# Three Studies on the Value and Risk of Higher Education

by

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For Mama, Papa, and Christopher.

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# CHAPTER I

# Introduction

College in the United States is very expensive. This statement has been true for at least a generation, but costs have reached new heights in recent years. List tuition prices have grown at a rate of about 5% above inflation over the last ten years, and the financial aid budgets of both the US government and individual institutions are expanding to keep up.[1] The studies presented in this dissertation tackle some of the finance-related questions that arise in discussions of the higher education market in the United States. We examine college funding and affordability, aid policies, and college choice. This work may help to inform governments, institutions, families, and students about the risks and rewards of higher education.

In chapter II, we examine the role of public and private funding for higher education in countries throughout North America and Western Europe. We compare and contrast the various systems of higher education funding that are found in wealthy Western nations, and examine the impact of recent reforms meant to overhaul some of these systems. We focus on drivers of overall enrollment in higher education, and study the impact of spending, social inequality, and GDP. This work provides context for further study of the US system. In general, the US higher education system relies more heavily on private funding and financial aid than its European counterparts,

[1] See e.g. The College Board (2012b) and The College Board (2012c) for more on college pricing and financial aid trends.

though recent European reforms tend to move away from traditional publicly funded systems.

Chapter III focuses on the US higher education market. By developing a two-stage least squares model of supply and demand in higher eduation, we build a better understanding of the effect of aid mechanisms on school and student decisions. We study the effect of financial factors such as tuition and aid amounts, expenditures, and schools' revenues on enrollment levels. Additionally, we compile an extensive dataset of macroeconomic variables that capture changes in the higher education market and financial aid market over a thirty-year period, and develop supply-side and demand-side models. A primary motivator for this work is the hypothesis that increased aid availability may actually be helping to fuel higher education price increases.

Chapter IV studies the impact of financial factors on higher education at an even more granular level. A unique individual-level dataset on college choice decisions allows us to create models of the decision to attend college and the choice between institutions. We study the relationship between post-college income, individual and school characteristics, and the student side of the college decision process. We examine drivers of income differences across students after adjusting for ability. This work introduces a new method of adjusting for bias introduced through differences in student ability across schooling decisions. Unique survey data that captures all stages of students' application processes allows us to condition on the selectivity level of the top school to which a student was admitted, capturing valuable information about that students' intrinsic ability. We focus on the effect of student and family charateristics as well as school and major decisions made by individual students after adjusting for ability. This chapter also outlines important areas of future research that will enhance understanding of the relationship between educational decisions and future income levels.

# CHAPTER II

# For What It's Worth: Higher education spending in North America and Western Europe

## 2.1 Introduction

Developed Western countries have taken very different approaches to financing higher education. On one extreme, students attending private four-year colleges and universities in the United States now pay an average of $36,993 per year to attend school (College Board Advocacy and Policy Center, 2010). On the other hand, European students in Finland, Norway, Austria, and other countries pay no official tuition, though fees and housing costs may apply (EDALO Education Promotional Services S.L., 2011). Some governments have instituted complicated financial aid systems throug which federal, state, and local governments can assist students, while other countries rely on private lenders. There is an extensive literature examining the similarities and differences, failures and successes of these different approaches to tertiary education. Overall, universities in North America and Western Europe provide some of the best education in the world, but experts and the media have warned in recent years that Western educational institutions may be losing ground (see e.g. Economist (2010) and Harris and Beschloss (2011)). In order for universities to remain competitive, affordable, and well-funded, governments must maximize the impact of aid and

subsidies.

This chapter examines differential effects of GDP, population, and tertiary education spending on enrollment across North America and Western Europe. Our goals are to study the effect of public versus private spending on enrollment, to identify economic drivers of enrollment, and to identify differences in enrollment levels caused by the introduction of certain reforms. New enrollment captures the initial decision to attend school and gives an indication of access to tertiary education. Improved access to higher education is a common goal for policymakers. We find that the strongest predictor of new enrollment in tertiary education is GDP in the country in question, not spending on tertiary education alone. We find a positive relationship between GDP and enrollment. Although this primarily captures the fact that larger countries have greater enrollment, we investigate differences in enrollment based on the enactment of reforms and public to private spending ratios.

We find that the effect of GDP on enrollment varies between countries with different levels of private spending and tuition. Specifically, we find that for the same GDP levels, enrollment is higher in countries with a high level of private spending on tertiary education. This may indicate that better economic conditions have a more positive effect in these countries. This result may also stem from the fact that private spending on education is more highly correlated with GDP than public spending, indicating that GDP increases raise enrollment both directly and indirectly through higher private spending levels. We find no significant differences in baseline enrollment or effect of GDP over time. We also do not see an effect of education and funding reforms.

## 2.2 Background

A rise in earnings inequality in the 20th century brought renewed relevance to the question of return on investment in higher education. During this time, influential

papers like Becker and Chiswick (1966) and Mincer (1974) first applied sophisticated human capital models to the question of returns on education. Those papers set the stage for future returns estimates based on ordinary least squares regression, various instrumental variables approaches, semi-log earnings functions, and natural experiments based on twin data and policy changes (see e.g. Psacharopoulos and Mattson (1998), Behrman and Rosenzweig (1999), Heinrich and Hildebrand (2005), and Hämäläinen and Uusitalo (2008)). Private returns are calculated based on out-of-pocket education costs and after-tax earnings differences between those with a tertiary degree and those without. Social returns are based on public expenditures and productivity differentials. In general, private returns exceed social returns, and higher levels of economic development and previous education reduce the impact of further education (see Psacharopoulos (1972)).

In this study, we focus on highly developed economies in Europe and North America. According to Psacharopoulos (1972), the richest countries in these regions have among the lowest returns on education in the world. Returns are higher in Eastern European countries, like the Czech Republic, Poland, and Hungary, but are still below international average returns. Returns on education in these areas are fairly consistent over time, even in countries of the former Eastern Bloc that have recently transitioned to market economies (see Flabbi et al. (2011)). Each country strikes a different balance between public and private funding of tertiary education. In the United States, close to 40% of the contribution to tertiary education comes from households. In much of Europe, this number is well below 10% (OECD, 1998). In the last several years, many European countries have struggled to reduce government spending, and educational expenditures are a popular place for cuts. Costs can be shared among governments and taxpayers, students and their families, and philanthropic organizations. Mechanisms for such cost-sharing include public and private grants, student tuition and fees, government sponsorship of schools (tuition-free edu-

cation), government subsidies for schools, government subsidies for students including subsidized loans, indirect government support such as child allowances, and tax credits (for more on these see Johnstone (2005)). This work does not seek to create a new estimate of returns on investment in tertiary education. Instead, we investigate differences in the effect of educational spending and GDP on new enrollment in tertiary education.

## 2.3 Data

Lack of consistent, reliable data is a primary barrier to research on higher education spending. It is difficult to get relevant spending and earnings data in each country, and reporting differences between countries make it hard to compare results. Additionally, a large number of control variables must be accounted for, such as differences in age, intelligence, motivation, and other personal information (see e.g. Psacharopoulos (1972)). Past estimates of returns of higher education use data reported by individual governments, international groups like the European Union, UNESCO, or OECD, and individual survey results from studies like the European Community Household Panel (see, for example, Heinrich and Hildebrand (2005)).

For this work, we use data from the OECD, UNESCO, and Eurostat to build a panel dataset of enrollment, population, GDP, and expenditures. We also include a variety of adjustment variables which allow us to conduct analysis on a per student basis. These results are not provided here but support conclusions similar to those from the aggregate analysis that is presented. This dataset is supplemented with information about recent tertiary education reforms in Europe from a variety of sources, including Centro de Estudios en Gestión de la Educación Superior (2007), CHELPS, IOE London, Technopolis Group (2010), Johnstone (2005), OECD (1998), EDALO Education Promotional Services S.L. (2011), and ICHEFAP (2011). The dataset spans an eleven-year period from 1997 to 2008 and includes twelve countries,

Table 2.1: Countries included in analysis.

| **Europe** | **North America** |
|---|---|
| Austria | United States |
| Finland | |
| Hungary | |
| Ireland | |
| Italy | |
| Netherlands | |
| Norway | |
| Poland | |
| Spain | |
| Sweden | |
| United Kingdom | |

as shown in table 2.1. We consider new enrollment in tertiary education, graduation rates, unemployment rates, and relative earnings of tertiary graduates versus non-graduates as metrics of educational success in each country. Only the new enrollment metric yields significant results, probably since relative earnings and graduation rates depend increasingly on the actual quality of education received. On the spending side, we examine GDP, total expenditures on tertiary institutions, public expenditures on tertiary institutions, a ratio of public over total spending, and population as candidate predictors. As described in the next section, we employ a fixed effects approach to account for country differences, allowing us to limit the number of predictor variables in the model. A list of main variables used is provided in table 2.2.

## 2.4 Model

We use simple ordinary least squares regression to model the relationship between spending metrics and outcomes. The panel data compiled for this study are non-stationary as determined by inspection and unit root tests.[1] We therefore take

[1]Fail to reject presence of unit roots in time series for new enrollment (p-value = 0.99 at lag 1).

Table 2.2: Summary of data and sources.

| Category | Summary | Data source |
|---|---|---|
| **Outcome metrics** | | |
| New enrollment | New entrants into tertiary (college-level, non-professional, ISCED 5A[a]) education, per population | OECD (2011) |
| Graduation rate | Graduates per enrollment in tertiary (ISCED 5 & 6) education | OECD (2011) |
| Employment rate | Relative employment rate for tertiary (ISCED 5 & 6) graduates versus upper secondary (ISCED 3 & 4) graduates | OECD (2011) |
| Earnings difference | Relative earnings for tertiary (ISCED 5 & 6) graduates versus upper secondary (ISCED 3 & 4) graduates | OECD (2011) |
| **Spending and economic metrics** | | |
| Total expenditures | Expenditure on education institutions (total, public and private sources), tertiary (5,6), $BN | OECD (2011) |
| Public expenditures | Expenditure on education institutions and administration, public sources, tertiary, $BN | OECD (2011) |
| Ratio public/total expenditures | Public expenditures/total expenditures | OECD (2011) |
| GDP | Gross domestic product, $BN | World Bank (2011) |
| Population | Population of each country studied | OECD (2011), European Commission (2011) |
| **Adjustment factors** | | |
| Enrollment | Total enrollment in tertiary education (ISCED 5 & 6) | UNESCO (2011) |

[a]ISCED is the International Standard Classification of Education developed by UNESCO. For more information, see UNESCO (2013).

ordinary differences of all data. Log differences were also considered and yielded similar results. The strongest relationship among the spending and outcome variables described in the previous section exists between GDP and new enrollment in tertiary education. Graduation rate, employment rate, and earnings difference are metrics of educational success rather than simply attendance. There may be too many other factors affecting quality of education to allow us to identify the relationship between these variables and per student spending. We therefore use only GDP and new enrollment for our analysis. Table 2.3 shows the simplest possible model demonstrating the relationship between GDP and new enrollment. We see that a $1 million increase in GDP leads to an enrollment increase of 0.19 students. This relationship captures primarily the fact that larger economies enroll more students in tertiary education. We use this as a baseline to compare differences not explained by country size.

Table 2.3: Effect of GDP on new higher education enrollment. $newEnrollment_{i,t} = \beta_0 + \beta_1 GDP_{i,t} + \epsilon_{i,t}$.[a]

| Ordinary least squares regression | | | |
|---|---|---|---|
| Adjusted $R^2$ | 0.2757 | | |
| Variable[b] | Coefficient value | St. error | p-value |
| (Intercept) | 2,402.52 | 2,678.64 | |
| GDP ($BN) | 190.46 | 26.74 | $6.47 \times 10^{-11}$ |

[a]Data include yearly GDP and enrollment figures for countries listed in table 2.1 from 1997 to 2008.

[b]For detailed variable descriptions see table 2.2.

We investigate many alternative models to the one presented in table 2.3. A similar model using log-differenced data yields consistent results. Models where all data are normalized to account for country size (i.e. enrollment is given as a percentage of population and per capita GDP is used) also provide similar results. We also experiment with using population and spending on tertiary education instead of GDP. We find that the portion of these variables directly correlated with GDP provide most of the predictive power. Results regarding enrollment differences are confirmed. These models are provided in appendix A.1.

We use the model given in table 2.3 to test for differences between countries. We introduce country and time fixed effects in order to reduce possible omitted variable bias. Time fixed effects account for unobserved shifters of enrollment that change over time and affect all countries. Country fixed effects account for unobserved shifters of enrollment that may affect a particular country but are constant over time. We find no significant time fixed effects. However, we do see that, for the same GDP levels, enrollment is higher in the United States, the United Kingdom, and Poland, as shown in table 2.4. Investigating the causes of this difference is beyond the scope of this chapter, but we suggest it may be due to a larger private return on education; these countries have higher levels of social inequality than other countries studied, as shown in figure 2.1. This figure plots Gini coefficients for the countries in our sample. Gini coefficients measure social inequality, with a larger index suggesting greater inequality.[2] Figure 2.2 plots country fixed effects from the model in table 2.4 for each country against the corresponding Gini coefficient, showing a strong trend of greater enrollment for the same GDP level as Gini coefficient increases. Countries with higher Gini coefficinets and higher enrollment relative to GDP also have a higher ratio of private to total spending, implying that more education funding comes from tuition than in other countries.

We can study the effect of private versus public spending by categorizing countries according to their private to total spending ratios. Table 2.5 shows this model, revealing higher enrollment levels for countries with higher private to total spending ratios when GDP and total spending are held constant. A possible explanation for this phenomenon is that GDP growth may translate more directly into more education spending in countries with high private spending. Private individuals can choose to take on loans or grants for educational purposes in response to a growing economy more quickly than governments can increase spending. Additionally, GDP growth is

[2]Gini coefficient data compiled from Central Intelligence Agency (2011).

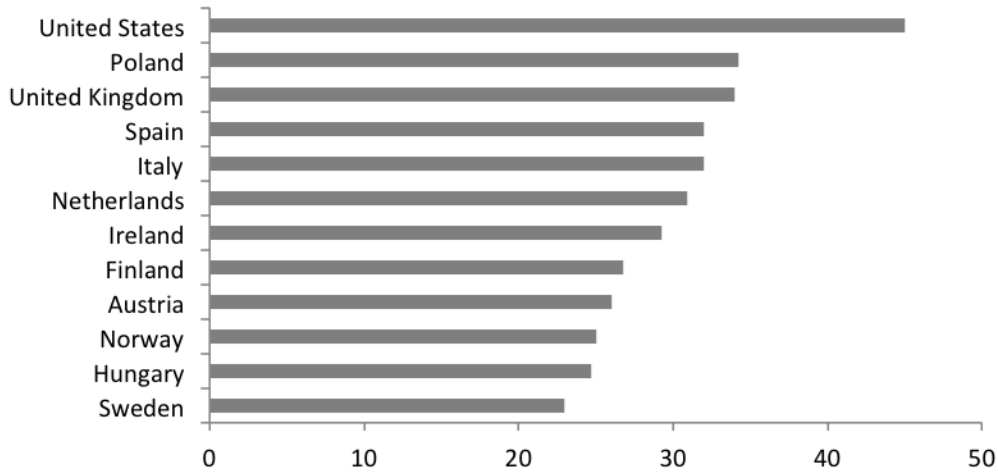



Figure 2.1: Gini coefficient by country.[a]

[a]Gini coefficient data compiled from Central Intelligence Agency (2011). Gini coefficient measures social inequality, with a larger index suggesting greater inequality.

more highly correlated with private spending on education than public spending, so increases in GDP raise enrollment levels directly as well as through higher private spending levels.

Table 2.4: Effect of GDP on new enrollment, including country fixed effects. $newEnrollment_{i,t} = +\beta_1 GDP_{i,t} + \gamma_i countryDummy_{i,t,} + \epsilon_{i,t}$.[a,b]

| | Fixed effects regression | | |
|---|---|---|---|
| Adjusted $R^2$ | 0.6000 | | |
| Variable[c] | Coefficient value | St. error | p-value |
| GDP | -2,157.66 | 42.19 | $2.87 \times 10^{-4}$ |
| Poland | 15,400.86 | 6,609.50 | 0.02 |
| United Kingdom | 18,483.89 | 6,958.13 | $8.98 \times 10^{-3}$ |
| United States | 138,237.45 | 14,327.32 | $2.00 \times 10^{-16}$ |

[a]Only coefficients significantly different from zero are presented.

[b]Data include yearly GDP and enrollment figures for countries listed in table 2.1 from 1997 to 2008.

[c]For detailed variable descriptions see table 2.2.

We further investigate interaction effects between country dummies as well as ratio categories and GDP. These interaction effects test for differences in the effect of GDP changes across countries or different private to total spending ratios. The interaction terms in the regression equation allow the impact of GDP on enrollment

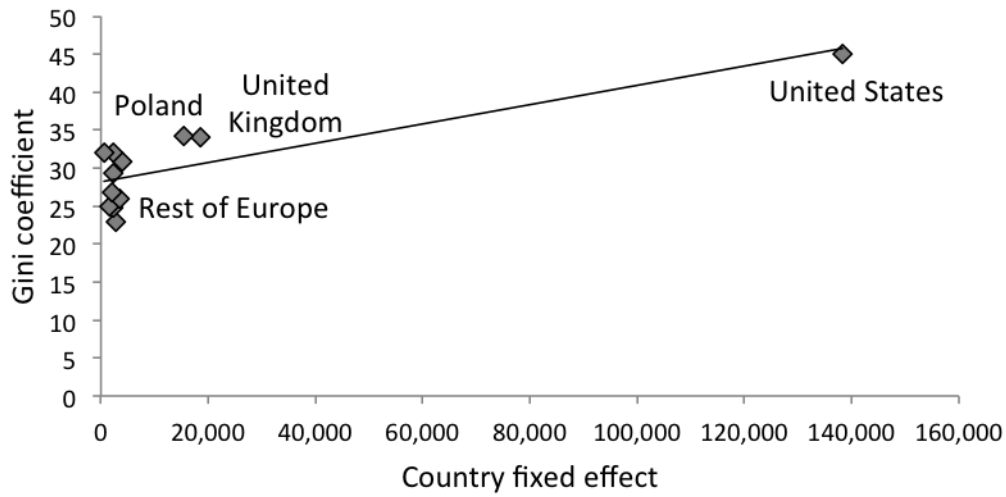



Figure 2.2: Country fixed effect versus Gini coefficient.[a,b,c]

[a]Gini coefficient data compiled from Central Intelligence Agency (2011). Gini coefficient measures social inequality, with a larger index suggesting greater inequality.

[b]Fit line equation given by $giniCoefficient = 0.0001 fixedEffect_{country} + 28.193$.

[c]Countries plotted are those listed in table 2.1.

Table 2.5: Effect of GDP on new enrollment, including fixed effects for public/total spending ratio categories. $newEnrollment_{i,t} = \beta_1 GDP_{i,t} + \delta_i ratio_{i,t} + \epsilon_{i,t}$.[a]

| Fixed effects regression | | | |
|---|---|---|---|
| Adjusted $R^2$ | 0.4002 | | |
| Variable[b] | Coefficient value | St. error | p-value |
| GDP ($BN) | 74.01 | 37.36 | 0.05 |
| Public/total spending $< 0.6$ (high relative tuition) | 45,881.63 | 10,759.5 | $3.86 \times 10^{-5}$ |

[a]Spending ratio is calculated as public educational spending/total educational spending for each country. Fixed effects are estimated for each ratio category. Categories are those countries with a ratio $> 0.9$ (low relative tuition), countries with a ratio between 0.6 and 0.9 (medium tuition), and countries with a ratio $< 0.6$ (high relative tuition). Only coefficients significantly different from zero are presented. Data include yearly GDP, enrollment, and spending figures for countries listed in table 2.1 from 1997 to 2008.

[b]For detailed variable descriptions see table 2.2.

(i.e. the slope of the regression line) to vary between countries or ratio categories, as shown in equation (2.1).

$$newEnrollment_{i,t} = \beta_0 + \beta_1 GDP_{i,t} + \gamma_i (countryDummy_i * GDP_{i,t}) + \epsilon_{i,t} \quad (2.1)$$

where $\beta_0$ is the intercept, $\beta_1$ is the coefficient of GDP, $\gamma_i$ is the estimated country

fixed effect for country $i$, and $\epsilon_{it}$ is a white noise error term. We find no significant interaction terms for the regression of enrollment on GDP. This suggests that GDP changes have a similar effect across countries.

We also look for evidence of regression discontinuity caused by recent reforms in European countries. In the past few decades, countries like Austria, Finland, and Hungary have eliminated or severely reduced tuition. Others, like Portugal and the United Kingdom, have introduced or increased tuition and fees. Still others have handed university administration over to non-government bodies for the first time, increasing institutional autonomy. Poland and Hungary, among others, introduced student loan and grant systems to help families pay for increasingly expensive tertiary education. For the current analysis, reforms are categorized according to a taxonomy suggested by ICHEFAP (2011), as seen in table 2.6. We test for differences in the effect of GDP on enrollment before and after reforms in several of these categories, including increased school autonomy, more government oversight of higher education, tuition bans, changes to loan programs, and changes to grant programs. We find no significant differences in the effect of GDP on enrollment based on these reform categories.

## 2.5 Conclusion

Our results indicate that GDP growth increases enrollment, with GDP being the main driver of enrollment changes. Although this result may simply demonstrate that larger countries have higher enrollment in tertiary education, the differences between countries provide interesting insights. Enrollment is higher for the same GDP and spending levels in countries where private spending contributes significantly to education. This may be because rising GDP levels in these countries fuel enrollment both directly and by improving families' ability to afford higher education. We find no significant differences in the effects of GDP based on recent European higher

Table 2.6: Reform categories: Higher education reform in Europe.

| **Reform category** | **Specific reform** | **Countries where reforms implemented** |
|---|---|---|
| Cost sharing | Introduction of tuition or significant fees | Austria, Finland, Hungary, Italy, Poland, United Kingdom |
| | Tuition or significant fees banned | Austria, Finland, Hungary, Ireland |
| | Introduction of a second pay-track for non-government supported students | Hungary |
| | Tuition increase | United Kingdom |
| | Increase in the amount of money received from governments, or how it is allocated | Austria, Ireland, Italy, Spain |
| Autonomy | Increase in university autonomy | Austria, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom |
| Financial aid | Loans introduced or expanded | Austria, Hungary, Netherlands, Poland, United Kingdom |
| | Grants introduced or expanded | Austria, Hungary, Poland |
| | Introduction of loan limits | United States |

education reforms, suggesting that these reforms have not had a significant impact on the effectiveness of subsidies to education, at least in terms of attendance and access. This is an important result for policymakers as they strive to improve access to higher education. Future work should seek to confirm the existence of enrollment differences based on public versus private spending differentials. A more complete dataset over a longer period of time would be required.

# CHAPTER III

# The Credits that Count: The effect of credit growth and financial aid on college tuition and fees

## 3.1 Introduction

Fifty-eight percent of US college students take out loans to help pay for tuition and fees. According to *The Wall Street Journal*, their average debt load upon graduation is $23,186 and rising (Chaker, 2009). This comes as no surprise; college tuition prices increased by a staggering 326% between 1987 and 2007 (5.8% annually). To provide some comparison, the rise in medical costs during the same period was just 186% (Bureau of Labor Statistics, 2009). Rising tuition rates make it more and more difficult for families to pay for a college education. Student loans contribute to high levels of both personal and public debt, which are exacerbated by high tuition prices and easy credit from government student loan programs, respectively. These trends may be unsustainable.

Rising tuition rates have become a popular topic in the media and a priority for policymakers. Federal and state governments try to improve access to higher education for Americans through expanding financial aid programs. These programs allow thousands of Americans to attend school, but prices continue to rise, prompting governments to offer more and more financial aid. As early as 1987, Secretary of Edu-

cation William Bennett, Jr. suggested that readily available student loans and grants may actually be fueling the increase in tuition prices (Bennett, 1987). The current economic environment has infused renewed relevance into investigating a revised version of the "Bennett Hypothesis": If public funding artificially inflates prices, they may eventually collapse, forcing schools to close, shattering perceptions of the worth of higher education, and destabilizing the education lending system through tighter lending standards and higher interest rates. In the meantime, prices may become too high for many Americans to afford without plunging into debt. Additionally, there is growing concern that US institutions may be losing ground in relation to international peers (see e.g. Harris and Beschloss (2011)), and that top tier elite institutions no longer carry their former prestige and value (see e.g. Kim et al. (2009)). Increasingly easy access to educational materials and skilled labor around the world is rapidly changing the US higher education market, creating uncertainty about the feasibility of high tuition prices in the future.

The main objective of this work is to conduct a macro-level analysis of the factors affecting supply and demand of higher education. By creating a single picture of supply and demand dynamics, we provide a context for previous research that studies the importance of individual shifters of supply and demand. We confirm that tuition, financial aid, and credit have a significant effect on US higher education supply and demand and build a better understanding of their directional impact within a holistic model. We use a two-stage least squares regression with a first order autoregressive error term to estimate supply and demand models for undergraduate education. Supply and demand are measured by enrollment quantity (undergraduate enrollment per high school graduate). We find that the benefit of a college education, household debt, and student loans shift demand, while cost of operations for schools, government aid to schools, and tuition and non-tuition revenue affect supply. Our model supports the theory that schools benefit from spending more on their students and increasing

tuition prices. However, our results indicate that credit constraints are a concern for students and their families, driving down demand and possibly limiting the ability of schools to continue on their trend of improving facilities, better services, and higher costs. Tuition and debt are highly correlated, suggesting that people use loan aid to cover greater schooling costs.

## 3.2 Literature review

A primary challenge in postsecondary education research is the availability of data. In the US, the federal government is the main data provider, and maintains sources of both aggregate and individual student data over time. Federal aggregate data are compiled in the Digest of Education Statistics and the Integrated Postsecondary Education Data System, while individual student data are provided through a series of longitudinal surveys (National Center for Education Statistics, 2008),(National Center for Education Statistics, 2009). Several private institutions such as *US News & World Report* and *The College Board* also keep data on rankings, tuition price, financial aid, and student bodies.

