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# Beliefs, Choice Structure, and Human Capital Investment

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**Abstract**

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The decision to pursue a college education has extensive economic implications, and economists have studied this decision for decades. However, the current economic approach to educational choice oversimplifies the decision, and cannot adequately explain student behavior. I relax several standard assumptions of educational choice models to allow for a more realistic approach to student beliefs and a more flexible approach to the structure of the choice. First, using a novel survey data set, I demonstrate that observed labor market conditions are a poor proxy for student perceptions of labor market payoffs to education. Then, using those student perceptions, I estimate student demand for education. I show that, contrary to common assumption, financial reward plays only a small part in educational choice, and consumption value is more central in driving student plans. Finally, I model college choice more realistically as a two-agent bargaining problem between parent and student. Using a choice experiment, I show that parent and student preferences differ, and demonstrate the implications of this difference on choice and the construction of effective education policy.

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## DEDICATION

To Spike, because he will never read this, to mom and dad, because they will try, and to Joan, because she would have told me it was fantastic.

## Chapter 1

### INTRODUCTION

The amount and type of formal education are crucial determinants of productivity for a person in the labor market, and in the aggregate for the labor market as a whole. This is the basic premise underlying much of the economic study of education. This premise points towards positive personal and social gains to be had by increasing the educational attainment among students. One margin of increased attainment that receives a lot of attention in the modern United States is at the college level. What determines whether or not a student will enroll in college? What determines which kind of college or program they will enroll in?

The study of college attainment is different from the study of attainment at lower levels in a fundamental way. Students and their parents face a much broader range of options and retain a much higher level of autonomy in college choice than in choice at lower levels. The decision is not just whether or not to attend, but how to choose which colleges to apply to out of thousands of options, whether community colleges or four-year colleges are best, which particular community or four-year college they prefer, what program to enroll in, and which classes to take. There is choice at the Kindergarten to high school (K-12) level, but at a much smaller scale. Families have a limited number of public and private K-12 schools to choose from in their area, although they may consider moving to an area with better schools, and they may have some limited choice choice in terms of curriculum or which classroom they are in.

The United States higher education system has a highly autonomous nature. It is vital to have a realistic and high-quality model of educational choice in order to understand educational attainment at this important margin, and thus supply in the high-skill labor

market.

Economists usually approach educational choice using a variant of the human capital model (Schultz, 1963; Becker, 1964). There are many variants of this model. However, at its core the human capital model of educational choice is based around the idea that education improves human capital, increasing worker productivity and thus earnings, and that people take part in education in pursuit of those earnings increases.

In this study I examine several issues with the standard economic model of educational choice at the college level, and derive several conclusions about college choice that would be difficult to reach with a standard approach. I show that several of the simplifications commonly made in the economic study of educational choice, historically made either for reasons of theoretical parsimony or by limitations of standard data sources, are both incorrect and consequential. These simplifications are: (1) the assumption that beliefs about future returns can be approximated by labor market data, (2) the assumption that choice is largely driven by the pursuit of future earnings, and (3) the assumption that college choice is a single-agent decision. These assumptions significantly affect inference in a way that harms our understanding of college choice. Given a general societal goal of increasing educational attainment and the positive macroeconomic implications of doing so (Sianesi and Reenen, 2003; Goldin and Katz, 2009), misunderstandings about the choice process will stymie the ability to act on policy goals and improve economic welfare.

In Chapter 2, I analyze the assumption that beliefs about future returns can be approximated by labor market data. In order to estimate a function describing student choice, it is necessary to use some sort of data to represent the earnings payoffs for the alternatives. Without these data, there is no way to understand how students respond to the potential for future return, since we do not know the stakes. The standard approach is to use data from the labor market to represent the potential payoffs. In a crude implementation, a researcher would take an average of earnings over all workers with a given level of education, and assume that this represents what a student will earn if they, too, choose that level of education.

However, using labor market data for this purpose requires the assumption that a student's expectation of the return to education matches what is observed in the labor market. Students can only respond to what they perceive the return to be, which may or may not match what is calculated using observed data from the labor market. If expected returns do not match those derived from observed data, then students' preferences, and thus the demand function, cannot be identified. Without a way of holding beliefs constant, there are an infinite number of pairs of beliefs and preferences that could generate a given behavior (Manski, 2004).

To evaluate this assumption, I compare student reports of what they believe their earnings would be with different levels of college education. I compare the implied returns with those projected using observed labor market data. In my data, projected returns estimates are a poor proxy for students' subjective returns derived from stated subjective beliefs. The projected returns do not match subjective returns in terms of absolute level, they do not vary over observable characteristics in the same way that subjective returns do, and they do not correlate with subjective returns at the individual level. While educational choice may respond to actual labor market returns for some other reason (such as indirectly via parental encouragement), the response should not be labeled as student preference for future earnings.

This is not the first study to collect subjective education returns data, or to compare these returns to labor market returns. Freeman (1975) collected subjective expectations data from new lawyers, and in an influential paper Dominitz and Manski (1996) compared the subjective returns of high school and college students to observed data. However, to the best of my knowledge, this is the first study to address a vital concern relating to whether projected returns can be reasonably used as a proxy: whether or not projected returns vary over a sample in the same way that subjective returns do.<sup>1</sup> As such, this study makes the

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<sup>1</sup>Other studies, such as Dominitz and Manski (1996) and Avery and Kane (2004), examine how such comparisons vary over the sample, but they do so only over a single binary demographic predictor. In Chapter 2 I examine the question in much more detail.

strongest case that not only are labor market returns not identical to expectations, but the way in which they differ makes labor market returns a poor proxy for subjective beliefs.

The findings from Chapter 2 imply that in order to understand the determinants of student choice, a researcher should use subjective expectations data. Chapter 3 carries this forward and uses the same subjective expectations data to estimate demand for different levels of college education among current high school students.

Chapter 3 addresses another common assumption in the economic study of education: that the decision is driven primarily by financial returns. Students also receive utility from the experience of attending college, both in terms of enjoying the classes and experiences that go along with a college education. They also receive utility from fulfilling appropriate social expectations. These incentives are referred to as “consumption value.”

Economists have long acknowledged consumption value as an incentive (Schultz, 1963). Alongside the long literature establishing a relationship between financial return and educational choice there is a smaller literature establishing a relationship between consumption value and educational choice. However, consumption value has been treated as a secondary concern. Modeling and estimation of student choice focuses largely on the response to financial return, and empirical studies with only financial incentives and demographic background characteristics as predictors are not uncommon.

This lack of attention may be somewhat due to a lack of data. It is difficult to measure differences in consumption value across students, and so studies have often been limited to measuring consumption value as an unexplained individual fixed effect or studying the demand for specific aspects of consumption value, such as avoiding military service (Card and Lemieux, 2001) or mental strain (Heckman et al., 2006; Stinebrickner and Stinebrickner, 2014). This limited view provides important insight about these particular incentives but leaves gaps in our understanding of a broader model of choice.

I measure consumption value in a multidimensional manner, combining measures of familial and social expectations with stated preference data concerning expectations of enjoyment and mental strain. These data allow me to estimate student demand as a function of financial

return as well as a more holistic measure of consumption value than is typically used.

I find that financial returns inform only a small part of student plans. Consumption value, in particular the expectation of mental strain, the expectation of enjoying the classes, and parental encouragement are much more influential parts of the demand function. These results on the choice of the level of college education are in line with a growing literature on the choice of college major (Arcidiacono, 2004; Alstadsæter, 2011; Beffy et al., 2012; Long et al., 2014; Wiswall and Zafar, 2015) that also finds a smaller part for financial returns than is typically expected. The low weight that students place on future earnings puts in doubt any policy that relies on a strong student response to future earnings (e.g. the College Scorecard System, see College Affordability and Transparency Center, 2014). Additionally, these results mean that attempts to study educational choice without reference to student-level variation in consumption value will only be able to explain a small part of the decision, and will be left with a major unexplained factor.

Chapters 2 and 3 focus on student beliefs and student demand. This is a very common approach in the economic literature on college choice. College choice is assumed to be a choice made by the student who will be (or will not be) attending. Many studies acknowledge that parents have influence over college choice. However, this typically comes in the form of including parental background and perhaps parental encouragement as predictors in a model that fundamentally attempts to model only student choice. Very little work (Attanasio and Kaufmann, 2009, 2014; Giustinelli, 2010; Long and Conger, 2013) formally addresses educational choice as a two-sided problem in which both parent and student preferences matter.

That the study of educational choice typically bypasses dual-agent modeling is particularly striking given the successes of dual-agent modeling in the broader household economics literature. An appreciable body of empirical and theoretical results (e.g. Thomas, 1990; Fortin and Lacroix, 1997; Lundberg et al., 1997; Duffo, 2003) find that a single-agent model of household choice is both rejected and misses important implications about how targeting policy at particular members of the household (husband or wife) can considerably change

the effects of that policy.

In Chapter 4, which represents more of a departure from the standard model than either Chapter 2 or Chapter 3, I estimate a dual-agent model of educational choice. In particular, I model the choice between different hypothetical colleges on the basis of the attributes of those colleges. I then estimate student and parent preferences separately, and estimate a parameter that determines how those preferences are combined to form a household objective function.

To identify the parameters of the model I use a conjoint choice experiment. Conjoint experiments are commonly used in marketing, environmental economics, and health economics, but have so far seen little use in labor or education economics. In these experiments, subjects are presented with a choice between goods with researcher-varied attributes. The choice between goods provides evidence about how much the respondent values a particular attribute. In the case of this paper, a total randomization of attributes allows for straightforward identification of student and parent indirect utility functions and the household objective function.

I find that the household objective function favors student preferences over parent preferences, but that both matter. Students and parents also have different priorities about college: students care more about future earnings and the enjoyability of the classes, while parents care relatively more about tuition. I reject the single-agent model of college choice. Further, I find that the single-agent model of educational choice produces biased estimates of the student demand function, and leads to poor prediction relative to the dual-agent model. The single-agent model is not simply statistically rejected, but leads to meaningfully different, and poorer, inference and policy prescriptions.

These three chapters form my dissertation. The theme running through these papers is that the standard approach to studying college choice is lacking in important ways. I provide data and modeling alternatives that allow for the study of college choice to address these weaknesses.

All models are imperfect, and the standard model used to understand and empirically

study educational choice is no exception. A general finding that one of the assumptions underlying the model is statistically rejected is not necessarily a major concern. A general preference for parsimony, or pragmatic concerns regarding data availability, may favor the use of the standard approach anyway. It is for this reason that in each of these studies I focus on the magnitude of the difference. I emphasize that these studies are not merely statistical rejections of the standard model, but imply major differences in inference about demand functions and policy prescriptions. In Chapters 3 and 4 in particular I outline how current policy based on this too-simple model of educational choice may be suboptimal. Future studies will not all be able to address the issues raised here, if only due to the difficulty of collecting subjective data or data on parental preferences. However, those studies should be aware that these issues can be sources of bias in estimation.

The results here stand to suggest that the current model is too simple to understand several major important factors of the college decision. Future attempts at modeling educational choice should take these concerns in mind.

## Chapter 2

# SUBJECTIVE AND PROJECTED RETURNS TO EDUCATION

### *2.1 Expectations in Educational Choice*

Human capital theory suggests that students make decisions about their educational attainment based on future returns. Models of educational choice must include assumptions about how students form expectations of future outcomes. Without such assumptions, preferences and expectations cannot be identified separately using observed choices, since there are many pairings of preferences and expectations that can generate given behavior (Manski, 2004; van der Klaauw, 2012). In practice, researchers build econometric models on the basis of these assumptions and generate forecasts to use as proxies for student expectations. However, if a researcher's assumptions about expectations formation are false, estimates of preferences and demand will be biased. Without a strong literature on expectations formation, it is difficult to put much faith in these assumptions. In response, there has been growing interest in decision makers' stated, or "subjective," expectations.

There is a growing literature on the measurement of subjective expectations data and their use in behavioral models. Subjective expectations data has been used to study intertemporal labor supply (Pistaferri, 2003), curriculum choice at the high school (Giustinelli, 2010) and college (Wiswall and Zafar, 2011; Stinebrickner and Stinebrickner, 2014) levels, teacher quality (Jacob and Lefgren, 2008), and a wide range of topics studied in developing nations, including agricultural, education, and labor choices (as reviewed in Attanasio, 2009; Delavande et al., 2011).

In the context of the choice of the level of education, a number of studies examine one of the inputs relevant to the human capital model—students' estimates of wages conditional on schooling level. These papers focus on reporting student estimates (Dominitz and Manski,

1996; Avery and Kane, 2004; Botelho and Pinto, 2004) or observing changes in estimates in response to information or experience (Jensen, 2010; Oreopoulos and Dunn, 2013). The literature on the subjective returns of employment probability to education is more sparse (Kodde, 1987; Varga, 2002; Attanasio and Kaufmann, 2012). All of these studies expand understanding of the structure and importance of student expectations. However, they look at limited sets of educational counterfactuals, many (although not all) only comparing a high school degree to a bachelors degree, which offers a limited portrait of the options available to students<sup>1</sup> and does not take into account the possibility of college dropout, which students in my analytic sample estimate occurs 37.5% of the time.<sup>2</sup>

I evaluate high school students expectations of wages and the employment rate over six different levels of education (high school dropout, high school graduate, some college but no degree, two-year degree, four-year degree, and advanced degree). These expectations allow me to calculate how each student estimates the wage return to different levels of college attainment, and the change in the employment rate associated with degree attainment. I compare these subjective returns to projections calculated using observed data.

I focus particular differences between students and demographic groups in their expectations. Heterogeneity in returns, at the group or individual level, are an important factor to study when determining whether or not projected returns estimated by a researcher are a good proxy for students stated subjective returns in models of educational choice. If subjective and projected returns are not correlated at the individual level, then the common practice of using projected returns as a proxy for actual student expectations will introduce bias to the analysis. This bias could arise from measurement error, which could bias estimates positively or negatively, since the difference between subjective and projected returns

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<sup>1</sup>53.9% of respondents aged 29-31 in the 2008-2010 American Community Survey have a highest grade completed that is not a high school degree or a bachelor's degree.

<sup>2</sup>Students in the APCAB (Assessing Perceived Costs and Benefits) sample used in this paper were asked to estimate the six-year completion rate at a generic four-year college. The mean estimate was 62.5%. This number is relatively accurate, compared to estimates of 63.3% (Washington) and 58.0% (national) using the Beginning Postsecondary Students Longitudinal Study cohort tracked from 2003/04 to 2009.

is not symmetrical and mean-zero. If projected returns positively influence student choice through a mechanism other than student belief, such as parental encouragement, then student preference for future earnings will be biased upwards since the estimated effect will include a response to more than just future earnings.

At the mean, students' subjective wage returns are higher than my projected wage returns, while employment rate returns match closely. However, for both wage returns and employment rate returns, heterogeneity in subjective returns across demographic and background characteristics is poorly aligned with heterogeneity in projected returns; for example, Hispanic students have a higher projected four-year degree wage return than white students, but Hispanic students expect lower returns than do white students. At the individual level, subjective estimates are uncorrelated with wage returns projected on the basis of background characteristics.

I additionally find that student plans for educational attainment relate positively to stronger subjective wage returns, and both subjective and projected employment returns. The fact that student choice is correlated with subjective returns indicates that students' subjective reports are related to intended behavior, underlining the importance of avoiding poor proxies for expectations in the study of student choice.

## **2.2 Data**

I make use of three data sources. Subjective data come from the Assessing Perceived Costs and Benefits of Post-High School Opportunities Survey (APCAB), a novel data set that I collected, which includes 1,224 high school juniors and seniors from King County, Washington. 56 students who skipped the subjective expectations questions were dropped, leaving 1,168 students in the final sample. Subjective expectations data is compared with observed data from Washington residents aged 29-31 in the 2008-2010 American Community Survey (ACS (WA)). To allow for disaggregation across background variables not available in the ACS, several analyses are also performed using the national sample of respondents aged 29-31 in the National Longitudinal Survey of Youth, 1997 Cohort (NLSY).

The APCAB survey was offered to juniors and seniors at thirteen high schools in King County, Washington. Subjects were surveyed between late April and early June, 2012, and were offered a \$5 gift card in exchange for their participation. The survey was administered in two different settings. About half of the data come from environments where students were in a homeroom or assembly setting and were formally presented with the survey as an option. In these scenarios, the response rate was very high, over 95%. The rest of the data comes from more open environments, like a cafeteria during lunchtime. Response rates in this scenario depend on non-exact estimates of the number of present students, but were about 50%. Results are robust to the sample being limited to students in homeroom or assembly settings. The resulting sample does not appear to over- or under-represent students based on socioeconomic status, gender, or academic ability, as compared to school registration.<sup>3</sup>

I focus on three substantive questions drawn from this survey. Two ask for subjective expectations of full-time, full-year wages conditional on education level, and the third asks for subjective expectations of the non-employment rate conditional on education level. Following a short explanation of terms, the questions prompt:

What do you think the **annual salary** is for an average **30-year old** full-time worker in Washington...

What do you think **YOUR** annual salary would be at **age 30** if you had a full-time, full-year job...

For each question, imagine 100 people in Washington who are 30 years old with the given level of education. How many of these 100 people would you expect to be **unemployed** today

Following each prompt, the sentence concludes in six different ways for six levels of education, concluding with, for example, “who has some college experience but no degree”

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<sup>3</sup>Comparison school demographic profiles were taken from 2012 Washington State Report Card data at <http://reportcard.ospi.k12.wa.us/>.

or “among 100 people who have some college experience but no degree” and allowed students to respond. See Appendix B for the full wording of these questions and more information about survey administration. Full survey text is available upon request.

