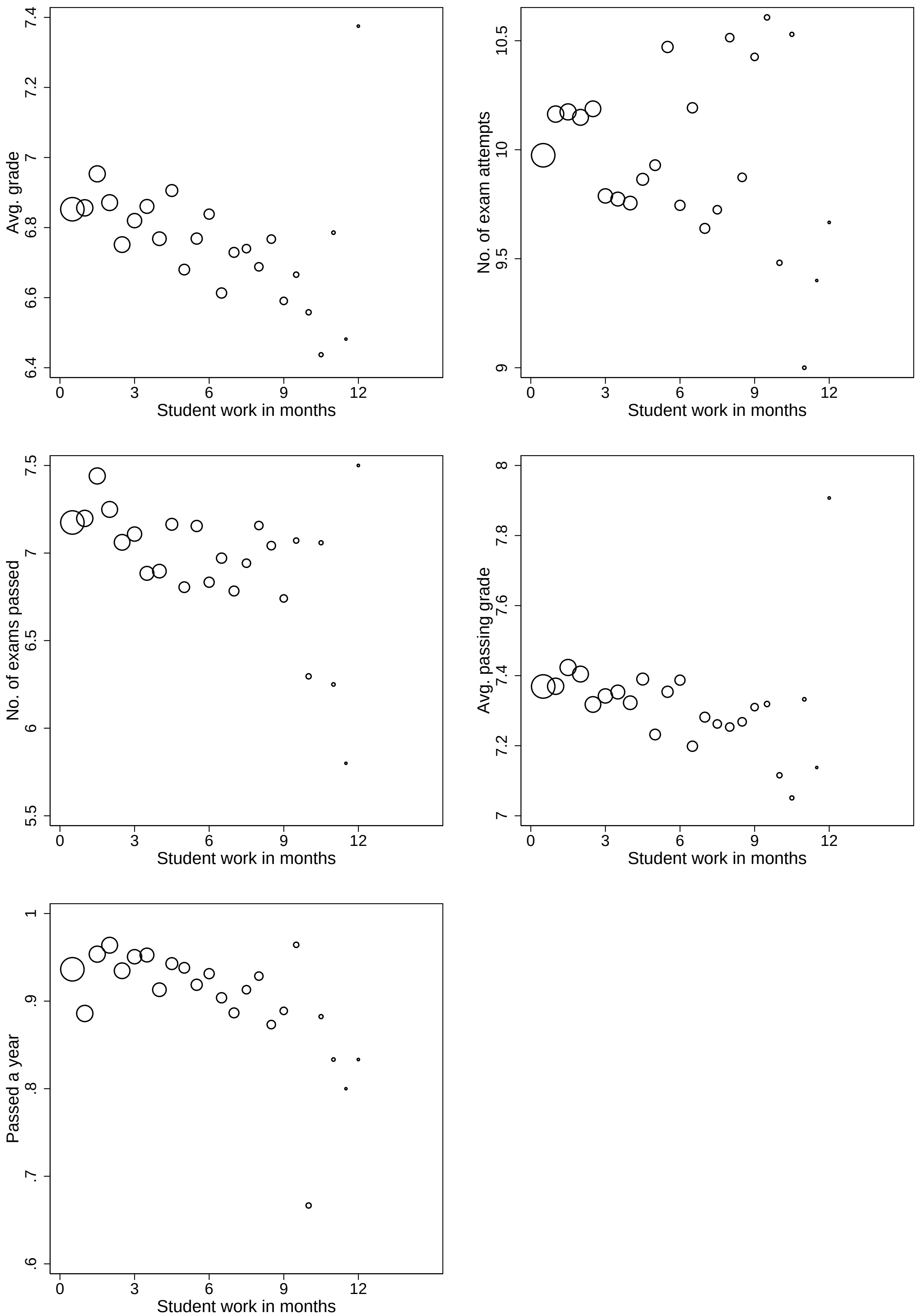
Notes: The size of markers is proportional to the frequency of students with a specific value of student work. Markers with frequency lower than 10 are omitted.

Figure D.3: Academic Performance by Student Work in the Second Year of Study



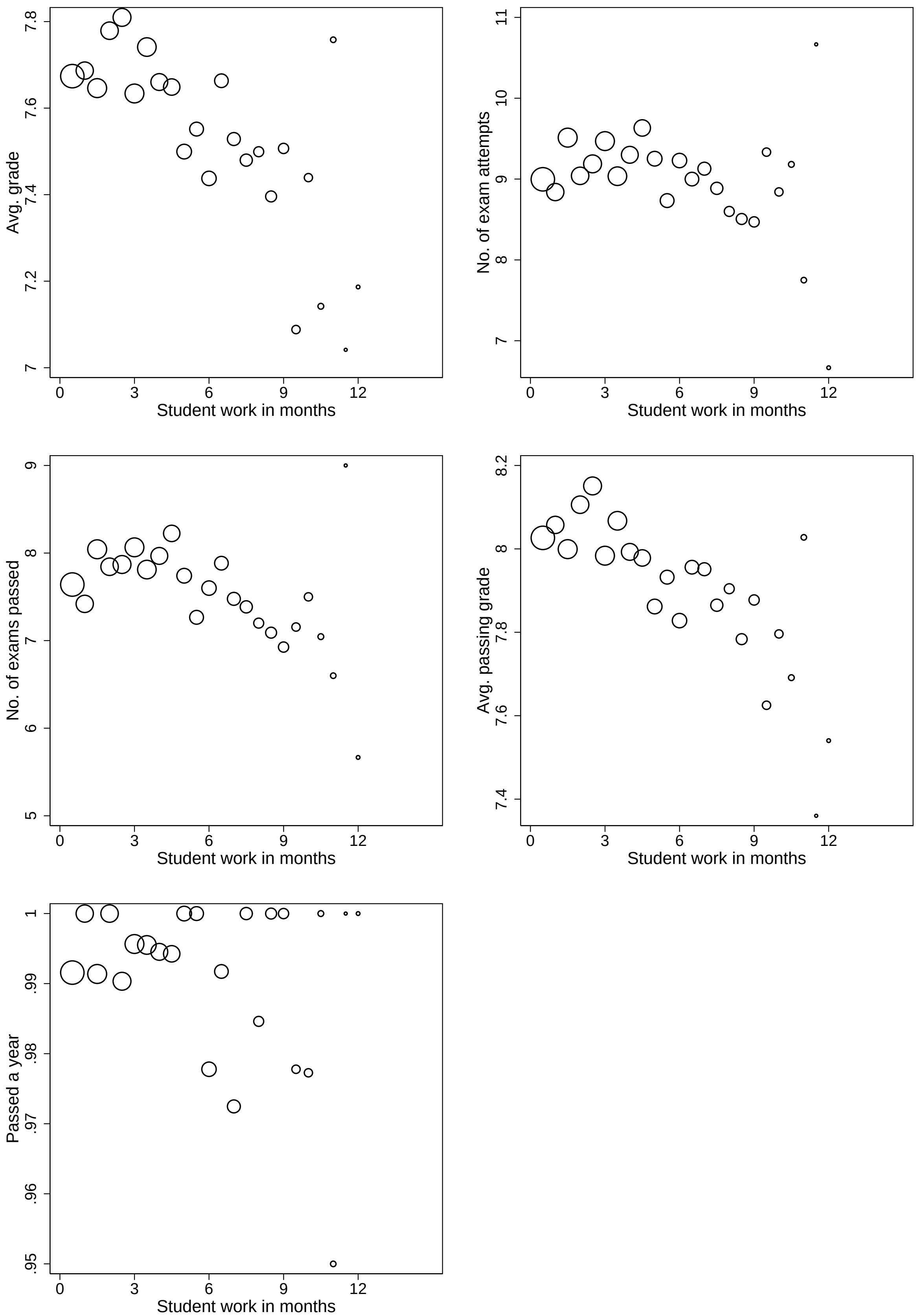
Notes: The size of markers is proportional to the frequency of students with a specific value of student work. Markers with frequency lower than 10 are omitted.