A second major challenge in this field is that the benefits of education are difficult to quantify. There are signs that the benefit of college has begun to decline in recent years, with more people with bachelor's degrees finding it difficult to secure employment in a field that takes advantage of their qualifications. For example, according to *The Chronicle of Higher Education*, 13% of parking lot attendants currently hold bachelor's degrees or higher (Vedder, 2010). However, recent return-on-investment studies (see e.g. Heckman et al. (2008)) claim that returns on a college education are steady or even increasing. These studies do not fully account for inherent differences between those that attend college and those that do not, or adjust for the possibility that college is unfordable for some. The benefit of college varies widely with the quality of school attended, and depends on each student's individual goals, financial

situation, and location. Dale and Krueger (1999) show that the best predictor of a college education's worth is tuition charged at a particular university, with a more expensive education consistently yielding better pay, even after adjusting for the differing quality of student bodies at various institutions. However, a more recent study by Dale and Krueger (2011a) shows that controlling for inherent student ability based on SAT scores almost eliminates the wage increase effect. Higher tuition price may also lead to increased public perception of prestige, especially at elite schools (John, 1992). Hsing and Chang (1996) show that college enrollment has become more and more sensitive to tuition and related costs, with enrollment falling as costs increase. All else being equal, higher tuition prices for the same education reduce the net value of a college education. There may also be significant peripheral benefits to education that allow educated people to participate more effectively in consumer markets. For example, Grinblatt et al. (2009) show that education and intelligence may improve performance in mutual fund markets. Education may also have a signaling value that goes beyond the improvement to earnings potential actually created by education itself. Hämäläinen and Uusitalo (2008), for example, use recent reforms in the Finnish Polytechnic education system to show that there is a signaling effect on earnings difference between Polytechnic and vocational school graduates. This type of signaling may allow more prestigious schools to charge more for the same services, since admission to a top tier school signals ability to employers. In this study, we use a combination of the factors identified in past literature as a measure of college education benefit, namely unemployment rate, the earnings difference between college and high school graduates, expenditures by schools, and disposable income.[1]

Past research on drivers of demand for higher education provides mixed results. Campbell and Siegel (1967) study historical demand levels from 1919 to 1964 and

[1]Disposable income is included here because it is highly correlated with the other proxies for benefit of college, meaning its inclusion as an individual variable leads to cross-correlation and biased estimators in the final model.

find that enrollment rises with income and falls with tuition prices. Hight (1975) studies the period from 1927 to 1972, uncovering an increasingly complicated demand structure. Hight finds that the divergence in demand for public versus private education is fueled by tuition gaps and differing effects of income levels. With the growth of federal, state, and private financial aid programs, demand structures are becoming even more complicated. Carneiro et al. (2010) use an instrumental variables approach to estimate the marginal effect of policy changes, including tuition prices, on demand. They find that the level of effectiveness in encouraging college enrollment varies greatly with the type of policy change made. It also differs from student to student, depending on their specific situation and especially their prior probability of attending college.

Several groups have specifically examined the effect of financial aid and student loans on demand and/or tuition price. Conclusions on the institutional effect of financial aid vary. Due to difficulties in data compilation and the large number of possible factors affecting supply and demand, most studies focus on a particular program, locality, or event. Long (2004a), for example, looks at the impact of the Georgia HOPE Scholarship program, and concludes that scholarships are causing schools to increase tuition and fees for all students. Dynarski (2004) shows that Georgia's subsidies also increase college attendance, as do similar programs in other states. In a larger sample of four-year schools, however, Long (2003) shows that there is no significant relationship between federal tax credits and tuition price. Further, Long (2006) suggests that aid is not a significant factor in raising tuition prices, and that the link of aid and tuition must be studied by examining net tuition prices actually paid by students instead of list prices. We make this adjustment in the current study. Singell and Stone (2007) evaluate the validity of the "Bennett Hypothesis" with regard to Pell grants and conclude that these grants do not raise public universities' in-state tuition. At private institutions, however, they find that tuition growth parallels Pell grant in-

creases. Curs et al. (2005) conclude that the institutional impact of Pell grants varies greatly with school selectivity. Rizzo and Ehrenberg (2004) suggest that schools do not increase tuition in response to state or federal financial aid to students. However, they do not examine aid directly to schools.

College supply dynamics are less well studied. A focus on cutting edge research has allowed America's universities to rise to the top internationally, but is also tremendously expensive and may be detracting from the teaching that students pay so much for (Schumpeter, 2010). Peña (2006) finds that rising tuition costs are highly correlated with increased wealth among colleges, at least at four-year private institutions.[2] According to Peña, the growing benefits of college and increase in wealth are the main drivers of tuition increases in recent years. Wealthier families are able to pay for more expensive schooling, allowing institutions to raise tuition prices without reducing their applicant pool. If schools compete (and spend) to be top tier, high-tuition institutions, Americans looking for a decent education at a reasonable price will have fewer and fewer options. Rankings are, at least in part, driven by spending levels (U.S. News and World Report, 2012). However, it is not clear that a better ranking necessarily means students receive a better education. Most schools are non-profit entities whose prestige increases with spending more, which is problematic for accessible education pricing.

It is difficult to distinguish cause from effect in this analysis of financial aid and tuition prices. However, something is clearly driving prices upwards, and student loan debt levels are causing severe financial problems for many graduates. In 2009, total student loan debt surpassed total credit card debt in the United States, with close to $850 billion in outstanding student loan debt (Pilon, 2010). Additionally, default rates are on the rise. Private for-profit institutions such as the University of Phoenix, which are quickly gaining market share, post an average 11.6% default rate among

[2]Wealth is measured by endowment values and the gap between tuition revenue and expenditures.

their students (McCluskey, 2010). We cannot say that financial aid causes tuition prices to rise, but it may be that current pricing mechanisms are somehow unbalanced, leading to higher and higher prices rather than to a more efficient, accessible education system. A report by the Goldwater Institute finds that the number of administrators per 100 students at leading US universities has increased by almost 40% since the early 1990s (Greene, 2010). Meanwhile, the number of researchers and teachers has grown by less than 20%. Increasing government subsidies help universities cover ever larger administrative costs, reducing schools' need to increase efficiency. Top tier schools, such as Yale and MIT, spend more on administration costs per student than many other schools spend in total. Yale, for example, spends about $60,000 per student on administration, while the University of North Texas, among the most frugal, spends under $10,000 per student in total (Greene, 2010). Schools spend vast amounts of money on professional-grade athletic facilities, sports programs, and clubs, and pay the most money to tenure-track professors who teach the fewest students (Hacker and Dreifus, 2010). These professors may be extracting high economic rents.

Instead of studying causal effects of specific reforms or policies, this chapter provides a comprehensive picture of the supply and demand market designed as a backdrop for understanding other findings. We are able to use aggregate data for individuals and schools across the United States to understand the market as a whole. We consider the whole college and university system, not e.g. private and public schools separately or competition among colleges. Our results provide support for many theories developed through study of natural experiments or more restrictive datasets, supporting the generalizability of these results. We see that consumers desire the most expensive education possible, but are hampered by credit constraints. Schools can thus use prices as a signal of quality, raising prices. In light of these higher prices, governments and private lenders offer loans to help student to achieve their educational goals, possibly allowing schools to raise prices even further. Our

model allows us to build a picture of overall supply and demand dynamics, revealing conditions that are exactly right for the existence and perpetuation of such a cycle of higher prices and higher debt.

## 3.3 Data collection

Due to the empirical nature of this study, all of our analysis rests on the compilation of a complete and accurate dataset. We compile a dataset of proxy variables for drivers of higher education supply and demand as well as a metric of quantity (enrollment). Candidate drivers cover spending, costs, financial aid, and college benefit. We focus on average behavior across four-year post-secondary institutions in the United States. Data include public, private, for-profit, and non-profit schools during the period 1976-2007. We select this period based on data availability and because it is recent enough to support an understanding of the current situation. In order to account for changes in the overall industry size, most data are reported per student, allowing for comparisons over the thirty-year period examined. Similarly, we measure enrollment quantity divided by high school graduates in that year. All analysis was also conducted without this normalization, modeling the effect of country-wide spending, cost, aid, and college benefit on total enrollment in number of students. This model yields similar results and consistent coefficient signs, alleviating concern that our results are based solely on the chosen normalization.

We define the quantity of both supply and demand as enrollment (in number of students) per high school graduate. The normalization factor is included here to account for the growth trend in the college-eligible population over the period under study. Using these data we construct two separate linear regression models, one for supply and one for demand. We identify candidate drivers of supply and demand from past literature and conversations with faculty, parents, students, and administrators. It is impossible to include every factor that may shift supply and demand in a given

year. However, the goal here is to include main drivers identified in past literature and identify internally consistent relationships between them. We focus especially on drivers related to financial aid and credit. We include those variables that we believe should have the largest impact as candidate drivers. We then use data availability to identify viable proxies. Candidate drivers of supply are the cost of operations for schools, financial aid given directly to schools, non-tuition revenue, and net tuition price. Candidate drivers of demand are the benefit of a college education, household financial situation, financial aid directly to students, and tuition price. For a list of candidate drivers see table 3.1. We separate aid given directly to schools from aid given through individual students in order to examine whether the mechanisms of aid-giving plays a role. In order to capture the price actually paid by students and received by universities, we use a net tuition estimate, defined as the list tuition price minus institutional aid (aid given directly to students by schools). Most students receive additional aid from other sources, thus further lowering the price they actually pay. For consistency between the supply and demand models, however, we include these adjustments in financial aid variables rather than in the tuition price itself. Additional financial aid sources provide aid to students, but do not affect institutional revenue.

The candidate drivers of supply capture schools' expenses as well as revenue from aid, tuition, and other sources. These are the main financial drivers of colleges' decisions, representing major cash flows. Non-financial drivers, such as rankings, are excluded here because they are relative metrics with unclear aggregate interpretations.[3]

Candidate demand drivers are designed to capture the factors individuals use when making decisions about whether and where to attend school, covering both the desire and the ability to attend. Estimates of the college education benefit capture

[3]It is possible that some sort of "ranking inflation" exists, meaning that higher rankings overall may indirectly affect other metrics. This is not explicitly treated in our model. Relative metrics could be included in future studies at the individual school level.

the actual value of the education received. Tuition, aid, and credit variables measure the price paid for an education and the ability to afford it. Of course, many personal factors, such as preferences regarding location, school size, non-financial career goals, and comfort with indebtedness, also influence enrollment decisions. These factors are again difficult to capture in an aggregate dataset, and are not explicitly included here.

We include a total of thirteen proxy variables for the underlying factors in the dataset, with seven variables aimed at explaining demand, five at explaining supply, and one endogenous variable (net tuition price) believed to shift both supply and demand. Other proxy variables were considered in the original dataset and are provided in appendix B.3. These other variables were discarded in preliminary analysis as inferior proxies for underlying variables. Table 3.1 gives a summary of the candidate proxy variables. The majority of data are from the Digest of Education Statistics maintained by the National Center for Education Statistics. A complete dataset for the period 1976–2007 is constructed by extrapolation based on the available data points. For the complete dataset and calculation details see appendix B.3.

Table 3.1: Dataset summary.

| Candidate driver | Proxy variables | Model | Variable description |
|---|---|---|---|
| Quantity | Enrollment | | Full-time equivalent enrollment at degree-granting institutions per high school graduate |
| Non-tuition revenue per student[a] | Endowment value per student | Supply | Average Harvard/Yale endowment market value, per student[b] |
| | Endowment distribution per student | Supply | Yale endowment spending, per student |
| | Donations per student | Supply | Donations, per student (voluntary support from persons and companies) |
| Cost of operations | Higher Education Price Index | Supply | HEPI inflation index[c] |
| Financial aid to schools per student | Aid to schools per student | Supply | Total government support directly to schools, per student (federal, state, and local) |
| Benefit of college | Earnings difference | Demand | Earnings difference (bachelor's degree or higher average - high school degree average) |
| | Expenditures by schools | Demand | Expenditures by schools, per student |
| | Unemployment | Demand | US unemployment rate |
| | Disposable income | Demand | US per capita disposable income |
| Grant aid to students per student | Grants per student | Demand | Average federal grant aid amount per full-time-equivalent student |
| Credit effects per student | Student loans per student | Demand | Average federal loan amount per full-time-equivalent student |
| | Household debt per student | Demand | US household debt, per student |
| Net tuition per student | Net tuition per student | Both | Average tuition and fees - institutional aid, per student |

[a]Non-tuition revenue per student, benefit of college, and credit effects are each summarized in a single proxy variable which represents the first principal component of the underlying proxies listed here. These principal component proxies appear in the final models.

[b]Harvard and Yale endowment values are chosen as proxies since their investing strategies serve as a model for other schools and because data are publicly available.

[c]The Higher Education Price Index (HEPI) is an inflation index which tracks price changes for the basket of good commonly purchased by institutions of higher education, making it more specific than e.g. Consumer Price Index. It is computed annually and distributed free of charge by the Commonfund Institute (Commonfund Institute, 2009). The Index is used by schools to assist in the budgeting process. Categories included in the HEPI index are salaries for faculty and other employees, fringe benefits, utilities, supplies and materials, and miscellaneous services. HEPI index is adjusted for inflation during the time period studied here.

## 3.4 Model

The dataset described above creates several problems for regression modeling. Since multiple proxy variables for the same underlying candidate supply/demand driver are considered, there is strong correlation among the variables. In order to

reduce this correlation, we use principal component analysis to identify a single proxy variable for some candidate drivers. Specifically, we develop single proxy variables for non-tuition revenue in the supply model as well as for the benefit of a college education and credit in the demand model (see table 3.1 for proxy variables and candidate driver categories). We do not use principal component analysis across all candidate drivers since this would make coefficient signs difficult to interpret in the final models. Similarly, we avoid using principal components for variables which are of particular interest. A summary of the first principal components for non-tuition revenue, benefit of college, and credit are provided in table 3.2.

Table 3.2: Summary of first principal components.[a]

| **Supply** | | **Demand** | |
|---|---|---|---|
| Non-tuition revenue per student | | Credit factors | |
| Proportion of variance | 0.916 | Proportion of variance | 0.633 |
| Standard deviation | 1.654 | Standard deviation | 1.126 |
| *Loadings:* | | *Loadings:* | |
| Endowment value per student | 0.706 | Household debt per student | 0.707 |
| Endowment distribution per student | 0.708 | Student loans per student | 0.707 |
| Donations per student | -0.018 | | |
| | | Benefit of college | |
| | | Proportion of variance | 0.53 |
| | | Standard deviation | 1.46 |
| | | *Loadings:* | |
| | | Earnings difference | -0.507 |
| | | Expenditures by schools | -0.361 |
| | | Unemployment | 0.459 |
| | | Disposable income | -0.633 |

[a]For detailed variable descriptions see table 3.1.

A second problem with the dataset is that variation is often driven by a strong time trend. To reduce concern that model fit is strong only because we are able to capture growth patterns, all variables are inflation adjusted. Additionally, we remove a linear trend as in equation (3.1) from all data:

$$x(t)_{detrended} = x(t)_{actual} - b - a(t - 1976) \tag{3.1}$$

where $x(t)$ is the variable in year $t$, with linear growth rate $a$ and intercept $b$. This adjustment eliminates correlation among residuals in the supply model and reduces correlation in the demand model (for details see appendix B.7). A linear trend is chosen because this provides a better fit than an exponential curve for most variables. A sample plot of the actual and detrended net tuition variable is provided in figure 3.1. We continue to see heteroskedasticity and cyclical residuals even after this adjustment (see appendix B.5). To account for this, we introduce a first order lagged autoregressive error term (see e.g. Chatfield (2009)).

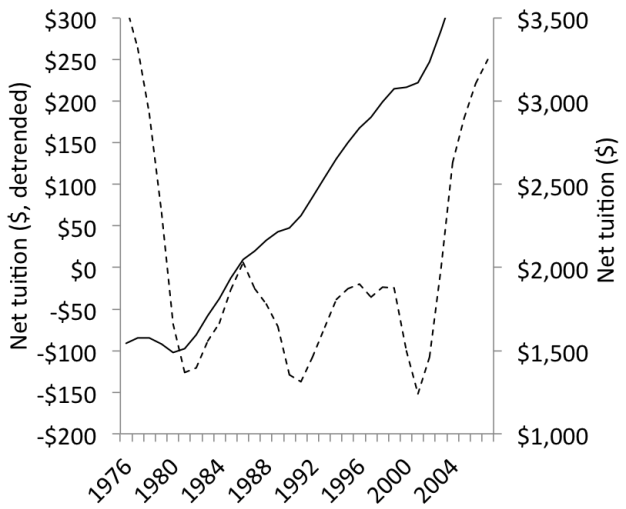



Figure 3.1: Example of variable detrending. Detrended net tuition per student (left axis, dotted) and actual net tuition per student (right axis, line). For detailed variable descriptions see table 3.1.

A third issue we must address is the endogeneity of the price variable, net tuition. Net tuition price shifts both demand and supply, violating ordinary least squares orthogonality assumptions. The two-stage least squares approach provides a method for adjusting a least squares model to account for the presence of endogenous variables (see e.g. Hayashi (2000)). Table 3.3 provides a list of candidate instrumental variables for the first stage estimation in each model.

Using the two-stage least squares approach, we develop the basic structure of the two models, which are provided in equations (3.2)–(3.4). These are not the

Table 3.3: Instrumental variables for the first stage regression of net tuition, equations (3.2)–(3.4).

| **Model** | **Instrumental variables used**[a,b] |
|---|---|
| Supply model | College benefit |
| | Credit effects per student |
| Demand model | HEPI |
| | Non-tuition revenue per student |
| | Aid to schools per student |

[a]Instrumental variables in the supply model are factors that shift net tuition but not supply. Instrumental variables in the demand model are factors that shift net tuition but not demand.

[b]For detailed variable descriptions see table 3.1.

final supply and demand models, but rather starting points for model identification. We include the first order autoregressive error term to account for heteroskedastic error terms caused by the time series nature of the input data (Chatfield, 2009). In this model, we use exogenous variables from the demand model as the instrumental variables in the supply regression (see e.g. Angrist and Krueger (2010)) and vice versa, yielding the same first stage regression for supply and demand. The first stage equation is presented in equation (3.4). All model equations are developed at a particular time (particular year) $t$ for simplicity. Square brackets and bold font indicate vector notation.

Supply model:

$$
\begin{aligned}
enrollment_t = a_0 & \\
& + \mathbf{a}_{ex}[costOfOperations,\ nonTuitionRevenue,\ aidToSchools]_t \\
& + \mathbf{a}_{en}[netTuition]_t + Y_t \\
Y_t = b_0 Y_{t-1} + e_{S,t} &
\end{aligned}
\tag{3.2}
$$

Demand model:

$$
\begin{aligned}
enrollment_t = c_0 & \\
& + \mathbf{c}_{ex}[benefitOfCollege,\ grantAidToStudents,\ creditEffects]_{\mathrm{t}} \\
& + \mathbf{c}_{en}[netTuition]_t + W_t \\
W_t = d_0 W_{t-1} + e_{D_t} &
\end{aligned}
\tag{3.3}
$$

First stage:

$$
\begin{aligned}
netTuition_t = f_0 & \\
& + \mathbf{f}_S[costOfOperations,\ nonTuitionRevenue,\ aidToSchools]_t \\
& + \mathbf{f}_D[benefitOfCollege,\ grantAidToStudents,\ creditEffects]_t + e_{1_t}
\end{aligned}
\tag{3.4}
$$

We estimate the two-stage least squares models in equations (3.2)–(3.4) in a single step using R's built-in two-stage least squares function[4]. We transform the original input variables in equations (3.2)–(3.4) to remove autocorrelation of error terms by first estimating $\mathrm{b}_0$ and $\mathrm{c}_0$ in equations (3.2) and (3.3). Upon model estimation, all results are transformed back into the original data space for reporting. All statistics and standard errors reported in the following sections assume that $\mathrm{b}_0$ and $\mathrm{c}_0$ are estimated without error. For more about the estimation of models with autocorrelated error terms, see e.g. Pandit and Wu (1990).

## 3.5 Results

Since we reduce the number of candidate variables and eliminate sources of collinearity prior to model fitting, almost all variables in the initial models are significant drivers of enrollment and are therefore present in the final models. There are two

[4]Fox, John. *Package 'sem'*. CRAN. 2010.

notable exceptions in the demand model. Firstly, grant aid to students (per student) falls out due to strong correlation with student loans (per student), which is included in the credit effects principal component. Secondly, tuition is excluded from the final model here. We test a model where tuition in the demand model is adjusted for grant aid, i.e. net tuition = list tuition - institutional aid - grant aid. Signs in this adjusted model are consistent with the model in table 3.4, but correlation between grants and student loan aid makes it difficult to interpret credit effects. Tuition price has a positive sign when included in the model.[5]

Table 3.4: Supply model (enrollment per high school graduate, equation (3.2)).

| Two-stage least squares regression | | | |
|---|---|---|---|
| $b_0$ (residual autocorrelation) | 0.838 | | |
| Correlation (model estimates vs. actual)[a] | 0.73 | | |
| Exclusion restrictions | Test statistic | p-value | |
| Sargan | 1.9837 | 0.1590 | |
| Basmann | 1.7183 | 0.1899 | |
| Variable[b] | Coefficient value | St. error | p-value |
| (Intercept) | -0.0069 | 0.0140 | |
| Cost of operations (HEPI) | 0.0434 | 0.0101 | 0.0002 |
| Non-tuition revenue per student | -0.2423 | 0.0546 | 0.0002 |
| Financial aid to schools per student | 0.0002 | 0.0001 | 0.0320 |
| Net tuition per student | -0.0015 | 0.0006 | 0.0152 |

[a]Model fit is captured by the correlation between the model estimates and actual values of supply and demand.

[b]For detailed variable descriptions see table 3.1.

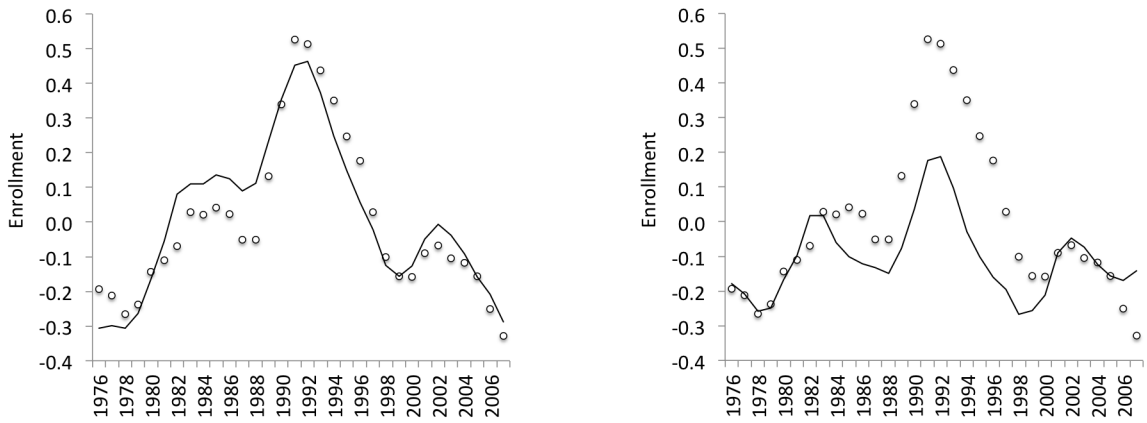
Table 3.5: Demand model (enrollment per high school graduate, equation (3.3)).

| Ordinary least squares regression | | | |
|---|---|---|---|
| $d_0$ (residual autocorrelation) | 0.653 | | |
| Correlation (model estimates vs. actual)[a] | 0.73 | | |
| Variable[b] | Coefficient value | St. error | p-value |
| (Intercept) | -0.0027 | 0.0119 | |
| Benefit of college | 0.0319 | 0.0148 | 0.0399 |
| Credit effects per student | -0.0790 | 0.0241 | 0.0028 |

[a]Model fit is captured by the correlation between the model estimates and actual values of supply and demand

[b]For detailed variable descriptions see table 3.1.

[5]Note that since tuition falls out of demand model, we use ordinary least squares with a first-order autocorrelation term to estimate the demand model.




(a) Supply model.

(b) Demand model.

Figure 3.2: Model enrollment (line) and actual enrollment (circles), detrended.[a]

[a]Models are presented in tables 3.4 and 3.5. Models are based on equations (3.2)-(3.3).

Model robustness is difficult to test explicitly since small sample size precludes out-of-sample testing. When using time series data as individual observations, we must account for endogenous differences between different time periods. However, it is not possible to include, or even observe, all factors that may change over time (see e.g. Deming and Dynarski (2009)). Since we are using time points as individual observations, traditional fixed effects techniques (see discussion e.g. in Park (2009)) cannot be applied here. Alternatively, the autocorrelation term accounts for changing effects, creating a dynamic model which adjusts for changes in unobserved variables over time. This is similar to a dynamic approach for panel data that uses lagged observations to account for time trends (see e.g. Dhring and Mordonu (2007)). Additionally, we compare model estimates using different types of standard errors, noting that standard and robust errors yield similar results (see e.g. Knutsen (2012)).