For each of these education-conditional questions, students were asked to estimate the relevant wage or the non-employment rate (the probability of not being employed) for six different terminal amounts of education: No high school degree, a high school degree but no further, some college but no degree, a two-year college degree, a four-year college degree, and an advanced degree (including Master’s degrees, PhDs, MDs, and JDs).

The two conditional wage questions differ in terms of their subject. One asks students to estimate wages for the typical 30-year-old in Washington State who is employed and has the specified level of education; these are referred to as Typical wages. The other asks students to think about when they, personally, are 30 years old, have the specified level of education, and are employed in Washington; these are Self wages. The distinction between these two variables allows control for self-promotion effects and the theoretical distinction between the internal rate of return to education and the population wage return. In both cases, these are point estimates, intended to represent the central tendency of the underlying theoretical wage distribution.

Table 2.1 presents summary statistics for all three data sets and allows for demographic comparisons between data sets.<sup>4</sup> Where the APCAB mean is tested against the observed-data mean, the standard deviation of the mean (as opposed to the standard deviation of the variable) is reported in parentheses. A racial difference that jumps out is the high percentage of nonwhites in the APCAB sample, higher than the ACS (WA) and NLSY percentages. APCAB students also have somewhat higher socioeconomic status proxy variables than those in the NLSY sample: there is a lower proportion of Free and Reduced Price Lunch (FRPL) students in APCAB, although some of this difference may be accounted for by the fact that the APCAB FRPL variable is a self-report of actual receipt of free or reduced price

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<sup>4</sup>For all analyses in this paper, APCAB data are weighted according to survey response rate by school, and the ACS and the NLSY data are weighted according to supplied sample weights.

lunch, while the NLSY FRPL variable concerns being qualified for FRPL. Parental education rates are higher for APCAB respondents, which could represent some mix of geographical differences and cohort differences (APCAB students graduate high school about twelve years after the NLSY students do) as well as reporting error.

GPA's are higher by about half a point for APCAB students than for the NLSY sample. Much of this difference can likely be attributed to self-reporting in APCAB GPA's (Kuncel et al., 2005, find that self-reported GPA's are strongly, although not perfectly, correlated with actual GPA's). The difference appears to be a level difference: the standard deviation for the variable itself (as opposed to the standard deviation of the mean) in both data sets is about .62. Given these comparison groups it is possible to contrast subjective estimates of wages and the non-employment rate relative to projected estimates. In Table 2.2 Panel A I compare median salary conditional on education for both Typical and Self estimates against median salary in the ACS (WA) sample. In Panel B I make similar comparisons, contrasting mean non-employment rates conditional on education with ACS (WA) estimates. Table 2.2 shows that subjective expectations of salary and the non-employment rate are high relative to current observed levels. In the case of salary, different student interpretations of how to incorporate inflation into expectations, or different projections of the inflation rate, may alter the comparison between subjective and observed wages for any given educational level. A focus on wage returns instead of wage levels, which are the same no matter what level of inflation is assumed, sidesteps this problem. Mean non-employment rates are a fairly consistent ten percentage points higher than observed data. In all cases, the variance of the difference is large, representing heterogeneity in wage and employment expectations across APCAB respondents. These comparative ratios and differences are shown directly in Appendix A Table A.1.<sup>5</sup>

I use the same data presented in Table 2.2 to calculate returns to degrees. Wages and employment rates conditional on one education level are compared to wages and employment

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<sup>5</sup>Results are robust to the use of other age ranges for the comparison group. Results available from the author check results using ages 34-36 and 39-41 instead of 29-31.

Table 2.1: Summary Statistics (Means and Standard Deviations of the Means)

	APCAB	ACS (WA)	NLSY
Female	.475 (.016)	.489 (.007)	.484 (.010)
White	.683 (.015)	.785*** (.006)	.727*** (.008)
Black	.114 (.010)	.049*** (.003)	.158*** (.006)
Asian	.190 (.013)	.108*** (.004)	.023*** (.003)
Hispanic	.121 (.010)	.144** (.005)	.128 (.006)
Other	.047 (.007)	.021*** (.002)	.025*** (.004)
Free/Reduced Lunch	.344 (.015)		.478*** (.010)
Parent has Bachelors	.645 (.016)		.295*** (.010)
GPA	3.36 (.021)		2.84*** (.014)
Bachelors or Higher		.316	.334
Not employed		.240	.226
Salary (\$, median)		41,313	35,000
N	1,168	7,179	2,773

For APCAB and ACS (WA), subjects are allowed to have more than one race. In the NLSY, white, black, and Asian variables are mutually exclusive. In all data sets, Hispanic status is allowed to overlap with the racial variables. \*/\*\*/\*\* indicate averages significantly different from the APCAB sample at the 10%/5%/1% level.

Table 2.2: Absolute Salary and Employment Estimates

Panel A: Annual Full-Time Salary (\$, thousands)									
	APCAB (Self)			APCAB (Typical)			ACS (WA)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
No HS Degree	33.6	24.0	26.7	28.9	21.0	22.2	25.6	20.5	21.0
HS Degree	36.7	30.0	21.9	33.7	30.0	19.2	31.5	30.0	20.5
Some College	44.1	39.0	22.5	40.7	36.0	20.2	36.4	32.0	26.1
2-Year Degree	54.0	49.5	23.8	50.3	45.0	21.7	38.2	35.6	22.7
4-Year Degree	69.1	68.3	25.5	65.8	63.0	23.6	51.1	46.4	35.1
Advanced	90.5	97.5	27.9	89.5	94.5	27.2	61.9	52.1	49.7

Panel B: Non-employment Rates									
	APCAB (Typical)			ACS (WA)					
	Mean	Median	SD	Mean	Median	SD			
No HS Degree	.484	.500	.273	.408		.492			
HS Degree	.432	.400	.238	.327		.469			
Some College	.382	.350	.225	.247		.431			
2-Year Degree	.337	.300	.235	.198		.399			
4-Year Degree	.285	.200	.259	.168		.374			
Advanced	.218	.100	.297	.105		.307			

rates conditional on another. These returns estimates, as calculated in the next section, are the basis for most analyses in the paper.

### 2.3 Calculating Returns to Degrees

This paper is interested in the returns of education in terms of wages and the non-employment rate, how estimates of those returns differ between subjective responses and effects derived from observed data, and how both the subjective returns and the differences between subjective and projected returns differ over student observables. I calculate the return to wages and the non-employment rate for each of four higher education outcomes: some college but no degree, two-year degree, four-year degree, and advanced degree, compared to the outcome associated with holding a high school degree and not attending college.

Students report their subjective expectations under each counterfactual attainment level. As such, the perceived return at each attainment level can be calculated for each student. For student  $i$ , the returns to degree  $d$  for wages ( $W$ ) and the non-employment rate ( $N$ ) are

$$\gamma_{di}^W = \ln(W_i|d) - \ln(W_i|HS) \quad (2.1)$$

$$\gamma_{di}^N = (N_i|d) - (N_i|HS) \quad (2.2)$$

Where  $W_i|d$  is the expected wage conditional on having attained educational level  $d$  at age 30 in Washington State,  $N_i|d$  is the expected non-employment rate at age 30 in Washington State conditional on having attained educational level  $d$ , and HS indicates that the terminal level of education is a high school degree. Note that  $N_i$  is a measure of “non-employment” that includes both unemployment and being out of the labor force.

Since counterfactuals are not observed at the individual level in the ACS and NLSY data, cross-sectional estimates are generated using sample averages of the outcomes of interest for workers aged 29-31.<sup>6</sup>

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<sup>6</sup>In the ACS, employment is a binary variable indicating whether or not the subject is currently employed. In the NLSY, employment is measured as the fraction of weeks in the previous year for which the subject was employed.

$$\gamma_d^W = \overline{\ln(W_i|d)} - \overline{\ln(W_i|HS)} \quad (2.3)$$

$$\gamma_d^N = \overline{(N_i|d)} - \overline{(N_i|HS)} \quad (2.4)$$

Equations 2.3 and 2.4 show how I calculate projected student returns to education. For wages, only full-time, full-year workers are included. This method does not attempt to correct for endogeneity in schooling. The returns estimated in this way are intended to be comparable in interpretation to those estimated using APCAB data.<sup>7</sup> I discuss the appropriateness of these comparisons in further detail in the next section.

## 2.4 Comparing Returns to Degrees

The goal of this paper is to make a meaningful comparison between estimates of returns to education based on subjective data and projected estimates of returns to education based on observed data. In this section I address the way in which these measures are comparable, how the similarity or difference between them can be interpreted, and what assumptions must be made about the subjective data in order for these comparisons to be meaningful.

The projected returns estimated using observed data in the ACS record differences across educational attainment in wages and employment for current workers in the state of Washington. This is to be compared to subjective data collected about the expected outcomes of the student (Self) or of the typical person (Typical). There are a number of issues that complicate the comparison of these measures.

One of these issues, relevant to the comparison between subjective Self estimates and projected returns, is selection into college. For Self data, each student reports their own expected outcomes under each counterfactual. The subjective estimates of returns calculated using Self data are then internal rates of return, and the average subjective return using Self

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<sup>7</sup>An alternate method of estimating these is to regress the outcome of interest on an indicator of having attained  $d$ , using a sample of only those who have attained exactly  $d$  or graduated high school but did not attend any college. This method produces identical results, but allows for the possibility of including controls for gender and race/ethnicity. No results change if these controls are included.

data is the average internal rate of return over the sample. This internal rate of return is contrasted against the projected return, which is an observed premium that does not attempt to control for selection. The projected return can then differ from the subjective rate both because ability is correlated with educational attainment, and because there may be heterogeneity in the internal return to education. Students with higher returns may be more likely to pursue an education, driving up the projected return in relation to the average causal return over the whole sample.

This issue of comparability suggests that Typical returns are more comparable to projected returns, since neither controls for selection. To elicit Typical returns, respondents were asked to think about the outcomes for the average person with a typical level of education in Washington State at age 30, which has a single correct answer that should match the overall mean of the observed data. While Typical returns avoid the issue of selection, the fact that there is a single “correct” answer across all students means that it does not make sense to compare demographic-specific subjective estimates. The correct Typical return estimated by a black student is the same as that estimated by a white student, even if their internal returns are different. Further, it is possible that different students have different ideas about who a “typical person” is. Because of this, differences between projected and Typical returns may be due only partially to differences in wage perceptions and partially to differences in demographic perceptions. However, even if the idea of the “typical person” varies among students, the comparison between subjective Typical and projected returns is valid as long as the average student in the APCAB sample has a realistic idea of who the “typical person” is.<sup>8</sup>

When making comparisons that are broken down by demographic characteristics, Self estimates represent internal rates of return unlike projected returns, but should include demographic differences. Since the subjective and projected returns are compared across

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<sup>8</sup>Similarly, for Self estimates, students may have personal information not available to the researcher that is relevant to their return, which may be another reason for Self estimates to not match projected returns. However, comparisons of average returns can be considered valid as long as the average student has unobserved personal information similar to the average person in the observed data.

demographics, selection bias is only a problem here to the extent that the difference between the projected return and the average causal return to education differs across demographic groups. It cannot be taken as given that all groups exhibit the same level of selection bias or heterogeneity in the returns. When discussing demographic-specific results, I make use of selection-corrected demographic-specific returns to education found in the literature to support the conclusions drawn from comparisons made between Self and observed data.

In practice, I report, in the paper or in appendices, the result of comparisons between observed data and both Self and Typical subjective data for all analyses. Since the weaknesses of these comparisons in general are not overlapping, the use of both strengthens the results. Self and Typical returns estimates have very similar distributions (as seen in Section 2.5.1) and are correlated across students (correlations between Self and Typical returns are .319, .446, .571, and .705 for returns to some college but no degree, two-year degree, four-year degree, and advanced degree, respectively). The close connection between the two measures suggests that students think of the “typical person” as being somewhat like themselves, at least when it comes to returns to education, and that students do not think the selection effect is very strong. Results are robust to the use of either subjective measure.

Another issue facing comparability is the question of which feature of the wage distribution is being reported by students. Unlike some other work (Dominitz and Manski, 1996; Attanasio and Kaufmann, 2014; Wiswall and Zafar, 2015), APCAB data features only a point estimate of the underlying wage distribution, rather than a subjective distribution with many points of support. The necessary assumption here, in order to reasonably compare the subjective estimates to those from observed data, is that the reported subjective estimate is, as instructed, a central tendency of the distribution.

There is also the issue of comparisons across time, especially for subjective Self estimates, in which students may be aware of current returns but are considering a future for themselves where the returns to education have changed considerably. They may also be taking business cycles and seasonality into account, which if applied to the observed data may change the projected return to which subjective returns are compared.

These issues of comparability across time pose some problem for comparisons between subjective and projected returns, but also highlight some of the issues in attempting to use projected returns as a proxy for student beliefs in the wider literature. For example, it is possible that student expectations of returns incorporate expected changes in returns in the future. However, claiming that these future changes represent student expectations is a tenuous claim without expectations data, and requires further assumptions about the way in which these predictions are made.<sup>9</sup>

One final consideration, important given that this paper focuses on comparisons between subjective and projected returns rather than raw expectations of outcomes, is that of measurement error. Subjective reports are noisy representations of actual beliefs. Returns estimates, which involve the combination of two reports, are noisier. Noise will bias downwards any relationship between subjective and projected returns, and I discuss the implications of this further in Section 2.5.2. However, a focus on returns estimates rather than raw reports, which would presumably have less measurement error, is still worthwhile. The return, rather than the raw level, is the input of interest in the human capital model, and so it should be an object of interest. Additionally, as stated previously, raw reports may have less statistical noise but may also incorporate varying student perceptions about inflation or their own ability to earn unconditional on schooling. Returns estimates, as opposed to raw estimates of wage and non-employment rate levels, are noisier than raw estimates, but on the other hand avoid the above issues.

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<sup>9</sup>Students do not appear to be making these predictions using prior trends, as the use of trend data does not make projected estimates of returns closer to subjective estimates. I estimate  $\gamma_d^W \forall d$  again using Washington residents aged 25-34 in the Current Population Survey data from 1997-2011. Over that 15-year time span,  $\gamma_d^W$  showed no statistically discernible upward trend. In the absence of an anticipated upward future shock, upward growth is too slow to predict an increase over the next 12 years which would make significantly decrease the gap between average subjective and projected returns.

## 2.5 Results

### 2.5.1 Aggregate Returns

In Figure 2.1, I compare the subjective wage and employment rate returns to the projected wage and employment rate returns calculated using observed data. Each image relates to the return to a different attainment level (some college but no degree, two-year degree, four-year degree, and advanced degree). In each image, the kernel density plots of the subjective estimates are compared against the average estimated projected return, marked by a vertical line. I explore heterogeneity in the projected return in the next section. There are two primary areas of interest to focus on in these graphs: the distributions of the subjective returns, and the relationship between the subjective and projected returns.

For both wage and non-employment rate returns, there is wide variation in student beliefs. The distribution of returns becomes less concentrated for higher degrees, possibly reflecting a higher degree of uncertainty about returns at these more remote levels. The means and medians of these distributions move in the expected directions—the average expected return for each degree is stronger than the average expected return for the degree below it. For example, the mean subjective expectation for the increase in log wages and the decrease in non-employment rate for a four-year degree are .736 and -.157, respectively. The mean returns for an advanced degree are 1.038 and -.228, respectively. However, there are still small groups of students who believe that attainment of higher education will lower their wages (the return is below 0) or increase the non-employment rate (the return is above 0). About 4.5% of students estimate that the Typical wage return to a bachelor’s degree is negative.