Figure D.4: Academic Performance by Student Work in the Third Year of Study



Notes: The size of markers is proportional to the frequency of students with a specific value of student work. Markers with frequency lower than 10 are omitted.

Figure D.5: Academic Performance by Student Work in the Fourth Year of Study

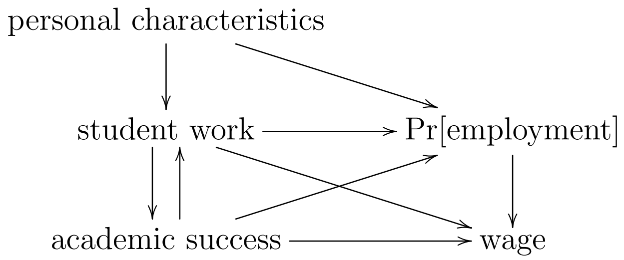


Notes: The size of markers is proportional to the frequency of students with a specific value of student work. Markers with frequency lower than 10 are omitted.

Appendix E: Chapter 5

E.1 Causal Chain

Figure E.1: Representation of causal chain



E.2 Structural Form Equation and Treatment Effects

Let w be hourly wage, SW_k dummy variable for treatment k, x personal characteristics and A academic success. The equations for student work, academic success, probability of employment and hourly wage can therefore be written as:

$$SW_{ki} = \alpha + \alpha_x x_i + \alpha_A A_i + \epsilon_i$$

$$A_i = \delta + \delta_x x_i + \delta_{SW} SW_{ki} + v_i, \quad v \equiv A - E(A|x, SW_k)$$

$$Pr[w > 0] = \beta + \beta_x x_i + \beta_A A_i + \beta_{SW} SW_{ki} + e_i$$

$$w = Pr[w_i > 0](\gamma + \gamma_x x_i + \gamma_A A_i + \gamma_{SW} SW_{ki} + u_i)$$

Total effect of student work on probability of employment is then:

$$\begin{aligned} &E(Pr[w > 0]|SW_k = 1, x) - E(Pr[w > 0]|SW_k = 0, x) \\ &= \beta_A \delta_{SW} + \underbrace{\beta_{SW}}_{\text{estimated ATET}}, \end{aligned}$$

and total effect of student work on hourly wage is:

$$\begin{aligned} &E(w|SW_k = 1, x) - E(w|SW_k = 0, x) \\ &= \beta_A \delta_{SW}(\gamma_A \delta_{SW} + \gamma_{SW}) + \beta_{SW} \gamma_A \delta_{SW} + \underbrace{\beta_{SW} \gamma_{SW}}_{\text{estimated ATET}}. \end{aligned}$$

E.3 Additional Tables

Table E.1: Sample Size by Gender for Subsamples

	1st year	2nd Year
	Indefinite-contract subsample	
Number of observations	2,279	2,007
Males	948	823
Females	1,331	1,184
	Type-of-student-work subsample	
Number of observations	1,186	983
Males	491	398
Females	695	585

Table E.2: Summary Statistics for Indefinite-Contract Subsample

	1st Year		2nd Year	
	Mean	Sd	Mean	Sd
Employed after college	0.598	0.490	0.840	0.367
Hourly gross wage after college	4.024	6.147	6.836	10.884
Student work experience in years	1.853	1.171	1.875	1.172
Age at enrollment	18.890	0.413	18.885	0.417
High school GPA	0.514	0.155	0.522	0.152
Graduated	0.655	0.475	0.816	0.387
Time to final year	4.530	0.744	4.519	0.722
No. of exam attempts	54.762	12.392	54.354	12.212
Avg. grade	6.791	0.738	6.812	0.749
University or higher—mum	0.205	0.404	0.201	0.401
University or higher—dad	0.237	0.425	0.238	0.426
Family business	0.155	0.362	0.148	0.355
Step parent	0.244	0.430	0.246	0.431
No. of sibling	0.798	0.756	0.810	0.752
Student parent	0.006	0.089	0.004	0.074
Non-labor income	7,938	5,578	7,887	5,555
Conditional-income share	0.152	0.238	0.157	0.242
Stochastic-income share	0.041	0.087	0.040	0.087
Expected net wage	15.833	2.482	15.745	2.449
Year	2,006.4	2.0	2,007.0	1.8

Notes: All income-related variables are in constant (2004) Euros. The exchange rate in 2004 was 1 EUR = 1.24 USD. Variables describing family characteristics and economic situation during studies are measured in the final year of study.