Since we are primarily interested in determining accurate coefficient signs, we focus model testing around these signs. We compare model signs with those from a pre-estimation test, in which each proxy variable is used to individually predict enrollment (for more detail regarding the pre-estimation test see appendix B.4). Signs are generally consistent between the final model and the pre-estimation test, except

as noted in appendix B.4. We further test model robustness by examining coefficient signs across two sub-periods, from 1976 to 1990 and from 1991 to 2007. We find that coefficients are generally stable between these two periods. Detailed results of this analysis are provided in appendix B.6. Finally, we test the validity and strength of the instrumental variables used in the first stage regression of the supply model. Sargan's and Basmann's chi-squared tests reveal that the instrumental variables used for tuition in the supply model are valid, as shown in tables 3.4 and 3.5 (see e.g. Hipp et al. (2011) for more on these tests). The first stage regression yields an F-statistic of only 3.97 and a p-value of 0.01. This is a weakness in the specification, but limited data availability and consistency prevents us from adding additional instruments. However, model fit appears good given the small sample size, with an adjusted $R^2$ of 0.33. We also find consistent coefficient signs when using models that use ordinary differences instead of log differences, and when using aggregate rather than normalized per student data. This demonstrates that coefficient signs are not driven by the normalization factors.

The final models shown in tables 3.4 and 3.5 indicate that price and credit factors play a significant role in determining supply and demand for higher education. On the demand side, preliminary models which include tuition suggest that demand rises with tuition price, consistent with findings such as Dale and Krueger (1999) and John (1992). Tuition seems to provide some indication of quality or benefit, leading consumers to respond this way to increasing prices.[6] On the other hand, the principal component variable of credit effects (per student), composed of the underlying proxy variables household debt (per student) and student loans (per student), has a negative effect on demand. Inside the principal component, both household debt (per student)

[6]Note that net tuition price used in these models, though adjusted for institutional aid, is not adjusted for grants, meaning this variable does not necessarily represent the price actually paid by students. Grant aid is highly correlated with net tuition (correlation is 0.76), and therefore falls out of the final model. Creation of a grant-adjusted net tuition variable (i.e. Tuition - institutional aid - grant aid) produces a model similar to that provided in table 3.5.

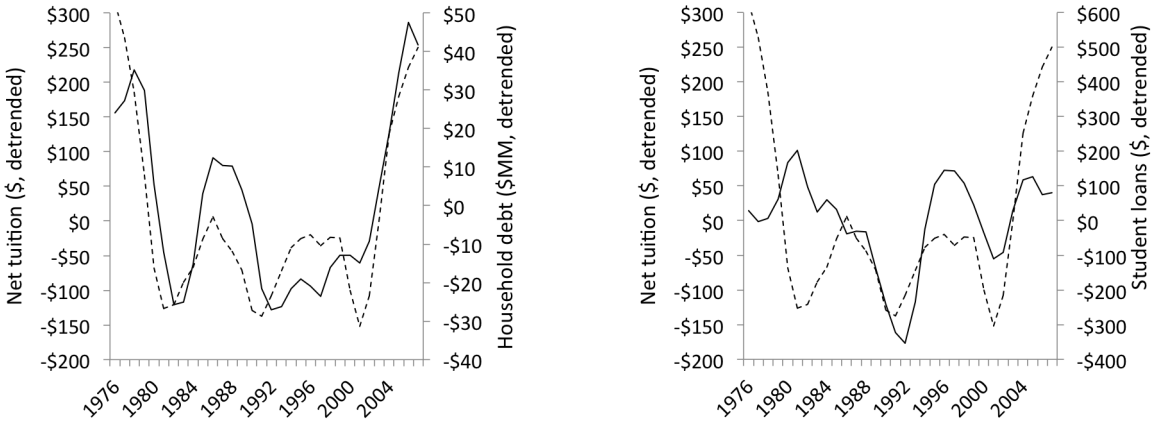
and student loans (per student) have a positive sign, implying that increased student loans and increased debt reduce enrollment demand. A possible explanation for this, which is supported by current high debt and default rates, is that families are not willing to take on additional debt to pay for an education. Students must find a balance between their desire to attend expensive schooling and their aversion to debt.

We find further support for this hypothesis by splitting the tuition variable into two components. The first component, expense change, is the portion of net tuition that is perfectly correlated with the cost of operations, i.e. the HEPI index. Expense change measures the rise in tuition caused by an increase in the cost for the same basket of goods purchase by schools. The second component, offerings change, represents the portion of net tuition price change that is not correlated with the HEPI index. This component represents changes in student offerings, such as better facilities and more academic and extracurricular resources. Inserting these two variables into the demand model in table 3.5, we see that offerings changes are significant and lead to demand growth, producing an effect counter to the traditional economic effect of decreasing demand as prices rise. Expense changes do not appear to be significant, suggesting price-inelastic demand in the traditional sense; demand for education does not fall as price increases when other factors remain constant. This degree of price-inelasticity is likely made possible by government loans and other subsidies. As explained above, credit constraints may allow rising tuition to reduce demand in an indirect way. This effect would likely be amplified if government loans to credit-constrained individuals were reduced. Details of the separated demand models are provided in appendix B.2.[7] Credit effects are the main drivers behind changes in demand, appearing as highly significant in all models tested.

We also see that credit variables and net tuition price are highly correlated. Figure 3.3 provides a visual representation of the relationship between these variables

[7]Note that we exclude expenditures from the principal component estimate of college benefit for these models, as expenditures is now included as a separate variable.

over time. Even after removing the time trend, net tuition price (per student) and household debt (per student) exhibit a correlation of 0.915, implying that families are responding to rising prices by borrowing. This relationship, though intuitive, has not been pointed out in past literature to our knowledge. We conclude that people cannot afford increasingly expensive schools and are willing to take on only limited debt, reducing the demand in times when credit is readily available, debt levels are already high, and net tuition is also high.




(a) Detrended net tuition (left axis, dotted) and detrended household debt (right axis, line), per student.

(b) Detrended net tuition (left axis, dotted) and detrended student loans (right axis, line), per student.

Figure 3.3: Detrended net tuition and credit variables. Detrended net tuition is the same in both plots above. For detailed variable descriptions see table 3.1.

The final significant variable in the demand model in table 3.5 is benefit of a college education. Due to the difficulty of measuring this benefit, we can say only that metrics of the benefits of college are important in predicting demand. Proxies used here include earnings difference between high school and bachelor's graduates, spending by schools as a metric of services and facilities offered, unemployment rate, and per capita disposable income. These variables are selected because they have been identified as drivers in past research and because they provide basic metrics of the health of the overall economy (Fortin, 2006).

In the supply model shown in table 3.4, cost of operations, non-tuition revenue

(per student), aid to schools (per student), and net tuition price (per student) are significant. Cost of operations is measured via Commonfund's Higher Education Price Index, which is an inflation index for the basket of goods that institutions of higher education generally purchase. An increase in this index implies that the cost for the same offering goes up, rather than that schools increase their offerings to students by adding new facilities, programs or staff. Since supply rises with cost of operations, we conclude that schools enroll more students partly in order to cover increasing costs. A similar trend is suggested by the coefficient of non-tuition revenue (per student). As shown in table 3.1, this driver includes endowment value (per student), endowment distribution (the portion of the endowment actually spent, per student), and voluntary donations (per student).[8] Enrollment falls with non-tuition revenue (per student), implying that schools can afford to enroll fewer students when they receive revenue from non-tuition sources. This makes sense in light of the non-profit nature of most colleges. An exception to this is government aid, which may come with stipulations about services offered or be associated with a particular group of students. However, aid directly to schools alone is not a significant driver of enrollment in the pre-estimation test (see appendix B.4). Increases in overall spending certainly increase enrollment, but our findings suggest that funding from some particular sources may have the opposite effect.

The last significant variable in the supply model in table 3.4 is net tuition price, which is adjusted for institutional aid to reflect the payment schools actually receive from students. We cannot treat net tuition price as a true predictor in the supply model because consumer demand is relatively price inelastic. Since many students are awarded grant aid, they do not pay list tuition price, meaning that schools are fairly free to set tuition prices as they see fit. However, the sensitivity to debt levels seen in

[8]Note that the endowment variables drive the non-tuition revenue principal component. Endowment data include only Harvard and Yale because of data availability and because these schools serve as models for other endowment funds.

the demand model suggests that some price sensitivity is present. Net tuition price is highly correlated with expenditures (correlation is 0.88), which we omit from the supply model for this reason and because expenditures are determined by revenue for many schools due to their non-profit status (see figure 3.4). This is similar to Peña (2006), who finds that institution-level tuition price is highly correlated with school's wealth.[9] The sign of the net tuition variable in our model suggests that higher net tuition price decreases supply, which is not intuitive. Taking into account the correlation with wealth (as in Peña (2006)) and expenditures, we can interpret the coefficient on tuition price at least partially as the effect of increased spending on new services and facilities for students. Higher quality, more expensive schools can afford to admit fewer students at higher prices, allowing schools to shrink supply. Students pay not only for an education, but for high-end athletic facilities and hundreds of student organizations. High school graduates are starting to expect these services from institutions of higher education (see e.g. Hacker and Dreifus (2010)). Our model supports the theory that schools succeed by increasing offerings and becoming more high-end and more expensive. These trends might pose a problem to students and may have contributed to the rapid price increases of the past thirty years.

## 3.6 Conclusion

This work models the dynamics of supply and demand in college education to provide a macro-level picture of the market. Our findings show that credit, financial aid, and pricing have a large effect on enrollment in higher education. We see that there exists a strong relationship between price, spending and wealth of schools, tuition levels, student loans, and indebtedness. We show how these relationships may lead to an upward spiral of tuition prices. Consumers desire more prestigious, more expensive education, allowing tuition price to become a signal for quality. Rankings

[9] Wealth is measured by endowment values and the gap between tuition revenue and expenditures.

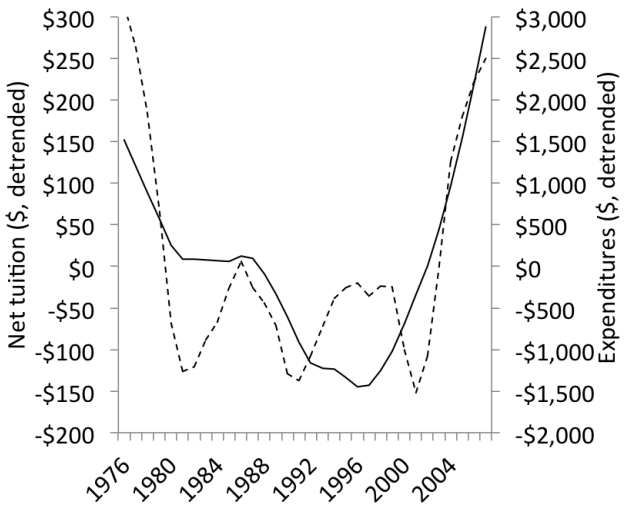



Figure 3.4: Detrended net tuition per student (left axis, dotted) and detrended expenditures per student (right axis, line). Detrended net tuition is the same as in figure 3.3. For detailed variable descriptions see table 3.1.

tied to tuition prices, facilities and services, and spending per student may amplify this effect. Based on the strong correlation between household debt levels and tuition price, we conclude that families turn to loans when faced with increasing prices. This leads to the need for a larger lending industry and, in turn, allows schools to charge more. On the other hand, credit constraints are a definite factor in demand side enrollment decisions, forcing consumers to battle with conflicting desires of attending a more expensive school and containing debt levels The benefit of college, including spending by schools, student loan amounts, and tuition price drive demand, while school's operational costs, government aid to schools, tuition price, and non-tuition revenue shift supply. Several factors, such as increased resources and facilities for students, public perception of prestige, and/or ranking criteria linked to tuition prices, drive schools to become more expensive. Meanwhile, current financial aid structures fail to curb the resulting trend towards higher prices.

The models developed here succeed in identifying relevant drivers and their directional relationships. However, the causal relationships between highly correlated variables should be investigated further. Specifically, future research will help estab-

lish causal links between credit factors, aid, and tuition in the demand model as well as expenditures and tuition in the supply model. Changes to financial aid programs and incentive structures may allow us to decrease the risk of financial instability, ease financial strain for American families, increase the impact of government financial aid, and ensure that the US education system remains affordable, accessible, and internationally competitive.

# CHAPTER IV

# A major choice: An examination of educational choices, student characteristics, and ability-adjusted income

## 4.1 Introduction

The purpose of this paper is to investigate the relationship between post-college income and educational choices. We study post-college income across a representative sample of college applicants, and develop a model to study drivers of the decision to attend college and the choice between institutions. This analysis informs students, parents, and policymakers about the effects of educational choices on future earnings and the role these earnings play in the decision process. We introduce a new technique for accounting for the bias caused by endogenous ability differences in students. We find that post-college income is driven by student ability and major choice, not by school choice decisions. However, factors such as school quality and selectivity are the primary drivers of students' attendance and institutional choice decisions.

We study post-college income and develop a model of college choice among recent high school graduates. We use uniquely detailed data on college applications, acceptance, and attendance from the 1997 cohort of the National Longitudinal Survey of Youths to examine the relationshp between schooling decisions and income levels

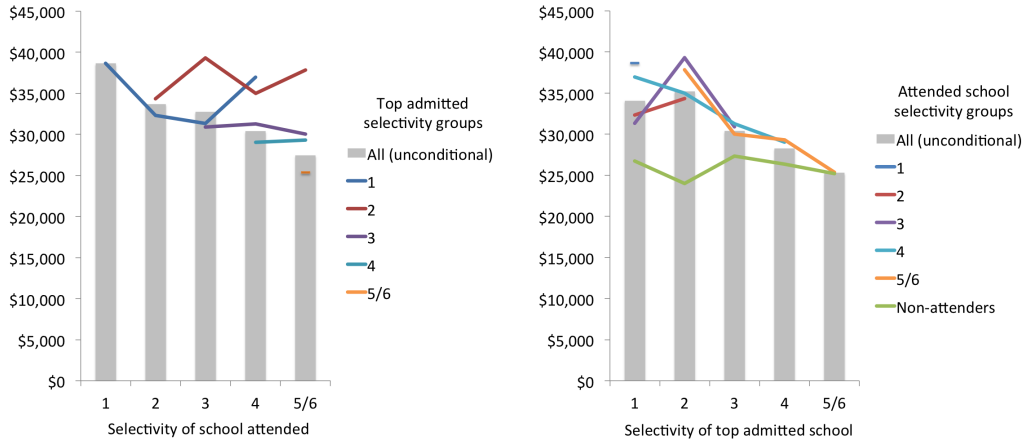
(Bureau of Labor Statistics, 2013). Detailed individual-level data allow us to use information on the best school to which a student was admitted to adjust for intrinsic ability differences and identify drivers of post-college income after this adjustment. Our school quality metric is based on the selectivity of each school, meaning the percentage of applicants that are accepted for study. The selectivity metric uses data from Barron's selectivity index (Barron's, 2009). We use post-college income data reported in the National Longitudinal Survey to study income differences. Additionally, this dataset provides information on major, student and family characteristics, and financial aid offers which allow us to accurately capture the decision facing each individual student.

Our model shows that endogenous ability is a much better predictor of future income than college attendance or school choice after removing sample bias. We cannot show that choice between schools has a significant effect on earnings after adjusting for the top school admitted to. Attending college at all is associated with a significant increase in earnings, but the benefit of college attendance is not significantly different across students of different abilities. Future income is determined primarily by student quality, the decision to attend college at all, and major choice. We can see these results in raw post-college income data, which is presented in figure 4.1. Figure 4.1a portrays average income by the selectivity level of the school attended. We see a strong downward trend in the whole sample (bar graph), with income declining as selectivity of the school attended decreases. However, income conditional on the top school to which an individual was admitted (lines) do not follow this trend. Note that students often do not attend the best school to which they were admitted for e.g. personal preference, affordability, or family reasons, meaning the selectivity of the school attended may be different from the selectivity of the best school admitted to. On the other hand, figure 4.1b shows average income over the first four years with respect to the most selective school to which an individual was admitted. Income

across the whole sample (bar graph) declines as the top school admitted to drops. We continue to see this trend after conditioning on the selectivity level of the school an individual chose to attend (lines), implying that the top school to which an individual was admitted provides information regarding future income above and beyond the quality of the school they attended. The exception to this trend is the group of non-attenders; among individuals that do not attend school at all, we find no significant differences in income based on the selectivity of the top school admitted to. The models presented in section 4.4 provide further evidence for this, examining the effects of admission and attendance across our whole sample. The downward salary trend in the unconditional bar graph of figure 4.1a appears stronger than the trend in 4.1b. This small difference is likely an artifact of the sample used here, but is not surprising given the fact that the top school attended carries more information that the top school admitted to. For example, all students who attend a type 1 school must have been admitted to at least a type 1 school, meaning we capture a great deal of the admissions information from the school attended.

The one aspect of the school choice decision that seems to have a significant effect on future income levels is major choice. Figure 4.2 shows average income by selectivity of the top school admitted to (bar graph) annotated with averages across the same groups for those majoring in engineering-related fields (blue line) and humanities-based fields (red line). We see that engineering majors can expect higher salaries across all groups, while humanities majors have lower expectations. This is true even after adjusting for student ability, suggesting that wage premiums for engineering majors are not caused only by self-selection of the best students into these programs. We continue to see this difference between majors after adjusting for mathematical ability (math SAT score), further suggesting that major choice affects salary beyond underlying student characteristics.

We construct a two-stage model of college choice, using a binary logit model for




(a) Average income over the first four years after expected college graduation by selectivity of school attended. Lines indicate income by selectivity of school admitted after conditioning on selectivity of school attended. Type 1 indicates most selective schools.

(b) Average income over the first four years after expected college graduation by selectivity of the best school admitted to. Lines indicate income by selectivity of school admitted to after conditioning on selectivity of school attended. Type 1 indicates most selective schools.

Figure 4.1: Average income over the first four years after expected college graduation by selectivity of school attended and top school admitted to.[a,b,c]

[a]Expected college graduation is considered to be four years after the beginning of a college education for those attending college, and four years after the start of the academic year for which students applied to college for those not attending.

[b]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted.

[c]Selected sample is presented in table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and are not missing critical data. Students who do not attend any school are omitted from part (a). The sample in these plots excludes seven individuals who do not supply sufficient income information in the immediate post-college years.

the attendance decision and an alternatives-based conditional logit model for the choice between schools. We find that student ability, school quality of the most desirable school admitted to, and gender predict college attendance, while choice between schools is driven by financial concerns and school quality. While predictor variables are highly significant, model fits are quite poor, especially in the attendance decision model. School choice is likely affected by a large number of factors not measured in our dataset, including the subjective preferences of individual students.

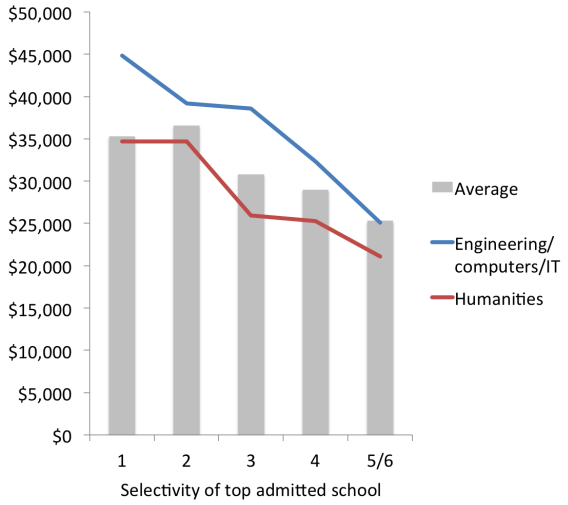



Figure 4.2: Average income over the first four years after expected college graduation by selectivity of school attended (bar graph). Lines indicate average incomes for sub-groups selecting engineering (blue line) and humanities (red line) majors.[a]

[a]Major choice is based on the initial program decision made upon entering college. It does not necessarily reflect the final major in which a degree was attained, since some students change majors or do not complete their studies. Engineering majors include engineering and computer-related fields. Humanities majors include liberal arts, fine arts and architecture, political sciences, classical fields, and interdisciplinary studies.

The choice models developed in this chapter show that school quality and prestige are important factors in student's decisions about college attendance, suggesting that students and parents either believe that strong income differences exist based on selectivity of the school attended, or that they find these qualities inherently valuable. We show that major choice has a much greater effect on post-college income than selectivity of the school attended.

Understanding the college attendance decision is important and currently relevant as college costs rise and the benefits of higher education become less obvious. Changes in the higher education and employment landscapes along with a new book by former Secretary of Education William Bennett have sparked a lively debate on the value and benefits of higher education in academic circles and the popular media (see e.g. Berger (2013), Selingo (2013), Carnevale et al. (2009)) (Bennett and Wilezol, 2013). Average list tuition and fees at four-year public colleges have been rising at an average annual

rate of 5.2% above inflation throughout the last decade (The College Board, 2012b). While private school tuition is growing less quickly, private institutions historically charge the highest prices. Students finance increasingly expensive educations with private and federal loans; the student loan business disbursed a total of $113.4 billion in such loans in the 2011-12 academic year (The College Board, 2012c). Private and government groups voice concerns about the quality and risk of student loan debt, and consumers are more and more reluctant to take on loans in a society that is deleveraging across the board (see e.g. Klein (2013)). With a general slow-down in the economy, salaries of bachelors degree recipients are stagnant, but degree-holders still earn considerably higher salaries than high-school graduates without a higher degree (The College Board, 2012a). Additionally, unemployment rates are much lower for those with a college or higher degree than those without, though unemployment has risen across the board. Wage increases from college attendance are especially large for minorities and women, who have historically had lower rates of college attendance (Becker and Murphy, 2007).

Returns on a degree vary widely based on the school attended and major chosen, with aid-adjusted returns ranging from $-15\%$ to $+15\%$ across schools (PayScale.com, 2013). The benefits of a college education also depend on successful completion of a degree. Out of full-time college students tracked by the US government, only around 30% are recorded as graduating from the university they originally chose to attend, with many failing to complete any degree at all (The Chronicle of Higher Education, 2013). A college degree no longer guarantees a secure, well-paying job as it did a generation ago. A rise in the variance of earnings among college graduates makes college a much more risky investment than it used to be (Brown et al., 2012). Growth in the for-profit education sector, the rise of Massive Open Online Courses (MOOCs) and other alternative higher education models, and the general re-balancing of the economy threaten the status quo in the higher education market, and may change

the way students make decisions about college attendance in the future.

Some positive changes are starting to be implemented in the college decision environment. For example, there is a push to inform consumers and provide more information to enable improved decision-making and risk assessment. Government and private groups are pushing for increased emphasis on college accountability, oversight, and reporting of outcomes. One example of such a campaign is the Obama administration's introduction of the College Scorecard, which provides accepted students with information on costs, graduation rates, and default rates relative to other schools around the country (Department of Education: College Affordability and Transparency Center, 2013). User-friendly interfaces on government and private databases also provide information that may help in the college decision process (see e.g. National Center for Education Statistics (2009), Department of Education (2013), and PayScale.com (2013)). Several states, including Arkansas, Colorado, Tennessee, Texas, and Virginia, now work with College Measures, a group that compiles data on employment outcomes of graduates from different institutions. Students and parents can compare post-graduation earnings by school and major (College Measures, 2013).

The work in this chapter contributes to the debate on the returns to education and the current reevaluation of the higher education market by examining income differences across students who make different educational choices. Individual-level choice data allow us to understand what students in a particular situation value and are willing to pay for, and how these choices affect post-college income. We ask whether higher returns at some universities are due to a better education being offered or simply having a higher ability student body, and investigate drivers of post-college income after adjusting for ability differences.

It is very difficult to remove selection bias from any study of college choice and returns. Those students who attend and complete a degree at great schools may have been more successful than their peers regardless of educational choices. The

debiasing method presented in this chapter allows us to correct for selection bias before evaluating the effect of education and other factors on salary outcomes. Our analysis reveals that a large portion of the benefit attributed to college education in general and "prestigious" college education in particular stems from intrinsic ability of the student body. We find no significant effect of choice between schools on earnings after adjusting for student ability, though our analysis does support the existence of income gains based on whether an institution of higher education is attended at all and based on which major is chosen. As more data points are collected on the cohort under study here, the National Longitudinal Survey cohort of 1997, we hope that our model will continue to be improved and expanded to answer more specific questions on college choice and returns to different educational decisions. We introduce methodology that expands our study of post-college income data to include projected earnings over the lifetime.

This chapter is divided into eight sections. Section 4.2 provides some context for this work. Section 4.3 familiarizes the reader with the input data. Sections 4.4 and 4.5 explain the new debiasing approach introduced in this chapter and the analysis of post-college income. Section 4.6 presents the two-stage model of college choice. Sections 4.7 and 4.8 provide concluding remarks and related future work.

## 4.2 Background and literature review

A rich literature studies the structure, mechanisms, and evolution of the higher education market. Researchers create complex structural models of the higher education market, developing theoretical or empirical models of the entire application/acceptance/attendance game. Fu (2012), for example, examines the effect of noisy signals on student and school quality on the equilibrium in the higher education market, while e.g. Epple et al. (2006) and Kawagoe et al. (2013) focus on the effects of price discrimination, financial aid, and affirmative action. DesJardins

et al. (2006) revisit the traditional three-stage model of college choice developed in e.g. Hossler et al. (1989) through a random utility model that studies interactions between the application, admission, financial aid, and enrollment phases of the college choice process. In the current work, we focus on the last step of the college admissions game, namely individual students' choice between schools. We assume that they have already been admitted to and received aid offers from various schools, and that school's decisions on acceptance and financial aids are exogenous to the demand side (student) college choice decision.

Narrowing in on the attendance decision, the literature has historically focused on access to higher education, methods for increasing college attendance, and differences in college attendance rates across groups (Perna, 2006). College enrollment in the United States has increased steadily over the past twenty years, but attendance rates continue to be lower for students from less wealthy families (Mortenson, 2001). Bachelor's degree recipients earned on average 66% more in 2010 than those with only a high school degree, motivating studies focused on increased college access and better financial aid policies (The College Board, 2012a). As variance in earnings for those attending different institutions grows, researchers have begun to focus on the choice between schools in addition to the decision of whether or not to attend school at all. For example, Avery and Hoxby (2003) examine the effect of financial aid on choice between institutions, finding that students are highly sensitive to grant and loan packages. Similarly, Hurwitz (2012) takes advantage of exogenous differences between schools' financial aid policies to study effects of institutional grant aid. Drewes and Michael (2006) find that institutional characteristics such as school size, services offered, class size, research activity, and rankings have an effect on a school's attractiveness to potential enrollees.