These subjective distributions can be compared (given the caveats in Section 2.4) to the average projected returns. For non-employment rate returns, despite the considerable *level* differences in non-employment rate estimates shown in Table 2.2, students at the mean make estimates of the non-employment rate return that match the projected return closely. On average, students estimate that the effect of some college but no degree or a two-year degree

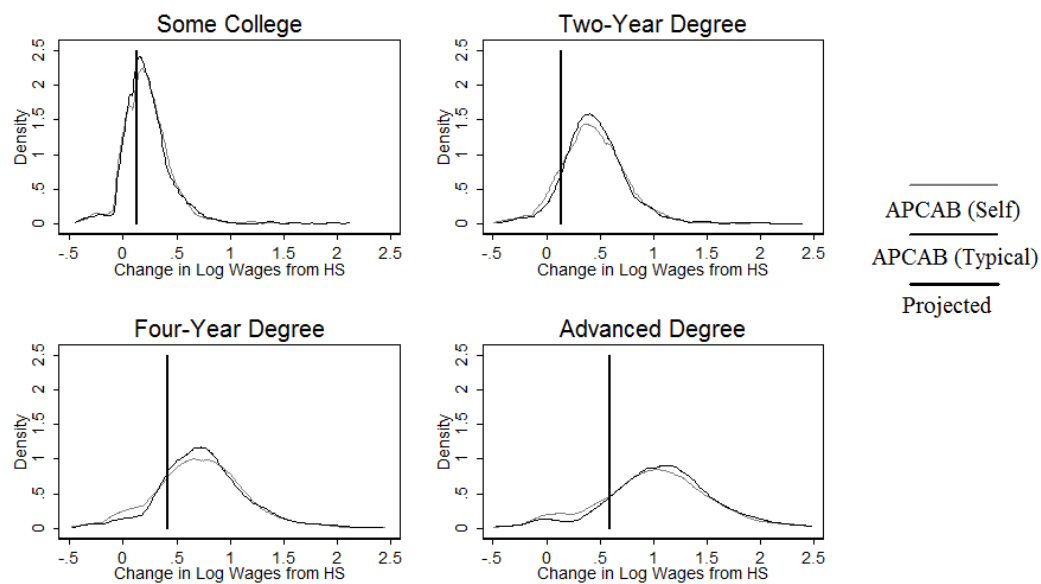
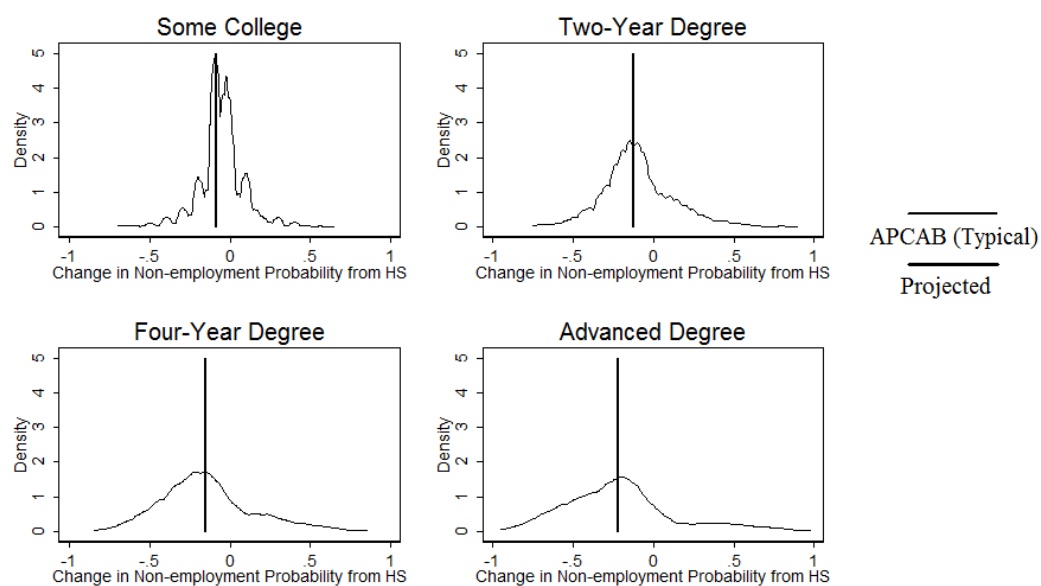
on the non-employment rate is about .020 smaller than the projected return, and about .005 larger for four-year and advanced degrees. While there is clearly a large amount of variation in subjective expectations of the return, on average, non-employment rate returns estimates generated using observed data appear to match student expectations. For wage returns the story is different. While the mean subjective and projected returns to some college are close, the average student expects to get a much bigger wage bump for any college degree than is found in the projected return. The average expected Typical wage return is 30, 32, and 43 percentage points higher than the projected return for two-year, four-year, and advanced degrees, respectively. In each case, about 85% of students estimate the Typical return to be higher than the projected return. Since these Typical estimates ask students to estimate the figures calculated in the observed data, the mismatch can be interpreted roughly as an error or lack of information on the students part. This result suggests that students are not aware of the population wage premium for higher education.<sup>10</sup>

Because Self and Typical estimates share nearly identical distributions, estimates of Self returns are similarly higher than projected returns. The difference between Self and projected estimates of wage returns to degrees suggests that estimates of returns made using observed data will have a difficult time matching student estimates of their own return, unless the correction to projected returns made by controlling for selection increases the return by approximately 30-40%, an amount larger than currently found in the literature on selection-controlled returns to education (see, e.g. Card, 1999). Unlike the mismatch between Typical returns and projected returns, which can be interpreted as the inability of the students to match the data, this result points towards a difficulty in using the data to match the students. Additionally, the wide distribution of subjective returns suggests that any universal projected

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<sup>10</sup>I run two robustness checks on this finding. First, it is possible that seniors, who are closer to the labor market than juniors, have better information about returns. However, there is no significant difference at the 95% level between the mean expected return for juniors and for seniors for any wage or employment return at any degree level. Second, it is possible that students are reporting returns for more localized areas such as King County or the surrounding Tri-County area, rather than all of Washington State. I re-estimate projected returns using the ACS data for these regions; regional returns are very similar to state-level returns.

Figure 2.1: Subjective and Projected Returns Distributions

(a) Log Wage Returns to College ( $\gamma_d^W$ )(b) Non-employment Rate to College ( $\gamma_d^N$ )

return to education will be unable to match student expectations of the return, no matter how that universal return is adjusted. In the next two sections, I evaluate whether projected returns that allow for heterogeneity across students are aligned with the heterogeneity present in student expectations.

### *2.5.2 Disaggregated Results*

The subjective and comparison data sets are large enough that separate returns estimates can be produced for different subgroups. In this section I analyze the group-level match between subjective returns and projected returns, meaning comparisons of returns estimated using some subgroup of those in the APCAB (Self) data and those in the same demographic subgroup in the ACS (WA) or NLSY data.<sup>11</sup> Analysis of returns at this level is crucial. As established in the previous section, projected wage returns are below subjective wage returns, and non-employment rate returns match closely. However, this result is not enough to conclude that projected returns are a bad proxy for wage returns but a good proxy for non-employment rate returns. If students who would be expected to have a high projected wage return also expect high wage returns, then projected wage returns are still a good proxy for subjective wage returns, since they will be highly correlated at the individual level. Conversely, if students who would be expected to have a high projected non-employment rate return expect low non-employment rate returns, then projected non-employment rate returns are not a good proxy for subjective non-employment rate returns.

Analysis from this point focuses on APCAB (Self) estimates, since these estimates should track demographic similarities in observed data. As mentioned in Section 4, comparison is not completely straightforward here since APCAB (Self) estimates represent the internal rate of return while projected estimates do not. I invoke estimates of selection-corrected returns in the literature and additional comparisons between APCAB (Typical) estimates and observed data to address this issue. Non-employment rate reports do not have a Self

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<sup>11</sup>For demographic variables present in both the NLSY and the ACS, returns estimates are very similar in the two data sets.

component and so estimates for the typical person are used.

To illustrate the analysis that will follow, Table 2.3 depicts differences in wage returns estimates broken down by gender. Women expect slightly higher returns than men, and with the exception of some college but no degree this is consistent with the projected return. So, the differences between subjective and projected wage returns are similar for men and women for non-advanced degree levels. We can then conclude that subjective and projected returns are aligned over gender, similar to what is found in Rouse (2004). This alignment is what one would expect if estimates were based on observations of labor market outcomes, albeit with an upward shift in the subjective return applied to all subjects at the population level.

Table 2.3 gives a detailed account of one demographic disaggregation. Keeping this example in mind, I demonstrate disaggregation over gender, race, GPA, FRPL, and parental education. Figure 2.2 presents a plot with the projected return for a four-year degree  $\gamma_{4Y}^W$  estimated using observed data on the y-axis and the average of the subjective return  $\gamma_{4Y_i}^W$  estimated using APCAB (Self) on the x-axis. The comparison data set is the ACS (WA) for the aggregate as well as for the disaggregation over gender and race<sup>12</sup> and the NLSY for the disaggregation over GPA, FRPL, and parental education. In each case, the returns are demeaned so the population-weighted average of the returns is 0. Vertical lines divide groups with higher and lower average subjective returns than the aggregated sample, and horizontal lines divide groups with higher and lower average projected returns than the aggregated sample.

For wages, we can see male and female falling roughly along a 45 degree line through the Origin point, indicating that the subjective and projected returns are appropriately aligned over gender, as previously demonstrated in Table 2.3. However, other groups of disaggregated estimates do not fall along a 45 degree line. Since the distance between subjective and projected returns differs by group, a population-level upward correction to

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<sup>12</sup>For black workers, instead a national ACS sample is used due to the small number of black people at certain educational levels in the ACS (WA) sample.

Table 2.3: Mean Log Wage Returns to College Attainment by Gender

	Men			
	Some College	Two-Year Degree	Four-Year Degree	Advanced Degree
Subjective Return (Self)	.216	.426	.677	.901
Subjective Return (Typical)	.214	.439	.706	.982
Projected Return	.163	.167	.415	.652
Difference (from Self)	.053	.259	.262	.249
	Women			
	Some College	Two-Year Degree	Four-Year Degree	Advanced Degree
Subjective Return (Self)	.222	.457	.739	1.05
Subjective Return (Typical)	.228	.453	.769	1.10
Projected Return	.141	.203	.494	.656
Difference (from Self)	.081	.254	.245	.394

Figure 2.2: Subsample Analysis: Wage Return to a Four-Year Degree

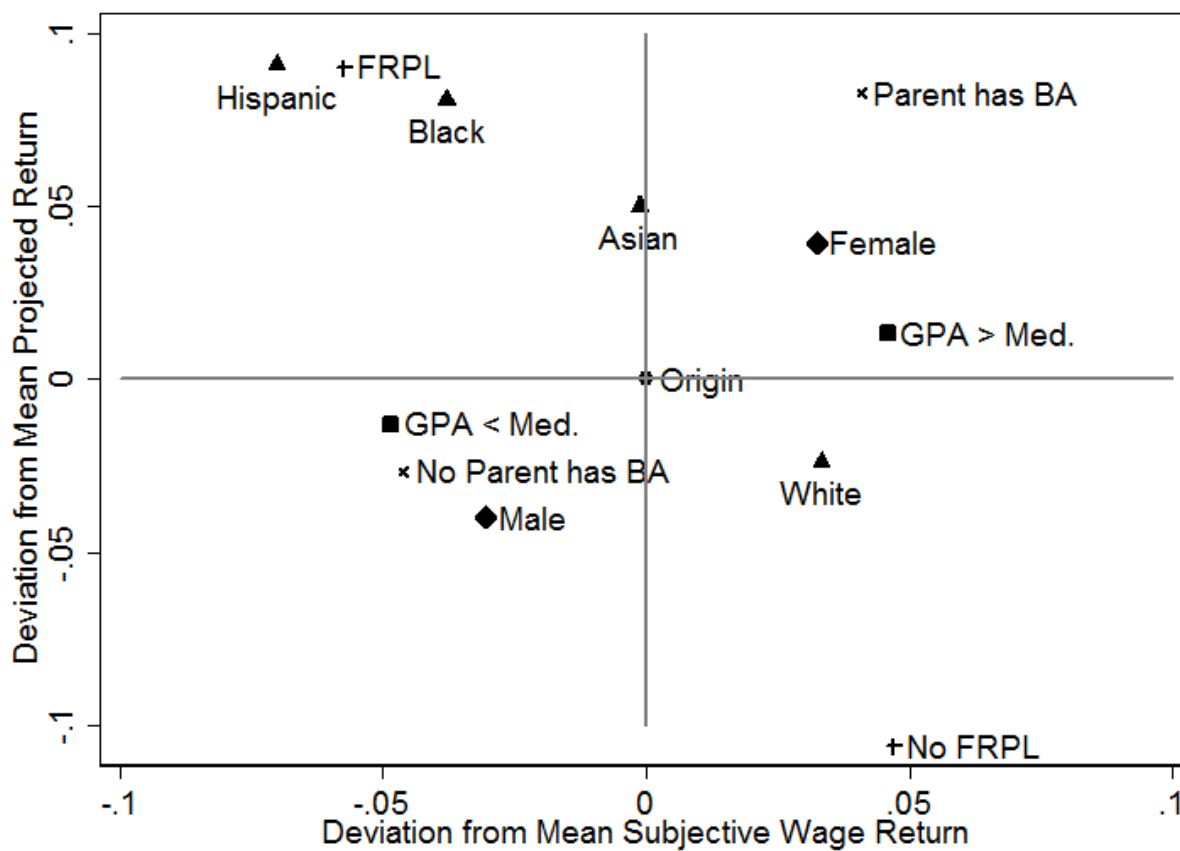
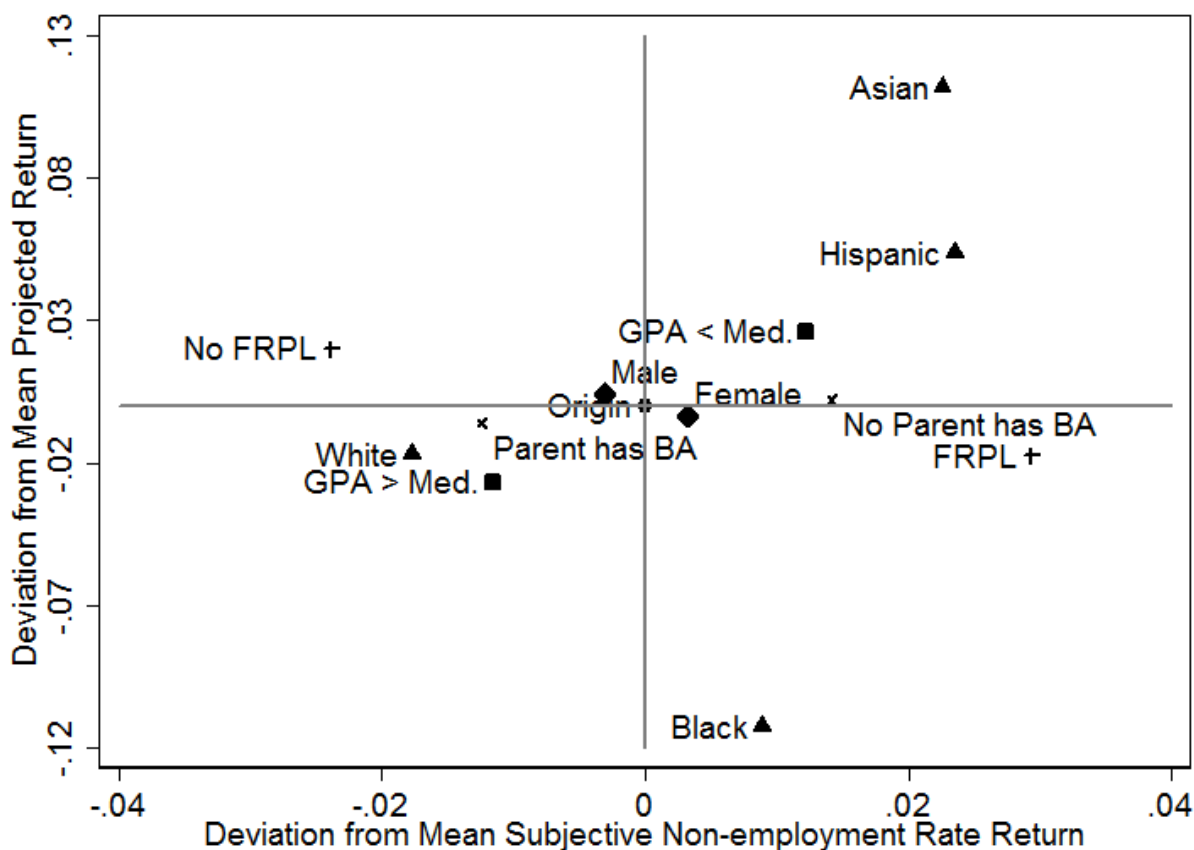


Figure 2.3: Subsample Analysis: Non-employment Rate Return to a Four-Year Degree



projected estimates of  $\gamma_{4Y}^W$  would not cause projected estimates to match subjective estimates.

In Figure 2.3, differences seem better aligned, but the scale of the x and y axes do not match, and projected returns vary over background characteristics much more strongly than do subjective returns, leading to poor alignment. The two exceptions are the cases of parental BA status and GPA, where the groups with higher subjective returns also have higher projected returns.<sup>13</sup>

<sup>13</sup>In Figures 2.2 and 2.3, returns to four-year degrees are shown. Returns to other degree levels, and for Typical wage returns, can be found in Appendix A Figure A.1. These other returns reiterate the findings in Figures 2.2 and 2.3: there is no strong relationship between subjective and projected returns at the subgroup level for any degree return.

In the wage returns comparison, the subjective returns represent the average internal rate of return but the projected returns do not. As such, the lack of a relationship between subjective and projected returns in wages could be explained by the selection effect differing in strength across subgroups. While this is difficult to address in general, what can be found in the literature about demographic-specific selection-controlled returns to education supports the initial conclusion.

For example, in Figure 2.2, projected wage returns for black students are larger than returns for white students, but the opposite is found with subjective returns. A higher average rate of return to a four-year degree for black students than for white students is found commonly in the literature (Henderson et al., 2011), even in the case of average internal rates of return over the population (Heckman et al., 2006). So in a comparison of subjective and average projected internal returns for white and black students, the same result would be found. Similarly, the result found here that women have higher wage returns than men is also found in the literature (Jacob, 2002; Brand and Xie, 2010; Marcotte et al., 2014), although these studies do not address selection bias arising from the correlation between the internal rate of return and educational attainment. If the difference between the return for the marginal and average student varies greatly over these groups, this will threaten results. The general match over gender and white/black does not necessarily mean that the use of an average internal rate of return would leave the other subgroups unchanged, but they are suggestive and at least support the result for comparisons over gender and between white and black students. More generally, there is evidence in the literature that those who face more obstacles in going to college have higher returns (Brand and Xie, 2010). With parental BA status as an exception, this does not hold up in the subjective returns in Figure 2.2. Whites, students with high GPAs, and students who do not receive FRPL all expect higher returns than others.

The analysis so far in this section does not take into account overlapping demographics. It is possible, for example, that while black students expect lower returns than white students, counter to the projected return, but that this problem may be resolved or lessened when

looking at black men and black women separately. To allow for this, I generate individualized estimates of projected returns for comparison to the subjective returns, which are already calculated at the individual level. Additionally, this approach allows for a test of whether or not the subjective and projected returns are correlated at the individual level, which more directly addresses the use of projected returns as a proxy for subjective beliefs.