Table E.3: Summary Statistics for the Subsample with Information on Type of Student Work

	1st Year		2nd Year	
	Mean	Sd	Mean	Sd
Employed after college	0.659	0.474	0.859	0.349
Hourly gross wage after college	4.391	6.684	6.852	11.063
Student work experience in years	1.373	0.898	1.452	0.920
Age at enrollment	18.908	0.393	18.894	0.402
High school GPA	0.486	0.156	0.496	0.155
Graduated	0.593	0.492	0.743	0.437
Time to final year	4.582	0.774	4.601	0.789
No. of exam attempts	55.899	13.071	55.713	13.011
Avg. grade	6.761	0.736	6.768	0.737
University or higher—mum	0.221	0.415	0.221	0.415
University or higher—dad	0.232	0.422	0.229	0.420
Family business	0.145	0.352	0.130	0.337
Step parent	0.225	0.418	0.233	0.423
No. of siblings	0.770	0.741	0.777	0.733
Student parent	0.004	0.077	0.002	0.045
Non-labor income	8,487	6,623	8,381	6,514
Conditional-income share	0.135	0.229	0.143	0.238
Stochastic-income share	0.047	0.095	0.046	0.095
Expected net wage	15.944	2.522	15.722	2.463
Year	2,008.4	1.2	2,008.8	1.1

Notes: All income-related variables are in constant (2004) Euros. The exchange rate in 2004 was 1 EUR = 1.24 USD. Variables describing family characteristics and economic situation during studies are measured in the final year of study.

Appendix F: Summary in Slovenian Language/Daljši povzetek disertacije v slovenskem jeziku

Niz člankov analizira dejavnike, ki vplivajo na dve odločitvi študentov terciarnega izobraževanja, ter učinke teh odločitev na rezultate posameznikov na trgu dela oziroma na njihov študijski uspeh. Natančneje, analiziramo kako se študentje odločajo za smer študija in kaj vpliva na njihovo odločitev za študentsko delo. Poleg tega ocenimo vpliv teh izbir na rezultate, kot so zasebni donosi izobraževanja, učnih uspeh, višina plače oziroma verjetnost zaposlitve. Najprej se osredotočimo na dejavnike, ki vplivajo na odločitev o smeri študija, s posebnim poudarkom na razlikovanju vpliva splošne sposobnosti in sposobnosti specifične za določeno študijsko smer. Izbira študijske smeri pa med drugim vpliva na zaposlitvene možnosti in plačo. Ena od možnosti merjenja tega učinka je ocena stopenj donosov izobraževanja, zato nadaljujemo z analizo evolucije donosov različnih stopenj in smeri terciarnega izobraževanja v obdobju tranzicije v Sloveniji. Toda povpraševanje po delavcih, ki sooblikuje te donose, ni odvisno zgolj od njihove smeri študija, pač pa je odvisno tudi od pridobljenega znanja in delovnih izkušenj. Slednje določa za iskalce prve zaposlitve njihova izbira alokacije časa namenjenega študiju in delu. Doktorsko delo zato nadaljuje z analizo stiliziranega dejstva o študentskem delu, ki pravi, da so glavni vzrok za študentko delo nizki družinski dohodki. Sledi ocena vpliva študentskega dela na študijske rezultate. Zaključimo pa z analizo učinkov študijskega uspeha in študentskega dela na rezultate na trgu dela. Disertacija je sestavljena iz petih člankov, njihove glavne ugotovitve in raziskovalne metode opisuje spodnje besedilo.

Ena izmed najpomembnejših ekonomskih odločitev študentov je izbira študijske smeri, saj ne vpliva le na njihove zaposlitvene možnosti, ampak tudi na strukturo delovne sile, ravnotežne plače in stopnje brezposelnosti. Empirične in teoretične raziskave so prepoznale več dejavnikov, ki vplivajo na izbiro študijske smeri. Med najbolj pomembne uvrščamo spol, sposobnost, sovrstnike in pričakovan prihodnji dohodek. Medtem ko se avtorji strinjajo glede učinkov spola in pričakovanega dohodka, so rezultati vpliva sposobnosti in sovrstnikov na izbiro študijske smeri različni. V prvem članku zato proučujemo vpliv sposobnosti na izbiro študijske smeri slovenskih študentov in zagovarjamo stališče, da so nekonsistentni rezultati obstoječe literature posledica nerazlikovanja med različnimi vrstami sposobnosti. Za to uporabimo administrativno podatkovno bazo, ki vsebuje zapise o vseh redno vpisanih študentih štiriletnega študija ekonomskih in poslovnih smeri, ki jih ponuja največja slovenska univerza. V nasprotju z obstoječimi študijami, nam podatki omogočajo razlikovanje med dvema merama sposobnosti. Prva je splošna sposobnost, ki je merjena s povprečno srednješolsko oceno in oceno na maturi. Druga pa je sposobnost specifična za določeno smer. Ker je predmetnik prvega in drugega letnika Ekonomske fakultete v Ljubljani enak za vse študente (oziroma je bil enak v opazovanem obdobju), lahko to vrsto sposobnosti merimo z ocenami pri predmetih, ki pokrivajo enako tematiko in uporabljajo metodologijo, za katero so potrebne podobne sposobnosti kot na posamezni smeri.

Ocenimo dva ekonometrična modela. Prvi je mešani logit (angl. *mixed logit*) model, pri katerem je verjetnost, da študent i izbere smer j definirana kot:

$$p_{ij} = \frac{e^{\mathbf{z}'_{ij}\boldsymbol{\alpha}+\mathbf{w}'_i\boldsymbol{\gamma_j}}}{\sum\limits_{l=1}^{m} e^{\mathbf{z}'_{il}\boldsymbol{\alpha}+\mathbf{w}'_i\boldsymbol{\gamma_l}}}, \qquad j = 1, ..., m,$$

kjer so $\mathbf{z}_{ij}$ regresorji značilni za posamezno smer (angl. *alternative-varying* ali *alternative-specific*), $\mathbf{w}_i$ regresorji značilni za posameznika (angl. *case-specific* ali *alternative-invariant*), $\boldsymbol{\alpha}$ in $\boldsymbol{\gamma}$ pa označujeta pripadajoče koeficiente. Model predpostavlja, da so napake enakomerno in neodvisno porazdeljene po porazdelitvi ekstremnih vrednosti tipa I (angl. *Type I extreme value distribution*) s funkcijo gostote verjetnosti $f(\varepsilon_{ij}) = e^{-\varepsilon_{ij}} \exp(-e^{-\varepsilon_{ij}})$. Mejni učinki regresorjev značilnih za posamezno smer (angl. *alternative-varying*) so torej enaki:

$$\begin{aligned} \frac{\partial p_{ij}}{\partial \mathbf{z}_{ij}} =& p_{ij}(1-p_{ij})\boldsymbol{\alpha} \text{ if } j = k \\ \frac{\partial p_{ij}}{\partial \mathbf{z}_{ik}} =& - p_{ij}p_{ik}\boldsymbol{\alpha} \text{ if } j \neq k, \end{aligned}$$

mejni učinki regresorjev značilnih za posameznika (angl. *case-specific*) pa:

$$\frac{\partial p_{ij}}{\partial \mathbf{w}_{ij}} = p_{ij}(\boldsymbol{\gamma_j} - \overline{\boldsymbol{\gamma}}_{\boldsymbol{i}}).$$

V naši raziskavi med regresorje značilne za posameznika uvrščamo povprečno srednješolsko oceno, povprečne ocene pri predmetih prvega in drugega letnika, binarno spremenljivko za spol, starost ter set binarnih spremenljivk, ki označujejo različne regije. Edini regresor značilen za posamezno smer pa je logaritem neto plače. Ker pa mešani logit model predpostavlja neodvisnost od nepomembnih alternativ (angl. *independence of irrelevant alternatives - IIA*), ki je v tem kontekstu verjetno kršena, ocenimo še drevesni ali gnezdeni logit (angl. *nested logit*) model, ki alternative razdeli v skupine (angl. *nests*) in opusti IIA predpostavko, saj dovoljuje, da so napake znotraj skupin (ne pa med skupinami) korelirane. Verjetnost, da bo študent izbral skupino k, ta model definira kot:

$$p_{ik} = \frac{\exp(\mathbf{q}'_{ik}\boldsymbol{\delta} + \tau_k I_{ik})}{\sum_{k'=1}^{K} \exp(\mathbf{q}'_{ik'}\boldsymbol{\delta} + \tau_{k'} I_{ik'})},$$

pri čemer so $\mathbf{q}_{ik}$ spremenljivke značilne za skupino (angl. *nest specific variables*), τ_k parameter neenakosti (angl. *dissimilarity parameter*), ki je odvisen od koeficienta korelacije napak znotraj skupin, in I_{ik} pričakovana koristnost ob izbiri skupine k. Verjetnost, da bo študent izbral smer j, ob pogoju, da je izbral skupino k, pa je:

$$p_{ij|k} = \frac{\exp(\mathbf{x}'_{ij}\boldsymbol{\beta}/\tau_k)}{\sum_{j' \in B_k} \exp(\mathbf{x}'_{ij'}\boldsymbol{\beta}/\tau_k)},$$

pri čemer zaradi poenostavljanja z $\mathbf{x}_{ij}$ označujemo set spremenljivk značilnih za posamezno smer, lahko pa model enostavno razširimo tudi na spremenljivke značilne za posameznika.

Ocene mešanega in gnezdenega logit modela kažejo, da se študentje z višjo splošno sposobnostjo z večjo verjetnostjo vpišejo na ekonomske smeri, višja specifična sposobnost za neko smer (npr. višja ocena pri predmetu računovodstvo) pa povečuje verjetnost vpisa na to smer (računovodstvo). Naši rezultati potrdijo rezultat uveljavljen v literaturi, da povečanje plače diplomantov neke smeri, ceteris paribus, poveča verjetnost izbire te smeri ter hkrati zmanjša verjetnost, da bo študent izbral drugo smer. Poleg tega ugotovimo, da sta oba spola bolj odzivna na specifične sposobnosti za smeri, ki so tradicionalno bolj značilne za določen spol (npr. poslovna informatika za moške).

Čeprav so naši rezultati osnovani na podatkih ene institucije majhne države, zaradi dveh razlogov verjamemo, da lahko našo glavno ugotovitev (da imajo sposobnosti specifične za smer pomembno vlogo pri razlagi izbire smeri) posplošimo tudi na ostale institucionalne okvirje. Prvič, dobljeni rezultati so skladni z rezultati ostalih avtorjev. In drugič, čeprav institucionalni okvir ni povsem primerljiv, npr. z ZDA, na obnašanje študentov vplivajo enaki dejavniki. Kljub temu da so ocene objektivna mera sposobnosti specifičnih za smer, pa lahko poleg teh sposobnosti odražajo tudi preference študentov glede študijskih smeri, zaradi česar so lahko ocenjeni mejni učinki pristranski navzgor. Ne glede na to, verjamemo, da pozitivni mejni učinki sposobnosti specifičnih za smer na verjetnost izbire tudi najmanj popularnih smeri dokazujejo pomembnost takšnih sposobnosti pri odločitvi o smeri študija.

Kot je že bilo omenjeno, izbira študijske smeri vpliva na strukturo ponudbe delovne sile, ki skupaj s povpraševanjem po delu oblikuje donose izobraževanja. Neposredno določanje plač v obdobju socializma, ki je po eni strani zagotavljalo majhno dohodkovno neenakost, je na drugi strani povzročilo nizko donosnost izobraževanja, slednja pa je vodila k majhnemu deležu diplomantov v delovni sili. Poleg tega je vlada z določanjem prostih mest na fakultetah ter direktno alokacijo kapitala določenim industrijam povzročila relativno visoko število diplomantov tehničnih smeri ter relativno nizko število diplomantov družbenih ved, prava in poslovnih smeri. Čeprav so nekatere študije analizirale vpliv sprostitve določanja plač ob prehodu iz socialističnega v tržno gospodarstvo in ugotovile, da je to povzročilo povišanje donosnosti izobraževanja, pa so se osredotočile zgolj na zgodnje obdobje tranzicije ter niso raziskale razlik v donosih med različnimi stopnjami ter smermi terciarnega izobraževanja. Namen drugega članka je zapolnitev te vrzeli v literaturi z uporabo dohodninskih podatkov vseh aktivnih slovenskih prebivalcev med leti 1994 in 2008. Da bi zmanjšali pristranskost ocen zaradi pozitivne povezave med sposobnostjo in izobrazbo, v Mincerjeve funkcije dohodkov dodamo mero splošne sposobnosti, ki je osnovana na maturitetnih rezultatih. Zaradi razlik v določanju plač med javnim in privatnim sektorjem, robustnost naših rezultatov preverimo z ločeno oceno donosnosti izobraževanja delavcev zaposlenih v privatnem sektorju. Poleg tega ne analiziramo zgolj donosnosti izobraževanja na podlagi plač, pač pa tudi donosnost osnovano na celotnem delovnem dohodku.