Many methods are available for measuring the returns to schooling. Traditionally, papers on educational returns follow either the human capital or signaling schools of

thought. In the human capital view, education benefits its participants by improving their skill set and making them more valuable to employers.[1] Under the signaling model, school admissions and attendance serves primarily as a signal of intrinsic student ability, making it easier for employers to identify high-value candidates. Because it is difficult to separate these effects, researchers often focus on controlled or natural experiments to distinguish between them. Hämäläinen and Uusitalo (2008), for example, take advantage of a policy change in Finland to investigate the effect of attending a more prestigious "polytechnic" instead of a vocational college. They find evidence for the signaling model of education, suggesting that educational benefit on earnings is driven by the signal of ability instead of superior education taking place at the more prestigious schools. Manoli (2008) uses a change in compulsory schooling policy in the United Kingdom to compare signaling and human capital models. He finds that attainment of a diploma has a greater effect in terms of future earnings than the number of years of schooling received, again showing support for the signaling model. When natural experiments are not available, an alternative approach is to develop a sophisticated method for debiasing, adjusting for intrinsic student ability differences between groups before measuring educational returns. The current study contributes to this literature by introducing an improved debiasing method based on admissions decisions made by universities.

Returns to schooling may depend on a variety of factors. Papers such as Brewer et al. (1999), Dale and Krueger (2011b), and Cunha and Miller (2012) examine the effect of institutional characteristics on earnings outcomes. While Brewer et al. (1999) find that attending a highly selective school has a positive impact on future earnings, improved debiasing methods used by Dale and Krueger (2011b) reveal that effects are smaller than previously thought. A similar result is found by Cunha and Miller (2012), who show that large differences in earnings, graduation rate, and persistence across

[1]For more on human capital models see Becker (1994) and related works.

schools attended are greatly reduced after adjusting for student characteristics. The current work's results, using our new debiasing approach, support those of Dale and Krueger (2011b) and Cunha and Miller (2012). A study by Hoekstra (2009) suggests that earnings gains from attending a state's flagship university over other schooling options may yield as much as a 20% increase in earnings. However, this work does not include data on alternative schooling choices made by those who do not attend the flagship university. Our data include detailes about admissions success at several schools, capturing much more information on the ability and schooling decisions of each student. For example, we show that attending any school at all has a significant effect on income, so earnings differences in Hoekstra (2009)'s work may be driven by differences in the percentage of students attending college at all. Aside from school choice, major choice is also a significant source of income disparity. Carnevale et al. (2013) show that income variation across majors in often larger than the variation across institutions attended. In this paper, we show that major choice affects income even after adjusting for ability differences. This is consistent with similar results in e.g. Arcidiacono (2004), who studies the effect of student ability on major sorting and finds that major choices are driven by personal preferences instead of the promise of monetary benefit.

The choice model presented in this study follows most directly from the work of Long (2004b), who studies the changing factors influencing college attendance and choice decisions over time. Long uses an earlier cohort of the National Longitudinal Survey of Youth as well as the High School and Beyond dataset and the National Education Longitudinal Study 1988. Long presents a two-stage logistic choice model, modeling the attendance decision via a binary logit model and college choice via an alternative-based conditional logit model. She finds that college preferences are affected by price, distance to the college, and similarity to ability levels of peers at that college. Long finds that the importance of price has declined over time in the

attendance decision, but that price continues to be a significant factor when deciding between schools. We compare our findings to Long's work throughout this chapter, and find that our results are generally consistent with her conclusions. Although our dataset is too small to confirm all of Long's results, we take advantage of richer information on each individual and potential school to test the importance of a larger number of factors. We expand upon past research and Long's model by combining a college choice model with a focus the effect of schooling decisions on income, by introducing a new method of adjusting for ability bias, and by focusing on drivers of income differences after making this adjustment.

## 4.3 Data

### 4.3.1 Data sources

Individual student data used in this project come from the 1997 cohort of the National Longitudinal Survey of Youth (NLSY 97) (Bureau of Labor Statistics, 2013). NLSY surveys are designed to follow a representative groups of students throughout their adult life, tracking employment, life events, health, and other areas of interest. The NLSY 1997 survey follows approximately 9,000 individuals who were born between the years of 1980 and 1984. They have been interviewed on an annual basis since 1997, and data continue to be collected. The latest available data are from the 2010 survey. While older cohorts of the NLSY would provide more data points, especially for our evaluation of labor income, older cohorts do not include a set of questions focusing on college choice and are less relevant to today's high school graduates.

Our work draws on a subset of the NLSY 97 data, namely youths born in 1984. This subgroup of NLSY 1997 participants was selected to participate in a unique college choice portion of the survey, in which they were asked questions regarding all colleges they applied to, whether they were accepted, and whether aid was received.

While all students, including those in older versions of NLSY, are asked about the college(s) they chose to attend, the college choice dataset is unique in that it allows us to explicitly track college applications, admissions, and financial aid. Students in our cohort of interest turned eighteen years old in 2002 and are included in our sample if they applied to and were admitted to at least one college within two years of high school graduation. Demographic, residential, and other personal information about students is available within the survey data. So-called "geocode" data that has the potential to uniquely identify students, such as geographical and school name information, were attained through a special license from the Bureau of Labor Statistics.

Data on individual students are supplemented by information on the colleges that survey respondents applied to and attended. While some school-specific information, such as financial aid awarded, is captured in NLSY 97, most information pertaining directly to schools comes from the Department of Education's Integrated Postsecondary Education Data System (National Center for Education Statistics, 2009). Data include information on college finances, academic quality, location, and student body characteristics. To ensure consistency with information available to students at the time of their college decision, data from the 2002-2003 school year are used wherever possible.

Other sources of data include school selectivity information derived from Barron's Competitiveness Index and United States Postal Service zip code latitude and longitude information (Barron's, 2009). Barron's rankings were obtained through a restricted use license from the Department of Education. A list of variables used in model development is available in appendix C.1.

### 4.3.2 Sample selection

From the 9,000 individuals surveyed in NLSY 1997, we select individuals that fit a variety of criteria making them suitable to our analysis. We are interested in the traditional post-high-school college decision process for those individuals that consider four-year institutions, and we require information on admissions for our debiasing work. Therefore, we reduce the sample as follows:

- Focus on cross-sectional sample that is designed to give a representative sample, excluding those from the Black and Hispanic oversample group. This leaves 6,748 individuals.[2]

- Select individuals from the 1984 cohort who completed high school. These individuals participated in the college choice section of the survey. There are 2,191 such individuals in the sample.

- Select individuals that applied and were accepted to at least one four-year institution, leaving 1,223 individuals.

- Remove individuals that apply to only international or specialty schools or where schools listed are not in IPEDS dataset. This leaves 1,121 applicants applying to a total of 914 colleges.

- Remove individuals where income data or critical regression data are missing. We require sufficient post-college income data for the analysis techniques outlined in section 4.5. Unfortunately, this restriction limits the sample quite severely, shrinking the size of the usable dataset by about half. Regression inputs for key variables have very low missingness rates and do not have a significant impact on the number of usable data points. Individual data points are

[2]Oversample groups are included in NLSY for researchers who wish to study impact of race and ethnicity. Oversampling ensures enough data points from individuals in minority groups for whom it would otherwise be difficult to establish sufficient sample sizes.

occasionally omitted from a particular regression if data are not available for a particular school, student, or school-student combination.

- The final sample contains 525 individuals, including 400 four-year college attenders, as described in table 4.1.

Table 4.1: Number of students in sample, by attendance and admission groups.[a] Type 1 indicates most selective schools.[b]

| | | | **Selectivity of school attended** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | More selective | | | Less selective | | | |
| | | | 1 | 2 | 3 | 4 | 5,6 | Non-attenders | Total |
| | More | 1 | 15 | 8 | 11 | 9 | 0 | 7 | 50 |
| **Best** | selective | 2 | | 15 | 24 | 16 | 3 | 8 | 66 |
| **school** | | 3 | | | 77 | 35 | 11 | 24 | 147 |
| **admitted** | Less | 4 | | | | 123 | 13 | 57 | 193 |
| | selective | 5,6 | | | | | 40 | 29 | 69 |
| | | Total | 15 | 23 | 112 | 183 | 67 | 125 | 525 |

[a]Sample is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and are not missing critical data.

[b]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted.

Table 4.1 gives some interesting insights into the college attendance decision. We see that it is quite common for students to attend schools below the level of the top school to which they were admitted. It is especially common to attend a school one type below one's top admitted option. Very few of the top students choose to attend schools in the least selective category. The top school admitted to is an especially common choice for those who were not admitted to the very highest types. We also see that most students fall into the middle admission categories, with a top admitted school in type 3 being the most common. Non-attendance is most common among students admitted only to lower-type schools, but occurs among all students.

As we reduce our sample from the complete set of NLSY 97 respondents, we ensure that the original demographics of our data are preserved. Students with very few data points are removed from the sample, and we must ensure that this does not introduce

severe bias. Students with fewer post-college income data points may include high caliber students who attend graduate school or pursue unpaid learning opportunities as well as lower ability students who take longer to complete college or have very low paying jobs. As shown in table 4.2, we find that the rate of data deletion is similar across attendance and admission groups.

Table 4.2: Percentage of selected NLSY 1997 sample used in analysis, by attendance and admission groups. Individuals removed from sample do not report sufficient income data points. Type 1 indicates most selective schools.[a,b]

| | | | **Selectivity of school attended** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | More selective | | | Less selective | | | |
| | | | 1 | 2 | 3 | 4 | 5,6 | Non-attenders | Total |
| | More | 1 | 35% | 36% | 41% | 50% | NA | 44% | 40% |
| **Best** | selective | 2 | | 25% | 47% | 53% | 43% | 38% | 39% |
| **school** | | 3 | | | 48% | 52% | 58% | 38% | 48% |
| **admitted** | Less | 4 | | | | 51% | 50% | 50% | 51% |
| | selective | 5,6 | | | | | 51% | 55% | 53% |
| | | Total | 35% | 28% | 47% | 52% | 52% | 46% | 46% |

[a]Selected sample is presented in table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and are not missing critical data.

[b]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted.

## 4.4 Debiasing: Creating university and student groups

### 4.4.1 A new approach for addressing selection bias in school choice

One of the main contributions of this study is the introduction of a novel method for adjusting for endogenous student ability. Thanks to our unique data on the college application process, we can use an individual's success in college admissions to develop an understanding of his or her intrinsic ability. We condition on the Barron's selectivity index score of the best school to which a student was admitted, allowing us to reduce sample bias in our study of the effect of the attendance decision on income.. School selectivity categories correspond to Barron's selectivity categories.

We group type 5 and 6 schools (least selective) together due to the small number of observations for these school types.

Selectivity is used as the basis for forming school groups since it is common in the literature, it is available for our dataset, and it captures the detailed evaluation of student ability that is part of the college application process. An example of school groupings in the literature can be found in Fu (2012). In Fu's example, only four-year schools are addressed, which are subdivided into public and private groups. Within each of those groups, Fu creates a sub-group of selective schools and unselective (other) schools, yielding a total of four groups.[3] Stratification based on public/private status and other metrics of school quality were considered in our work, but dismissed due to small sample size within each group. Adjustments of income expectations based on students' individual characteristics were not used for similar reasons.

This method of accounting for ability bias is superior to previously used methods such as debiasing by grades or standardized test scores. This approach uses data that is common to all college applicants—information about where they applied and were admitted—instead of requiring participation in a particular exam or program that may not be offered to all potential college-goers. Additionally, college admissions staff are uniquely qualified to assess student ability given the large amount of information submitted with an application. We believe that the decisions of college admissions officers are likely to reflect intrinsic ability beyond differences in test score or grades. We treat the acceptance decision as exogenous, assuming that students are generally admitted to schools which they are well qualified to attend. School grouping methods other than Barron's selectivity index were also investigated and Barron's scores are supplemented with SAT score percentiles and admission rates.[4] Similarly, we do not

[3]Selective schools are those in the top thirty of US News & World Report's college rankings (U.S. News and World Report, 2012).

[4]In the sample of schools applied to by the students in this analysis, correlation between Barron's selectivity index and the percentage of applicants admitted is 52%. Correlation between Barron's and the student body's $25^{\text{th}}$ and $75^{\text{th}}$ SAT score percentiles is $-37\%$ and $-23\%$, respectively.

include individual characteristics such as SAT scores, high school grades, or location of residence in our model since this reduces sample sizes within each group.[5]

There is some concern that school quality is endogenous, with school quality determined by the quality of the student body. Our metric of school quality is based on selectivity, directly linking school quality to the quality of students admitted. Such endogeneity is not problematic for our work since we model individual level decisions. Individual choices of attendance do not significantly affect the overall composition of the student body at a school. Additionally, our results support the hypothesis that school quality is based on student quality, since students admitted to selective schools perform well in terms of income even when they do not attend the selective institutions. This suggests that the education received at a selective school may not be superior to that at a different institution.

We do not explicitly model unemployment risk, graduation risk, or future tax burdens. Instead, we account for this type of uncertainty by including all individuals who begin education at a certain level in our sample. Thus, unemployment and graduation risk are included since they affect the future income of each group. Currently available income data from the NLSY 97 does not capture all unemployment risk or future education decisions over the lifetime. As more data points are collected in NLSY 97, we hope that more sophisticated income models can be developed, capturing income levels and variance over the whole lifetime.

### 4.4.2 Potential criticisms and shortcomings of the NLSY 1997 data

The main challenges in writing this chapter are due to shortcomings in the available data. The short time period for which NLSY 97 data are available is a concern.

[5]Data on high school grades have high degrees of missingness. Regressions including location of residence, verbal SAT score, and top school admitted reveal that categorical location dummies and verbal SAT scores do not have a significant effect on post-college income after adjusting for top school admitted to (p-value $> 0.05$). Math SAT score appears correlated with higher salary even after adjusting for top school admitted (p-value $= 0.008$) but also exhibits high missingness.

We are interested in studying the relationship between post-college income and schooling decisions, but we have only limited data on lifetime incomes. The latest NLSY 97 data are from 2010, and the 1984 cohort reached age eighteen (high school graduation) and age twenty-two (on-time college graduation) in 2002 and 2006, respectively. Therefore, we have only about four years of post-college income data available for those individuals who stayed in college for four years. We study income expectations first by using only the available post-college data, thus minimizing model risk. To illustrate how future studies could expand these results to include information on income over the lifetime, we use data on the US Census Bureau's synthetic lifetime income estimates to create a model of lifetime income expectations. We do not have complete information about future unemployment prospects, and base assumptions about future earnings on US Census data. Additionally, we are not able to account for future schooling decisions that may take place later in life, such as the decision to attend graduate school. This may lead to a low lifetime income estimate for some students. However, we believe this bias is consistent throughout our sample, and feel that relative income differences between groups remain accurate. As additional income data is collected in NLSY 97, income estimates can be improved, allowing us to study income variance and effect of individual characteristics more closely.

A further criticism may come from the fact that we examine only individuals from a single cohort. As pointed out by Davis and von Wachter (2011), individuals who graduate during a recession experience the repercussions of their inopportune entrance into the working world for the duration of their career, lowering salary expectations and utility of future income streams. Since we are primarily interested in the substitution effect between schools (e.g. what makes a person pick school A over school B), we believe that accurate modeling of the magnitude of future earnings is less important than the relationship between salaries for those attending different schools. It is not clear that graduation during a recession would significantly change

the relative factors leading a student to choose one school over another. Previous cohorts of the NLSY did not include the college choice questions which provide the data used in our models. Therefore, comparative analysis cannot be performed using older cohorts.

We must make several assumptions in order to model the college choice portion of the application/acceptance/attendance game in isolation. We assume that students' application decisions reflect their ability as well as their desires about which school to attend. Throughout the model, we treat the application decision as exogenous and assume that students apply to the schools in which they are most interested. We also assume that high ability students apply to selective institutions, even though they may also apply to less selective schools, and that school's supply side decisions such as admissions and financial aid amounts are exogenous. While these assumptions may be violated in a small number of cases, they reflect the usual behavior of college applicants. The number of schools applied to is not a significant predictor of post-college income in our models (p-value¿0.9).

## 4.5 Modeling income

### 4.5.1 Post-college earnings

To understand the effect of educational choices on income, we begin by comparing raw post-college income data across students of different ability levels and educational decisions. Through this work, we build an understanding of the likely income level for a student of a particular ability who makes a specific schooling decision. The goal here is to recreate as closely as possible the information available to a high school student at the time of his or her college decision. We do not necessarily seek to determine the income actually earned by that student in the future, but rather to model how much that student can expect to earn if he or she selects a particular

school. As shown in figure 4.1, income levels are driven by student ability (measured by the selectivity of the top school to which a student was admitted) rather than by the schooling decision made. Tables 4.3 and 4.4 provide further evidence for this conclusion by studying the difference in slopes between the unconditional salary levels (grey bars) and conditional salary levels (lines) in figure 4.1. Table 4.3 corresponds to figure 4.1a, and investigates slope differences across selectivity of the school attended for the unconditional versus conditional samples. Conditioning in table 4.3 is based on the top school admitted to. We find that the interaction term between selectivity of school attended and an indicator for conditional data is highly significant, suggesting that a difference in slope exists between the unconditional and conditional samples. Investigating the coefficients, we see that the net coefficient on selectivity of attended schools for conditional data is close to zero $(2,466 - 2,570)$, suggesting that attendance selectivity is not a strong predictor of income after conditioning on the selectivity of the top school admitted to. Table 4.4 investigates the difference in slope across selectivity of the top school admitted to for the unconditional versus conditional samples, corresponding to figure 4.1b. The interaction term between top admitted selectivity and an indicator of whether data points come from a conditional (adjusted for school attended) curve is not significant in this regression, suggesting that the effect of admission at a particular quality of school is the same across attendance groups. Income declines as top admitted school selectivity decreases even after adjusting for selectivity of the school attended.

Tables 4.3 and 4.4 study aggregate data across attendance and admission selectivity groups. We can show a similar result using individual level data. We begin by studying income trends across attendance and admission groups separately in the individual level data. Table 4.5 presents results of fixed effects regressions estimating post-college income based on school attended and top school admitted to separately. Our results indicate that both being admitted to top schools and attending top schools

Table 4.3: Slope differences in post-college income across selectivity of school attended. Unconditional data represent the whole NLSY 97 sample, while conditional data are adjusted by selectivity of top school admitted to. $avgIncome = \alpha_0 + \alpha_1 attend^a + \alpha_2(attend * conditonalIndicator) + \alpha_{3,admit}.^{b,c,d,e}$

Fixed effects regression

| | | Adjusted $R^2$: | 0.7054 |
|---|---|---|---|
| | Estimate | St. Error | p-value |
| (Intercept) | 40,292 | 2270 | $1.70 \times 10^{-10}$ |
| Attend | -2,570 | 684.4 | 0.0024 |
| Attend*Conditional Indicator | 2,466 | 906 | 0.0175 |
| Top Admitted = 1 | -5,216 | 2,920 | 0.0973 |
| Top Admitted = 2 | -3,319 | 3262 | 0.3287 |
| Top Admitted = 3 | -9,744 | 3,507 | 0.0157 |
| Top Admitted = 4 | -10,645 | 3,825 | 0.0155 |
| Top Admitted = 5 | -14,415 | 4,318 | 0.0053 |

[a]Attendance category, treated as a continuous variable to capture slope of the income curve from categories 1 to 5/6.

[b]Fixed effects allowing different intercepts for conditional income lines corresponding to each admitted category.

[c]Baseline for fixed effects is the unconditional average across the whole sample. Fixed effects are included to reduce bias in slope-related estimates.

[d]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted.

[e]Selected sample is presented in Table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and not missing critical data. Students who do not attend any school are omitted from this analysis. The sample in this table excludes seven individuals who do not supply sufficient income information in the immediate post-college years.

is correlated with higher income levels.

Categorization of individuals by the selectivity of school attended introduces sample bias since those students who are able to attend top schools must have been admitted to these institutions. The question we wish to answer is whether or not school attended has an effect on future income *after adjusting for intrinsic ability*, which we measure by top school admitted to. We test for the effect of admission within each attendance group separately as well as the effect of attendance within each admission group separately, but find that sample sizes in sub-groups are generally too small to draw definitive conclusions. The fixed effects factor models are presented in appendix

Table 4.4: Slope differences in post-college income across top school admitted to. Unconditional data represent the whole NLSY 97 sample, while conditional data are adjusted by selectivity of school attended. $avgIncome = \alpha_0 + \alpha_1 admit^a + \alpha_2(admit * conditonalIndicator) + \alpha_{3,attend}.^{b,c,d,e}$

Fixed effects regression

| | | Adjusted $R^2$: | 0.5408 |
|---|---|---|---|
| | Estimate | St. Error | p-value |
| (Intercept) | 28,002 | 2,952 | $5.63\text{x}10^{-8}$ |
| Admit | -2,452 | 890 | 0.0187 |
| Admit*Conditional Indicator | 140.5 | 1,131 | 0.9034 |
| Top Attended =1 | 2,949 | 4,138 | 0.4909 |
| Top Attended = 2 | -1,201 | 3,711 | 0.7522 |
| Top Attended = 3 | 451 | 3,648 | 0.9038 |
| Top Attended = 4 | 850 | 3,707 | 0.8229 |
| Top Attended = 5 | 1,303 | 4,189 | 0.7615 |

[a]Admissions category, treated as a continuous variable to capture slope of the income curve from categories 1 to 5/6.

[b]Fixed effects allowing different intercepts for conditional income lines corresponding to each attended category.

[c]Baseline for fixed effects is the unconditional average across the whole sample. Fixed effects are included to reduce bias in slope-related estimates.

[d]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted.

[e]Selected sample is presented in Table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and not missing critical data. Students who do not attend any school are omitted from this analysis. The sample in this table excludes seven individuals who do not supply sufficient income information in the immediate post-college years.

Table 4.5: Predicted post-college income by selectivity of top school admitted to and school attended.

(a) Predicted post-college income, by top school admitted to. Type 1 indicates most selective schools. $avgIncome = \alpha_0 + \alpha_1 topAdmit + \epsilon.^{a,b,c}$

Fixed effects regression

| | | Adjusted $R^2$: | 0.0940 |
|---|---|---|---|
| | Estimate | St. Error | p-value |
| (Intercept) | 44,253 | 3,024 | $2.00\text{x}10^{-16}$ |
| Type 2 | -8,382 | 3,759 | 0.0274 |
| Type 3 | -11,535 | 3,634 | 0.0019 |
| Type 4 | -11,605 | 3,299 | 0.0006 |
| Types 5/6 | -16,069 | 4,000 | $9.81\text{x}10^{-5}$ |

[a]Base case is type 1 (most selective).

[b]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted.

[c]Selected sample is presented in Table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and not missing critical data. The sample in this table excludes seven individuals who do not supply sufficient income information in the immediate post-college years.

(b) Predicted post-college income, by school attended. Type 1 indicates most selective schools. $avgIncome = \alpha_0 + \alpha_1 attend + \epsilon.^{a,b,c}$

Fixed effects regression

| | | Adjusted $R^2$: | 0.1525 |
|---|---|---|---|
| | Estimate | St. Error | p-value |
| (Intercept) | 28,503 | 1,527 | $4.58\text{x}10^{-5}$ |
| Type 1 | 20,148 | 4,781 | 0.0070 |
| Type 2 | 11,287 | 4,122 | 0.0002 |
| Type 3 | 9,717 | 2,537 | 0.0156 |
| Type 4 | 5,130 | 2,094 | 0.0002 |
| Types 5/6 | 4,668 | 3,706 | 0.2100 |

[a]Base case is non-attenders.

[b]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted.

[c]Selected sample is presented in Table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and not missing critical data. The sample in this table excludes seven individuals who do not supply sufficient income information in the immediate post-college years.

C.3. To limit the effects of small sample size, we change the categorical data on attendance and admission to interval data based on the admission criteria of schools within each category. Specifically, using documentation on Barron's selectivity index, we categorize selectivity groups based on the admissions rate of applicants. Type 1 schools have admissions rates of at most 33% while type 5 and 6 schools admit 100% of their applicants. Correlation between selectivity of top school admitted and selectivity of school attended is 71%. We would like to know which of these two variables appear to have a causal effect on post-college income.

To answer this question, we examine the effect of deviation from the expected

school type attended given the best school admitted to, and the effect of deviation from the expected best school admitted to given the quality of the school attended. Table 4.6 shows this analysis. We call the residuals of the regression of attended school on top admitted school "attendance error." This is uncorrelated with the top school admitted to. As shown in table 4.6a, the attendance error has no predictive power after adjusting for top school admitted to. Furthermore, attendance error alone has no predictive power when predicting post-college income. We call the residuals of the regression of top admitted school on attended school "admission error", which is uncorrelated with the school attended. As shown in table 4.6b, the admission error has significant predictive power after adjusting for school attended. Admission error alone is significant when predicting post-college income.

### 4.5.2 Effect of college attendance and other factors

The low $R^2$ values in the regression in table 4.6 suggest that selectivity of the best school admitted to is not the only important predictor of post-college income. We use the individual student data available in NLSY 1997 to examine which other factors may affect income expectations. As shown in table 4.7, we find that mathematical ability (measured by math SAT score) and major choice have an effect on income. Verbal SAT score does not have any explanatory power after adjusting for the top school admitted to. We also investigate the impact of gender, race, and location of residence, but find no significant effect from these. We do see some evidence suggesting that household wealth has a positive effect on post-college incomes. However, household wealth is correlated with math SAT score, making it difficult to isolate these effects. More information on the effect of household income is provided in appendix C.4. We do not include the effect of income variance across groups in this model since we do not have sufficient data to assess this variance. Income levels are estimated from a small number of data points early in the career, which do not

Table 4.6: Separating effects of top school admitted to and school attended selectivity on income, interval selectivity data.