I generate individualized returns using observed data by allowing returns estimates to vary over background characteristics. Using an observed sample of high school graduates and those with the educational attainment of interest, I regress the outcome (either log wages or non-employment) on the presented list of background controls, degree attainment, and the interaction between degree attainment and all background controls. The individualized projected return is generated using each APCAB students mix of background factors.

I plot the relationship between these projected returns and the reported subjective returns for a four-year degree in Figure 2.4. For both wages and employment, individualized subjective and projected returns are completely unrelated. The correlation between the individual-level projected and subjective returns is a statistically insignificant  $-.064$  for wages and  $.052$  for the non-employment rate.

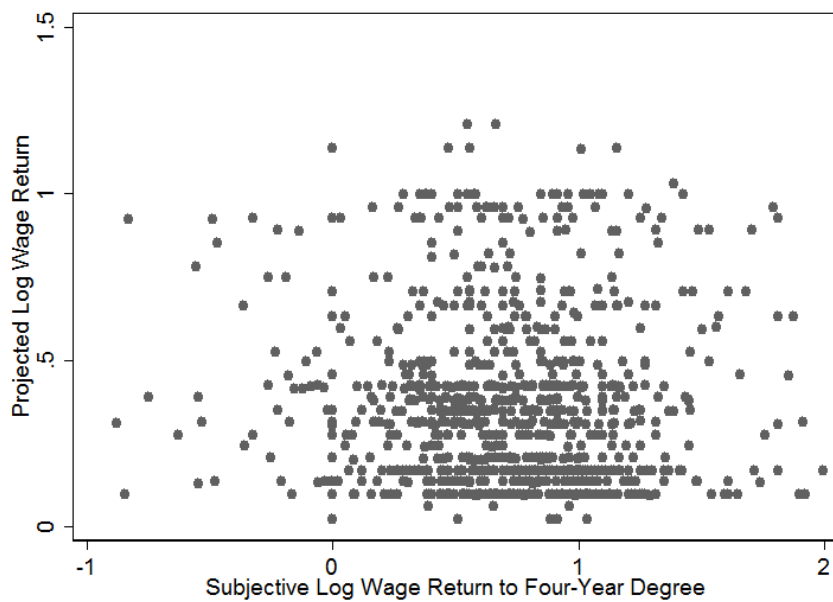
This correlation is likely attenuated by measurement error in the subjective returns estimate. For wages, measurement error could imply an opposite sign if the error in the subjective returns estimate were correlated with the value of the return. For non-employment rate returns, a disattenuated correlation (Spearman, 1910) could imply a correlation more in the range necessary for an acceptable proxy.<sup>14</sup> For this to happen, the reliability of the subjective return would need to be very low; the product of the reliabilities for the subjective and projected reliabilities would need to be about  $.01$  to produce a disattenuated correlation of  $.5$ . Such low reliabilities would imply that, if the subjective and projected returns were equally reliable, about 90% of the variation in each return would be only noise.

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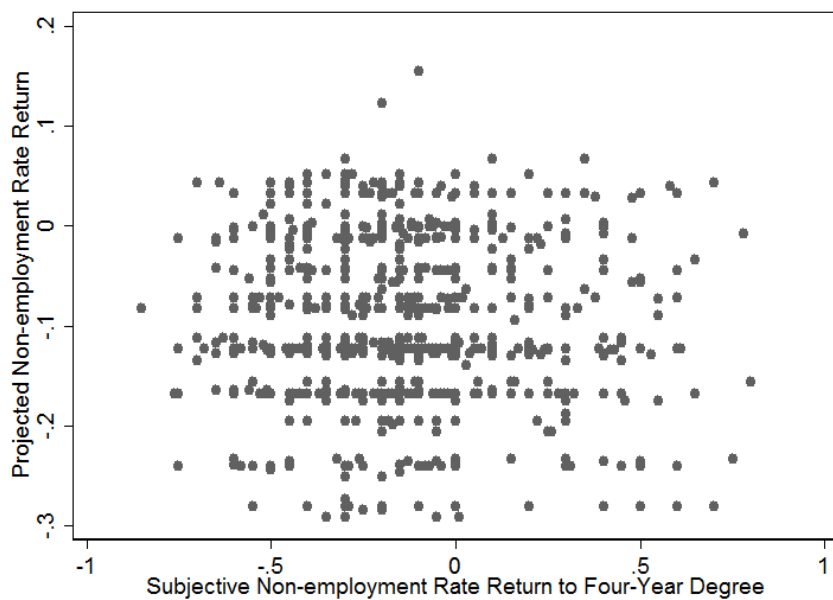
<sup>14</sup>The standard formula for is that the disattenuated correlation for two given variables is equal to the sample correlation of the variables divided by the square root of the statistical reliability of the first variable multiplied by the square root of the statistical reliability of the second variable.

Figure 2.4: Scatterplot of Subjective and Projected Returns

(a) Wage Returns



(b) Non-employment Rate Returns



Both figures use the NLSY as comparison data so as to allow for disaggregation across FRPL, parental education, and GPA, and focus on the return to a four-year degree. However, results are consistent for comparisons to the ACS (using only gender and race/ethnicity as background characteristics) and for returns to nearly all other degrees. Looking at all degree levels, for either Self wages, Typical wages, or the non-employment rate, and using either the NLSY or the ACS, correlations are small and generally insignificant, with a notable exception of wage returns to advanced degrees, for which the correlation is about .11 depending on the measures used.

The heterogeneity over observables exhibited by subjective returns estimates does not align with the heterogeneity over observables exhibited by projected returns estimates, either at the subgroup or individual level.<sup>15</sup> At the available level of demographic detail, projected returns are not a good proxy for subjective returns.

### *2.5.3 Educational Attainment Goals*

The lack of a relationship between subjective and projected returns to education naturally leads to the question of which of these seemingly orthogonal variables actually relates to decision-making. The goal in this section is not to develop a formal model of attainment as in Attanasio and Kaufmann (2014), but rather to present a verification exercise. In any model of student choice in which students care about future earnings, returns should be related to student choice. If subjective returns do not correlate with student plans, then either students do not care about future earnings or the subjective returns are picking up something other than actual beliefs. In the second case the inability of projected returns to match subjective returns is not much of a concern.

Final educational attainment is not observed, but attainment is measured in two ways here. First, students were asked to state the final level of education they would like to attain. Consistent with other studies that elicit desired educational attainment, this variable is rather

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<sup>15</sup>This lack of a relationship holds if projected returns estimates are taken using more localized ACS data from King County only or from the surrounding Tri-County area.

optimistic and students are likely to actually attain less education than they state (Choy, 2001; Avery and Kane, 2004). However, the variable gives us a measure of their *desired* final attainment, which should be consistent with their beliefs about the returns to education. Second, seniors were asked to report whether they were attending college the following fall, and which schools they were looking at or were registered for. These schools are coded as two or four-year institutions. This second measure is a more direct measure of student activity, but is noisy for other reasons a student may change plans before the fall or may be planning delayed enrollment. A student attending a two-year school may not plan to finish their education there.

Table 4 shows pairwise correlations between measures of attainment and both subjective and projected returns. Projected returns are calculated on the individual level using the ACS data as in the previous section to allow for variation over all background characteristics; results are similar if the NLSY data is used instead. For subjective wage returns, Self returns are used, although results are similar if Typical returns are used instead.

The subjective wage return to a college degree is correlated with the decision to pursue a college degree. The returns to four-year or advanced degrees are correlated with all types of planned attainment, and the return to a two-year degree is correlated with the plan to attain any level of college degree but not with the plan to attend a four-year college. The return to attending some college but receiving no degree is related to desired attainment levels but not whether a senior is planning to attending college in the following fall. Projected wage returns, on the other hand, are not strongly related to educational choice in the expected manner. The return to some college, a two-year degree, or a four-year degree is actually negatively correlated with attainment plans, although the return to an advanced degree is positively correlated with attainment plans. As the return to the non-employment rate is negative (more education leads to less non-employment), a negative sign on the correlation of attainment with the return to non-employment in Table 4 indicates that a stronger return is associated with more attainment, which is to be expected. Subjective returns are almost always negatively correlated with attainment plans, although the relationship is only signif-

Table 2.4: Correlation of College Decisions with Wage and Non-employment Rate Returns

Panel A: Correlation of College Decisions with Wage Returns									
Decision	Subjective Return				Projected Return				
	Some	2-Year	4-Year	Adv.	Some	2-Year	4-Year	Adv.	
	College	Degree	Degree	Degree	College	Degree	Degree	Degree	
Desires Any	.111**	.127***	.153***	.160***	-.019	-.014	-.018	.164***	
Desires 4Y+	.080**	.078*	.135***	.146***	-.000	-.014	-.089***	.308***	
Attending Any	.023	.116**	.143***	.200***	-.005	-.018	-.126***	.235***	
Attending 4Y	.063	.073	.118***	.131***	-.026	-.087*	-.294***	.391***	

Panel B: Correlation of College Decisions with Non-Employment Rate Returns									
Decision	Subjective Return				Projected Return				
	Some	2-Year	4-Year	Adv.	Some	2-Year	4-Year	Adv.	
	College	Degree	Degree	Degree	College	Degree	Degree	Degree	
Desires Any	.047	-.003	.000	-.026	-.010	-.058*	-.098***	-.108***	
Desires 4Y+	-.002	-.039	-.010	-.015	-.096***	-.131***	-.161***	-.206***	
Attending Any	-.004	-.043	-.109***	-.103**	.029	-.125***	-.150***	-.165***	
Attending 4Y	-.028	-.021	-.066	-.107***	-.113***	-.221***	-.167***	-.294***	

Note: “Desires Any” and “Desires 4Y+” indicate that the students desired attainment level is, respectively, of any college degree or of a four-year or advanced degree. “Attending Any” and “Attending 4Y” was asked only of seniors and indicates, respectively, that they are attending any college in the following fall, or attending a four-year college in the following fall. \*/\*\*/\*\* indicates statistical significance at the 10%/5%/1% level.

icant between whether the student is attending college in the following fall and returns to four-year and advanced degrees. Projected returns are negatively and significantly correlated with student attainment plans in a consistent manner.

That both subjective wage and non-employment rate returns correlate with college plans (although the employment relationship is weak) is indicative that they may be involved in the decision making process. Notably, though, the projected non-employment rate returns also relate strongly. Attanasio and Kaufmann (2012) also find that decision-making correlates with both subjective and observed-data returns. There are a few possible reasons why projected returns might relate to decision-making even though the student does not appear to be aware of them. First, projected returns may contain some information that students know internally and are capable of responding to but not reporting. Second, it is possible that parents in groups with stronger projected returns have higher incentives to offer more encouragement that their children go to college. Even if students are not directly aware of the projected returns, they may be indirectly influenced by them in this way.

Student attainment plans are correlated positively and significantly with subjective wage returns expectations. The sign of the correlation between student attainment plans and subjective non-employment rate returns expectations is reassuringly negative, although the relationship is not strong. These correlations imply that the information being picked up by the data does relate to the actual decisions that students make. That the subjective returns are related to student plans indicates that the projected returns are indeed missing something important by not being related to subjective returns.

## **2.6 Conclusions**

What information does this paper give us about student expectations? We have a number of general results to contend with. First, most students expect that the returns to education are large, positive for wages, and negative for the non-employment rate. Second, on average, the subjective internal wage return is higher than the projected wage return, but subjective estimates of non-employment rate returns are about the same as projected returns. Third, there

is a lot of heterogeneity in subjective estimates for wages and non-employment rate returns. This heterogeneity does not align with heterogeneity in projected returns on an individual or subgroup level. Fourth, student anticipated educational attainment relates positively to subjective wage returns, negatively (and weakly) to subjective non-employment rate returns, and correlates with projected non-employment rate returns (more so than subjective non-employment rate returns) but not most projected wage returns.

Projected returns calculated using observed data are not correlated with subjective returns as elicited from students. As such, projected returns as a poor proxy for subjective returns. Despite this, both educational research and educational policy commonly assumes that the two are closely related. This assumption leads us to biased results and suboptimal policy. Subjective expectations data offers one means of avoiding this problem and improving the study and practice of education in the future.

These results can be used to evaluate some approaches to studying educational choice and policy geared towards changing student beliefs.

The mismatch between subjective and projected returns has important implications for the way that educational choice is studied. Models of educational choice commonly relate students' responses to some measure of the return to attending school, usually projected using observed data. The strength of the students' response is taken to be a measure of preference for future income. If subjective and projected returns do not align, then the estimated coefficient will be biased. We see students responding to projected returns both in choice models and in the correlational analysis in this paper. However, it does not necessarily follow that this response is a direct preference for future consumption. Response to projected returns could be mediated through parental influence, for example. Many studies of educational choice treat the preference for future consumption as a parameter of interest, since the perceived rate of earnings returns can be a policy lever. A bias in this coefficient is of importance to researchers and policymakers.

If projected labor market returns do not relate to stated expectations, then research on educational choice must take this into account. One clear approach is to collect subjective

expectations data and include it as a predictor of student choice. This work is already being done in a number of contexts (e.g. Arcidiacono et al., 2011; Attanasio and Kaufmann, 2012; Wiswall and Zafar, 2015) but could be expanded. Currently, most researchers planning to use subjective expectations data in educational contexts must gather it themselves, but inclusion of these questions in standard large-scale surveys would aid research on education.

Another, more difficult, approach to improving research when observed labor market returns do not relate to stated expectations is to flesh out a usable model of expectations formation such that the econometric model underlying the projected returns better reflects the expectations formation process. If this is the case then subjective and projected returns will likely be strongly correlated. However, since this paper finds subjective returns to be uncorrelated with projected returns, such a model would need to be based on something other than belief updating in response to observations of the labor market. A number of studies in disparate contexts have examined the impact of information on beliefs and how beliefs respond to information-based research interventions and experiential learning (Zafar, 2011b; Oreopoulos and Dunn, 2013; Jensen, 2010; Wiswall and Zafar, 2015). Information sources and the provision of information do impact beliefs, but even with direct intervention the influence of information is limited, and so this cannot be the whole story. Unfortunately, subjective beliefs are difficult to explain. Using APCAB data, a regression of subjective individual returns on demographics, family encouragement, (endogenous) information sources, senior status, and attitude towards education yields some significant coefficients but explains very little of the variance, like the intervention studies failing to provide a full portrait of what generates expectations.<sup>16</sup> Other explanatory sources are necessary, especially outside of an experimental context.

Beyond its implications for economic research, these results have policy implications as

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<sup>16</sup>Full results available from author.  $R^2$  values range from .02 to .08, depending on which return it is. The included list of covariates includes all background characteristics used in prior sections as well as controls for senior status, whether the students family wants and/or expects them to go to college, and whether they got college information from (nonexclusive): parents, family, teachers, school staff, other adults, college events, friends, printed materials, college representatives, college visits, the internet, or TV and movies.

well. There is recent policy research interest in interventions designed to change students' perceptions of returns (e.g. Jensen, 2010; Hoxby and Turner, 2013), as well as a recent policy intervention, in the form of the College Scorecard system. The aggregate analysis suggests a possible pitfall in policy approaches that attempt to “correct” student beliefs to match projected returns. Student estimates of wage returns are actually above projected wage returns. If informational interventions are effectively convincing such that student beliefs match projected returns, then for many students the intervention would have the effect of lowering expectations of wage returns from college. Given that these expectations correlate with student choice, and that experimental approaches suggest this relationship is likely causal (Jensen, 2010; Wiswall and Zafar, 2015), the intervention may have an adverse effect.

## Chapter 3

# CONSUMPTION VALUE AND THE DEMAND FOR COLLEGE EDUCATION

### 3.1 Introduction

College education is an important determinant of economic productivity and individual welfare. The incentives that drive individuals to seek further education tell us how shifts in the labor market or policy interventions will affect labor supply. In this paper I examine what matters to high school students when they plan their college education.

Following from the human capital model, economic studies of educational choice often treat the pursuit of financial reward as the primary reason to attend college.<sup>1</sup> However, financial incentives are not the only reason to attend. Consumption value is the immediate utility gained while receiving an education, in contrast to benefits (financial or otherwise) gained as a result of completing some amount of education. Students enjoy going to school and prefer to fulfill social expectations. Consumption value can take the form of enjoying particular programs or amenities (Beffy et al., 2012; Jacob et al., 2013; Alter and Reback, 2014; Wiswall and Zafar, 2015), following social norms and responding to encouragement (Akerlof and Kranton, 2002, 2010; Sandefur et al., 2006), experiencing the mental strain of education (Jacob, 2002; Heckman et al., 2006; Stinebrickner and Stinebrickner, 2014), and as a general concept (Lazear, 1977; Eckstein and Wolpin, 1999).

Recent developments in the literature on the choice of college major have worked towards an understanding of not just whether financial and consumption value incentives matter, but also how important these different incentives are in the bigger picture of student choice. Is

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<sup>1</sup>The human capital model itself is flexible enough to allow for consumption value and other non-financial incentives, and even early human capital researchers were aware of these incentives (Schultz, 1963, p. 8). However, this flexibility is often ignored.

student choice driven largely by financial incentives, as implied by a basic human capital model, or are other considerations more important? These studies suggest that student response to financial incentives is weak, and preference for the experience offered by a particular program may be a stronger predictor. These results offer an explanation for the poor alignment between which majors are popular and which lead to lucrative jobs (Arcidiacono, 2004; Alstadsæter, 2011; Beffy et al., 2012; Wiswall and Zafar, 2015).

In this paper I build on the work being done on the topic of major choice and study student demand for different levels of college education as a function of financial incentives and consumption value. I analyze choice at the margin between high school and different levels of college education, estimating demand among high school students whose priorities and information sets may be rather different than that of enrolled college students.