Donose izračunamo z oceno Mincerjeve funkcije dohodkov po metodi najmanjših kvadratov:

$$\ln y = \alpha + \sum_{j=1}^{J} \beta_j D_j + \gamma_1 z + \gamma_2 z^2 + \varepsilon,$$

kjer y označuje posameznikove dohodke, D_j je binarna spremenljivka, ki je enaka 1, če ima delavec izobrazbo j, z predstavlja število let delovnih izkušenj po končanem študiju in ε napako modela. Letna stopnja donosa za vsako raven izobrazbe r_j, pa je nato izračunana kot:

$$r_j = (1 + \beta_j - \beta_k)^{\frac{1}{T_j - T_k}} - 1,$$

pri čemer je $T_j - T_k$ čas potreben za dokončanje stopnje j, potem ko je posameznik že opravil stopnjo k. $\beta_j - \beta_k$ pa je razlika regresijskih koeficientov za ti dve stopnji izobrazbe.

V članku pokažemo, da imajo tako izračunane zasebne letne (monetarne) stopnje donosa obliko narobe obrnjene črke U. Med leti 1994 in 2001 so se donosi vseh stopenj izobraževanja, razen doktorskega študija, povečevali kljub povečanemu deležu delavcev z univerzitetno izobrazbo. Ta ugotovitev namiguje, da se je povpraševanje po diplomantih povečevalo hitreje od njihove ponudbe. V obdobju 2001–2008 je sledil padec v donosnosti izobraževanja. Poleg variacije donosov v času, odkrijemo tudi znatno heterogenost stopenj donosov med spoloma, stopnjami izobrazbe in študijskimi smermi, s posebej visokimi donosi na začetku opazovanega obdobja za smeri, ki so bile v času socializma zanemarjene, npr. družbenih ved, prava in poslovnih smeri, in relativno nizke donose tehničnih smeri študija, ki so bile pri socialističnih vodjih bolj priljubljene. Čez čas so se razlike med donosi izobraževanja različnih smeri, zaradi povečane ponudbe dela diplomantov družbenih ved, prava in poslovnih ved, zmanjšale. S pomočjo rezultatov pridobljenih na podvzorcu delavcev, za katere imamo podatek o meri sposobnosti, potrdimo prisotnost pozitivne pristranskosti ocen zaradi povezave med sposobnostjo in izobrazbo. Poleg tega ugotovimo, da imajo v homogenejših skupinah moški navadno višje stopnje donosa od žensk. In nenazadnje, donosi ocenjeni na osnovi celotnega poročanega dohodka kažejo, da alternativni viri dohodka predstavljajo nezanemarljiv del zasebnih stopenj donosa, posebej za delavce z magisterijem in doktoratom oziroma z diplomo iz umetnosti ali humanističnih ved.

Pokazali smo torej, da izbira študijske smeri vpliva na povpraševanje po delu posameznika in zato tudi na njegove rezultate na trgu dela. Kljub vsemu pa so zaposlitvene možnosti odvisne tudi od pridobljenega znanja in delovnih izkušenj. Slednje si diplomanti, ki vstopajo na trg delovne sile, lahko pridobijo s študentskim delom, obseg katerega se je v zadnjih letih povečeval, tako da danes okrog 40 odstotkov študentov v ZDA in približno 70 odstotkov študentov v EU med študijem opravlja delo. Eno od pogosto citiranih stiliziranih dejstev o ponudbi študentskega dela se glasi, da študentje z nizkim družinskim dohodkom delajo več kot tisti iz ekonomsko bolje situiranih družin, da lahko pokrijejo stroške študija. Vendar pa so nekateri tuji avtorji opazili zanimiv fenomen, katerega razlaga je bila do sedaj zanemarjena – povezava med delom študentov in dijakov ter ekonomsko situacijo njihovih družin ni vedno negativna. Podobno tudi naša analiza redno vpisanih dodiplomskih študentov Univerze v Ljubljani zavrne monotono padajočo povezavo med študentskim delom in družinskim dohodkom.

V tretjem članku zagovarjamo stališče, da sta ti dve navidezno nasprotujoči si empirični dognanji dejansko rezultat dveh učinkov, ki delujeta v nasprotni smeri. Kot predvideva osnovni statični model ponudbe dela, ponudba dela pada z nedelovnim dohodkom, če je prosti čas normalna dobrina. Še več, če so stroški študija visoki, jih študentje z nizkim družinskim dohodkom ne zmorejo pokriti zgolj z nedelovnim dohodkom, zato morajo povečati obseg študentskega dela, da lahko nadaljujejo s študijem. Rezultat tega je negativna povezava med študentskim delom in družinskim dohodkom, ki jo opisuje prvo stilizirano dejstvo. Vendar ob upoštevanju dinamičnih vidikov odločitve o ponudbi študentskega dela in odsotnosti sedanje finančne omejitve, revnejši študentje delajo manj, da se izognejo strožji kazni v prihodnosti - večji verjetnosti opustitve študija. Zaradi tega ponudba dela za slabše situirane študente narašča z družinskim dohodkom in opazovano je drugo stilizirano dejstvo.

Ker so podatki o študentski zaslužkih pristranski zaradi (samo)selekcije in ker sta odločitvi o delu in o opravljenih urah lahko odvisni, za oceno učinkov različnih spremenljivk na ponudbo dela uporabimo Heckmanovo dvostopenjsko metodo. Prvi korak metode predstavlja selekcijska enačba:

$$Pr(y_{1i} = 1) = Pr(x'_{1i}\beta_1 + \epsilon_{1i} > 0),$$

v kateri y_1 označuje ali posameznik dela ali ne in je ocenjena s probit regresijo. V drugem koraku pa je višina študentskih zaslužkov (y_2) določena kot:

$$y_{2i} = x'_{2i}\beta_2 + \sigma_{12}\lambda(x'_{1i}\hat{\beta}_1) + \epsilon_{2i},$$

kjer $\hat{\beta}_1$ predstavlja ocenjene koeficiente iz prve stopnje, $\lambda(x'_{1i}\hat{\beta}_1) = \frac{\phi(x'_{1i}\hat{\beta}_1)}{\Phi(x'_{1i}\hat{\beta}_1)}$ pa je ocenjeni inverz Millsovega razmerja (angl. *inverse Mills ratio*). Enačbo drugega koraka ocenimo po metodi najmanjših kvadratov, pri čemer so uporabljene zgolj pozitivne vrednosti y_2.