(a) Predicted post-college income by selectivity of top school admitted to and attendance error. $avgIncome = \alpha_0 + \alpha_1 topAdmit + \alpha_2 attendError + \epsilon.$[a,b]

Ordinary least squares regression

| | | Adjusted $R^2$: | 0.0591 |
|---|---|---|---|
| | Estimate | St. Error | p-value |
| (Intercept) | 434,401 | 2,467 | $2.00\text{x}10^{-16}$ |
| Acceptance rate, top admitted school | -166 | 32 | $4.00\text{x}10^{-7}$ |
| Attendance error | -37 | 59 | 0.5330 |

[a]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted. Interval scale is created be replacing category label with the percentage of applicants admitted in each selectivity category. Type 1 schools have admissions rates of at most 33% while type 5 and 6 schools admit 100% of their applicants.

[b]Selected sample is presented in Table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and not missing critical data. Students who do not attend any school are omitted from this analysis. The sample in this table excludes seven individuals who do not supply sufficient income information in the immediate post-college years.

(b) Predicted post-college income by selectivity of school attended and admission error. $avgIncome = \alpha_0 + \alpha_1 attend + \alpha_2 admitError + \epsilon.$[a,b]

Ordinary least squares regression

| | | Adjusted $R^2$: | 0.0591 |
|---|---|---|---|
| | Estimate | St. Error | p-value |
| (Intercept) | 44,976 | 3,442 | $2.00\text{x}10^{-16}$ |
| Acceptance rate, attended school | -171 | 42 | $4.89\text{x}10^{-5}$ |
| Admission error | -146 | 46 | 0.0016 |

[a]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted. Interval scale is created be replacing category label with the percentage of applicants admitted in each selectivity category. Type 1 schools have admissions rates of at most 33% while type 5 and 6 schools admit 100% of their applicants.

[b]Selected sample is presented in Table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and not missing critical data. Students who do not attend any school are omitted from this analysis. The sample in this table excludes seven individuals who do not supply sufficient income information in the immediate post-college years.

provide sufficient information on volatility. Even with the inclusion of student characteristics, this model does not explain a large portion of overall income variance, suggesting that many other factors matter in determining income levels.

Even though we see no effect of college type attended on income after adjusting for the best school admitted to, our results do indicate that attending college at all

Table 4.7: Effect of student characteristics on income after adjusting for selectivity of top school admitted to. $avgIncome = \alpha_0 + \alpha_1 admit + \alpha_2 mathSAT + \alpha_3 engineeringIndicator + \alpha_4 humanitiesIndicator + \epsilon$. [a,b]

Ordinary least squares regression

| | Adjusted $R^2$: | 0.1265 | |
|---|---|---|---|
| | Estimate | St. Error | p-value |
| (Intercept) | 40,920 | 2,722 | $2.00\text{x}10^{-16}$ |
| Acceptance rate, top admitted school | -82 | 41 | 0.0471 |
| Math SAT score | 2,236 | 783 | 0.0047 |
| Engineering indicator | 7,101.4 | 2,907 | 0.0153 |
| Humanities indicator | -5.036 | 1,678 | 0.0030 |

[a]Selected sample is presented in table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and are not missing critical data. The sample in this table excludes individuals for whom regression data is missing. Math SAT scores are missing for about one third of the students in our sample, reducing the sample size for this model. An alternate model excluding math SAT score is provided in appendix C.4.

[b]Major choice is based on the initial program decision made upon entering college. It does not necessarily reflect the final major in which a degree was attained, since some students change majors or do not complete their studies. Engineering majors include engineering and computer-related fields. Humanities majors include liberal arts, fine arts and architecture, political sciences, classical fields, and interdisciplinary studies.

is beneficial for students. These results are presented in appendix C.5. We further examine to what extent the expected salary increase from attending school at all varies across top admitted school categories. Salary for non-attenders is the same across all top admitted groups. However, salary of attenders differs across top admitted groups, even though which school is actually attended has no effect on income. Figure 4.3 shows these differences; income for attenders is higher for those whose top admitted school is more selective. The second panel in figure 4.3 examines whether there is a significant difference in the benefit of attending school at all across top admitted groups. We plot the difference between earnings of attenders and non-attenders for each top admitted group with 95% confidence intervals, and see that these differences are in fact indistinguishable across groups. This implies that the choice of whether or not to attend school has the same effect on future earnings across ability groups.

As stated in section 4.4, the samples used in this analysis include any student that initially enrolled in a school of a given quality. Adjusting this sample to only students that successfully graduate from institutions in each category reduces the sample size, but suggests similar results. We also investigate the effect of attending the best school one was admitted to versus a lower quality school, and find no difference in expected earnings between these groups.

### 4.5.3 Lifetime income

We expand on this analysis of raw income data by developing a model of the expected value of the future lifetime income stream that results from attending a school with a particular selectivity type. We project the shape of each individual's most likely labor income curve over the lifetime. Income estimates are based on employment status, school enrollment status, and employment income reported in the NLSY 97. All reported employment income is used, so long as students claim full-time working status and report at least 12,000 hour of employment and at least

$10,000 of labor income in a given year. The salary lower bound helps reduce noise in the data caused by unusual employment situations such as unpaid internships, volunteer work, or career training. Income from years of unemployment or severe under-employment is not used in the estimation of the shape of the lifetime income curve.[6] Unemployment is not explicitly modeled in the projected income for future years since we do not have future employment status information. As more NLSY 97 data become available, projected lifetime income curves will be replaced by actual curves, which will include information on future unemployment.

To extrapolate from the early career income data provided in NLSY 97 to the expected lifetime income curve for the students in our sample, we supplement NLSY 97 data with current synthetic work-life earnings projections from the US Census Bureau (Census Bureau, 2012). Synthetic earnings estimates are adjusted by level of education received (Dya and Newburger, 2002). The method described in this section allows us to gain maximal insight into future earnings by

- using all income data points available for a particular individual,
- taking advantage of information about the shape of lifetime income curves from US Census data,
- accounting for differences in the number of years worked between those who attend college and those who do not, and
- accounting for earnings over the whole lifecycle instead of taking the net present

[6]Income projection was also performed without the $10,000 upper bound, without restrictions on full-time employment status, and allowing use of income from sources such as unemployment insurance and investments. The approach used here was chosen because it maximizes the number of individuals for whom income projection is possible. The result that income parameters do not vary across school type attended after adjusting for the top attended school is consistent across all projection approaches. Additionally, models that do not use the earnings parameter $\beta_0$ directly, but rather calculate discounted expected lifetime earnings based on this parameter and equation (C.4) also yield similar results. In these models, we assume that non-attenders follow the estimated income curve from ages 22 to 100, while attenders follow it from 18 to 100. Earnings are discounted by a yearly factor of 0.96. The value of the discount factor is based on estimates found in past literature, for example in Cocco et al. (1998) and Gourinchas and Parker (1999).

value of only the available data points.

This supplements the analysis of raw data explained in the previous section, and establishes a model for future analysis to be performed as more income data is collected. Analysis of our lifetime income projections yields results similar to those found in the raw data, suggesting that student ability rather than schooling decisions drive differences in income.

Lifetime income estimates are created by fitting a restricted Nelson-Siegel equation to synthetic lifetime earnings curves created by the US Census Bureau.[7] We then calibrate the model, estimating a single shape parameter for each individual in our sample that captures the likely shape of his or her lifetime income curve. We study differences in income across student ability and school quality groups by comparing these shape parameters and the lifetime income they imply. Details of this analysis are provided in appendix C.2, and results confirm the hypothesis that the selectivity of the school attended does not affect income after adjusting for selectivity of the top school admitted to. As more data is collected from the NLSY 97 survey, more sophisticated income projection methods may allow for further study of the effects of lifetime income levels and variance.

## 4.6 Drivers of college choice

We fail to show that there is a difference in post-college income based on selectivity of the school attended after adjusting for the selectivity level of the top school a student is admitted to. This result from the previous section implies that we cannot test for the effect of future income expectations on the schooling decision, since the schooling decision has no sizable impact on future income. In this section, we test which other factors affect the way students make decisions about whether and where

[7] See Nelson and Siegel (1987). The Nelson-Siegel equation is commonly used to model yield curves.

to attend college. We see that concerns about school quality and selectivity as well as monetary interests are key drivers of the decision, even though school quality does not appear to predict post-college earnings.

Candidate drivers consist of individual, school, and interaction characteristics. School characteristics include list tuition, financial aid including in-state residency discounts, instructional spending per student, public versus private status, financial aid received by the student body, school size, and the student body gender ratio. Individual characteristics include student gender, ethnicity, parents' educational attainment, household size and income, and high school type. Interaction terms compare the most preferred school's selectivity to that of the student's top admitted school, examine urban versus rural status of the student's home and school, and capture distance between home and the college campus.

The college decision is broken down into two components: First, we use a binary logistic model to capture the decision of whether or not to attend college at all. Second, we use a conditional logistic model to determine factors important in choosing between colleges for those students that in fact do attend school.[8] Additional background on binary and conditional logistic choice models is provided in appendix C.6.

### 4.6.1 Choice of attendance: The first stage binary logit model

The first decision in the college choice process is the decision of whether or not to attend college at all. The first stage input dataset contains one entry per student which stores individual characteristics, information about the most preferred school admitted to, and interaction terms quantifying the fit of the student at this school. For students attending college, the most preferred school admitted to is the school

[8] We use R to construct all models. First stage binary logit models are estimated using the glm package, while second stage conditional choice models are constructed using the mclogit package and clogit function from the survival package (R Core Team, 2013), (Therneau, 2013), (Elff, 2013).

attended. For students that do not attend school, we use the predicted utility of each candidate school from the second stage model to determine which school should be the most preferred (see table 4.9 below for the second stage model). The second stage model is estimated first, allowing us to derive an equation for the utility of attendance at a particular school for a particular person. Once this equation is known, we can determine which of the possible schooling options facing each non-attender would have provided them with the highest utility. This school is used as the most preferred school for non-attenders in the first stage model. This method assumes that non-attenders have similar preferences over school characteristics to attenders, even though not attending is the highest utility option for non-attenders.

In the first stage of the model, we are able to include both individual and school characteristics, since each choice situation is defined by a particular student and his or her most preferred school. Individual student data include student ability measured by the selectivity level of the top school admitted to, gender, ethnicity, parents' education, household size, and wealth. We also test for the significance of higher order terms and likely interactions between variables, but do not find these to be significant.

The probability of attending college at all given that the most preferred school is $j^*$ is given by the binary logistic model below:

$$\begin{aligned} P_{i,j^*=1} = \pi_{i,j^*} &= \frac{e^{\delta' x_{i,j^*}}}{e^{\delta' x_{i,j^*}} + 1} \\ &= \frac{1}{1 + e^{-\delta' x_{i,j^*}}} \\ &= \frac{1}{1 + e^{-\delta'(gender_i + earningsDifference_i + graduationRate_{j^*})}} \end{aligned} \tag{4.1}$$

Model coefficients are provided in table 4.8.

We find that student ability (the top school admitted to) is a strong predictor of college attendance, with students admitted to schools with low acceptance rates

Table 4.8: First stage model: Binary logit model of whether to attend college or not. Equation (4.1).[a]

| Logit regression | | | |
|---|---|---|---|
| | McFadden's $R^2$: | 0.0522[b] | |
| | | AIC: | 553.72[c] |
| | Estimate | St. Error | p-value |
| (Intercept) | 1.3039 | 0.9828 | 0.1845 |
| Female[d] | 0.3980 | 0.2116 | 0.0600 |
| Acceptance rate, top admitted school[e] | -0.0179 | 0.0086 | 0.0365 |
| Graduation rate[f] | 2.1232 | 0.8341 | 0.0109 |

[a]Selected sample is presented in table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and are not missing critical data.

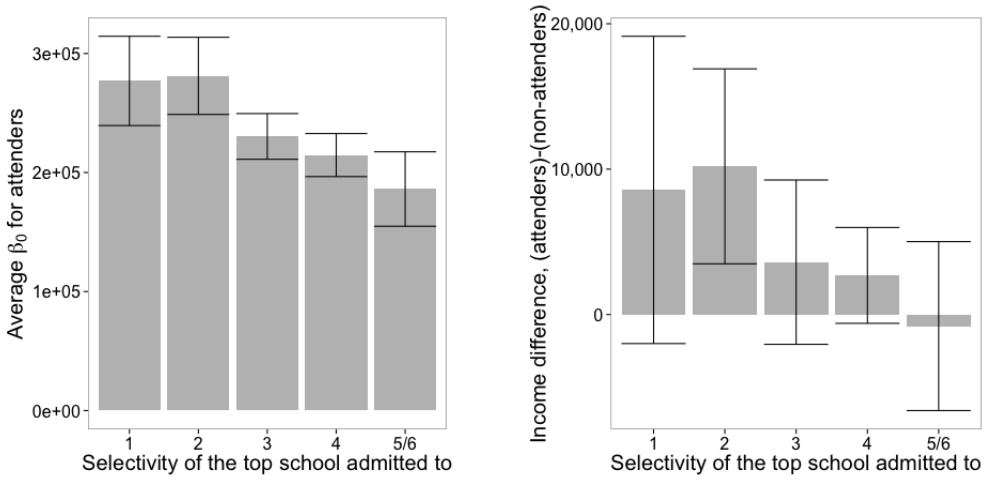
[b]McFadden's $R^2 = 1 - \frac{ln(\hat{L}_{\text{full}})}{ln(\hat{L}_{\text{intercept}})}$ where $\hat{L}_{\text{full}}$ gives the estimated likelihood of the model with predictors and $\hat{L}_{\text{intercept}}$ gives the estimated likelihood of the intercept-only model.

[c]Akake Information Criterion, see e.g. Akaike (1969).

[d]Categorical gender variable. Gender baseline = male.

[e]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted. Interval scale is created be replacing category label with the percentage of applicants admitted in each selectivity category. Type 1 schools have admissions rates of at most 33% while type 5 and 6 schools admit 100% of their applicants. We also estimate this model using categorical data for the top admitted school. Results are similar but provide lower power due to the need to estimate more parameters.

[f]Graduation rate as reported in IPEDS. Graduation rate is highly correlated with other measures of school quality, such as faculty salary, expenditures, and selectivity.




(a) Average post-college income for attenders at any college, by top admitted category. Error bars show 95% confidence intervals on the mean. Type 1 indicates most selective schools.

(b) Differences in post-college income for attenders versus non-attenders, by top admitted category. Error bars show 95% confidence intervals on the difference. Type 1 indicates most selective schools.

Figure 4.3: Average post-college earnings by selectivity of top school admitted to. No significant differences exist in average earnings for non-attenders across top admitted categories. [a,b,c]

[a]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted.

[b]Selected sample is presented in table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and are not missing critical data. The sample in these plots excludes seven individuals who do not supply sufficient income information in the immediate post-college years.

[c]Significant differences in lifetime earnings for attenders exist between the following top admitted groups (p-values): Type 1 and type 3 (0.0314), type 1 and type 4 (0.0020), type 1 and type 5/6 ($8.70\text{x}10^{-5}$), type 2 and type 3 (0.0014), type 2 and type 4 ($2.00\text{x}10^{-5}$), type 2 and type 5/6 ($1.60\text{x}10^{-06}$), and type 3 and type 5/6 (0.0075).

(high selectivity) being more likely to attend college. After conditioning on student ability, only a few variables provide additional explanatory power. The first, graduation rate, is presented as an overall metric of school quality. Graduation rate is highly correlated with other metrics of school quality, including selectivity, list tuition, average faculty salary, and private versus public control status. While it is not clear that students making the college decision focus explicitly on the graduation rate

of the school they are considering, the significance of this variable captures students' assessment of the overall quality of the institution. Graduation rate is treated here as an exogenous characteristic of the school in question, even though quality of student body is clearly determined by institutional policies. A study of the supply side decisions that affect graduation rate is outside of the scope of this work, and we treat it as a set characteristic of each institution. The high level of significance of this variable suggests that the likelihood of attendance is affected by student ability and the quality of the top school they were admitted to even within the top admitted groups defined using Barron's selectivity index. As shown in the next section, students tend to prefer schools that perform highly on quality metrics relative to other schools in their choice set. In this model, we see that having such a high quality school available as a possible choice makes it more likely for a student to attend school. The final significant variable in the first stage model is gender, with females being slightly more likely to attend college than males.

Overall, the model in table 4.8 does not explain very much of the variance in the college attendance decision, and does not successfully predict whether or not a student will attend school. Student and school quality appear to be the primary drivers of attendance, and other variables fail to provide additional information on attendance probability after adjusting for these factors.

This model closely parallels the work of Long (2004b) and allows us to update Long's models using a more recent cohort of the NLSY. Comparison to Long's work provides some context for our study and lets us verify consistency with the literature. Long studies changes in the factors affecting college attendance and the choice between schools over time, studying data from the high school graduating classes of 1972, 1982, and 1992. Our work adds a new set of models for the high school graduating class of circa 2002. Comparing our first stage model to the attendance decision model for 1992 graduates in Long (2004b), we find that our model provides more

significant predictors of college attendance. Additionally, the variables which predict attendance in our model are not candidate variables in Long's work. Attempting to recreate Long's model with our data yields results very similar to Long's original model. These results are presented in appendix C.7. Both Long's original models and the model presented in this section fail to capture the majority of variance of the binary college attendance decision. Long finds that tuition price became less important in the attendance decision between 1972 and 1992. Our analysis confirms these findings, as tuition is not a significant predictor of attendance in the first stage model in table 4.8.

### 4.6.2 Choice between colleges: The second stage conditional logit model

The second stage of our model captures the choice between colleges *given that an individual has decided to attend school at all.* In this model, alternatives are defined entirely by school characteristics, allowing us to include specific details about each of the colleges represented in our sample. School characteristics include price information, financial aid availability, student body characteristics, and school quality and wealth metrics. The data include one sample point for each student/school combination. Data are stratified by student, with each student's stratum including one set of data per alternative school considered. The likelihood of selecting a particular school is calculated relative to the other schools in a specific student's choice group, meaning that we cannot account for individual characteristics in this portion of the model. This means that we cannot adjust explicitly for student ability (top school admitted to), since this parameter is constant across a choice situation (for a given student). However, we can include student ability information through the use of interaction effects. Selectivity difference captures the difference between the selectivity level of the top school to which a student was admitted and the selectivity of the current candidate school, providing a metric of whether a school is a "stretch" or "safety"

choice for the particular student.[9] Other interaction terms we consider include distance between a student's home and the college and the proportion of tuition that is covered by financial aid. It is this portion of the model that makes significant use of the Independence of Irrelevant Alternatives (IIA) property, which states that the relative utility of schools in the choice set does not change mathematically if some alternative schools fail to be included in the sample. Additional details on the IIA property in logistic choice models are provided in appendix C.6.

Since our data on school characteristics are very rich, we begin by examining collinearity between school characteristics that may measure similar traits. As mentioned in the previous section, graduation rate is highly correlated with other metrics of school quality. Our sample also includes several variables that measure expenditures, tuition and net cost, and federal aid access. Given the interrelatedness of some variables, we develop a robust method of model selection for the second stage model. We investigate candidate models that include all combinations of variables predicting tuition and net cost, selectivity, expenditures and wealth, and school quality, selecting the combination of variables that yields the best fit. Appendix C.8 provides more details on pre-estimation analysis of the relationships between predictors and the model selection process. We also investigate the use of higher order and interaction terms, but do not find these to be significant in the model.

We find that net tuition, school quality as measured by graduation rate, instructional spending per student, and the selectivity difference between the current potential school and a student's top admitted school predict the likelihood of choosing a particular institution. Net tuition is calculated by subtracting financial aid from list out-of-state tuition. Financial aid includes the in-state discount, if it applies, financial aid awarded by the school, and financial aid awarded by other sources for use at this school or any school attended. Students prefer less expensive schooling. Alter-

[9] Selectivity difference = Selectivity of this schooling option - selectivity of the top school admitted to.

native models that include both list tuition and financial aid amounts also support this hypothesis. We do not find any evidence that higher list tuition with more aid is prefered to lower list tuition. Graduation rate and instructional spending are metrics of school quality, and are highly correlated with related variables such as faculty salary and selectivity. The significance of these variables implies that students prefer the highest quality schools in their choice portfolio. A higher selectivity difference value indicates attending a school that is less selective than one's top school admitted to. While we see that students prefer higher quality institutions, it appears that less selective institutions may be preferred after adjusting for quality as measured by other factors such as graduation rate. The model equation is given below:

$$\begin{aligned} P_{i,j} &= \frac{e^{\delta' x_{i,j}}}{\sum_{k \in J} e^{\delta' x_{i,j}}} \\ &= \frac{e^{\delta_1 netTuition_j + \delta_2 graduationRate_j + \delta_3 instructionalSpending_j + \delta_4 selectivityDifference_{i,j}}}{\sum_{k \in J} e^{\delta_1 netTuition_j + \delta_2 graduationRate_j + \delta_3 instructionalSpending_j + \delta_4 selectivityDifference_{i,j}}} \end{aligned} \tag{4.2}$$

Model coefficients are provided in table 4.9. As described in the previous section, this model is also used to predict which of their candidate schools each non-attender would most prefer. This information is used as an input in the first stage model.

The second stage model has more explanatory power than the first stage model, but still fails to capture all of the variance in the choice between schools. As with the first stage model, we see that school quality plays a key role, with students picking higher quality institutions within their choice sets. This is countered by a desire to pay a lower tuition price, and decisions are likely a trade-off between these two main drivers. The first stage model shows that higher ability students are more likely to attend school. In the second stage model, we see that students tend to select the higher quality institutions within their choice set across student ability categories.

As with the first stage model, we compare our model to that presented for 1992

Table 4.9: Second stage model: Conditional logit model of college choice given college attendance. Equation (4.2).[a]

| Conditional logit regression | | | |
|---|---|---|---|
| | | McFadden's $R^2$: | 0.0988[b] |
| | Estimate | St. Error | p-value |
| Net tuition[c] | -9.56x$10^{-5}$ | 1.85x$10^{-5}$ | 2.33x$10^{-7}$ |
| Graduation rate[d] | 3.151 | 0.9250 | 0.0007 |
| Instructional spending[e] | 5.71x$10^{-5}$ | 2.92x$10^{-5}$ | 0.0505 |
| Selectivity difference[f] | 0.0211 | 0.0112 | 0.0559 |

[a]Selected sample is presented in table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and are not missing critical data.

[b]McFadden's $R^2 = 1 - \frac{ln(\hat{L}_{\text{full}})}{ln(\hat{L}_{\text{intercept}})}$ where $\hat{L}_{\text{full}}$ gives the estimated likelihood of the model with predictors and $\hat{L}_{\text{intercept}}$ gives the estimated likelihood of the intercept-only model.

[c]Net tuition is calculated as list out-of-state tuition price minus financial aid. Financial aid includes financial aid awarded for attending the particular school in question, financial aid for use at all schools, and the in-state tuition discount.

[d]Graduation rate as reported in IPEDS. Graduation rate is highly correlated with other measures of school quality, such as faculty salary, expenditures, and selectivity.

[e]Total expenses associated with instructional divisions of the institution, including compensation of instructors, community and adult education, tutoring, and other academic-related activities.

[f]Selectivity levels of this schooling option minus selectivity of the top school admitted to.

graduates in Long (2004b). The model in table 4.9 does not fit the data as well as Long's model, likely due to the smaller size of our sample. Additionally, higher order terms are not significant in the current model. However, we do find that related variables have signs consistent with Long's model and that many of the same drivers can be identified. Results from an attempt to recreate Long's original model with our data are presented in appendix C.7.

## 4.7 Conclusions

The models presented in this work provide evidence for the hypothesis that post-college labor income is driven primarily by individual characteristics and major rather than institutional choice. The unique data available through the college choice interview section of the NLSY 1997 allow us to study income differences using a new debiasing method. The method of debiasing introduced in this chapter accounts for differences in ability levels across groups of students attending schools of varying quality and selectivity by conditioning on the selectivity of the best school an individual was admitted to. With the exception of the decision to attend college at all and major choice, we fail to show significant differences in income based on schooling decisions. Earnings expectations are improved by the decision to attend college at all. Earnings for those that do not attend any college are the same across top admitted categories, while earnings for attenders are highest for those admitted to top schools. The difference in salary expectations between attenders versus non-attenders is not significantly different across top admitted categories. Engineering and computer-related majors offer a wage premium even after adjusting for ability, suggesting that wage increases are not simply due to the best students self-selecting into these majors.

Even though school quality does not appear to have an effect on post-college income, it is a primary driver of school choice. The decision to attend school at all is driven by student quality, measured by the top school admitted to, and the quality

of the most-preferred (top choice) school to which a student was admitted. Females are also slightly more likely to attend college. Increased cost of schooling decreases the likelihood of selecting a particular school, while aid amounts, school quality as measured by graduation rate, and instructional spending increase the likelihood of attending that school. School quality is therefore important in both portions of the college decision process (attendance and choice between schools), even though there is no obvious income benefit related to quality. The schooling decision is a tradeoff between desires for attendance at a more selective institution and a cheaper institution, yet the benefit of paying for increased selectivity is unclear.

## 4.8 Future work

The primary challenge in the development of the models presented here is the lack of a long time series of income information for each student. However, as the NLSY 1997 continues to be administered and more interview data are collected, this model can be updated to reflect additional income information. As NLSY 1997 respondents continue to report income data, educational outcomes, and attained degrees, projection methods similar to the one presented in section 4.5.3 could be used to create a model that focuses on income across the whole lifetime, modeling difference in income curve shape as well as income variance between admission and attendance groups. Additionally, income differences based on institutional choices may exist for particular subsets of the population (such as a particular major). These differences could be included in the choice models, modeling schooling decisions as selection between future income streams.