I am able to expand on the consumption value literature in general by using stated preference data to construct a multidimensional measure of consumption value, which allows for important detail. Unlike most of the above papers, I am not limited to examining one aspect of consumption value at a time. Nor am I limited to estimating consumption value as an unexplained individual fixed effect, without student-level variation in observed data. While there will always be unmeasured components, I can examine a larger part of consumption value than if I looked at one aspect at a time. I can observe the relative importance of the aforementioned different aspects of consumption value.<sup>2</sup> Being able to compare these different inputs is especially important when considering the use of consumption value as a policy lever, or when attempting to understand forms of education that offer experiences very different from traditional settings, like for-profit colleges or online education. Jacob et al. (2013) also allow for a multidimensional measure of consumption value in their study of choice between colleges as a function of campus amenities.

Detailed measurement is partially made possible by the use of subjective preference and

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<sup>2</sup>Additionally, by specifying the variables that determine consumption value beforehand, I avoid conflating consumption value with other non-financial returns, such as returns in the marriage market or to health (e.g. Oreopoulos and Salvanes, 2011). These rewards are delayed and so are not a part of the immediate consumption value of education.

expectations data. Subjective data include student reports of their direct preference for different types of consumption value, and reports of what they believe their wage, employment rate, and student debt would be given different levels of schooling.

Subjective expectations data are not typically included in large-scale nationally representative data sets such as the National Longitudinal Survey of Youth. As such, I collect the necessary survey data from 1,224 high school juniors and seniors in Washington State. The data set includes educational plans, background, social pressure, expectations of the educational experience, and subjective expectations about the labor market.

Subjective data have several attractive properties in educational choice analysis because expected counterfactual payoffs can be directly observed, and strong assumptions about expectations formation can be relaxed. Recent interest in the use of subjective expectations data in education (e.g. Jensen, 2010; Arcidiacono et al., 2011; Stinebrickner and Stinebrickner, 2014; Attanasio and Kaufmann, 2014; Wiswall and Zafar, 2015) follows from the influential Dominitz and Manski (1996) study of the expectations of the wage return to a college degree, which highlighted some of the potential benefits of subjective expectations data. Subjective expectations studies can estimate behavioral response to subjects' reported beliefs, rather than assuming a particular link between beliefs and data collected elsewhere. Since expectations about future earnings are reported directly, standard assumptions of rational expectations formation are not necessary to identify the student's decision process (Manski, 2004). Since students are asked to estimate counterfactual outcomes, the observation of payoff data does not depend on student choice or ability. In the case of this paper, since the student reports all decisions at a single point in time, assumptions about how student preferences or perceptions of their own ability evolve over time are not necessary.

I gather these student-level data in order to estimate student demand for educational options at the time they are finishing high school using a structural model of educational choice. These estimates tell us how students form their educational plans. Educational plans are an important part of the model of attainment.<sup>3</sup> Policies that aim to alter attainment

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<sup>3</sup>This is different from the typical approach that analyzes actual attainment, which is a result of student

often operate with the intended mechanism of changing student plans.

I test whether or not the investment returns to college explain student plans better than consumption value. They do not. Students do pursue financial returns, but their response is small compared to other incentives. Elasticity of demand for education with respect to wages ranges from .033 to .089 depending on education level. This weak response is not what is expected by a model of educational choice primarily built around investment.

Among consumption value inputs, expectations of ease and how enjoyable the academic experience will be have the strongest influence on student plans, although background and social pressure are also important. Consumption value's influence is the strongest when choosing among different undergraduate options, but weaker when making plans about graduate school.

This paper contributes to the literature on educational choice at the college level. I present a model of educational choice. I collect detailed novel data on student preferences, background, and expectations suitable for use in estimating the model. I simulate the influences of consumption value and financial incentives on college choice and compare the magnitude of the influences against each other. The ability of the model to describe student choice is meaningfully stronger than models that omit measures of consumption value.

The importance of human capital accumulation as an incentive for high school students to plan for higher levels of education is overstated. Consider an observer attempting to explain why one student plans to attain a college degree while another student does not. That observer would have more success looking at the variation in the consumption value of education between those two students than at variation in their financial returns. This calls into question the research focus on estimating student response to wages and taking advantage of that response to suggest policy. Researchers attempting to understand choice without reference to consumption value will see only a small part of the picture. Policies

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preferences but also parental preferences, unexpected life events, credit constraints, and shocks to perceived academic skill. A general model of attainment is incomplete without a detailed understanding of student choice in particular.

built on student response to financial incentives are likely to lead to behavioral change, but that change will be small compared to what could be achieved by emphasizing consumption value incentives.

A focus on consumption value seems counterintuitive for the purpose of policy; policy-makers interested in the social and economic benefits of education may be inclined to ignore consumption value, which does not directly provide a large positive externality. However, a driving assertion of education policy is that the addition of a college-educated worker to the labor market does generate a social benefit. An incentive that leads to the appropriate amount of college-educated workers should be of interest even if that incentive is not directly beneficial to others. Policy makers and economists may be dangling the wrong carrot. In doing so, they neglect a more realistic model of what drives student educational plans.

## 3.2 Model

### 3.2.1 A Model of the Demand for College Education

Students value college education because of the financial benefits received due to the accumulation of human capital and the non-financial benefits received in the form of experiences or social benefits. Students must weigh these benefits against the financial and non-financial costs of college. Education concludes when the costs of continuing outweigh the benefits.

Each student has an annualized time-separable utility function that depends on the consumption of goods, the consumption value of education, and distaste for work. The student plans a number of future decisions, each time choosing the option that offers the highest utility. In this section I make the simplifying assumption that all years of schooling are identical, as are all years of work, which I relax in the next section.

Utility conditional on attending an additional year of higher education is

$$U^s = U(G_s, CV_s, H_s | \gamma) + \epsilon_s \quad (3.1)$$

where  $G_s$  is the consumption of non-education goods during college,  $CV_s$  is educational consumption value, and  $H_s$  is the annual number of hours worked while in college.  $\gamma$  is a

vector of preferences, and  $\epsilon_s$  is a random taste shifter. The budget constraint is:

$$Tu + G_s = L + F + H_s W_s \quad (3.2)$$

where  $Tu$  is annual tuition,  $L$  is the loan the student takes on that year,  $F$  is financial aid and grants that do not have to be paid back, either in the form of student aid or endowments from parents, and  $W_s$  is the hourly wage while in college.<sup>4</sup>  $L$  adds to the total stock of student debt  $\mathbb{L} = \mathbf{t}_s L$ , where  $\mathbf{t}_s$  is the accumulated number of years of higher education.

Additionally, attending college increases the stock of human capital  $\mathbb{K}$ .  $\mathbb{K}$  does not enter into schooling utility directly, but improves earnings while in the labor market. Work experience also increases the stock of human capital. Total human capital stock at a given point is then a function  $\mathbb{K} = \mathbb{K}(\mathbf{t}_s, \mathbf{t}_w)$  of the number of accumulated years of higher education  $\mathbf{t}_s$  and the number of years of work experience  $\mathbf{t}_w$ .

Utility conditional on being in the labor market is

$$U^w = U(G_w, 0, H_w | \gamma) + \epsilon_w \quad (3.3)$$

where 0 takes the place of  $CV_s$  from equation 3.1, since the student does not receive the consumption value of education while in the labor market. The budget constraint is:

$$H_w W_w(\mathbb{K}) = G_w + R(\mathbb{L}) \quad (3.4)$$

where  $R(\mathbb{L})$  is the annual loan repayment as a function of the stock of school loans  $\mathbb{L}$ .  $W_w(\mathbb{K})$  is the hourly wage while not in school, which is a function of the amount of accumulated human capital.

Equations 3.1 and 3.3 represent the conditional utilities of continuing one's college education or entering the labor market. The tradeoff pits likely higher levels of goods consumption outside of school  $G_w$  and the avoidance of more loans  $L$  against the immediate consumption

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<sup>4</sup>In the case of both schooling and work, there is an additional constraint that leisure and hours of work must add up to the time endowment. Since the labor/leisure choice is not a central focus, I omit this for clarity and instead have hours of work enter directly into the utility function.

value of education  $CV_s$  and, if  $\partial\mathbb{K}/\partial t_s > \partial\mathbb{K}/\partial t_w$ , the chance to increase the stock of human capital  $\mathbb{K}$  more rapidly and thus increase the future consumption of goods.

The student balances these incentives according to their unconditional utility function

$$U^* = \max\{U^s, U^w|\gamma\} \quad (3.5)$$

which depends on the conditional utility functions  $U^s$  and  $U^w$ , and is restricted by budget constraints 3.2 and 3.4.

The relative utility gained in school and in work changes with the stocks of debt  $\mathbb{L}$  and human capital  $\mathbb{K}$ . A student chooses to conclude their education when the costs of continuing outweigh the benefits. This frames educational choice as an optimal stopping problem, which takes into account the sequential nature of academic credentialing and has been used in other dynamic studies of academic choice (Belzil and Hansen, 2002; Heckman and Navarro, 2007). At any given time, the indirect utility from choosing school  $\bar{U}^s$  and the indirect utility from choosing work  $\bar{U}^w$  depend on the current and future utility associated with the decision, given preferences  $\gamma$ , random taste shifters  $\epsilon_s$  and  $\epsilon_w$ , budget constraints, and the way in which future budget constraints are tightened or eased by changes in  $\mathbb{L}$  and  $\mathbb{K}$ . Following from unconditional utility as in equation 3.5, education is completed when the indirect utility provided by work outweighs the indirect utility provided by more schooling:

$$\bar{U}^w - \bar{U}^s > 0. \quad (3.6)$$

Student demand for different educational options is given by the probability that a student selects that educational option, determined by the decision rule in equation 3.6, which contains the stochastic element  $\epsilon_w - \epsilon_s$ . I recover these demand functions, which relate directly to the parameters  $\gamma$  of the indirect utility functions. The parameters of these demand functions can be estimated in a random utility framework given parametric assumptions about the distribution of  $\epsilon_w - \epsilon_s$ , empirical formulations of  $\bar{U}^s$  and  $\bar{U}^w$ , and data on choices and the inputs to  $\bar{U}^s$  and  $\bar{U}^w$  (McFadden, 1973).

### 3.2.2 Empirical Specification

In this section I present an estimable model of college education choice.<sup>5</sup> Each student chooses their level of college education by balancing the immediate rewards of the labor market against the investment and consumption value incentives to continue their education.

At the end of their high school education, each student  $i$  is faced with the decision of how much further schooling he or she plans to attain. The student makes this decision using the information and preferences they have at the time they graduate high school,  $t = 0$ . There are five potential options: attend no further schooling past high school ( $S_i = 0$  years of college), attend college with no plans to complete a degree ( $S_i = 1$ ),<sup>6</sup> earn a two-year degree ( $S_i = 2$ ), earn a four-year degree ( $S_i = 4$ ), or earn an advanced degree ( $S_i = 7$ ).

At  $t = 0$ , the student plans for three decisions. First, they decide whether to enter the labor market immediately after high school or enter college. Second, if the student plans to enter college, they must decide whether to plan to leave college without a degree, attempt a two-year degree, or attempt a four-year degree. Third, if they chose to attempt a four-year degree, they must decide whether to enter the labor market with their four-year degree or continue on to an advanced degree. This simplified structure of choice in higher education is illustrated in Figure 3.1.<sup>7</sup>

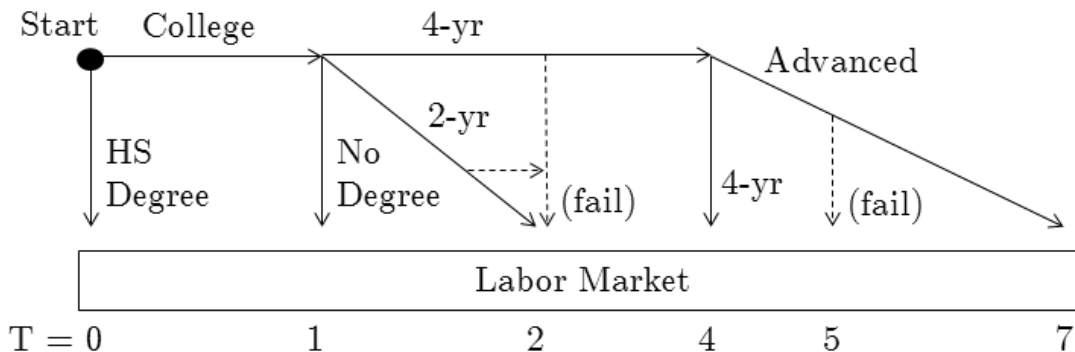
Student  $i$  makes choices about when to continue or conclude their education (and thus end up with a certain level of  $S_i$ , analogous to  $\mathbf{t}_s$  from the model in the previous section) conditional on data  $X_i$ .  $X_i$  includes beliefs about the level of goods consumption conditional on being in school, or working with a given level of education ( $W_w(\mathbb{K})$ ,  $W_s$ ,  $H_w$ , and  $H_s$ ) as

<sup>5</sup>I test alternative specifications and assumptions in Appendix C. Results are robust to all tested models.

<sup>6</sup>This option represents an intentional plan to attend college and leave without attaining a degree, perhaps seeking some consumption value or a small wage increase. Students who initially plan to earn a degree but end up not completing school are handled separately.

<sup>7</sup>This structure imposes a hierarchy of educational options, particularly in regards to leaving college with no degree, here portrayed as “less schooling” than a two-year degree. However, if students expect that leaving without a degree is more lucrative than leaving with a two-year degree, they may indicate so in their subjective expectations. Also, the model restricts degree completion times, ignoring that many people take five or six years to complete a bachelor’s degree. However, for this assumption to be restrictive, students must expect a priori to take a non-standard amount of time to finish the degree.

Figure 3.1: Model Structure of Higher Education Choice



well as beliefs about the consumption value of education ( $CV_s$ ).

The labor market is an absorbing state; once in labor market there are no more choices to make. This simplifies the model greatly, since the value of choosing the labor market option at any given point is simply the present discounted value  $V_{it}^w(X_i, S_i)$  of all future workplace utility.  $V_{it}^w(X_i, S_i)$  is the present discounted value of student  $i$  entering the labor market at time  $t$  with the schooling level  $S_i$  and observable characteristics and beliefs  $X_i$ .

While in the workforce, indirect utility depends on two factors. One is the utility gained from goods consumption ( $G_w$  in the previous section). Given the budget constraint from equation 3.4, goods consumption in a particular year is equal to expected earnings  $Y_{it}(X_i, S_i)$  net of annual loan repayment  $R_{it}(X_i, S_i|\Psi, \Omega)$ , which I refer to as “net earnings” to avoid confusion between “goods consumption” and “consumption value.” Both  $Y_{it}(X_i, S_i)$  and  $R_{it}(X_i, S_i|\Psi, \Omega)$  are calculated using beliefs  $X_i$ . Expected earnings  $Y_{it}(X_i, S_i)$  are total earnings in year  $t$  conditional on having attained  $S_i$  years of schooling. Annual loan repayment  $R_{it}(X_i, S_i|\Psi, \Omega)$  is the amount that student  $i$  expects to have to repay in year  $t$ , which depends on their beliefs about the amount of loans they must take on annually, the number of years they take on loans  $S_i$ , and the interest rate  $\Psi$  and repayment period  $\Omega$  of student loans. Since all decisions are made at the beginning of the time period, the log of the perceived discounted lifetime stream of net earnings enters directly into the value function.

Completed schooling affects utility while in the labor market in ways other than through direct changes in goods consumption, such as one’s chances on the marriage market. The model does not account for all of these alternate incentives, but it accounts for one. The other part of workplace utility function is the utility gain associated with the achievement of educational goals and “fitting in” - a dummy equal to one if the student’s education level matches that of the others in their expected workplace ( $I(\text{JobEd}_i = S_i)$ , where  $I(\cdot)$  is an indicator function). The present discounted value of entering the labor market at the time  $t$  when the student considers the option is then

$$V_{it}^w(X_i, S_i) = \gamma_0^w + \gamma_1^w \sum_{\tau=t}^{47} \delta^{\tau-t} I(\text{JobEd}_i = S_i) + \gamma_2^w \ln\left(\sum_{\tau=t}^{47} \delta^{\tau-t} (Y_{i\tau}(X_i, S_i) - R_{i\tau}(X_i, S_i, \Psi, \Omega))\right) + \varepsilon_{it}^w \quad (3.7)$$

where  $\delta$  is the discount factor.<sup>8</sup>  $\gamma_0^w$  is an intercept collecting averages of omitted components of utility in the workplace.  $\gamma_1^w$  and  $\gamma_2^w$  are parameters of interest indicating the contribution of education-workplace match and net earnings, respectively, to workplace utility.  $\varepsilon_{it}^w$  is a random taste shifter at time  $t$ .<sup>9</sup> Discounted net earnings are assumed to enter utility logarithmically.<sup>10</sup> The retirement age is set at 65; since  $t = 0$  occurs at age 18, there are at most 47 periods of labor market utility to consider; students who take more schooling and

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<sup>8</sup>Choices are all prospective, and even the earliest payouts will not occur for months after choices are made, reducing the influence of “present bias” and justifying the use of exponential discounting rather than hyperbolic. I estimate the model using hyperbolic discounting in Appendix C and find no evidence of present bias.

<sup>9</sup>This allows for a random error between the future net earnings that students report and what they actually expect. A systematic level difference between reports and expectations can be absorbed by the constant term.