Z našo analizo odkrijemo, da ima povezava med študentskim delom in družinskim dohodkom obliko narobe obrnjene črke U, torej je učinek sedanje finančne omejitve šibkejši od učinka pričakovane strožje sankcije za študente z nizkim nedelovnim dohodkom, kar nam omogoči edinstveno priložnost analiziranja do sedaj spregledanega dinamičnega učinka družinskega dohodka na študentsko delo. Naš prispevek k literaturi je dvodelen. Najprej pokažemo, da imajo (ob kontroliranju ostalih lastnosti) med študenti, ki ponavljajo letnik, tisti z nizkim nedelovnim dohodkom večjo verjetnost opustitve študija. Nato pa naša empirična dognanja motivirajo naš teoretičen model, ki v skladu z literaturo predpostavlja, da (i) verjetnost uspešno opravljenega letnika pada s študentskim delom in da (ii) absolutna nenaklonjenost tveganju staršev pada s premoženjem. Model napove nižjo ponudbo študentskega dela za študente z nizkim nedelovnim dohodkom in prihodnjo finančno omejitvijo, ki preprečuje nadaljnji študij, kot za študente z višjim nedelovnim dohodkom in možnostjo ponavljanja letnika. Naraščajoči del povezave med študentskim delom in družinskim dohodkom lahko torej pojasnimo z racionalnim odzivom študenta na kredibilno grožnjo staršev z nizkim dohodkom, ki z manjšo verjetnostjo nadaljujejo z investiranjem v tvegano naložbo (izobrazbo študenta), če študent ne opravi letnika, kot starši z visokim dohodkom. Z drugimi besedami, študentje z nizkim nedelovnim dohodkom se samo-omejijo, da bi povečali verjetnost napredovanja v višji letnik in zmanjšali verjetnost opustitve študija, če ne opravijo letnika, ker njihovi starši ne bodo več pripravljeni plačevati njihovega študija. Za vse ostale študente grožnja ni kredibilna, saj se zavedajo padajoče absolutne nenaklonjenosti tveganju staršev, zato predvidevajo, da bodo imeli možnost ponavljanja letnika. Na te študente učinkuje zgolj dohodkovni učinek nedelovnega dohodka in zato opazujemo padajoč del povezave med študentski delom in družinskim dohodkom v obliki narobe obrnjene črke U.

Ker socialni transferji v Sloveniji lahko predstavljajo pomemben del družinskega dohodka in zato tudi študentovega nedelovnega dohodka, se poraja pomislek o njihovem potencialnem vplivu na odvračanje študentov od dela, da bi ohranili državno pomoč. Toda robustnostni test naših rezultatov pokaže, da razlog za opazovano obnašanje študentov niso socialni transferji. Prav tako zavrnemo možnost, da bi bile vzrok za opazovano obliko relacije med študentskim delom in družinskimi dohodki razlike v povpraševanju. Na žalost pa ne moremo raziskati možnosti, da želijo študentje z nižjimi dohodki hitreje dokončati študij, da bi se lahko prej osamosvojili, ker nam naši podatki ne omogočajo analiziranja takšnih vidikov obnašanja. To prepuščamo prihodnjim raziskavam.

Po teoriji človeškega kapitala lahko študentsko delo povečuje ali zmanjšuje količino pridobljenega znanja in posledično izboljšuje ali poslabšuje posameznikovo produktivnost. Študentsko delo povečuje človeški kapital s pridobivanjem novih veščin in znanja, ki lahko pripomorejo k boljšemu študijskemu uspehu in, kar je pomembneje, k večjemu uspehu na trgu dela po končanem študiju. Obenem pa lahko študentsko delo izriva čas namenjen študiju in zato škodi študijskim rezultatom, kar pa zmanjšuje človeški kapital. V četrtem članku se osredotočimo na empirično proučevanje učinkov študentskega dela na študijski uspeh.

Čeprav se je obsežen del obstoječe empirične literature osredotočil na učinek dijaškega dela na srednješolske ocene, pa njihovi rezultati niso enotni, prav tako pa ne morejo biti uporabljeni za študente terciarnega izobraževanja zaradi pomembnih razlik med srednješolskim in visokošolskim študijem. Slednji je namreč manj strukturiran in ima navadno manj tedenskih učnih ur ter zato dovoljuje več ur študentskega dela tudi za redno vpisane študente. Obenem morajo študentje prevzeti polno odgovornost za svoje odločitve, pri tem pa jih ne usmerjajo starši in/ali profesorji. Zato obstaja večja verjetnost, da bodo študentje škodovali študijskemu uspehu s preveliko količino študentskega dela kot pa dijaki. Ne glede na to pa so rezultati dosedanjih raziskav s tega področja podobno neenotni kot za dijaško delo, saj nekateri opisujejo nične učinke, medtem ko drugi najdejo negativen vpliv na študijski uspeh.

Naša raziskava prispeva k tej literaturi z analizo učinkov študentskega dela na različne študijske rezultate ločeno po letnikih študija. V ta namen uporabimo podatke slovenskih študentov vpisanih na štiriletni dodiplomski študij Ekonomske fakultete Univerze v Ljubljani, ki vsebujejo bogato zbirko kontrolnih spremenljivk. Študijske rezultate merimo s petimi različnimi spremenljivkami – številom poskusov opravljanja izpitov, številom opravljenih izpitov, povprečno oceno, povprečno pozitivno oceno in verjetnostjo, da bo študent opravil letnik. Medtem ko vse mere odražajo učinek študentskega dela na količino časa namenjenega študiju, se nekatere bolj osredotočajo na ekstenzivnost (število poskusov opravljanja izpitov), druge pa na intenzivnost (povprečna ocena) študija. Verjetnost, da bo študent opravil letnik, je kombinirana mera, katere namen je zajeti splošen učinek študentskega dela na študijski uspeh. V nasprotju z mnogimi ostalimi raziskavami, naša dopušča nelinearne učinke študentskega dela in analizira efekte ločeno po letnikih študija.