Recently, several groups have suggested the use of sophisticated risk-adjusted lifecycle choice models for evaluating returns to higher education. In a lifecycle choice model, employment and savings decisions are made over time, and the expected value and variance of future income is used to determine the worth of income streams

resulting from a particular educational choice. The lifecycle choice approach can be applied to the school choice problem by viewing school choice as selection between different risky income streams and estimating empirically the income dynamics for each possible choice. As more data are collected as part of NLSY 1997, it will become possible to estimate the necessary dynamics of realized an hypothetical future income streams for each individual and each educational choice they face.

The lifecycle choice model was popularized by two seminal papers by Robert C. Merton (Merton, 1969) (Merton, 1971). Individuals face a risky future income stream and must make savings and consumption decisions so as to maximize their overall lifetime consumption. More complex version of Merton's models include multiple hedging assets, incomplete markets, multiple sources of income uncertainty, and a variety of other adjustments that must in many cases be solved numerically or iteratively (see e.g. Gourinchas and Parker (1999), Henderson (2005), and Carroll (2004)). Early papers applying these lifecycle choice models to questions in higher education include work by Brown et al. (2012) and Bhuller et al. (2011). Brown et al. (2012) show that proper adjustment for income risk over the lifetime reduces estimates of the benefit of college education. Bhuller et al. (2011) model differences in the lifetime earnings curve based on different levels of education, pointing out that lifecycle bias arises if post-graduation income is used as a proxy for all future earnings. Cocco et al. (1998) study the effect of human capital and education on investment and savings decisions throughout the lifecycle, examining the impact of credit constraints and labor income uncertainty. As new data become available, the current model will benefit from increased sample size, more information about earnings differences between groups, and future application of a lifecycle choice approach for improving the income estimates found in section 4.5.

A second natural extension of this work is a more in-depth study of non-income drivers of the college decision. Since we find that income is not significantly affected

by school choice, it is somewhat surprising to see that school quality metrics such as graduation rate and faculty salary are the main drivers of institutional choice. Future research should investigate whether these are indeed the true drivers of students' decisions, or whether a perceived boost in income from attendance at a better institution is behind these choices.

# CHAPTER V

# Conclusion

This dissertation tackles three important questions related to higher education markets and the role of monetary factors and financial aid in these markets. Chapter II provides context for a more thorough examination of US higher education by studying the role of public and private funding in twelve countries in North America and Europe. Chapter III looks at the effect of financial factors on the supply and demand balance in the US higher education market, studying drivers of enrollment on both sides. Finally, chapter IV provides a glimpse into the individual-level college choice process, helping us understand whether and how financial considerations play into student decisions.

The US higher education market function quite differently from most Western European systems. In the United States, most institutions of higher education expect students to pay tuition and fees with private funds, though aid is often available. In many European countries, government subsidies have eliminated or severly reduced tuition and fees for tertiary studies, with students and families responsible for only small enrollment fees, living expenses, and specialty program charges. Throughout the Western world, governments are interested in providing high quality education to as many qualified students as possible. In addition to developing a well-educated workforce, high quality universities attract foreign talent, funding, and businesses.

The study presented in chapter II examines drivers of higher education enrollment, and finds that overall wealth (measured by GDP) is the primary driver of enrollment changes. Especially in countries like the United States, where private funds form the basis for educational spending, GDP increases are translated quite directly into increased enrollment at institutions of higher education. We do not see significant differences in the effect of GDP on enrollments as a result of recent European reforms, most of which lead to increased privatization and autonomy in the higher education market.

The United States government has reacted to the problem of ever increasing tuition prices by vastly expanding its federal financial aid programs. Private aid has also grown, and individual institutions are stepping up their support through scholarships, tuition waivers, work study, and discounts. Chapter III presents a macro-level analysis of supply and demand in the changing higher education market from 1976 through 2007. We find that financial factors are important on both the supply and demand sides. Revenue and cost concerns appear to drive supply-side (institutional) decisions, while students focus on post-college benefit of higher education and debt levels. We find support for the hypothesis that schools are incentivised to continually increase spending, though increased debt aversion amongst consumers may lead to increased price sensitivity.

Concerns about college affordability are becoming more pervasive in individual decisions about higher education. In chapter IV, we study the factors driving the college attendance and school choice decisions, with a focus on the effect of future income. We find that affordability is a primary decision driver, with college quality providing a significant counter-force to the desire to attend an affordable institution. However, we do not see that attendance at a higher quality institution translates directly into higher post-college earnings. Student ability and major choice appear to drive post-college income even after adjusting for ability differences, suggesting

that the choice of major has a bigger effect on income expectations than the choice of school. As more income data are collected on the individuals studied in this chapter, increasingly sophisticated models of income expectations over the lifetime will allow us to develop further insights into the effect of post-college payoffs on the attendance and choice decisions.

# APPENDICES

# APPENDIX A

# Appendices for Chapter II: Higher education funding in the Western world

## A.1 Starting point for alternate models

This appendix provides two alternate baseline models considered during analysis. These models use population (table A.1) and spending (table A.2) instead of GDP to construct the baseline relationship between country size and enrollment. Models developed from these starting points produce results very similar to those presented in the main analysis of chapter II. Note that the portion of both spending and population that is correlated with GDP provides most of the predictive power.

Table A.1: Effect of population correlated and uncorrelated with GDP on new enrollment. $newEnrollment_{i,t} = \beta_0 uncorrelatedPopulation_{i,t} + \beta_1 correlatedPopulation_{i,t}$.[a,b]

| Ordinary least squares regression | | | |
|---|---|---|---|
| Adjusted $R^2$ | 0.3352 | | |
| Variable[c] | Coefficient value | St. error | p-value |
| (Intercept) | 2905.1 | 2506.7 | |
| Population uncorr. w. GDP | -916.8 | 664.3 | 0.17 |
| Population corr. w. GDP | 18087.5 | 2262.3 | $6.38 \times 10^{-13}$ |

[a]Population is broken out into components that are correlated and uncorrelated with GDP. The portion of population correlated with GDP measures increases in wealth associated with population growth.

[b]Data include yearly GDP, population, and enrollment figures for countries listed in table 2.1 from 1997 to 2008.

[c]For detailed variable descriptions see table 2.2.

Table A.2: Effect of spending on tertiary education correlated and uncorrelated with GDP on new enrollment. $newEnrollment_{i,t} = \beta_0 uncorrelatedSpending_{i,t} + \beta_1 correlatedSpending_{i,t}$.[a,b]

| Ordinary least squares regression | | | |
|---|---|---|---|
| Adjusted $R^2$ | 0.3032 | | |
| Variable[c] | Coefficient value | St. error | p-value |
| (Intercept) | 1058.2 | 2680.9 | |
| Spending uncorr. w. GDP | -2013.2 | 809.6 | 0.01 |
| Spending corr. w. GDP | 7643.4 | 997.1 | $3.77 \times 10^{-12}$ |

[a]Spending is broken out into components that are correlated and uncorrelated with GDP. The portion of spending correlated with GDP measures increases in tertiary education spending that are related to population growth.

[b]Data include yearly GDP, population, and enrollment figures for countries listed in table 2.1 from 1997 to 2008.

[c]For detailed variable descriptions see table 2.2.

# APPENDIX B

# Appendices for Chapter III: The effect of credit growth and financial aid on college tuition and fees

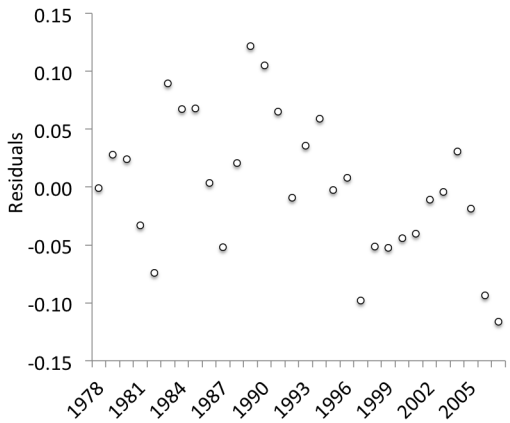
## B.1 Final model residual plots

This appendix provides plots of residuals over time for the final models in tables 3.4 and 3.5 that make both the two-stage least squares adjustment for endogeneity of net tuition price and the AR(1) autoregressive error term adjustment for heteroskedasticity. These plots do not show the second stage model residuals $\mathbf{Y}$ and $\mathbf{W}$ but rather the white noise terms from the autoregressive equation for estimation of residuals, $\mathbf{e}_D$ and $\mathbf{e}_S$, as seen in equations (3.2) and (3.3). Heteroskedasticity is dramatically reduced, with errors appearing to be white noise.


(a) Supply model.[a,b]

[a]Model is provided in table 3.4.

[b]This plots does not show the second stage supply model residuals $\mathbf{Y}$ but rather the white noise term from the autoregressive equation for estimation of residuals, $\mathbf{e}_S$, as seen in equation (3.2).




(b) Demand model.[a,b]

[a]Model is provided in table 3.5.

[b]This plot does not show the second stage demand model residuals $\mathbf{W}$ but rather the white noise term from the autoregressive equation for estimation of residuals, $\mathbf{e}_D$, as seen in equation (3.3).

Figure B.1: Residuals over time, final models in tables 3.4 and 3.5.

## B.2 Demand model with offerings change tuition component

In the model below, we examine the effect of the component of net tuition that is uncorrelated with the cost of operations (HEPI index). We refer to this as offerings change, since it measures tuition fluctuations caused by changes in offerings to students, meaning changes in service level or quality of the educational experience. We see that new offerings increase demand. The component of tuition perfectly correlated with the cost of operations appears to have no effect.

Table B.1: Demand model, offerings change only (enrollment per high school graduate).[a,b]

Two-stage least squares regression

| Correlation (model estimates vs. actual) | 0.56 | | |
|---|---|---|---|
| Exclusion restrictions | Test statistic | p-value | |
| Sargan | 4.8347 | 0.0892 | |
| Basmann | 4.6194 | 0.0993 | |
| Variable | Coefficient value | St. error | p-value |
| (Intercept) | 0.0031 | 0.0173 | |
| Benefit of college | 0.0230 | 0.0201 | 0.2624 |
| Credit effects per student | -0.1478 | 0.0489 | 0.0055 |
| Offerings change per student[c] | 0.0022 | 0.0012 | 0.0640 |

[a]Model equation is given in equation (3.2), with net tution per student replaced by offerings change per student.

[b]For detailed variable descriptions see table 3.1.

[c]Offerings change refers to the portion of net tuition that is uncorrelated with the cost of operations of schools, as measured by the HEPI index. This measures changes in tuition caused by changes in offerings to students instead of price increases for services already being offered.

## B.3 Main dataset

This appendix provides the input dataset for all models described here. Note that not all variables are included in the final models. The data provided here are extrapolated from publicly available data as indicated in footnotes. These data points have not been detrended according to equation (3.1).

Table B.2: Main dataset

| Category | | Quantity | Cost of operations | Non-tuition revenue | | | |
|---|---|---|---|---|---|---|---|
| Variable | Year | Enrollment at all institutions (all years)/high school graduate[a] | HEPI index value[b] | Current fund expenditures per student[c,d] | Yale/Harvard endowment market value per student[e,f] | Yale endowment spending per student[g,h] | Donations (voluntary support) per student[i] |
| Unit | | | Index value in 1983=100 | $ | Thousand $ | Thousand $ | Thousand $ |
| | *1976* | 2.645 | 59.65 | 8,388.06 | 109.18 | 5.850 | 0.548 |
| | *1977* | 2.680 | 63.60 | 8,410.72 | 110.34 | 5.362 | 0.580 |
| | *1978* | 2.681 | 68.10 | 8,433.38 | 107.04 | 4.942 | 0.610 |
| | *1979* | 2.763 | 74.00 | 8,456.04 | 101.41 | 4.486 | 0.598 |
| | *1980* | 2.909 | 81.65 | 8,478.70 | 98.13 | 3.979 | 0.557 |
| | *1981* | 2.997 | 89.85 | 8,655.86 | 98.97 | 3.663 | 0.555 |
| | *1982* | 3.091 | 96.95 | 8,987.53 | 95.56 | 3.573 | 0.591 |
| | *1983* | 3.242 | 102.40 | 9,319.20 | 109.52 | 3.631 | 0.637 |
| | *1984* | 3.288 | 107.80 | 9,650.86 | 118.98 | 3.551 | 0.693 |
| | *1985* | 3.362 | 113.55 | 9,982.53 | 122.93 | 3.630 | 0.736 |
| | *1986* | 3.397 | 118.60 | 10,385.20 | 151.39 | 3.970 | 0.773 |
| | *1987* | 3.377 | 123.55 | 10,699.16 | 177.90 | 4.300 | 0.786 |
| | *1988* | 3.431 | 129.50 | 10,855.76 | 183.87 | 4.827 | 0.786 |
| | *1989* | 3.668 | 136.80 | 10,957.11 | 182.90 | 5.312 | 0.772 |
| | *1990* | 3.929 | 144.50 | 11,021.73 | 186.48 | 5.596 | 0.760 |
| | *1991* | 4.168 | 150.85 | 11,054.75 | 183.60 | 6.017 | 0.745 |
| | *1992* | 4.210 | 155.70 | 11,146.74 | 184.41 | 6.483 | 0.762 |
| | *1993* | 4.187 | 160.60 | 11,422.95 | 197.98 | 7.016 | 0.788 |
| | *1994* | 4.153 | 165.70 | 11,750.52 | 213.88 | 7.711 | 0.811 |
| | *1995* | 4.103 | 170.55 | 11,991.40 | 231.88 | 8.298 | 0.857 |
| | *1996* | 4.086 | 175.70 | 12,217.89 | 269.77 | 8.984 | 0.920 |
| | *1997* | 3.993 | 181.55 | 12,581.53 | 324.67 | 9.984 | 1.010 |
| | *1998* | 3.917 | 186.90 | 13,097.61 | 381.26 | 11.325 | 1.112 |
| | *1999* | 3.914 | 193.00 | 13,664.01 | 421.41 | 12.834 | 1.196 |
| | *2000* | 3.967 | 201.70 | 14,336.99 | 496.26 | 14.033 | 1.222 |
| | *2001* | 4.089 | 210.75 | 15,030.70 | 541.76 | 15.725 | 1.154 |
| | *2002* | 4.164 | 218.10 | 15,707.21 | 514.57 | 18.665 | 1.071 |
| | *2003* | 4.181 | 226.35 | 16,499.41 | 512.24 | 21.227 | 1.028 |
| | *2004* | 4.221 | 235.65 | 17,353.85 | 558.92 | 22.627 | 1.018 |
| | *2005* | 4.235 | 245.80 | 18,270.53 | 625.43 | 23.956 | 1.040 |
| | *2006* | 4.195 | 256.05 | 19,249.45 | 695.85 | 25.623 | 1.069 |
| | *2007* | 4.171 | 266.75 | 20,290.60 | 800.92 | 27.417 | 1.073 |

[a] National Center for Education Statistics (2008), Table 219.

[b] National Center for Education Statistics (2008), Table 31, Commonfund Institute (2009).

[c] National Center for Education Statistics (2008), Table 360.

[d] We assume linear growth between 1976-1979 and 1981-1984. 1997-2001 values are based on regression estimation from public expenditures. We assume quadratic growth 2002-2007 based on best fit from historical data.

[e] Harvard University Office of the Provost (2009), Yale University Office of Institutional Research (2009).

[f] Harvard endowment values 1975-1977 assume linear growth at the same rate as 1978-82, and Harvard enrollment 1975-87 assume linear growth at 1988-91 rate. Harvard and Yale are used because their investment models are used by other schools and for data availability reasons.

[g] Yale University Office of Institutional Research (2009).

[h] We assume Yale endowment 1976-1987 values grow linearly at same rate as 1988-1992. Yale and Harvard values are used because their investment models are used by other schools and for data availability reasons.

[i] National Center for Education Statistics (2008), Table 358.

Table B.3: Main dataset (continued)

| Category | | Financial aid to schools | Benefit of college | | | Household credit |
|---|---|---|---|---|---|---|
| Variable | Year | Total government support per student[a,b] | Earnings difference, (bachelor's or higher minus high school)[c] | Fraction of population with bachelor's degree[d,e] | Unemployment rate[f] | Household debt per student[g] |
| Unit | | $ | $ | % persons 25 and older | Proportion of 16+ civilian labor force | Million $ |
| | *1976* | 4,444 | 6,091 | 0.147 | 0.077 | 173.14 |
| | *1977* | 4,520 | 6,253 | 0.153 | 0.071 | 185.64 |
| | *1978* | 4,543 | 6,013 | 0.159 | 0.061 | 203.08 |
| | *1979* | 4,528 | 6,039 | 0.166 | 0.058 | 207.10 |
| | *1980* | 4,417 | 6,000 | 0.171 | 0.071 | 192.10 |
| | *1981* | 4,303 | 5,868 | 0.176 | 0.076 | 183.93 |
| | *1982* | 4,245 | 6,053 | 0.181 | 0.097 | 179.68 |
| | *1983* | 4,350 | 6,440 | 0.186 | 0.096 | 189.71 |
| | *1984* | 4,561 | 6,407 | 0.190 | 0.075 | 208.94 |
| | *1985* | 4,843 | 7,288 | 0.194 | 0.072 | 236.70 |
| | *1986* | 5,114 | 7,729 | 0.195 | 0.070 | 255.41 |
| | *1987* | 5,258 | 7,545 | 0.200 | 0.062 | 262.77 |
| | *1988* | 5,419 | 7,727 | 0.205 | 0.055 | 271.84 |
| | *1989* | 5,556 | 8,265 | 0.212 | 0.053 | 275.13 |
| | *1990* | 5,564 | 7,917 | 0.213 | 0.056 | 275.73 |
| | *1991* | 5,575 | 6,975 | 0.214 | 0.068 | 268.27 |
| | *1992* | 5,629 | 7,096 | 0.215 | 0.075 | 272.11 |
| | *1993* | 5,648 | 7,797 | 0.219 | 0.069 | 282.43 |
| | *1994* | 5,753 | 7,887 | 0.224 | 0.061 | 296.49 |
| | *1995* | 5,835 | 7,524 | 0.231 | 0.056 | 308.35 |
| | *1996* | 5,867 | 7,976 | 0.236 | 0.054 | 315.77 |
| | *1997* | 6,000 | 8,401 | 0.240 | 0.049 | 322.49 |
| | *1998* | 6,247 | 9,034 | 0.246 | 0.045 | 339.49 |
| | *1999* | 6,555 | 9,297 | 0.253 | 0.042 | 351.91 |
| | *2000* | 7,011 | 9,917 | 0.257 | 0.040 | 361.34 |
| | *2001* | 7,511 | 9,779 | 0.262 | 0.047 | 368.71 |
| | *2002* | 7,956 | 9,573 | 0.269 | 0.058 | 383.78 |
| | *2003* | 8,307 | 9,380 | 0.273 | 0.060 | 406.94 |
| | *2004* | 8,492 | 9,283 | 0.277 | 0.055 | 430.64 |
| | *2005* | 8,470 | 9,632 | 0.277 | 0.051 | 455.65 |
| | *2006* | 8,479 | 9,542 | 0.282 | 0.046 | 478.02 |
| | *2007* | 8,505 | 9,283 | 0.289 | 0.046 | 481.68 |

[a] National Center for Education Statistics (2008), Tables 348, 349, 353.

[b] Values in 2001-2003 are based on the sum of support for public and private schools reported in Digest of Education Statistics Tables 349 and 350. We assume linear growth rate in the percentage of financial aid going to public schools from 2004 to 2007. We assume linear growth in 2007 based on observations from 2004 to 2006.

[c] US Census Bureau and Bureau of Labor Statistics (2009), Table A-3. Mean Earnings of Workers 18 Years and Over, by Educational Attainment, Race, Hispanic Origin, and Sex (1975 to 2007).

[d] National Center for Education Statistics (2008), Table 8, US Census Bureau and Bureau of Labor Statistics (2009).

[e] We assume linear growth during 1976-1979 and 1981-1984.

[f] US Census Bureau and Bureau of Labor Statistics (2009).

[g] US Federal Reserve (2009), Table D.3.

Table B.4: Main dataset (continued)

| Category | | Household wealth | | Financial aid to students | | |
|---|---|---|---|---|---|---|
| Variable | Year | Per capita disposable income[a] | Standard & Poor's Case-Shiller Home price index (non-seasonally adjusted, real)[b,c] | Federal grants per student[d] | Federal student loans per student [e] | Federal work study award per student [f,g] |
| Unit | | $ | Index value in 1983=100 | $ | $ | $ |
| | *1976* | 10,496 | 1.46 | 3,160 | 373.12 | 72.42 |
| | *1977* | 10,749 | 1.41 | 3,648 | 404.48 | 83.82 |
| | *1978* | 11,074 | 1.35 | 4,281 | 474.85 | 83.38 |
| | *1979* | 10,959 | 1.25 | 5,773 | 592.27 | 84.93 |
| | *1980* | 10,672 | 1.13 | 7,643 | 760.59 | 84.60 |
| | *1981* | 10,700 | 1.05 | 7,817 | 857.48 | 75.53 |
| | *1982* | 10,767 | 1.01 | 6,986 | 814.11 | 66.40 |
| | *1983* | 11,140 | 1.00 | 7,763 | 804.56 | 66.01 |
| | *1984* | 11,773 | 0.99 | 8,379 | 901.61 | 67.03 |
| | *1985* | 11,999 | 0.97 | 8,350 | 935.24 | 63.20 |
| | *1986* | 12,354 | 0.98 | 8,443 | 926.34 | 60.07 |
| | *1987* | 12,452 | 0.96 | 9,934 | 995.53 | 56.48 |
| | *1988* | 12,854 | 1.00 | 10,078 | 1,057.23 | 52.80 |
| | *1989* | 13,011 | 1.02 | 9,761 | 1,014.19 | 49.93 |
| | *1990* | 13,010 | 0.98 | 9,633 | 971.34 | 50.31 |
| | *1991* | 12,872 | 0.93 | 10,104 | 952.48 | 49.57 |
| | *1992* | 13,140 | 0.91 | 10,423 | 983.36 | 49.08 |
| | *1993* | 13,086 | 0.89 | 13,686 | 1,164.52 | 48.43 |
| | *1994* | 13,278 | 0.89 | 16,071 | 1,437.81 | 46.45 |
| | *1995* | 13,432 | 0.88 | 17,554 | 1,626.74 | 45.02 |
| | *1996* | 13,611 | 0.88 | 18,732 | 1,730.86 | 48.50 |
| | *1997* | 13,866 | 0.89 | 19,255 | 1,789.28 | 50.97 |
| | *1998* | 14,438 | 0.93 | 19,627 | 1,817.12 | 53.68 |
| | *1999* | 14,619 | 0.98 | 20,136 | 1,816.73 | 51.81 |
| | *2000* | 15,066 | 1.03 | 20,363 | 1,797.24 | 49.59 |
| | *2001* | 15,136 | 1.09 | 21,614 | 1,783.82 | 48.84 |
| | *2002* | 15,452 | 1.17 | 24,379 | 1,864.86 | 49.33 |
| | *2003* | 15,655 | 1.26 | 27,574 | 2,047.41 | 48.76 |
| | *2004* | 16,033 | 1.40 | 29,574 | 2,197.85 | 46.09 |
| | *2005* | 16,036 | 1.56 | 30,316 | 2,268.44 | 42.91 |
| | *2006* | 16,447 | 1.59 | 30,806 | 2,280.17 | 40.01 |
| | *2007* | 16,613 | 1.47 | 33,877 | 2,346.54 | 37.90 |

[a] Bureau of Economic Analysis (2009), Table 2.1.

[b] Standard & Poor's (2009).

[c] We assume linear growth during 1976-1987, based on growth rate from 1987 to 1996.

[d] The College Board (2009), Table 1.

[e] The College Board (2009), Table 1.

[f] The College Board (2009), Table 1.

[g] Values prior to 1996 are discounted by 11% to reflect that these are commitments instead of disbursements, which are about 11% higher.

Table B.5: Main dataset (continued)

| Category | | Institutional aid | Tuition | Interest rate |
|---|---|---|---|---|
| Variable | Year | Institutional grants per student[a] | Tuition and fees (all institutions) per student[b] | Real interest rate (Treasury interest rate - change in CPI)[c] |
| Unit | | $ | $ | One year real treasury rate |
| | *1976* | 261.77 | 1,544 | 0.0012 |
| | *1977* | 250.02 | 1,575 | -0.0042 |
| | *1978* | 242.84 | 1,578 | 0.0075 |
| | *1979* | 237.50 | 1,540 | -0.0070 |
| | *1980* | 229.10 | 1,488 | -0.0150 |
| | *1981* | 219.23 | 1,510 | 0.0448 |
| | *1982* | 220.18 | 1,597 | 0.0611 |
| | *1983* | 239.16 | 1,711 | 0.0637 |
| | *1984* | 270.58 | 1,813 | 0.0659 |
| | *1985* | 297.32 | 1,936 | 0.0486 |
| | *1986* | 328.20 | 2,050 | 0.0459 |
| | *1987* | 355.53 | 2,099 | 0.0312 |
| | *1988* | 361.93 | 2,162 | 0.0351 |
| | *1989* | 383.22 | 2,216 | 0.0371 |
| | *1990* | 444.06 | 2,240 | 0.0249 |
| | *1991* | 488.42 | 2,313 | 0.0165 |
| | *1992* | 531.14 | 2,424 | 0.0088 |
| | *1993* | 581.06 | 2,541 | 0.0044 |
| | *1994* | 624.11 | 2,656 | 0.0276 |
| | *1995* | 660.41 | 2,750 | 0.0311 |
| | *1996* | 689.03 | 2,837 | 0.0257 |
| | *1997* | 728.09 | 2,903 | 0.0334 |
| | *1998* | 779.91 | 2,996 | 0.0349 |
| | *1999* | 825.27 | 3,077 | 0.0287 |
| | *2000* | 842.39 | 3,082 | 0.0275 |
| | *2001* | 822.27 | 3,112 | 0.0064 |
| | *2002* | 801.52 | 3,238 | 0.0042 |
| | *2003* | 828.43 | 3,427 | -0.0104 |
| | *2004* | 872.23 | 3,634 | -0.0077 |
| | *2005* | 914.44 | 3,769 | 0.0023 |
| | *2006* | 955.91 | 3,892 | 0.0171 |
| | *2007* | 982.15 | 4,002 | 0.0168 |

[a]The College Board (2009), Table 1.
[b]National Center for Education Statistics (2008), Table 331.
[c]US Federal Reserve (2011).