<sup>10</sup>The response to future net earnings is modeled as a response to a log transformation of total lifetime net earnings, rather than a sum of log transformations of annual net earnings. This specification emphasizes the one-shot nature of the decision, and allows the student to respond to a discounted lifetime income stream. This means that the  $\gamma_2^w$  term does not have an interpretation as a contemporaneous utility parameter, but this is not of particular importance for this paper. This specification also sidesteps the issue of taking a logarithm of a negative value, if students expect their loan payments to be greater than their earnings in a particular year but not over their lifetime. Qualitative results are robust to the use of a more general specification in which each component of earnings enters separately.

enter the labor market later have fewer periods to consider. All decisions are made near the beginning of the time period, so the exact retirement age does not matter much as all utility that far in the future is heavily discounted.

Anticipated net earnings depend on a number of school-conditional variables. Student  $i$ 's annual expected full-time wages  $W_{it}(X_i, S_i)$ , the probability of being employed  $E_i(X_i, S_i)$ , and student loans that must be repaid  $R_{it}(X_i, S_i | \Psi, \Omega)$  determine expected net earnings, all of which depend on the eventual level of higher education  $S_i$ .<sup>11</sup> The annual net earnings term in  $V_{it}^w(X_i, S_i)$  expands to

$$Y_{it}(X_i, S_i) - R_{it}(X_i, S_i, \Psi, \Omega) = E_i(X_i, S_i)W_{it}(X_i, S_i) - S_i L_i(X_i, S_i) \frac{(1 + \Psi)^\Omega}{\Omega} I(t \leq S_i + \Omega) \quad (3.8)$$

where  $S_i L_i(X_i, S_i)$  is the number of years in higher education  $S$  multiplied by the average amount of loans the student expects to accumulate each year in college  $L_i(X_i, S_i)$ , which is conditional on  $S_i$  since annual loan burdens may vary between two- and four-year institutions.  $\Psi$  is the annual interest rate on student loans and  $\Omega$  is the loan repayment period in years. Loans are repaid at a constant rate until the repayment period is exceeded, that is, when the indicator function  $I(t \leq S_i + \Omega)$  equals zero. After the repayment period ends, all students pay zero loans. I do not consider the possibility of loan default, assuming that students do not make decisions conditional on the possibility of a default.

It is necessary to further specify how expected earnings are determined, and one benefit of building a model using subjective expectations becomes apparent here. Expected wages and the probability of employment are dependent on beliefs  $X_i$  about wages and employment at a particular education level  $S_i$ . One notable way in which beliefs can affect expected wages and employment is the student's unobservable perception of their own ability  $A_i$ , which I

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<sup>11</sup>The use of annual full-time wages and the probability of being employed  $E_i$  is different from the use of hourly wages and the number of hours employed  $H_w$  in the model in the previous section. Since all earnings are taken in expectation, and the hours-of-work decision is not directly modeled, the mathematical representation is similar. However, this introduces some bias if students expect the number of hours worked to change with education level in a way that is not proportional to the change in employment rate.

here separate from other beliefs for clarity:

$$W_{it} = W_{it}(X_i, A_i, S_i)$$

$$E_i = E_i(X_i, A_i, S_i)$$

Perceived ability  $A_i$  is not directly observed. Typically, education models predict future wages using other variables, and so the inability to directly observe  $A_i$  is a problem. However, since subjective expectations are used, expected future wages  $W_{it}$  are reported directly as a part of student beliefs  $X_i$  and thus already incorporate the student's perception of their own ability. Students may be aware that their perceived ability could change in the future, but since the direction and size of these changes are not known to the student at the time the plan is made, this is simply folded into the error term for expected labor market utility  $\varepsilon_{it}^w$ . Similar arguments apply to other unobserved variables that mediate the returns to education, such as the choice of college major. Expected wages and employment can be reported as a function of student beliefs, in  $X_i$ , and schooling level  $S_i$ .

Expected wages are assumed to follow a known growth path that depends on work experience, reflecting human capital accumulation in the labor market. The growth path  $g_t(S_i)$  assumes continuous employment,<sup>12</sup> and calculates years of employment in period  $t$  as the number of years since leaving college.  $g_t(S_i)$  is then multiplied by wages at age 30 (age 30 is at  $t = 12$ , so this is  $W_{i,12}$ ) to produce the wage at other ages:

$$W_{it}(X_i, S_i) = g_t(S_i)W_{i,12}(X_i, S_i) \tag{3.9}$$

$$\text{where } g_t(S_i) = \exp(\Phi_{S_i1}(t - 12) + \Phi_{S_i2}(t - 12)^2).$$

$\Phi_{S_i1}$  and  $\Phi_{S_i2}$  are wage growth parameters determined outside the model that allow for wage growth to be shallower or steeper depending on education level. If  $\Phi_{S_i1} > 0$  and  $\Phi_{S_i2} < 0$

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<sup>12</sup>Allowing employment to be non-continuous based on the probability of employment does not significantly change results, nor does allowing employment probability to follow a growth path similar to that outlined for wages.

then log wages are concave in work experience. Substituting equations 3.8 and 3.9 into equation 3.7 gives

$$\begin{aligned}
 V_{it}^w(X_i, S_i) = & \gamma_0^w + \gamma_1^w \sum_{\tau=t}^{47} \delta^{\tau-t} I(\text{JobEd}_i = S_i) + \\
 & \gamma_2^w \ln \left[ \sum_{\tau=t}^{47} \delta^{\tau-t} (E_i(X_i, S_i) g_t(S_i) W_{i,12}(X_i, S_i) \right. \\
 & \left. - S_i L_i(X_i, S_i) \frac{(1 + \Psi)^\Omega}{\Omega} I(\tau \leq S_i + \Omega)) \right] + \varepsilon_{it}^w \quad (3.10)
 \end{aligned}$$

The above equation can be calculated explicitly using the  $\gamma^w$  and  $\delta$  parameters and available data once  $\Phi_{S_i1}$ ,  $\Phi_{S_i2}$ ,  $\Psi$ , and  $\Omega$  have been chosen.  $V_{it}^w(X_i, S_i)$  gives the present discounted value of entering the labor market at time  $t$  with schooling level  $S_i$ , so that labor market utility can be compared to the present discounted value of the schooling option(s) available.

While in college, flow utility depends on the amount of available financial support (which helps determine goods consumption,  $G_s$  in the previous section) as well as the consumption value of education ( $CV_s$  in the previous section). Human capital ( $\mathbb{K}$  in the previous section) contributes to the value of continuing one's education, but does not pay off until the future. Human capital accumulation factors into future earnings but does not enter into the immediate utility gained from a year of education.

Utility while in college includes measured consumption value variables suggested by the literature. These include a vector of experiential taste-for-education variables  $T_i$  (Heckman et al., 2006; Jacob et al., 2013; Stinebrickner and Stinebrickner, 2014; Alter and Reback, 2014; Wiswall and Zafar, 2015), which consists of direct enjoyment of the academic and non-academic parts of the college experience and the psychic cost of education. The student also gains utility from following social expectations surrounding the education they are to receive, recorded in the vector  $F_i^E$  (Akerlof and Kranton, 2002, 2010; Sandefur et al., 2006). An additional vector  $F_i^B$  allows for differences in the consumption value of education according to demographic and socioeconomic background.<sup>13</sup> Student academic ability enters directly

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<sup>13</sup>I discuss the interpretation of background characteristics as consumption value determinants in the next section.

into flow utility through the experiential taste-for-education vector  $T_i$ , since students with higher academic ability face lower mental costs of attending college.<sup>14</sup>

$$u_t^s = \gamma_0^s + \gamma_1^s \text{OwnTuition}_i + \gamma_2^s T_i + \gamma_3^s F_i^E + \gamma_4^s F_i^B + \varepsilon_{it}^s \quad (3.11)$$

$$u_t^{s'} = \gamma_0^{s'} + \gamma_1^s \text{OwnTuition}_i + \gamma_2^{s'} T_i + \gamma_3^s F_i^E + \gamma_4^s F_i^B + \varepsilon_{it}^{s'} \quad (3.12)$$

where  $\gamma_0^s$  represents both the average flow utility generated by any omitted components, including the average financial support for log goods consumption while in college.  $\text{OwnTuition}_i$  is a modifier of average log goods consumption while in college, equal to one if the student expects to have to pay the majority of tuition themselves by working.  $\varepsilon_{it}^s$  and  $\varepsilon_{it}^{s'}$  are error terms. Under the assumption that high school students consider graduate school to be a qualitatively different direct experience than undergraduate studies, I allow the intercept  $\gamma_0^{s'}$  and the coefficients on  $T_i$  vector variables  $\gamma_2^{s'}$  to be different when considering graduate school utility, using the utility function for graduate school  $u_t^{s'}$ . All other parameters are constrained to be the same for every level of education.

In-college flow utility is not the only incentive to remain in college; schooling has the capacity to improve future earnings, which is partially contingent on the completion of an actual degree. The probability of graduation  $P_i$  gives the perceived probability that a student who begins a degree program will earn the degree. Planned incompleteness of undergraduate studies is allowed by the availability of a “some college but no degree” option, so  $1 - P_i$  represents the probability of unplanned incompleteness and is a transition probability here. Unlike standard transition probabilities, which are estimated parameters,  $P_i$  is reported on the individual level in the subjective data.  $P_i$  is assumed to be the same for two-year, four-year, and advanced degrees. All students fail or are guaranteed graduation after their second year in undergraduate studies or their first year in graduate school.

Given flow utility, the present discounted value of being in the labor market, and  $P_i$ , it is possible to calculate the present discounted value of beginning a schooling option, conditional

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<sup>14</sup>Students may expect academic ability, socioeconomic status, race, or gender to mediate the financial returns to college. However, as outlined earlier in this section, this is already handled by direct estimates of  $W_{it}$  and  $E_i$ . The variables in the flow utility allows for differences in flow utilities across students.

on having completed any prerequisite schooling options. As an illustrative example, I walk through the construction of  $V_{it}^s(X_i, S_i = 4)$ , the value of deciding to attempt a four-year degree given that one has completed a year of college.

$$V_{it}^s(X_i, S_i = 4) = (1 + (\delta + \delta^2)P_i)u_t^s + \delta(1 - P_i)V_{i,t+1}^w(X_i, S_i = 1) + \delta^3 P_i \max\{V_{i,t+3}^w(X_i, S_i = 4), V_{i,t+3}^s(X_i, S_i = 7)\}. \quad (3.13)$$

The first term,  $(1 + (\delta + \delta^2)P_i)u_t^s$ , refers to the period utility gained by being in college.  $1 \times u_t^s$  is a guaranteed additional period of in-college consumption value utility, sophomore year. If the student is going to graduate (they do so with probability  $P_i$ ), they also receive in-college discounted utility  $((\delta + \delta^2)P_i)u_t^s$  in the next two periods, their junior and senior years.

The second term,  $\delta(1 - P_i)V_{i,t+1}^w(X_i, S_i = 1)$ , takes into account the possibility of failing out of college with probability  $1 - P_i$ . Students who fail enter the labor market after their sophomore year, discounted by  $\delta$  since the decision is made after the freshman year. Those who enter the labor market by failing out of college are workers with some college experience but no degree, and earn the appropriate labor market utility  $V_{i,t+1}^w(X_i, S_i = 1)$ .

The third term,  $\delta^3 P_i \max\{V_{i,t+3}^w(X_i, S_i = 4), V_{i,t+3}^s(X_i, S_i = 7)\}$ , represents the possibility of attaining the bachelor's degree. The student succeeds with probability  $P_i$  and finishes their degree after their senior year, discounted by  $\delta^3$ . At that point, they may choose whichever path grants them more utility - entering the labor market immediately after earning the bachelor's degree ( $V_{i,t+3}^w(X_i, S_i = 4)$ ) or continuing on to graduate school ( $V_{i,t+3}^s(X_i, S_i = 7)$ ).

The value of the other schooling options can be constructed similarly. The decision is based on these anticipated utility streams. In the case of the choice of undergraduate degree type, students who have previously chosen to begin college choose between the value of attempting a four-year degree  $V_{it}^s(X_i, S_i = 4)$ , the value of attempting a two-year degree  $V_{it}^s(X_i, S_i = 2)$ , or the value of endogenously leaving college and entering the labor market with some college but no degree  $V_{it}^w(X_i, S_i = 1)$ .

Assuming the structure of the model, all value functions can be calculated using backward induction given the externally determined parameters  $\Phi_{S_1}$ ,  $\Phi_{S_2}$ ,  $\Psi$ , and  $\Omega$ , parameters

estimated using the model  $\gamma$  and  $\delta$ , and student data  $X_i$ , which include expected labor market utility determinants  $W_{it}$ ,  $E_i$ ,  $L_i$ , and  $JobEd_i$ , consumption value inputs  $T_i$ ,  $F_i^E$ , and  $F_i^B$ , the financial support modifier  $OwnTuition_i$ , and the expected graduation rate  $P_i$ . Given the random utility shifters  $\varepsilon_i^w$ ,  $\varepsilon_i^s$ , and  $\varepsilon_i^{s'}$  specified in equations 3.7, 3.11, and 3.12, I can calculate the probability of any particular outcome for each student. This probability represents demand for that option as a function of student data. I estimate the parameters of the model using these probabilistic predictions of student choice.

### 3.2.3 Estimation

I estimate the model of student choice using a random utility approach. Under the assumption that error terms associated with each option follow a Type I Generalized Extreme Value distribution, the probability of choosing an option in a particular decision can be expressed as a logistic function that takes the present discounted value functions  $V$  as inputs.

The probability of a student choosing to enter the workforce at a particular time is the joint probability of making the decisions that lead to that outcome. I multiply together the probability of making these decisions to generate a probability that a student will attain a particular level of schooling. This product is the student-level likelihood  $\mathcal{L}_i$ . For example, a student who chose to attempt a four-year degree and then enter the labor market has a  $\mathcal{L}_i$  equal to the probability that they chose to attend college, chose to attempt a four-year degree, and then chose not to go to graduate school:

$$\mathcal{L}_i(\gamma^w, \gamma^s, \beta | X_i, S_i = 4) = \frac{\exp(V_{it}^s(X_i, S_i = 1))}{\exp(V_{it}^s(X_i, S_i = 1)) + \exp(V_{it}^w(X_i, S_i = 0))} \times \frac{\exp(V_{it}^s(X_i, S_i = 4))}{\exp(V_{it}^s(X_i, S_i = 2)) + \exp(V_{it}^s(X_i, S_i = 4)) + \exp(V_{it}^w(X_i, S_i = 1))} \times \frac{\exp(V_{it}^w(X_i, S_i = 4))}{\exp(V_{it}^s(X_i, S_i = 7)) + \exp(V_{it}^w(X_i, S_i = 4))}. \quad (3.14)$$

Using the above likelihood function and students' reports of their most likely final level of education, I use maximum likelihood to estimate parameter values given student data.

Identification of the model follows given the assumptions previously stated, between-student variation in educational plans and choice inputs, as well as the calibrated values of the student loan interest rate  $\Psi$  and repayment period  $\Omega$ , and the wage growth parameters  $\Phi_{S_i1}$  and  $\Phi_{S_i2}$ . In the primary analysis, these are set to  $\Psi = .05$  and  $\Omega = 10$ , in line with standard federal Perkins loan terms at the time of the survey.<sup>15</sup>  $\Phi_{S_i1}$  and  $\Phi_{S_i2}$  values are estimated outside the model using descriptive data from the American Community Survey.<sup>16</sup> This approach does not allow for the identification of the intercept terms  $\gamma_0^w$  and  $\gamma_0^s$ , since these always enter the likelihood as relative to each other. As such,  $\gamma_0^w$  is constrained to be zero, and the intercept term  $\gamma_0^s$  must be taken as relative to the labor market utility intercept.

Identification of the indirect utility coefficient on future net earnings  $\gamma_2^w$  relies on the ability to observe all counterfactuals for each individual, which is possible given the subjective and hypothetical nature of the data. Because all counterfactuals are observed, student characteristics such as unobserved ability or background characteristics are uncorrelated with the observation of payoffs, which eases selection bias in the estimated response to future net earnings. Additionally, since expectations of future net earnings are elicited directly, the identification of this parameter does not depend strongly on assumptions about expectations formation (Manski, 2004).

Identifying variation for the parameters of utility in college relies on between-student variation in consumption value inputs and the length of time labor market earnings are put off by continuing to attend college, as compared to between-student variation in the net earnings returns to college education.

The interpretation of these schooling utility variables as consumption value is weaker for

<sup>15</sup>As reported in Appendix C, results are robust to the use of  $r = .068$  for all students or for all non-FRPL students, in line with Stafford or direct federal loan terms at the time of the survey.

<sup>16</sup> $\Phi_{S_i1}$  and  $\Phi_{S_i2}$  are estimated using data on full-year, full-time workers aged 18-65 from the American Community Survey 2008-2010 public use sample. I run separate models regressing log annual salary earnings on  $(age - 30)$  and  $(age - 30)^2$  for each educational group. Values of  $\Phi_{S_i1}$  are .028, .037, .032, .041, and .044 for high school only, some college, two-year degrees, four-year degrees, and advanced degrees, respectively. Similarly, values of  $\Phi_{S_i2}$  are -.0007, -.0009, -.0007, -.0011, and -.0011, respectively.

some of the background characteristics which are likely to be affected by omitted variable bias. In particular, eligibility for Free or Reduced Price Lunch (FRPL), parental education, and race represent both variation in consumption value and are correlates of (and thus partial controls for) parental income, which can relax the schooling budget constraint in equation 3.2 as long as parental endowment is not entirely offset by a decrease in financial aid from the college or government. I do not attempt to separate these two effects, and so coefficients on these variables represent both a consumption value effect and an income effect. Coefficients on variables that are positively correlated with parental income (such as parental education) represent upper bounds on the contribution of that variable to consumption value, while coefficients on variables that are negatively correlated with parental income (such as FRPL) represent lower bounds.