K literaturi prispevamo tudi z uporabo metode paritve enake verjetnosti (angl. *propensity score matching*) za izračun povprečnih učinkov obravnave za obravnavane osebe (angl. *average treatment effects on the treated* – ATET). Čeprav je bila ta metoda že uporabljena v drugih vejah ekonomije, pa je to prvi poskus merjenja učinkov študentskega dela na študijske rezultate na ta način. V ta namen uparimo študente z drugačno zgodovino študentskih zaposlitev, a z enako verjetnostjo za določen obseg študentskega dela. Metoda paritve enake verjetnosti ima dve prednosti. Prvič, izogne se večdimenzionalnemu problemu iskanja parov študentov v primerih z veliko kontrolnimi spremenljivkami. In drugič, pri ocenah zahteva minimalno strukturo. Prednost te metode je tudi ta, da daje težo observacijam s podobnimi regresorji in manjšo težo oziroma ne daje teže observacijam na meji, kar je ravno nasprotno metodi najmanjših kvadratov, ki daje slednjim opazovanjem veliko utež.

Verjetnost (angl. *propensity score*), da bo študent opravil k ur študentskega dela med študijskim letom (SW_k), ocenimo z logit regresijo. Pri tem kot pojasnjevalne spremenljivke uporabimo osebne lastnosti (x) in študijski uspeh prejšnjega leta (A):

$$Pr[\mathrm{SW}_{ki} = 1] = \alpha_0 + \alpha_1 x_i + \alpha_2 A_i + u_i.$$

Ta pogojna verjetnost obravnave (opravljanja k ur študentskega dela) ob danih x in A je osnova za paritev obravnavanih (angl. *treated*) in kontrolnih (angl. *controls*) opazovanj. Izračun povprečnih učinkov obravnave za obravnavane osebe (ATET) pa je osnovan na (i) predpostavki pogojne neodvisnosti (angl. *conditional independence assumption*), ki pravi, da so rezultati obravnavane in kontrolne skupine (pogojno na pojasnjevalne spremenljivke) neodvisni od obravnave, in (ii) predpostavki paritve (angl. *matching assumption*), ki zahteva, da za vsako vrednost verjetnosti obravnave obstajajo opazovanja v kontrolni in obravnavani skupini.

Kontrolne observacije izberemo po metodi polmera (angl. radius matching) z zamenjavo observacij (vsak študent iz kontrolne skupine je lahko kot par izbran večkrat) in izključitvijo študentov, katerih ocenjene verjetnosti obravnave ležijo zunaj domene ocenjenih verjetnosti kontrolnih enot (angl. *common support*). Metoda polmera je različica metode kaliper (angl. *caliper matching*), ki uporabi vse kontrolne enote znotraj polmera in ne zgolj najbližjega soseda, kot je značilno za kaliper paritev. Ta lastnost pa pripomore k zmanjšanju pristranskosti ocen.

Ker pričakujemo, da imajo različni obsegi študentskega dela različen vpliv na študijske rezultate, ne razlikujemo le med študenti, ki delajo, in tistimi, ki ne, pač pa ustvarimo tri različne binarne spremenljivke, ki vodijo k oceni treh različnih povprečnih učinkov obravnave za obravnavane osebe. Natančneje, študente, ki med šolskim letom delajo manj kot dva meseca, uporabimo kot kontrolno skupino za tiste, ki delajo 2–7 mesecev in tiste, ki delajo več kot 7 mesecev. Nazadnje uporabimo še študente, ki delajo 2–7 mesecev kot kontrolno skupino za tiste, ki delajo več kot 7 mesecev znotraj enega šolskega leta.

Odkrijemo, da študentsko delo res škoduje študijskim rezultatom, vendar so negativni učinki navadno majhni in se pojavljajo v glavnem v prvem letniku študija. Na primer, negativni učinek dela na število poskusov opravljanja izpitov in na število opravljenih izpitov v prvem letniku ne presega desetih odstotkov vseh zahtevanih izpitov za študente, ki so delali 2 do 7 mesecev, v primerjavi s študenti, ki so delali manj kot 2 meseca. Podobno je verjetnost dokončanja prvega letnika za študente, ki so delali več kot 2 meseca, za 7 odstotnih točk manjša v primerjavi s študenti, ki so delali manj. Vendar pa ne najdemo statistično značilnih razlik v študijskih rezultatih študentov, ki so delali od 2 do 7 mesecev, in tistimi, ki so opravili več kot 7 mesecev študentskega dela med prvim letnikom študija. Poleg tega ocene razkrijejo nižjo povprečno oceno, nižjo povprečno pozitivno oceno, nižje število poskusov opravljanja izpitov in nižje število opravljenih izpitov za študente četrtih letnikov z največ delovnimi izkušnjami v primerjavi s tistimi, ki so delali 2 do 7 mesecev, vendar pa se skupini ne razlikujeta v verjetnosti dokončanja letnika.

Rezultati zgoraj opisane raziskave kažejo, da neenotne ugotovitve ostalih avtorjev glede učinkov študentskega dela na študijski uspeh niso zgolj posledica različnih cenilk, ki se tako ali drugače spoprijemajo s problemom izpuščenih spremenljivk, pač pa so tudi posledica vzorcev, ki se osredotočajo na različna študijska leta ter drugačne mere študijskega uspeha. Poudariti pa je potrebno, da so zgornji rezultati osnovani na podatkih študentov ene fakultete, ki študentom s ponavljanjem predavanj omogoča lahko prilagajanje študija in dela. Če imajo ostale fakultete manj fleksibilne urnike, potem študentje težje usklajujejo delo in študij, kar pa lahko poveča negativen učinek študentskega dela.

V zadnjem članku se osredotočimo na relativen vpliv izkušenj pridobljenih s študentskim delom in študijskega uspeha na rezultate na trgu dela po končanem študiju. Medtem ko se je nekaj študij osredotočilo na vpliv dijaškega dela na rezultate na trgu dela, pa njihovih ugotovitev ne moremo posplošiti na študentsko delo, saj dijaki med izobraževanjem lažje najdejo delo, ki je povezano z njihovim formalnim usposabljanjem. Ker pa je vpliv študentskega dela na profesionalno kariero analizirala zgolj peščica člankov, so ti učinki relativno neraziskani in to vrzel želimo zapolniti z zadnjim delom doktorske disertacije.