## B.4 Pre-estimation test

The pre-estimation test provides an indication of the value of a particular proxy variable in predicting enrollment. The quantity metric, enrollment per high school graduate, is regressed on each proxy variable individually using ordinary least squares regression. Although coefficients and standard errors are not necessarily correct because of the clear presence of omitted variable bias, these regressions provide some additional consistency checks for the final models provided in tables 3.4 and 3.5. We compare pre-estimation test signs with the signs found in the final models to ensure consistency.

Signs are generally consistent between the pre-estimation t-tests and the final models. One exception is financial aid to schools (per student) in the supply model, which has an insignificant pre-estimation test result (p-value = 0.39) but becomes significant once we include other relevant variables to eliminate omitted variable bias. Net tuition (per student) cannot be adequately pre-tested due to the presence of endogeneity, and because there is omitted variable bias in the pre-estimation model regressing enrollment on tuition price alone. This pre-estimation model cannot account for the fact that tuition price should have a different sign in the supply and the demand model. We also see some sign inconsistencies between the first principal component of college benefit in the demand model and the pre-tests of the underlying variables of this principal component. However, since the variables in the principal component have different signs, and because we do not have a strong theoretical basis for the "correct" sign of these metrics of the benefit of college, we cannot accurately compare the principal component sign to the sign of underlying variables.[1] A pre-estimation test of the principal component itself yields the same positive sign we see

[1]For example, an increase in the percentage of the adult population holding a bachelor's degree may make a degree less valuable, as described by Fortin (2006), thus presumably decreasing demand. On the other hand, prevalence of bachelor's degrees in a society may make a college education seem more relevant and increase the perceived importance of education.

in the final demand model.

Table B.6: Pre-estimation test results (p-values are p-values of coefficients).[a,b]

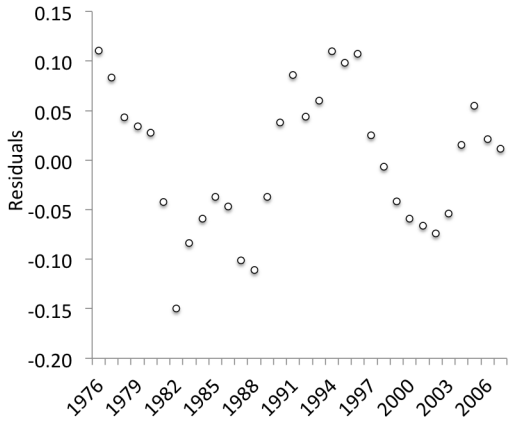
| **Variable name** | **Coefficient sign** | **p-value** |
|---|---|---|
| Aid to schools per student | - | 0.3861 |
| Bachelor's percentage | - | 0.1833 |
| Disposable income per student | - | 0.0189 |
| Donations per student | - | 0.0023 |
| Earnings difference | - | 0.1674 |
| Endowment distribution per student | - | 0.0067 |
| Endowment value per student | - | 0.0001 |
| Grants per student | - | 0.0166 |
| HEPI | + | 0.6928 |
| Household debt per student | - | 0.0016 |
| Student loans per student | - | 0.0073 |
| Unemployment | + | 0.0057 |

[a]For detailed variable descriptions, see table 3.1.

[b]Signs and p-values are the result of regressing enrollment per high school graduate on each candidate variable individually. These values are used to validate coefficient signs in the final models in tables 3.4 and 3.5.

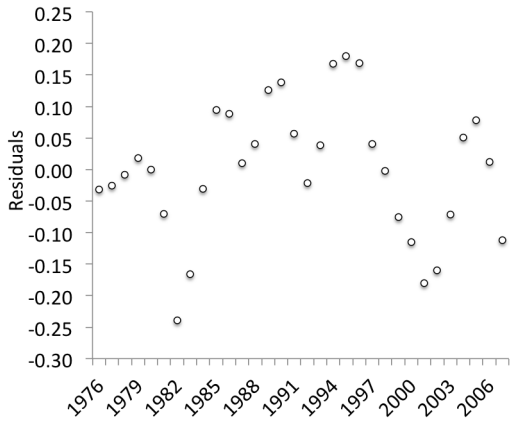
## B.5 Preliminary model residual plots

This appendix provides plots of residuals over time for the preliminary models that make the two-stage least squares adjustment for endogeneity of net tuition price but do not make the AR(1) autoregressive error term adjustment for heteroskedasticity. Note the cyclical (non-random) nature of these plots, indicating that heteroskedasticity is present. This is due to the autocorrelated nature of the underlying dataset.




(a) Supply model.[a]

[a]This plot shows the second stage supply model residuals before the AR(1) adjustment, **Y**, as seen in equation (3.2).




(b) Demand model.[a]

[a]This plot shows the second stage demand model residuals before the AR(1) adjustment, **W**, as seen in equation (3.3).

Figure B.2: Residuals over time, preliminary models.

## B.6 Comparison of parameter estimates in data subsets

In order to examine robustness of the models in tables 3.4 and 3.5, we construct models of the same structure using subsets of the data. We estimate separate models for the period 1976 to 1990 and the period 1991 to 2007. We estimate the autocorrelation component separately for each period, and then estimate coefficients for each variable. We find that effects of some variables change over time, as indicated in tables B.7 and B.8. These tables also show the result of a set of t-tests examining whether coefficients change significantly between the two periods. We find that some significant changes occur, but conclude that the second half of the data (1991 to 2007) yields results very close to those attained from the full dataset.

Table B.7: Parameter estimates in data subsets, supply model.[a]

Two-stage least squares regression

**Period 1976 to 1990**

| | | | |
|---|---|---|---|
| $b_0$ (residual autocorrelation) | 0.290 | | |
| Correlation (model estimates vs. actual) | 0.602 | | |
| Variable[b] | Coefficient value | St. error | p-value |
| (Intercept) | -0.1231 | 0.0899 | |
| Cost of operations (HEPI) | -0.0064 | 0.0504 | 0.9018 |
| Non-tuition revenue per student | -0.7053 | 0.3258 | 0.0556 |
| Financial aid to schools per student | -0.0004 | 0.0007 | 0.5171 |
| Net tuition per student | 0.0015 | 0.0021 | 0.4946 |

**Period 1991 to 2007**

| | | | |
|---|---|---|---|
| $b_0$ (residual autocorrelation) | -0.314 | | |
| Correlation (model estimates vs. actual) | 0.877 | | |
| Variable | Coefficient value | St. error | p-value |
| (Intercept) | 0.0042 | 0.0124 | |
| Cost of operations (HEPI) | 0.0462 | 0.0113 | 0.0018 |
| Non-tuition revenue per student | -0.2897 | 0.0534 | 0.0002 |
| Financial aid to schools per student | 0.0001 | 0.0000 | 0.0114 |
| Net tuition per student | -0.0008 | 0.0003 | 0.0279 |

t-test for coefficient difference, $H_0$: Coefficients for first and second period are the same

| | p-value | Result |
|---|---|---|
| Cost of operations (HEPI) | 0.0738 | Fail to reject $H_0$ at $\alpha = .05$ |
| Non-tuition revenue per student | 0.1177 | Fail to reject $H_0$ at $\alpha = .05$ |
| Financial aid to schools per student | 0.0399 | Reject $H_0$ at $\alpha = .05$ |
| Net tuition per student | 0.7716 | Reject $H_0$ at $\alpha = .05$ |

[a]Model equation is given in equation (3.2), with data split into two time periods.
[b]For detailed variable descriptions see tables B.2-B.5.

Table B.8: Parameter estimates in data subsets, demand model.[a]

Ordinary least squares regression

**Period 1976 to 1990**

| | | | |
|---|---|---|---|
| $d_0$ (residual autocorrelation) | 0.460 | | |
| Correlation (model estimates vs. actual) | 0.879 | | |
| Variable[b] | Coefficient value | St. error | p-value |
| (Intercept) | -0.0142 | 0.0258 | |
| Benefit of college | -0.0786 | 0.0504 | 0.1475 |
| Credit effects per student | -0.1840 | 0.0433 | 0.0014 |
| Net tuition per student | -0.0026 | 0.0018 | 0.1876 |

**Period 1991 to 2007**

| | | | |
|---|---|---|---|
| $d_0$ (residual autocorrelation) | -0.146 | | |
| Correlation (model estimates vs. actual) | 0.553 | | |
| Variable | Coefficient value | St. error | p-value |
| (Intercept) | -0.0446 | 0.0160 | |
| Benefit of college | 0.0243 | 0.0338 | 0.4866 |
| Credit effects per student | -0.0656 | 0.0511 | 0.2233 |
| Net tuition per student | 0.0007 | 0.0008 | 0.4121 |

t-test for coefficient difference, $H_0$: Coefficients for first and second period are the same

| | p-value | Result |
|---|---|---|
| Benefit of college | 0.0000 | Reject $H_0$ at $\alpha = .05$ |
| Credit effects per student | 0.0031 | Reject $H_0$ $\alpha = .05$ |
| Net tuition per student | 0.1659 | Fail to reject $H_0$ at $\alpha = .05$ |

[a]Model equation is given in equation (3.3), with data split into two time periods.
[b]For detailed variable descriptions see tables B.2-B.5.

## B.7 Ljung-Box test of residual autocorrelation

Table B.9 provides results of the Ljung-Box test of residual autocorrelation for supply and demand models with and without the first-order autoregressive error terms. As we see here, the AR(1) adjustment eliminates autocorrelation from the supply model. Demand model residuals still exhibit some autocorrelation, but it is reduced by the AR(1) adjustment.

Table B.9: Ljung-Box test for autocorrelation of residuals, p-values with and without AR(1) adjustment.[a]

| $H_0$: Residuals uncorrelated at lag 12 | |
|---|---|
| Supply model | p-values |
| With AR(1) adjustment | 0.301 (fail to reject $H_0$ at $\alpha = .05$) |
| Without AR(1) adjustment | 0.166 (reject $H_0$ at $\alpha = .05$) |
| Demand model | p-values |
| With AR(1) adjustment | 0.0001 (reject $H_0$ at $\alpha = .05$) |
| Without AR(1) adjustment | $1.87 \times 10^{-6}$ (reject $H_0$ at $\alpha = .05$) |

[a]Residuals for models with the AR(1) adjustment are presented in appendix B.1. Residuals for models without this adjustment are presented in appendix B.5.

# APPENDIX C

# Appendices for Chapter IV: An examination of educational choices, student characteristics, and ability-adjusted income

## C.1 Variables necessary for building discrete choice model

Table C.1 provides an overview of candidate variables considered in constructing the models outlined in this paper. Source information, descriptions of missing data, and details about each variable are provided.

Table C.1: Candidate variables used in model construction. Candidate variables are used for models in tables 4.8 and 4.9.

| Variable Name | Description | Notes | Source |
|---|---|---|---|
| **Student characteristics** | | | |

| | | | |
|---|---|---|---|
| Top school admitted to | Barron's selectivity index for top admitted school | 1 indicates most selective schools, 5/6 indicates least selective. Note that Barron's original categories 5 and 6 are combined into type 5/6. Specialty schools (7) are excluded. | NLSY 97[1], Barron's[2] |
| School attended | Barron's selectivity index of attended school | 1 indicates most selective schools, 5/6 indicates least selective. Note that Barron's original categories 5 and 6 are combined into category 5/6. Specialty schools (7) are excluded. School attended is blank for those who do not attend school. | NLSY 97, Barron's |
| Graduated | Indicates whether individual has graduated from college by the current survey date | Latest survey data available are from 2010. Students attending college right after high school and taking 4 years to complete a degree would have expected graduation of 2007. | NLSY 97 |
| $\beta_0$ | Nelson Siegel income curve parameter | Parameter is a measure of expected lifetime income. Larger parameters indicate a higher lifetime earnings curve. Derivation of this parameter is explained in section 4.5. | NLSY 97, Census Bureau[3] |
| Gender | Student's gender | | NLSY 97 |
| Race/ Ethnicity | Student's race and ethnicity | Possible values are White, Black, American Indian/ Eskimo/ Aleut, Asian/ Pacific Islander, Other. | NLSY 97 |
| Grades | High school grades | Categorical high school grades, with 1 indicating mostly A's received and 8 indicating mostly failing grades received. | NLSY 97 |
| SAT Math | Math SAT score | Categorical Math SAT score. 1: 200-300, 2: 301-400, 3: 401-500, 4: 501-600, 5: 601-700, 6: 701-800, 0: no score. | NLSY 97 |
| SAT Verbal | Verbal SAT score | Categorical Verbal SAT score. 1: 200-300, 2: 301-400, 3: 401-500, 4: 501-600, 5: 601-700, 6: 701-800, 0: no score. | NLSY 97 |

[1]Bureau of Labor Statistics (2013)
[2]Barron's (2009)
[3]Census Bureau (2012)

| | | | |
|---|---|---|---|
| Major | Major categories for major at attended school | Possible values are math and sciences, social sciences, business and communications, engineering and computers, health, and humanities. | NLSY 97 |
| College year | Year first attended college | Used to ensure student attends college within two years of high school graduation. | NLSY 97 |
| Choice year | Year of the college choice (generally senior year of high school) | Used to ensure IPEDS data from the student's choice year are used. | NLSY 97 |
| Father education | Number of years of father's formal education | | NLSY 97 |
| Mother education | Number of years of mother's formal education | | NLSY 97 |
| Household size | Number of individuals (including student) living in household | Data point closest in time to the choice year is used. | NLSY 97 |
| Household income | Gross annual household income | Data point closest in time to the choice year is used. | NLSY 97 |
| Urban-rural | Residence in rural or urban area | Data point closest in time to the choice year is used. | NLSY 97 |
| High school type | High school type | Public, private, religious, alternative, etc. | NLSY 97 |

**School characteristics**

| | | | |
|---|---|---|---|
| List tuition | List out-of-state tuition | The advertised out-of-state tuition price, often called the sticker price. | IPEDS[4] |
| Loan percentage | Percentage of the student body receiving student loans. | Indicates whether or not this school participates in loan programs. | IPEDS |
| Federal grant percentage | Percentage of students receiving federal grants. | Serves as an indicator of the wealth of the student body, since many grants are specifically for lower-income students (Pell grants). | IPEDS |
| Gender ratio | Gender ratio | Enrolled males/enrolled females. | IPEDS |
| Total students | Number of enrolled full-time students. | | IPEDS |
| Control | Publicly or privately controlled institution | | IPEDS |

[4]National Center for Education Statistics (2009)

| | | | |
|---|---|---|---|
| Carnegie class | Adjusted Carnegie Class of institution. | Level 1: Research/Ph.D. granting, 2: Other graduate, 3: Bachelor's/liberal arts schools, 4: Specialty and associates-type degrees. | IPEDS |
| Selectivity | Selectivity from Barron's selectivity index | Specialty schools (Barron's index = 7) are excluded. | Barron's |
| Expenditures | Total expenditures per full-time student | | IPEDS |
| Instructional expenditures | Instructional expenditures per full-time student | IPEDS definition of instructional spending is used. Total expenses associated with instructional divisions of the institution, including compensation of instructors, community and adult education, tutoring, and other academic-related activities. | IPEDS |
| Faculty per student | Faculty per student per full-time student | | IPEDS |
| Average salary | Average salary of full-time faculty | Proxy for faculty quality and the percentage of faculty holding a Ph.D. | IPEDS |
| Division | Athletic division | Indicator if whether school is in top athletic division (division 1 NCAA). | IPEDS |
| Graduation rate | | Graduation rate within 150% of normal completion time. | IPEDS |

**Student/school interactions**

| | | | |
|---|---|---|---|
| Financial aid | Total financial aid received for the first year of schooling, including aid offered specifically for a particular school, aid offered no matter which school is attended, and in-state tuition discounts | Students that claim that they do know know financial aid amounts are treated as receiving zero financial aid, since it does not factor into the decision. If aid information is missing in the school choice section, aid from the school attended section is supplemented. This aid amount is adjusted based on the relationship between reported numbers where they are available in both sections.[5] | NLSY 97 |

[5] Aid from the schools attended section$*0.445 + 963.86$ yields an estimate of aid reported in the schools admitted to section (adjusted $R^2 = 0.2522$).

| | | | |
|---|---|---|---|
| Distance | Distance between home and school zip codes | Students that do not provide a zip code are located based only on state data. Zip code data points are translated into latitude and longitude. For schools that fail to report zip information to IPEDS, latitude and longitude and longitude data from Google Maps are used. | NLSY 97, IPEDS |
| In-state status | Student has in-state residency | If no residence state data point is provided, we assume student does not have in-state status. | NLSY 97, IPEDS |
| Urban rural match | Match of student residence and school's urban/rural characteristics | For schools that do not report urban/rural information to IPEDS, schools were re-searched on their individual websites and Google Maps. | NLSY 97, IPEDS |
| Selectivity difference | Selectivity of current candidate school minus selectivity of top admitted school of student | Selectivity of school is sometimes missing in the Barron's selectivity index of the correct year, in which case it can is predicted by $25^{th}$ and $75^{th}$ percentile SAT scores, percentage of applicants admitted, Carnegie Class, and faculty salaries.[6] | NLSY 97, IPEDS, Barron's |

[6] $R^2$ of this regression is 0.4893.

## C.2 Projecting lifetime income

### C.2.1 Functional form of the income curve

Synthetic work-life earnings curves suggest the shape of the income curve over the lifetime. We experiment with several functional forms that allow us to approximate this shape. The traditional Mincer model of lifetime earnings calls for a quadratic age-income profile model for log income:

$$log(y(t)) = \gamma_0 + \gamma_1 t + \gamma_2 t^2 + v \tag{C.1}$$

where $t$ is age and $v$ gives the (potential) number of years of experience, to allow for an adjustment for length of schooling. Past literature has shown that this functional form provides bad fit, requiring at least a fourth order model (Polachek, 2007). As a replacement for Mincer's model in this application, we suggest a restricted Nelson-Siegel curve. The Nelson-Siegel equation allows us to estimate each individual's lifetime expected earnings profile with only a few data points and provides close fit to Census synthetic work-life earnings curves for all levels of educational attainment.[7]

The Nelson-Siegel equation has four parameters, $\beta_0$, $\beta_1$, $\beta_2$, and $\tau$, and the function is given by:

$$y(t) = -\beta_0 + \beta_1 \left( \frac{1 - e^{-t/\tau}}{t/\tau} \right) + \beta_2 \left( \frac{1 - e^{-t/\tau}}{t/\tau} - e^{-t/\tau} \right) \tag{C.2}$$

where

- $\beta_0$ (level parameter) gives the long-term level of the function.
- $\beta_1$ (slope parameter) is found in the second term of the Nelson-Siegel function. The second term is an exponential decay function. A positive parameter yields

[7]Plots of these fits by educational attainment are provided in Figures C.2 and C.3. More information on the fit of these models is provided in section C.2.2.

a downward slope, a negative parameter an upward slope.

- $\beta_2$ (curvature parameter) is found in the third term of the Nelson-Siegel function. The third term is a Laguerre function (product of an exponential and a polynomial function) that produces the hump (positive parameter) or valley (negative parameter) in the function. A larger absolute value means the hump or valley is more pronounced. This parameter gives the rate at which the slope and curvature parameters decay to zero.

- $\tau$ (shape parameter) determines the steepness of the slope factor and the location of the maximum or minimum of the Laguerre function (third/curvature term).

Estimation of the model parameters is done numerically by using nonlinear optimization, grid search, Kalman filters and/or state space modeling. However, since income curves have a fairly common shape across the lifetime of all individuals, we are able to fix several of the parameters of the Nelson-Siegel curve. This not only ensures that lifetime income curves have the correct shape, but also reduces data requirements by limiting the number of parameters we must estimate.

### C.2.2 Parameter estimation

We begin by fixing $\tau$ so that maximum income is achieved at the correct point during an individual's career. In the synthetic work-life income data for people ranging from high school graduates to master's recipients, this maximum yearly income occurs at around age 50 (Census Bureau, 2012). We want to determine the value of $\tau$ that forces the maximum value of the third term in equation (C.2) to achieve its maximum when $t$ equals the desired value. The third term is the Laguerre function curvature term, $f(t,\tau) = \frac{1-e^{-t/\tau}}{t/\tau} - e^{-t/\tau}$. Let $t^*$ be the time at which we would like the maximum to occur and $\tau^*$ be the $\tau$ value that achieves this maximum, as shown

below:

$$f(t,\tau) = \frac{1-e^{-t/\tau}}{t/\tau} - e^{-t/\tau} \tag{C.3}$$

$$t^* = \arg\max_t [f(t,\tau^*)]$$

Setting $\tau = \tau^*$, equation (C.2) reduces to:

$$y(\tau) = -\beta_0 + \beta_1 A(t,\tau^*) + \beta_2 B(t,\tau^*) \tag{C.4}$$

where $A(t,\tau^*) = \frac{1-e^{-t/\tau^*}}{t/\tau^*}$ and $B(t,\tau^*) = \frac{1-e^{-t/\tau}}{t/\tau} - e^{-t/\tau}$ and $A$ and $B$ can be computed directly from the age input $t$ and the fixed curvature parameter $\tau^*$. Parameters $\beta_0$, $\beta_1$, and $\beta_2$ are estimated using ordinary least squares.

Figure C.1 shows the surface of the value of the third (curvature) term, $\frac{1-e^{-t/\tau}}{t/\tau} - e^{-t/\tau}$, over time and tau. We determine numerically that a maximum of 50 occurs when $\tau = 27.88$. With $\tau$ fixed, we can achieve close shape fits for the Census synthetic work-life earnings data, as shown in Figure C.2.

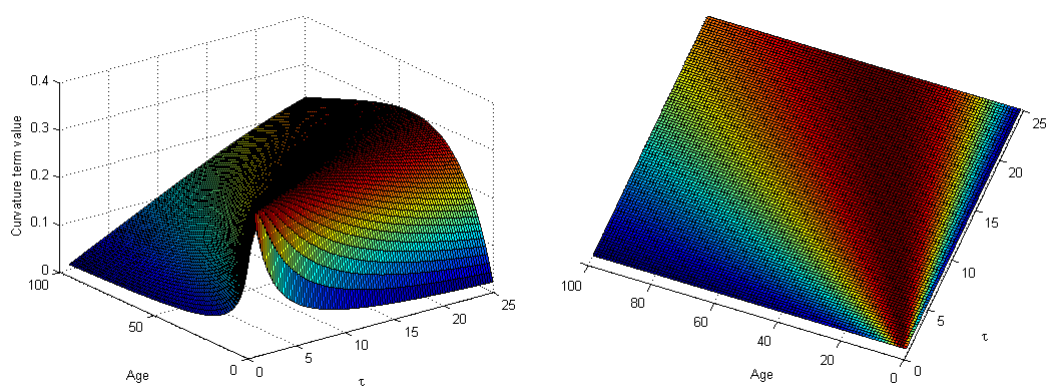



Figure C.1: Third (curvature) term in equation (C.2), $\frac{1-e^{-t/\tau}}{t/\tau} - e^{-t/\tau}$, over $\tau$ and age ($t$). Value of $\tau$ determines where maximum of equation (C.2) occurs.

Since we wish to further reduce the number of parameters to be estimated, we take advantage of the consistent relationship between the remaining Nelson-Siegel

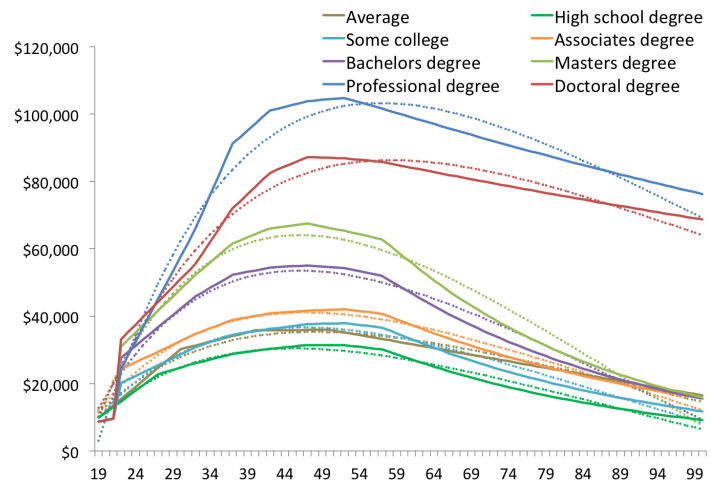



Figure C.2: Census synthetic lifetime income earnings curve fits based on equation (C.2) with fixed $\tau = \tau^*$ only. Dotted lines indicate Nelson-Siegel estimates and solid lines indicate Census data.[a],[b]

[a]Census Bureau (2012)
[b]$\tau^* = 27.88$ ensures that lifetime income maximum occurs at the desired age of 50.

parameters across education groups. Specifically, we notice that the ratios $\frac{\beta_0}{\beta_2}$ and $\frac{\beta_0}{\beta_1}$ are fairly consistent across education groups. We investigate three possible approaches of parameter reduction and test their ability to fit Census synthetic work-life income curves. The regression equation fit for each method is provided in below.

(a) Setting $\beta_1$ to equal its average value across high school, some college, associates, and bachelors degrees.