As stated, the estimated model makes the assumption that preferences are constant across all students, with the exceptions that the level of consumption value is allowed to vary across groups due to the inclusion of the  $F_i^B$  vector, and the coefficients on the  $T_i$  vector are allowed to vary for graduate school. This assumption is likely to be restrictive. By imposing this restriction in a multinomial logit context, I rely on the assumption of the independence of irrelevant alternatives (IIA). These assumptions can be weakened by allowing for heterogeneity in preferences.

#### 3.2.4 *Unobserved Preference Heterogeneity*

I estimate heterogeneity in preferences by allowing the coefficients on  $F_i^E, F_i^B$ , and all coefficients on job/education match ( $\gamma_1^w$ ) and future net earnings ( $\gamma_2^w$ ) to vary.<sup>17</sup> Directly modeling the heterogeneity in preferences relaxes the independence of irrelevant alternatives assumption inherent in multinomial logit analysis (McFadden and Train, 2000).

To address heterogeneity in preferences, I use the common method of applying a mixture

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<sup>17</sup>Direct experiential variables in vector  $T_i$  are not allowed to vary because these already represent heterogeneous measures of directly reported preferences. Allowing different sets of coefficients to vary leads to different estimated amounts of heterogeneity, but does not change qualitative results.

distribution. Each of the parameters follows a distribution rather than adhering to a single point. I allow the set of parameters to follow a discrete multivariate distribution with  $J$  points of support, each of which represents a student preference type. Students have a probability  $\rho_j$  of belonging to type  $j \in \{1, \dots, J\}$ .

I follow the method of Fox et al. (2011) in estimating the  $\rho_j$  parameters and the mixture distribution. Fox et al. (2011) use inequality-constrained least squares in order to estimate nonparametric parameter distributions.

Characterize  $\gamma^j$  as the vector of parameters relevant to the decisions of group  $j$  and  $X_i$  as a vector of data for student  $i$ .  $Pr(S_i = t|X_i, \gamma^j)$  is the probability of choosing  $S_i = t$  given that one is student  $i$  in group  $j$ , and thus has the preference parameters  $\gamma^j$ .

Then,  $\hat{\rho}$  is the coefficient vector  $\hat{\rho} = \{\hat{\rho}_1, \hat{\rho}_2, \dots, \hat{\rho}_J\}$  generated using the constrained least squares model

$$I(S_i = t) = \sum_{j=1}^J \rho_j Pr(S_i = t|X_i, \gamma^j) \quad (3.15)$$

$$\text{s.t. } 0 \leq \rho_j \leq 1 \quad \forall j, \quad \sum_{j=1}^J \rho_j = 1$$

estimated using  $5N$  observations: one observation per student per potential outcome ( $S_i \in \{0, 1, 2, 4, 7\}$  for high school only, some college but no degree, two-year degree, four-year degree, and advanced degree).

$\hat{\rho}$  is used in analysis as a set of distribution weights for preference types. The algorithm requires a choice of  $J$  and the vectors  $\gamma^j$ . Monte Carlo simulations in Fox et al. (2011) find that a small  $J$  is generally adequate, and that choosing  $\gamma^j$  vectors of uniform distance from each other provides good performance. I set  $J = 9$ ; nine types allows for a flexible parameter distribution, and results are robust to the use of different numbers of types. I estimate the model once without heterogeneity in preferences to generate the central parameter vector  $\gamma^5$ . I use the variance/covariance matrix of the parameters to generate the other  $\gamma^j$  vectors

in order to span a total of 5 standard deviations.<sup>18,19</sup>

The model outlined in this section can be estimated using the method described in Section 3.2.3. The addition of preference heterogeneity allows the model to flexibly describe indirect utility across different educational options. The model as described relies on the availability of student background and preference data as well as students' expectations of labor market outcomes under five different educational counterfactuals. In the next section, I describe the data set used to estimate the parameters of the model.

### 3.3 Data

#### 3.3.1 The Data Set

This paper makes use of the Assessing Perceived Costs and Benefits of Post-High School Opportunities Survey (APCAB) dataset, collected by the author. This is the same data set used in Chapter 2 and described in more detail in Appendix B. APCAB consists of data on the demographics, expectations, and plans of 1,224 high school juniors and seniors in the King County, Washington area. King County includes Seattle and the surrounding area. The survey was offered at thirteen high schools in three districts covering both urban and suburban, and high- and low-income areas.

Table 3.1 contains summary statistics of all variables used in analysis that do not vary by schooling level. For variables coded 1-5, I provide the entire distribution. Some results, including the number of observations, differs between Chapter 2 and this chapter because I use multiple imputation in this chapter (as described below) so no observations need to be dropped, and do not weight responses by school response rate. I do not use imputation in the previous chapter because the results of interest were often directly the data, and so

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<sup>18</sup>In estimation, the coefficient on future net earnings is constrained to be positive, and the discount factor  $\delta$  is constrained to be between 0 and 1. These constraints are not binding in the one-type model, but ensure that nonsensical values are not picked when selecting  $\gamma^1$  and  $\gamma^9$ .

<sup>19</sup>The use of the variance/covariance matrix as a determinant of the preference vectors means that there is relatively little allowed preference heterogeneity of precisely-estimated coefficients. I investigate the use of a much wider range of preference types for the coefficient on future net earnings in Appendix C.

Table 3.1: Summary Statistics

Panel A: Distributions of variables rated 1-5					
	1	2	3	4	5
Enjoy Academics	.023	.064	.232	.433	.248
Enjoy Non-academics	.035	.070	.164	.302	.428
Expect Easy	.077	.261	.377	.198	.087
Family to College	.097	.265	.179	.291	.167
Friends to College	.069	.192	.194	.391	.154
Panel B: Means					
Parent has BA	.554	Grad. rate ( $P_i$ )			.617
College is Important	.794	HS GPA			3.20
Female	.485	FRPL			.455
Black	.158	White			.570
Hispanic	.183	Asian			.198
Pay Own Tuition	.167				

imputation would not aid inference enough to justify its use. I do not weight responses by school response rate in this chapter (although results are robust to this weighting) because being representative of the school population for comparison purposes is not important here.

In the taste vector  $T_i$ , direct stated preferences about the expected enjoyment of the academic (Enjoy Academics) and non-academic (Enjoy Non-academics) parts of the college experience act as direct taste measures (for both, 5 corresponds to the strongest preference for the college experience). Self-reported high school GPA (HS GPA) and the expectation of ease (Expect Easy) of performing well in college relative to other students (5 is the easiest) act as measures of psychic costs.<sup>20</sup> These questions ask the students to rate their preferences

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<sup>20</sup>In analysis variables on a scale of 1-5 are treated linearly. In Appendix C I show that results are robust to the inclusion of these variables as sets of dummies.

on a five-point scale. For example, Enjoy Academics asks “How much do you think you would enjoy attending college classes?” and give the options “I would (hate it/dislike it/neither like it nor dislike it/like it/love it).” Students report expecting to heavily enjoy college - for both Enjoy variables, more than 65% of answers are 4 or 5. Expect Easy is more evenly distributed around 3.

The norms and family expectations vector  $F_i^E$  includes rough measures of the share of family (Family to College) and friends (Friends to College) who have gone or are going to college, whether or not the student has a parent or guardian with a Bachelor’s degree (Parent has BA), and whether or not the student has a parent or guardian who thinks that college is the most important thing to do after high school (College is Important).<sup>21</sup>

$F_i^B$  includes standard demographic controls - gender, low socioeconomic status (proxied by whether or not they have received free or reduced price lunch, or FRPL), and race or ethnicity. The race and ethnicity terms are not mutually exclusive, but White is dropped from analysis to avoid near collinearity.

The remaining variables in Table 3.1 that enter the model are the anticipated six-year graduation rate for a student entering a four-year college  $P_i$  (Grad. Rate) and whether or not the student expects to pay the majority of their own tuition by working  $OwnTuition_i$  (Pay Own Tuition). The average expected graduation rate is 61.7%. This average is fairly accurate - the actual six-year graduation rate in Washington state is 63.3%.<sup>22</sup>

The outcome variable (Expected Education), which is the level of schooling the student thinks they are most likely to conclude their education with, and the variables that enter into labor market utility all vary by schooling level and are presented in Panel A of Table 3.2. Restating some of the results from Table tab:c1absoluteests in Chapter 2, I present comparative observed values for full-time, full-year wages, the rate of employment, and educational outcomes in Panel B of Table 3.2. These estimates come from Washington state

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<sup>21</sup>The Family to College and Friends to College variables are in five categories, with 1 indicating hardly any and 5 indicating nearly all.

<sup>22</sup>The 63.3% estimate comes from the Beginning Postsecondary Students Longitudinal Study cohort tracked from 2003/04 to 2009.

residents aged 29-31 who had completed high school in the 2008-2010 American Community Survey.

Table 3.2: School Level-Varying Summary Statistics

$S =$	HS	Some Coll.	2-Year	4-Year	Advanced
Panel A: Sample Medians					
Annual Wage ( $W_{i,12}$ )	\$30,000	\$39,000	\$49,500	\$67,500	\$94,500
Loans/yr. ( $L_i$ )	\$0	\$3,692	\$1,884	\$4,068	\$4,068
Employment Rate ( $E_i$ )	.60	.69	.75	.80	.92
Distributions:					
Ed. Level at Work ( $JobEd_i$ )	.071	.056	.130	.400	.267
Expected Education	.145	.037	.107	.437	.274
Panel B: Observed Comparative Data					
Annual Salary (Med.)	\$30,000	\$32,000	\$35,600	\$46,400	\$52,100
Employment Rate	.67	.75	.80	.83	.90
Distributions:					
Education Outcomes	.258	.269	.116	.251	.107

Employment figures are reported with two digits of precision because the APCAB question elicited whole numbers on a scale of 0-100.

Workplace utility consists of net earnings and a dummy generated from  $JobEd_i$  (Ed. Level at Work), which is the level of education the student thinks the typical person has in the job they expect to hold at age 30. 92 students selected “I don’t know” in response to the question that produced  $JobEd_i$ ; these students are included in analysis but all dummies generated from  $JobEd_i$  are zero, so the proportions in the table do not add up to 1.

I calculate net earnings using three terms:  $W_{i,12}$  (Annual Wage), which is the annual salary the student expects to earn if they find themselves 30 years old in Washington State

working a full-time, full-year job with the given level of education;  $E_i$  (Employment Rate), the expected percentage of 30-year-old Washington residents with a given level of education who are employed; and  $L_i$  (Loans/yr.), the expected annual loan accumulation for a given level of education.  $L_i$  is constructed by averaging expected loan amounts for four specific well-known Washington public colleges - three four-year colleges and one two-year college.<sup>23</sup> Annual loan amounts associated with two-year degrees use only the estimate of loans at the two-year school, and similarly for other schooling levels. Medians of these three variables are reported in Table 3.2. Reported loan amounts are right-censored at \$50,000 to rein in some outliers.

Compared to the ACS data, student estimates of their wages as high school graduates are similar to ACS averages, but college wage premia are higher than in the ACS data. This comparison relates a measure of personal expectation against a population median, so it is not necessarily the case that these numbers *should* match. Still, the use of observed wages in estimation would misstate the students' expected wage return to college. Students' expectations of the probability of being employed are somewhat pessimistic compared to the ACS.

The dependent variable is the student's planned level of education Expected Education. Expected Education represents the level of education that the student thinks is the most likely outcome for them. Students by and large expect to attain a college degree, with about 85% of students expecting to receive at least a two-year degree. Compared to ACS data, these outcome levels are very optimistic. However, the difference does not take into account the graduation rate; a student may expect a four-year degree to be the most likely outcome, even with the knowledge that 40% of students who attempt one do not succeed. Roughly, a .617 graduation rate (as above) applied once to two-year and four-year degrees, and twice to advanced degrees (to account for failure in four-year and advanced degree programs) gives

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<sup>23</sup>These are the University of Washington, Washington State University, Western Washington University, and Seattle Community College. The elicited variable covers loans and grants. Loans are assumed to be 50% of this variable, similar to observed population averages. The use of numbers other than 50%, or allowing the percentage to vary by FRPL status, does not alter results.

a proportion of .066, .270, and .102 of the sample ending with two-year, four-year, and advanced degrees, respectively. This underestimates two-year degrees but roughly matches the observed data for four-year and advanced degrees. From an ex-ante perspective in which predictions are made at the individual level, anticipated levels of educational attainment are fairly close to those observed in the labor market.

Participation in the survey was voluntary. Students were offered a \$5 gift card to take the pencil-and-paper survey. 40% of surveys were collected in fixed-enrollment environments in which the survey opportunity was formally presented. The response rate in these environments was above 95%. 60% of the surveys were collected in open-enrollment environments such as a cafeteria during lunchtime. The calculated response rate in these environments depends on the uncertain calculation of the present population of students, but was approximately 50%. Results are similar in a sample limited to fixed-enrollment environments.

Given the voluntary nature of the survey and the 50% participation rate in the open-enrollment environments, participation bias is a possible cause for concern. Several features of the data ease these concerns. The demographic profile of the survey sample is similar to the demographic profile of the included schools; the proportions of female, white, Asian, and Hispanic students are not significantly different between the APCAB sample and the school populations. Students who qualified for free and reduced price lunch were slightly overrepresented, as were black students, but applying sample weights to counteract this over-representation does not change results.<sup>24</sup> The sample may be non-representative based on unobservable characteristics, such as the individual's response to the gift card. However, if students strongly motivated by financial incentives were more likely to take the survey due to the gift card offered, then the primary result of this survey, that financial incentives are not as influential as consumption value incentives, would likely be stronger in a wider sample.

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<sup>24</sup>School demographic profiles were taken from 2012 Washington State Report Card data at <http://reportcard.ospi.k12.wa.us/>. The presented analysis is without sample weights for simplicity, and because there is no inherent interest in matching the demographic profile of the selected schools.

In general, item response rates were very good and there is little missing data. By survey item, mean and median response rates were 92.8% and 94.5%, respectively. However, a large number of students skipped the question that generated  $L_i$ , and that variable has only a 66.4% response rate. To address this, multiple imputation with chained equations is used to fill in missing observations. Conditional on all available data, ten random draws of missing values were taken for all variables. Analyses using these draws are combined in a way that incorporates the uncertainty about the data. This method performs well in cases where the data can be said to be missing-at-random (Rubin, 1987).<sup>25</sup> Additionally, as shown in Appendix C, results are robust to the omission of  $L_i$  from the analysis entirely.

I use the APCAB data set to estimate the parameters of the model. As outlined previously, the theoretical constructions that these variables represent are particularly well suited compared to observed data for estimating model coefficients, given the ability to measure consumption value inputs that vary at a student level, and the ability to observe all labor market counterfactuals. While the use of subjective data is not the most common approach in economics, this paper joins a growing literature that effectively uses subjective data to estimate student demand for education.

### *3.3.2 The Use of Subjective Data*

The use of subjective data to estimate student demand depends on the assumption that behavior follows from stated preferences and beliefs. It is necessary that this subjective student data can be treated seriously. If plans, expectations, and reported preferences do not relate to later behavior, or if students do not report their actual beliefs, then analysis using subjective data is not of much interest.

Whether or not subjective data is useful in the estimation of choice models can be broken

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<sup>25</sup>The missing-at-random assumption, which requires that the value of the missing observation is not correlated with the fact that the observation is missing, is plausible here. In the case of the  $L$  variable, which has the most missing observations, post-survey discussions with survey respondents indicated that students skipped the question because they thought the survey logic directed them to do so. Expected student loans are unlikely to be correlated with making mistakes about survey logic.

down into two questions: 1) Do subjective data relate to behavior?, and 2) Do subjective data relate to behavior because they reflect actual beliefs and preferences?

A positive answer to the first question has extensive support in the literature on subjective expectations data. Studies that use subjective expectations data in analyses of the choice of education level (e.g. Dominitz and Manski, 1996; Jensen, 2010; Attanasio and Kaufmann, 2014) and the choice of college major (e.g. Arcidiacono et al., 2011; Stinebrickner and Stinebrickner, 2014; Wiswall and Zafar, 2015) find that subjective expectations data relate strongly to educational plans and actual choice. Research on subjective expectations in areas outside of education, such as the use and form of birth control (Delavande, 2008) or planting and harvesting decisions in developing nations (see Delavande et al. 2011 for a review of subjective expectations research in developing nations) finds similar results. Stated expectations data are clearly related to actual behavior. Intended behavior is similarly related to actual behavior, although predictions of actual behavior should be taken as probabilistic rather than intended to predict a single actual outcome (Manski, 1990).

The second question relates to whether or not the association between subjective data and behavior is because those data represent the actual underlying information that people use to make decisions, or because those data are related to some unobserved factor.

One way to address this question for subjective expectations data is to note that subjective expectations data resemble theoretical expectations in many ways, and by and large obey the laws of probability (Dominitz and Manski, 1996; Delavande et al., 2011). When presented with new information, subjects alter their reported expectations in appropriate ways, and change their behavior accordingly (Jensen, 2010; Zafar, 2011a; Wiswall and Zafar, 2015; Stinebrickner and Stinebrickner, 2014). These results imply that subjective expectations data represent information used to make the decision, rather than an unobserved factor. Botelho and Pinto (2004) perform an experiment in which subjective wage expectations data are elicited in two ways. One group of students was compensated for making accurate estimates, and the students in the control group were not. Both groups reported similar expectations, leading to the conclusion that subjects report the expectations they

believe to be correct, even when their payoff does not depend on accuracy. Literature supports the use of subjective expectations data to estimate preferences in structural models (van der Klaauw, 2012).