S teoretičnega stališča pričakujemo, da ima študentsko delo pozitiven učinek na posameznikovo produktivnost in zato tudi pozitiven vpliv na verjetnost redne zaposlitve ter višino plače. Študentsko delo lahko služi tudi kot signal o posameznikovi motivaciji in sposobnostih bodočim delodajalcem. Poleg tega se lahko delodajalci v procesu selekcije kandidatov za novo delovno mesto zanesejo na posameznikovo uspešnost pri študentskem delu. Po drugi strani pa so rezultati na trgu dela pozitivno odvisni tudi od študijske uspešnosti. Upoštevaje rezultate, ki kažejo na (majhen) negativen učinek študentskega dela na študijski uspeh, je smiselno oceniti njun relativen vpliv na odločitve zaposlovalcev.

Edinstvena lastnost naše raziskave je uporaba metode paritve enake verjetnosti, ki je že opisana zgoraj. Čeprav je to uveljavljena metoda, še ni bila uporabljena v takšnem kontekstu. Ker pa dovoljujemo, da študentsko delo vpliva na študijske rezultate in da hkrati slednji vplivajo na študentsko delo, moramo pri ocenjevanju vpliva študentskega dela (študijskega uspeha) na rezultate na trgu dela kontrolirati za študijski uspeh (obseg študentskega dela), saj bi bil v nasprotnem primeru študijski uspeh (obseg študentskega dela) neuravnotežen med obravnavanimi in kontrolnimi skupinami. Zaradi tega pa ocenjeni učinki ne zajemajo posrednega vpliva študentskega dela (študijskega uspeha) na rezultate na trgu dela preko študijskega uspeha (študentskega dela).

Rezultate na trgu dela merimo z verjetnostjo zaposlitve, urno postavko in verjetnostjo zaposlitve za nedoločen čas. Empirična analiza pokaže, da študentsko delo pozitivno vpliva na vse tri mere uspešnosti na trgu dela. Takšno delo najbolj koristi tistim, ki med štiriletnim dodiplomskim študijem delajo več kot 10 mesecev, a manj kot 2 leti. Medtem ko pozitivni učinki naraščajo z dodatnimi leti izkušenj, pa dodatne koristi niso statistično značilne. Poleg tega odkrijemo, da imajo različna študentska dela različen vpliv na rezultate na trgu dela. Največje pozitivne učinke odkrijemo za dela, ki zahtevajo terciarno izobrazbo, sledijo dela, ki zahtevajo srednješolsko izobrazbo, a so povezana s študijsko smerjo študenta, najmanjši vpliv pa imajo s študijem nepovezana manj strokovna dela.

Študijski uspeh opisujeta dve binarni spremenljivki, ki označujeta študente z diplomo oziroma s povprečno oceno v 75. percentilu ali višje. Čeprav so številne študije potrdile pozitiven vpliv učnega uspeha na rezultate na trgu dela, pa v glavnem niso primerjale tega učinka z učinkom študentskega dela. K literaturi tako prispevamo tudi z ugotovitvijo, da diploma poveča verjetnost zaposlitve, bruto urno postavko in verjetnost zaposlitve za nedoločen čas bolj kot povečanje študentskega dela z manj kot 10 mesecev na več kot 3 leta študentskega dela med štiriletnim dodiplomskim študijem. Poleg tega pokažemo, da je pozitiven vpliv nadpovprečnih ocen na urno postavko večji od učinka povečanja študentskega dela z manj kot 10 mesecev na več kot 3 leta v prvem letu na trgu dela, medtem ko je učinek v drugem letu nekoliko manjši. Učinek nadpovprečnih ocen na verjetnost zaposlitve v prvem letu na trgu dela pa je primerljiv z učinkom povečanja študentskega dela z manj kot 10 mesecev na več kot 10 mesecev, a manj kot 2 leti študentskega dela.

Rezultati torej kažejo, da s stališča rezultatov na trgu dela študentsko delo in študijski uspeh koristita študentom. Na žalost pa nam podatki ne omogočajo merjenja vloženega truda, ki je potreben za dosego diplome, nadpovprečno oceno ali opravljeno uro študentskega dela, zato ne moremo soditi o donosnosti odločitev študentov o razporeditvi časa med študijem in delom. Ne glede na to, pa da bi moralo biti študentsko delo, še posebej strokovno bolj zahtevno delo povezano z izbrano študijsko smerjo, spodbujano, vendar le do omejenega obsega, saj po neki točki dodatne študentske delovne izkušnje ne prispevajo več k izboljšanju rezultatov na trgu dela. Hkrati lahko zavrnemo predstavo nekaterih študentov, da praktične izkušnje med študijem pomenijo več kot teoretične. Opozoriti pa je potrebno, da so rezultati osnovani na podatkih ene fakultete, zato moramo biti pri posploševanju previdni, saj imajo lahko zaposlovalci ostalih področij drugačne preference glede akademskih in praktičnih znanj.

Zaključki te doktorske disertacije pa niso pomembni zgolj za literaturo pač pa tudi za oblikovalce politik. Naše ocene kažejo, da se donosi na izobraževanje razlikujejo po smereh študija. Večja kot je ponudba oziroma manjše kot je povpraševanje, nižja bo ravnotežna plača in zato tudi donosi na izobraževanje. Toda razumevanje dejavnikov, ki vplivajo na izbiro študijske smeri, oblikovalcem politik omogoča ustvarjanje spodbud, ki bodo ustrezno prilagodile ponudbo delovne sile potrebam trga dela in razvojnim ciljem. Natančneje, čeprav višje plače same po sebi pritegnejo študente na smeri, ki imajo višje donose, lahko oblikovalci politik s spreminjanjem smeri specifičnih sposobnosti spodbudijo hitrejšo prilagoditev ponudbe povpraševanju na trgu dela. Poleg tega naši rezultati kažejo, da bi morali študentsko delo, še posebej strokovno zahtevno delo povezano z izbrano študijsko smerjo, spodbujati v zadnjih letnikih študija, toda le do določenega obsega.