$\beta_1 = 29,332$, $y(\tau) - \beta_1 A = -\beta_0 + \beta_2 B$

(b) Fixing the relationship between $\beta_0$ and $\beta_2$ based on the strong relationship seen in Census data.

$\beta_2 = -m\beta_0 + b$ where $m = -3.8149$ and $b = 36,241$, $R^2 = 0.9967$, $y(\tau) - bB = -(1 + mB)\beta_0 + \beta_1 A$

(c) Fixing the relationship between $\beta_0$ and $\beta_2$ as above and the relationship between $\beta_0$ and $\beta_1$ based on the strong relationship seen in Census data.

$\beta_1 = -n\beta_0 + a$ where $n = -0.2445$ and $a = 2,234.3$, $R^2 = 0.9605$, $y(\tau) - bB -$

$$aA = -(1 + mB + nA)\beta_0$$

The resulting model fits are shown in Figure C.3. We determine that method (c) is able to fit synthetic work-life income curves very closely using only a single parameter, $\beta_0$.[8] We project $\beta_0$ for each individual in our dataset, and thereby attain an estimate of the future earnings expectations for each student.

### C.2.3 Income by educational attainment

Based on the income parameter $\beta_0$ for each individual, we analyze the differences in expected lifetime incomes between different attendance and admission selectivity groups. We find very similar trends to those seen in the raw post-college income data presented in section 4.5. It is sufficient to examine the value of $\beta_0$ across groups since this parameter fully defines future income expectations under the assumptions of the previous section. Note that we also examine differences in the expected lifetime earnings implied by $\beta_0$, with similar results.[9]

As in the analysis of raw post-college income data, we find that both the quality of the best school admitted to and the school attended to are predict the income parameter $\beta_0$. However, the predictive ability of the selectivity of school attended is lost if we control by best school admitted. Table C.2 shows that attendance information that is uncorrelated with the best school admitted to ("attendance error") provides no additional information on income expectations after adjusting for best

[8]Mean squared errors between estimated income and actual Census data for those with high school degrees, some college, associate's degrees, and bachelor's degrees increases only slightly when parameters are fixed. Mean squared error with only $\tau$ fixed is $3,933,487$ across these groups. Mean square errors for methods a) through c) in Figure C.3 are $4,600,744$, $4,845,014$, and $4,828,948$, respectively. Income estimates using methods a) and b) were also used to conduct the analysis described in section C.2.3. Results are similar to those presented here but income projection is possible for a smaller number of individuals.

[9]We calculate discounted expected lifetime earnings based on $\beta_0$ and equation (C.4), assuming that non-attenders follow the estimated income curve from ages 22 to 100, while attenders follow it from 18 to 100. Earnings are discounted by a yearly factor of 0.96. The value of the discount factor is based on estimates found in past literature, for example in Cocco et al. (1998) and Gourinchas and Parker (1999).

school admitted to. In contrast, "admission error" remains a significant predictor of income even after adjusting for the school attended; students that are admitted to top schools and choose to attend lower caliber institutions exhibit significantly higher earnings than their classmates.

Table C.2: Separating effects of top school admitted to and school attended selectivity on Nelson-Siegel income parameter using interval selectivity data.

(a) Predicted $\beta_0$, by selectivity of top school admitted to and attendance error. $\beta_0 = \alpha_0 + \alpha_1 topAdmit + \alpha_2 attendError + \epsilon.^{a,b}$

Ordinary least squares regression

| | | Adjusted $R^2$: | 0.0508 |
|---|---|---|---|
| | Estimate | St. Error | p-value |
| (Intercept) | 345,627 | 24,074 | $2.00\text{x}10^{-16}$ |
| Acceptance rate, top admitted school | -1,518 | 315 | $2.00\text{x}10^{-16}$ |
| Attendance error | -250 | 584 | 0.6690 |

[a]Parameter $\beta_0$ in the restricted Nelson-Siegel function derived from equation (C.2) fully determines the lifetime income curve under the assumptions made in section C.2.2.

[b]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted. Interval scale is created be replacing category label with the percentage of applicants admitted in each selectivity category. Type 1 schools have admissions rates of at most 33% while type 5 and 6 schools admit 100% of their applicants.

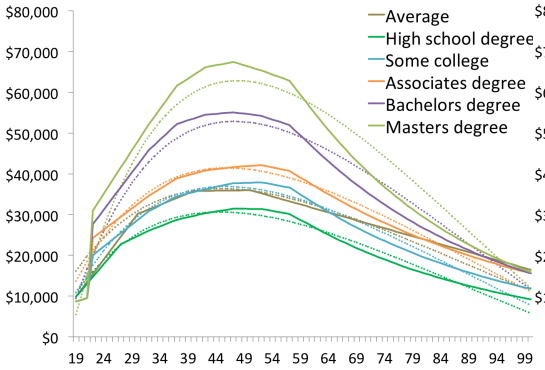
(b) Predicted $\beta_0$, by selectivity of school attended and admission error. $\beta_0 = \alpha_0 + \alpha_1 attend + \alpha_2 admitError + \epsilon.^{a,b}$

Ordinary least squares regression

| | | Adjusted $R^2$: | 0.0508 |
|---|---|---|---|
| | Estimate | St. Error | p-value |
| (Intercept) | 313,268 | 22,440 | $2.00\text{x}10^{-16}$ |
| Acceptance rate, attended school | -21,939 | 5,935 | 0.0002 |
| Admission error | -1,352 | 451 | 0.0029 |

[a]Parameter $\beta_0$ in the restricted Nelson-Siegel function derived from equation (C.2) fully determines the lifetime income curve under the assumptions made in section C.2.2.

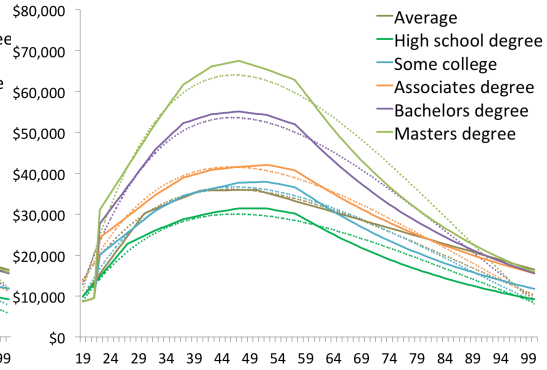
[b]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted. Interval scale is created be replacing category label with the percentage of applicants admitted in each selectivity category. Type 1 schools have admissions rates of at most 33% while type 5 and 6 schools admit 100% of their applicants.




(a) $\beta_1$ set to its average value across high school, some college, associates, and bachelors degrees. $\beta_1 = 29,332$, $y(\tau) - \beta_1 A = -\beta_0 + \beta_2 B$. Dotted lines indicate Nelson-Siegel estimates and solid lines indicate Census data.[a,b]

[a]Census Bureau (2012)

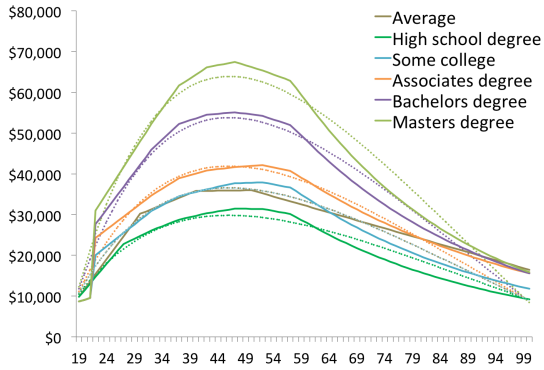
[b]$\tau^* = 27.88$ ensures that lifetime income maximum occurs at the desired age of 50.




(b) Fixed relationship between $\beta_0$ and $\beta_2$ based on trends seen in Census data. $\beta_2 = -m\beta_0 + b$ where $m = -3.8149$ and $b = 36,241$, $R^2 = 0.9967$, $y(\tau) - bB = -(1 + mB)\beta_0 + \beta_1 A$. Dotted lines indicate Nelson-Siegel estimates and solid lines indicate Census data.[a,b]

[a]Census Bureau (2012)

[b]$\tau^* = 27.88$ ensures that lifetime income maximum occurs at the desired age of 50.




(c) Fixed relationship between $\beta_0$ and $\beta_2$ as in (b) and relationship between $\beta_0$ and $\beta_1$ based on trends seen in Census data. $\beta_1 = -n\beta_0 + a$ where $n = -0.2445$ and $a = 2,234.3$, $R^2 = 0.9605$, $y(\tau) - bB - aA = -(1 + mB + nA)\beta_0$. Dotted lines indicate Nelson-Siegel estimates and solid lines indicate Census data.[a,b]

[a]Census Bureau (2012)

[b]$\tau^* = 27.88$ ensures that lifetime income maximum occurs at the desired age of 50.

Figure C.3: Census synthetic lifetime income earnings curve fits based on equation (C.2) for different estimation procedures.

## C.3 Conditional post-college income effects using categorical selectivity data

This appendix presents fixed effects models using categorical admission and attendance categories that investigate effects on income after conditioning. School categories 1, 2, 3, 4, and 5/6 are treated as factor levels instead of converting them to interval data based on acceptance rates defining these categories. This results in the need to estimate more parameters, making it difficult to see significant differences between groups. In Table C.3a, we compare post-college income for students in each attendance category based on their top admitted school. In Table C.3b, we compare post-college income for students in each top admitted category based on the school they attended. In general, we cannot show that a difference exists between incomes after conditioning. Tests of this hypothesis using interval instead of categorical data are provided in Tables 4.6a and 4.6b.

Table C.3: Separating effects of top school admitted to and school attended selectivity on post-college income, categorical selectivity data.

(a) Predicted post-college income by top school admitted to, adjusted by attended category. $\beta_{0_k} = \alpha_{0_k} + \alpha_{1_k} topAdmit + \epsilon_k$ for each attendance category $k$.[a]

Fixed effects regression

| Category | | | Coefficients, by top school admitted[b] | | | | |
|---|---|---|---|---|---|---|---|
| Type attended | # students | Types admitted to | (Intercept) | 2 | 3 | 4 | 5/6 |
| none | 120 | 1,2,3,4,5 | 26,741 | -183 | 582 | -374 | -591 |
| 1 | 15 | NA | NA | NA | NA | NA | NA |
| 2 | 22 | 1,2 | 3,2320 | 2,006 | NA | NA | NA |
| 3 | 111 | 1,2,3 | 3,1310 | 7,973 (.)[c] | -413 | NA | NA |
| 4 | 183 | 1,2,3,4 | 3,6981 | -1,968 | -5,715 | -7,950 (*)[d] | NA |
| 5/6 | 67 | 2,3,4,5 | NA | 37,833 | -7,799 | -8,509 | -12,478 (*) |

[a]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted.

[b]Coefficients are relative to baseline. Baseline is top admitted school of type 1 except for attendance category 5/6; in attendance category 5/6/, base case is top admitted school of type 2.

[c]. indicates significance at the 0.10 level.

[d]* indicates significance at the 0.05 level.

(b) Predicted post-college income by attended school, adjusted by top admitted category. $\beta_{0_k} = \alpha_{0_k} + \alpha_{1_k} attended + \epsilon_k$ for each top admitted category $k$.[a]

Fixed effects regression

| Category | | | Coefficients, by school type attended[b] | | | | | |
|---|---|---|---|---|---|---|---|---|
| Top admitted | # students | Types attended | (Intercept) | 1 | 2 | 3 | 4 | 5/6 |
| 1 | 49 | none, 1, 2, 3, 4 | 26,742 | 11,898 (.)[c] | 5,589 | 4,569 | 10,241 | NA |
| 2 | 65 | none, 2, 3, 4, 5 | 26,557 | NA | 7,779 | 12,726 (*)[d] | 8,456 | 11,276 |
| 3 | 144 | none, 3, 4, 5 | 27,322 | NA | NA | 3,574 | 3,944 | 2,712 |
| 4 | 193 | none, 4, 5 | 26,367 | NA | NA | NA | 2,664 | 2,957 |
| 5,6 | 67 | none, 5 | 26,150 | NA | NA | NA | NA | -794 |

[a]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted.

[b]Coefficients are relative to baseline. Baseline is attending no school at all.

[c]. indicates significance at the 0.10 level.

[d]* indicates significance at the 0.05 level.

## C.4 Alternate model of effect of student charateristics on ability-adjusted income

Table C.4 provides an alternate model to the on presented in table 4.7, examining student characteristics that affect post-college income after adjusting for ability. Due to the high degree of missingness in the math SAT score in our reported sample, we provide an alternate model including only variables with low degrees of missingness. We see that coefficients of the variables included in both models are similar. We replace math SAT score with household income in this model. The correlation between these variables is 17%, suggesting that at least some portion of SAT score is driven by family wealth. This may be because wealthier students have better study resources, multiple opportunities to take the exam, and access to test-prep courses. Meanwhile, the correlation between household income and our metric of student quality, the selectivity of the top school admitted to, is less than 1%, suggesting that our debiasting approach does a better job at removing wealth bias.

Table C.4: Effect of student characteristics other than SAT score on income after adjusting for selectivity of top school admitted to. $avgIncome = \alpha_0 + \alpha_1 admit + \alpha_2 ouseholdIncome + \alpha_3 engineeringIndicator + \alpha_4 humanitiesIndicator + \epsilon$. [a,b]

Ordinary least squares regression

| | Adjusted $R^2$: | 0.1118 | |
|---|---|---|---|
| | Estimate | St. Error | p-value |
| (Intercept) | 40,920 | 2,722 | $2.00\text{x}10^{-16}$ |
| Acceptance rate, top admitted school | -156 | 32 | $1.66\text{x}10^{-6}$ |
| Household income | 0.0287 | 0.0095 | 0.0027 |
| Engineering indicator | 5,022 | 2,095 | 0.0170 |
| Humanities indicator | -3,939 | 1,318 | 0.0030 |

[a]Selected sample is presented in table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and are not missing critical data. The sample in this table excludes seven individuals who do not supply sufficient income information in the immediate post-college years.

[b]Major choice is based on the initial program decision made upon entering college. It does not necessarily reflect the final major in which a degree was attained, since some students change majors or do not complete their studies. Engineering majors include engineering and computer-related fields. Humanities majors include liberal arts, fine arts and architecture, political sciences, classical fields, and interdisciplinary studies.

## C.5 Effect of attending college at all

Table C.5 examines the effect of the decision to attend college at all on future income for each top admitted category. Results indicate that attending college at all may have a positive effect on post-college income for all top admission categories, especially for those admitted to higher caliber schools. Results using projected lifetime incomes, as described in appendix C.2, support this finding. Further analysis reveals that there is no difference in expected salary coefficient for students who choose not to attend school at all between different top admitted categories. The average post-college annual salary for non-attenders is $\$26,526$. For college attenders, salary differences do exist between different top admitted groups. These differences are explained further in Figure 4.3.

Table C.5: Effect of binary decision to attend college on post-college income.[a,b]

Summary of fixed effects models by top admitted category

| Top admitted | # in category | Coefficients | | p-values | |
|---|---|---|---|---|---|
| | | Non-attenders[c] | Attenders | Non-attenders | Attenders |
| 1 | 49 | 26,741 | 35,313 | $2.12\text{x}10^{-6}$ | 0.1150 |
| 2 | 65 | 26,557 | 36,751 | $7.37\text{x}10^{-7}$ | 0.0505 |
| 3 | 144 | 27,322 | 30,925 | $6.65\text{x}10^{-2}$ | 0.1670 |
| 4 | 193 | 26,367 | 29,059 | $6.96\text{x}10^{-45}$ | 0.1120 |
| 5,6 | 67 | 26,150 | 25,355 | $4.35\text{x}10^{-18}$ | 0.7800 |

[a]Selectivity scores are based on Barron's selectivity index (Barron's, 2009). Types 5 and 6 are combined into a single category. Specialty schools (type 7) are omitted.

[b]Selected sample is presented in table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and are not missing critical data. The sample in these plots excludes seven individuals who do not supply sufficient income information in the immediate post-college years.

[c]Non-attenders are the base case in this regression.

## C.6 Logistic choice models

In a discrete choice framework, we model a decision-maker that makes a choice or set of choices over a set of alternatives. For a decision-maker $i$, we would like to understand what causes him or her to select a particular alternative, $j$. The choice is based on a set of observable factors, $x$, as well as a set of unobservable factors, $\epsilon$. These inputs fully determine the agent's choice by defining the utility of each alternative to person $i$, written as $U_{i,j}$. To simplify this model, we assume that the non-random component of utility is linear in parameters, allowing us to write down the utility function as follows:

$$U_{i,j} = \delta' x_{i,j} + \epsilon_{i,j} \tag{C.5}$$

where $\delta$ is the vector of parameters to be estimated and $x$ is the vector of input characteristics of the decision maker $i$, the choice $j$, and interaction terms between $i$ and $j$. To estimate parameters of the model, we analyze the probability of a given choice $j$ being made when a certain set of observable factors $x$ is present. Let us define an indicator function that indicates the outcomes of $\epsilon$ for which $j$ is the optimal choice:

$$I[h(x,\epsilon) = j] = \begin{cases} 1 & \text{if } h(x,\epsilon) = j, \\ 0 & \text{otherwise} \end{cases} \tag{C.6}$$

We then examine all possible realizations of $\epsilon$ for which $j$ is the choice outcome: $P(j|x) = Prob(\epsilon \text{ s.t. } h(x,\epsilon) = j)$. We can formulate $P(j|x)$ as an integral over the possible realizations of $\epsilon$:

$$\begin{aligned} P(j|x) &= Prob(I[h(x,\epsilon) = j] = 1) \\ &= \int I[h(x,\epsilon) = j] f(\epsilon) d\epsilon \end{aligned} \tag{C.7}$$

The integral in equation (C.7) can be expressed in closed form only in a few cases. One such case is when the components of $\epsilon$ are distributed according to i.i.d. type 1 extreme value distributions, making the choice model a logistic choice model (see e.g. McFadden (1974)). When we have this type of distribution for $\epsilon$ in equation (C.5), we can write the probability of selecting a particular choice $j$ only in terms of the non-random component of utility, as shown below:

$$P_{i,j} = \frac{e^{\delta' x_{i,j}}}{\sum_{k \in J} e^{\delta' x_{i,k}}} \tag{C.8}$$

Logistic choice models have several useful characteristics for this application. Firstly, the logistic models exhibits what is called the Independence of Irrelevant Alternatives (IIA) property. This means that preferences between alternatives do not change as the choice set changes. For any two alternatives $a$ and $b$, the ratio of their logit probabilities depends only on these two alternatives:

$$\frac{P_{i,a}}{P_{i,b}} = \frac{e^{\delta' x_{i,a}} / \sum_K e^{\delta' x_{i,k}}}{e^{\delta' x_{i,b}} / \sum_K e^{\delta' x_{i,k}}} = e^{\delta' x_{i,a} - \delta' x_{i,b}} \tag{C.9}$$

The IIA property is useful for this application since the choice set available to students depends on a previous decision, namely where to apply for school. The schools a student did not apply to may shift the utility of the schools to which they did apply. However, due to the IIA property the relative probability of attending one school over another remains constant. This allows us to model choice between colleges even when we are unsure that every possible school considered by the student is provided in the NLSY 97 dataset.

A second critical advantage of the logistic choice model is that we can create a choice model focused entirely on the characteristics of the alternatives, called a conditional choice model. A conditional choice model is used in the second stage of our model. Since every student's choice set is unique and may include schools that

do not appear anywhere else in the sample, we define schools solely based on their individual characteristics, such as tuition price, school size, and metrics of school quality. The alternative-based conditional logit model, described further in section 4.6.2, allows us to do exactly this.

## C.7 Comparison to models in Long (2004b)

The models presented in this paper closely follow the structure developed in Long (2004b). Our models are generally consistent with Long's previous findings, but results differ due to the use of different datasets. The dataset used in this paper is much smaller than Long's, but contains richer data on individual qualities, school characteristics, and income over time. Additionally, the current work focuses explicitly on four-year schools, while long includes two-year institutions. Tables C.6 and C.7 presents Long's original models as well as recreations of these models using our data. Signs are consistent throughout. Model fit is slightly better in the current model than in Long's for the first stage, while Long's fit is better in the second stage model. We use average faculty salary as a proxy for the percentage of faculty with a PhD, and selectivity difference between the school in question and top admitted school as a proxy for SAT performance relative to the student body. The comparison models from Long's work used here are those for the 1992 cohort. Note that coefficients in Long's original work are presented as odds ratios ($e^{\beta}$) but have been adjusted here for consistency with the rest of the paper.

Table C.6: Comparison model for first stage logit regression model of decision to attend college at all.

(a) First stage model from Long (2004b), 1992 cohort.

| Logit regression | |
|---|---|
| | Estimate |
| Tuition price (aid adjusted) | 0.0009 |
| Tuition price$^2$ | 0 |
| Distance | -0.1122 (.)[a] |
| Distance$^2$ | 0.0175 |
| Instructional expenditures | 0.0040 |
| Instructional expenditures$^2$ | 0.0000 |
| County unemployment rate[b] | 0.0173 |

[a]. indicates significance at the 0.10 level.

[b]County unemployment rate is not readily available for NLSY 97 data and is omitted from the comparison model.

(b) First stage model to replicate Long (2004b) using NLSY 97 data.[a]

| Logit regression | |
|---|---|
| | Estimate |
| (Intercept) | 1.1175 |
| Tuition price (aid adjusted)[b] | -5.75x10$^{-5}$ |
| (Tuition price)$^2$ | 0 |
| Distance | 0.0395 (.)[c] |
| (Distance)$^2$ | -1.71x10$^{-4}$ |
| Instructional expenditures | -3.63x10$^{-5}$ |
| (Instructional expenditures)$^2$ | 0 |

[a]Selected sample is presented in table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and are not missing critical data.

[b]This list tuition-financial aid, where financial aid includes in-state discounts, aid awarded by the individual school, and aid awarded for use at all schools.

[c]. indicates significance at the 0.10 level.

Table C.7: Comparison model for second stage conditional logit regression model of choice between candidate schools.

(a) Second stage model from Long (2004b), 1992 cohort.

| Conditional logit regression | |
|---|---|
| Pseudo $R^2$: | 0.4719 |
| | Estimate |
| Tuition price (aid adjusted)[a] | -0.4234 (*) |
| (Tuition price)$^2$ | 0.0146 (*)[b] |
| Distance | -1.3213 (*) |
| (Distance)$^2$ | 8.15x10$^{-2}$ (*) |
| Instructional expenditures | 9.85x10$^{-2}$ (*) |
| (Instructional expenditures)$^2$ | -2.10x10$^{-3}$ (*) |
| Student/faculty ratio | 1.26x10$^{-2}$ |
| % faculty with Ph.D.s | 5.98x10$^{-3}$ (*) |
| Student SAT %ile larger than school's | -0.3384 (*) |
| Student SAT %ile smaller than school's | 0.1663 (*) |
| 2-year college dummy | 1.580 (*) |

[a]This list tuition-financial aid, where financial aid includes in-state discounts, aid awarded by the individual school, and aid awarded for use at all schools.

[b]* indicates significance at the 0.05 level.

(b) Second stage model to replicate Long (2004b).[a]

| Conditional logit regression | |
|---|---|
| Pseudo $R^2$: | 0.064 |
| | Estimate |
| Tuition price (aid adjusted) | -0.0001 (*)[b] |
| (Tuition price)$^2$ | 0 |
| Distance | -0.0477 (*) |
| (Distance)$^2$ | 0.0002 (.)[c] |
| Instructional spending | 0.0001 |
| (Instructional spending)$^2$ | 0 |
| Average faculty salary[d] | 0 (*) |
| Selectivity difference[e] | 1.08x10$^{-2}$ |

[a]Selected sample is presented in table 4.1 and is derived from NLSY 1997 respondents (Bureau of Labor Statistics, 2013). Individuals included are those from the cross-sectional sample who completed high school, participated in the college choice section of the survey, were admitted to at least one four-year institution, and are not missing critical data.

[b]* indicates significance at the 0.05 level.

[c]. indicates significance at the 0.10 level.

[d]Average faculty salary is used as a proxy for faculty quality, similar to Long (2004b)'s use of % faculty with Ph.D.s.

[e]Selectivity difference is the difference in Barron's selectivity index between the top school admitted to for the current student and the selectivity of the school in question (selectivity of this school minus selectivity of top school admitted to). This is a proxy for ability fit of the student, similar to the SAT percentiles used in Long (2004b).

## C.8 Collinearity and model selection

As part of the model selection process, we determine which variables are highly correlated in order to eliminate collinearity from our models. We use correlation and condition numbers to identify problem areas, and create a robust model selection process that tests all permutations of variables in highly collinear categories. Table C.8 provides an overview of the approach used.

Table C.8: Overview of model selection process.[a]

| | Category | Description of variables |
|---|---|---|
| A | Tuition/aid | Net tuition*[b]<br>List out of state tuition and financial aid amount<br>List out of state tuition, financial aid amount without the instate discount, and instate discount amount |
| B | Selectivity | Interval-measured selectivity of school in question<br>Interval-measured difference between top admitted and school in question selectivity* |
| C | Expenditures/wealth | Instructional expenditures per student*<br>Expenditures per student<br>Faculty per student |
| D | School quality | Total students<br>Graduation rate*<br>Principal component of quality variables: total students, graduation rate, percentage receiving federal grants, average faculty salary, and selectivity[c] |

[a]Categories of highly related variables tested in model selection for second stage model (choice between schools).

[b]* indicates configuration used in final model

[c]While the principal component approach yields slightly better model fits, graduation rate is used in final models for the sake of easy interpretation

Note that we also test for linear separation of each predictor variable to ensure reasonable model results. Outliers are found in some cases. For example, an all male college adds an extreme data point to the gender ratio variable. In this and similar cases, we carefully investigate data for accuracy and ensure that inclusion/exclusion of the data point does not have large effects on the final model parameters.

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