Literature on stated preference is slimmer in economics, but there is reason to believe that stated preference data do relate to actual preferences. ? examine the use of stated preference or attitude data in a measurement error framework and find that stated preferences and attitudes are acceptable for use as explanatory variables, although they also point out that these variables are susceptible to omitted variable bias. Stronger evidence for the use of these types of variables comes from the fields of marketing and psychology. Marketers commonly use stated preference data in a hedonic setting. These widely-used models, which I will revisit in Chapter 4, routinely and closely match market shares of available products, a successful use of stated preferences to model actual preferences (Orme, 2006). Psychological research on elicited preference and attitudinal data finds that behaviors can be predicted quite well using subject attitudes towards that behavior (Ajzen and Fishbein, 2005).

The literature is clear that subjective data are related to actual behavior. Further, experimental approaches find that stated expectations and preferences behave as one would expect of actual expectations and preferences. That is, results are not driven by reverse causality (stated beliefs or preferences determined so as to justify the choice already made) or omitted variables.

This paper does not perform an experiment that would allow these concerns to be addressed directly for the present data. However, Attanasio and Kaufmann (2014) show that an experiment is not necessary to address the possibility of reverse causality. If students change their beliefs and preferences to rationalize their choices, then the distribution of stated beliefs and preferences should be more spread out for seniors than for juniors. As juniors become seniors and finalize their plans, those who chose more schooling should shift their beliefs in favor of schooling, and vice versa, leading to a distribution with more extreme values and a hollowed-out middle. I look at the variance of Enjoy Academics, Enjoy Non-academics, and Expect Easy, and expected wages and employment at all levels. In all cases I fail to find that

seniors exhibit a wider spread than do juniors. This test fails to support reverse causality as an alternate explanation of the results. Details of this test are in Appendix C.

### 3.4 Results

#### 3.4.1 Parameter Estimates

Estimated model coefficients are in Table 3.3. These coefficients represent indirect utility parameters, and predict the dependent variable of expected educational attainment. Direct interpretation of the magnitudes of these parameters is difficult without simulation, but the signs and some relative magnitudes are informative. In general, a positive coefficient on any variable that enters directly into in-school utility (everything except the discount factor, log lifetime net earnings, and education level at work) means that an increase in that variable increases planned attainment, and a positive coefficient on a variable that enters into workplace utility means that an increase in that variable for a particular schooling level attracts more students to that schooling level.

Table 3.3: Estimated Parameters

	One-Type		Multiple-Types (Means)	
	Coef.	Std. Err.	Coef	Std. Err.
Discount Factor ( $\delta$ )	.880	(.014)	.881	(.015)
Log Lifetime Net Earnings ( $\gamma_2^w$ )	.126	(.022)	.126	(.022)
Ed. Level at Work ( $\gamma_1^w$ )	.129	(.012)	.134	(.022)
Pay Own Tuition	.032	(.042)	.038	(.054)
$F_i^E$ : Family Expectations and Norms				
Family to College	.034	(.007)	.033	(.010)
Friends to College	.048	(.007)	.046	(.010)
Parent has BA	.016	(.026)	.018	(.031)
College is Important	.189	(.020)	.189	(.020)

$F_i^B$ : Background				
FRPL	.057	(.031)	.055	(.035)
Female	.038	(.022)	.042	(.030)
Black	.185	(.077)	.186	(.079)
Asian	.099	(.051)	.105	(.064)
Hispanic	.083	(.048)	.090	(.062)
$T_i$ and intercept (Undergraduate): Taste/Experience				
Enjoy Academics	.177	(.008)	.177	(.008)
Enjoy Non-academics	.037	(.007)	.037	(.007)
Expect Easy	.122	(.008)	.122	(.008)
HS GPA	.656	(.027)	.656	(.027)
Intercept	-1.951	(.142)	-1.951	(.142)
$T_i$ and intercept (Graduate): Taste/Experience				
Enjoy Academics	.066	(.047)	.066	(.047)
Enjoy Non-academics	-.162	(.041)	-.162	(.041)
Expect Easy	.002	(.038)	.002	(.038)
HS GPA	.146	(.076)	.146	(.076)
Intercept	-.610	(.334)	-.610	(.334)

Encouragement and norm coefficients ( $F_i^E$ ) have the expected positive signs, although the effects are small relative to other categories with the exception of College is Important.<sup>26</sup>

In background ( $F_i^B$ ), race and ethnicity coefficients are positive. These groups do not necessarily attain more schooling than whites, a finding that would be contradicted by the

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<sup>26</sup>The coefficient on either parent having a bachelor's degree is small compared to other coefficients, an unexpected result given that parental education is typically a strong predictor of child educational attainment and achievement. However, other forms of family education, background, and income are also controlled for here. This points towards an indirect influence of parental education on education plans, better explained by these alternate variables like parental encouragement, which has a large coefficient.

wider literature for black and Hispanic students. Rather, these positive signs suggest that, with other consumption value inputs and financial returns held constant, minority students expect to receive a higher level of utility from a year of education than do whites. Coefficients on FRPL and gender are small.

As discussed in Section 3.2.3,  $F_i^E$  and  $F_i^B$  coefficients represent an upper bound on the contribution of these variables to consumption value for those background characteristics that are indicative of higher family income, and a lower bound for characteristics indicative of lower family income. In this light, the positive coefficients on several variables negatively related to family income (FRPL, black, Hispanic) indicate considerable differences between these groups and non-FRPL white students in consumption value. Most of the affected variables are likely negatively related to income, and the variable likely to be most strongly positively related to income has a small coefficient (Parent has BA). Because of this, I suggest that these reduced form coefficients are unlikely to overstate the aggregate contribution of consumption value.

Taste parameters  $T_i$  are positive and large relative to the other consumption value coefficients during undergraduate education. The exception here is Enjoy Non-academics; students who expect lots of consumption value from the non-academic college experience plan for more education, but not extensively so. These students are also less likely to continue on to graduate school; students who expect to really enjoy the social and non-academic parts of the college experience do not expect that enjoyment to carry over to the graduate school experience. The other  $T_i$  coefficients shrink for the decision of whether or not to continue to graduate school, although they retain signs. From the point of view of high school students, variables in  $T_i$  have less to do with plans to get an advanced degree than with other levels of education.

The magnitude of consumption value coefficients can be compared to the coefficient on Log Lifetime Net Earnings, which is .126. In a rough sense we can see that the coefficient on Log Lifetime Net Earnings is of the same order of magnitude as the consumption value coefficients, although a direct comparison of the influence of these inputs requires behav-

ioral simulation. Changes in consumption value inputs can have influence of similar size as similarly-scaled changes in net earnings. The rough comparability of the net earnings and consumption value coefficients is striking, given that a one-unit increase in Log Lifetime Net Earnings represents more than a doubling of lifetime net earnings. This result gives an intuitive preview of what the more sophisticated simulation comparisons in Section 3.4.3 will find.

The estimated discount factor is .881. This figure is similar to some other estimates of constant discount factor in a lifetime model (Samwick, 1998; Laibson et al., 2007), although it should be noted that estimates of discount factors vary in different contexts. As Laibson et al. (2007) point out, standard exponential discount factor estimates in lifetime models are often closer to .95, although these estimates are for adults rather than 17-18 year old students. Importantly, the discount factor here is identified on the basis of the timing of the model. The timing is restrictive, for example assuming that all students expect to complete a bachelor's degree after exactly four years. As such, while the estimated discount factor allows future returns to be properly discounted in the model, the point estimate of the discount factor may be biased.<sup>27</sup>

The coefficient on Pay Own Tuition, a variable equal to one if the student expects to have to work to pay the majority of their own tuition, is positive, although it is imprecisely estimated. This positive coefficient suggests that the other variables control adequately for financial support while in college, leaving Pay Own Tuition as an indicator for motivation. Given two students with similar levels of financial support, the one who values college more strongly will be more willing to work in order to afford it.

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<sup>27</sup>Further, the discount factor and the preference for future earnings do enter the model separately via discounting on future consumption value. Still, a critical interpretation of the results might be that the coefficient on future earnings is biased downwards by an overestimate of the discount factor. If this is true, however, the general result that future earnings holds little influence remains, and so policy implications are unchanged. In this case the interpretation of the result would be more along the lines that future earnings don't matter because students care little about the future, as opposed to caring little about earnings.

Table 3.3 displays results from the model with and without heterogeneous preferences taken into account. While nine different types of student preferences were allowed, all weight in estimation was put on three types. A random student's preferences have a .717 probability of being best explained by the preference vector estimated in the single-type model. The two adjacent types  $\gamma^4$  and  $\gamma^6$ , in which parameters are close to that of  $\gamma^5$ , best explain student preferences with .024 and .259 probability, respectively. The parameters in each of  $\gamma^4$ ,  $\gamma^5$ , and  $\gamma^6$  are displayed in Table A.2 in Appendix A. The heavy weight on the single-type parameter vector explains why single-type estimates are so close to mean multiple-type parameters. Some alternate approaches to preference heterogeneity are discussed in Appendix C.

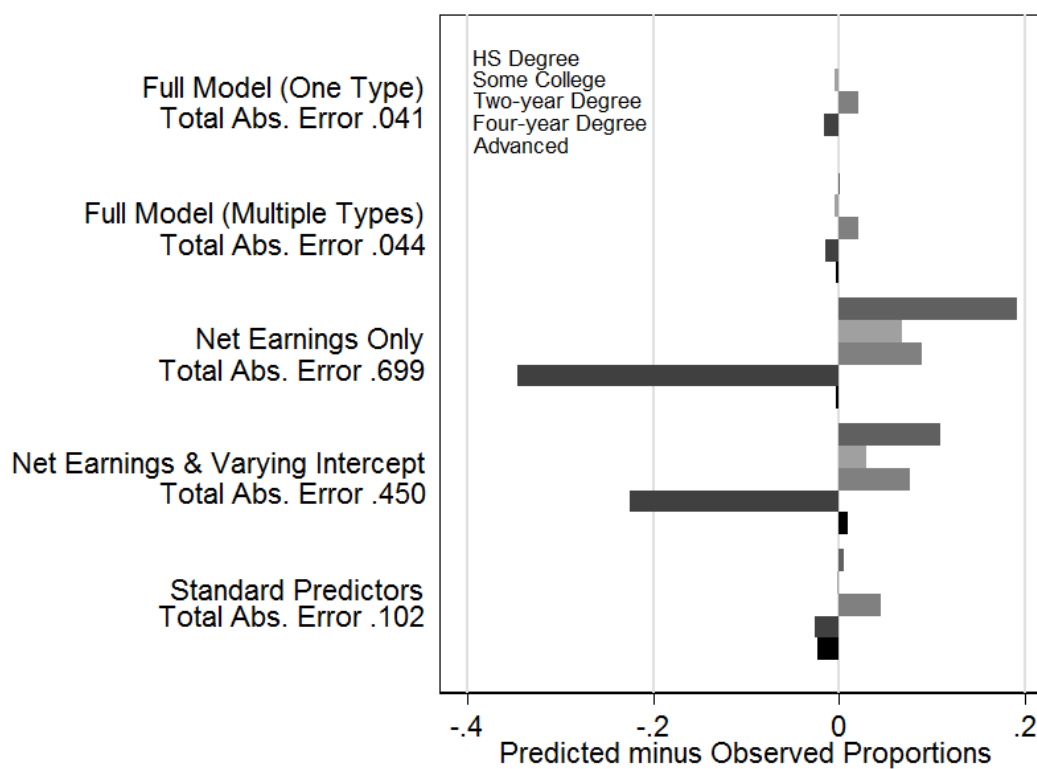
### 3.4.2 Model Fit

The value of the model relies not only on the reported coefficients but the ability of the model to fit the data better than models that do not incorporate the insights presented in this paper. Because the model in this paper is more detailed and has more predictors than standard models, it is to be expected that this model will better fit the data. However, if simpler models report similar error rates, or if the improved predictive power of the model appears to be due to overfitting of the data, then the focus on multidimensional consumption value (or possibly a focus on consumption value at all) does not add much.

Figure 3.2 shows the difference between the proportion of students predicted by the model to choose the given option minus the proportion of students who chose each option, in effect the error in the model's prediction. A positive bar to the right of zero indicates that the option is overpredicted by that model, while a negative bar to the left indicates that the option is underpredicted.

For the full model, predicted and observed options match closely; the fit of the model is quite good. The total absolute difference between observed and predicted proportions in the multiple-type model is .044, meaning that if predictions were shifted away from  $.044/2 = .022$  of the overpredicted options towards the underpredicted options, then the proportions would be exactly predicted. The model over-predicts the option of attending no college and planning

Figure 3.2: Error in Model Predictions



to attempt a two-year degree, and under-predicts planning to attempt a four-year or advanced degree, and planning to attend some college with no intent of attaining a degree.

Also in Figure 3.2 are three simpler, alternative models that demonstrate the advantage of the multidimensional consumption value approach taken in this paper.

First, I present a very basic model that focuses solely on financial costs and benefits, Net Earnings Only, an extremely simple model in which the only differences between the educational options are financial. The only parameters estimated in the model are the coefficient on future net earnings, the coefficient on Pay Own Tuition, and the constant.<sup>28</sup> This model is more limited than typical models that focus on finances, as it does not allow for even average differences in consumption value across educational options, but serves as a reductive illustration. I run the model without allowing for preference heterogeneity.

Since this Net Earnings Only model has fewer predictors with which to fit the model, it is not surprising that the fit is poorer than in the full model. However, the degree of misprediction is extremely large: 35% of the sample would need to be reassigned to perfectly predict aggregate choices. Student response to income is estimated to be stronger in this model than in the full model. In contrast to a coefficient on future earnings of .126 in the full model, as reported in the previous section, the same coefficient in this model is .518. Simulated student response to changes in earnings, as will be discussed more fully in the next section, were similarly larger in this model.<sup>29</sup>

Second, I mimic a consumption value model that treats consumption value as a holistic single parameter (Net Earnings & Varying Intercept). I repeat the analysis of the Net Earnings Only model, but allow the intercept to vary widely - the estimated intercept is 1.270 in the Net Earnings Only model, and is constant over educational types. In the Net

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<sup>28</sup>With less variation in time-varying payouts, the identification of the discount factor  $\delta$  is weakened in each of the simpler models. As such,  $\delta$  is not estimated in this model, but is set to .880 to match the estimate from the full single-type model. Allowing the discount factor to be estimated in these models does not improve their fit.

<sup>29</sup>In the Net Earnings Only model, the elasticity of demand for education ranges from .05 to .39, depending on education level.

Earnings & Varying Intercept model, I allow the intercept to vary, and treat each different intercept value as a different preference type using the method from Section 3.2.4. I allow for the constant to vary uniformly over nine types, from .870 to 1.670, representing the original intercept plus or minus about four standard deviations of the estimated parameter. I additionally allow average consumption value to be different for graduate school, as it is in the full model, and to vary over the same nine types. I allow for each combination of the two constants, for a total of 81 preference types. This model improves significantly on the Net Earnings Only model with an absolute error of .450, but still falls far short of the complete model in predictive power.

Third, I use the predictors that would be used in a standard educational choice model: the net earnings variables as well as the demographic characteristics in  $F_i^B$  (Standard Predictors), with nine preference types estimated in the same manner as in the full model. This Standard Predictors model, again, improves significantly on the Net Earnings Only model, and errors are in more acceptable ranges. However, this model still has more than twice the predictive error of the comparable full model, exemplifying the improvement made by the explicit treatment of consumption value inputs. Student response to future earnings is similar here as in the full model.

In each case the full model has an advantage in fitting the data due to the increased number of parameters, which can lead to overfitting and poor out-of-sample prediction. To test for out-of-sample predictive ability, I use ten-fold cross-validation: I randomly split the sample into ten subsamples. I then estimate the full model ten times, each time leaving out one of the subsamples. The estimated (one-type) parameters are used to predict choices for the omitted subsample. The minimum, mean, and maximum total absolute differences in proportions over the ten iterations are .046, .065, and .093, respectively. The average out-of-sample fit is poorer than the in-sample fit as displayed in Figure 3.2, but even the worst out-of-sample fit is superior to the in-sample fit for the Standard Predictors model. Overfitting is not driving the predictive power of the full model.

The comparative fit of the model used in this paper and alternates can be related to,

for example, Keane and Wolpin (1997). Keane and Wolpin find unsatisfactory fit with a basic human capital model, but they present an extended version including skill technology functions, search costs, and a number of psychic and non-pecuniary benefits, including educational consumption value allowed to vary with age. Their extended model fits well.

The full model as presented, with multidimensional student-varying measures of consumption value, is capable of closely predicting student plans in and out of sample. Consumption value inputs are important for understanding student choice, and meaningfully improve model fit over simpler models. In the next section, I simulate how student choice is predicted to change in response to changes in consumption value and financial inputs.

### *3.4.3 The Influence of Consumption Value and Net Earnings*

In this section, I use the multiple-types model estimated in Section 3.4.1 to simulate the degree of influence that student-level predictors have on student plans. These simulations show the extent to which student demand for education is driven by consumption value or perceived net earnings. I focus first on the response of student choice to changes in net earnings, and then broaden the analysis to look at consumption value inputs.

The influence of earnings-based inputs on the student's decision is complex, and so I simulate the effect of earnings increases in multiple ways. First, I produce elasticity estimates, looking at the response of student demand for educational options to expected net earnings increases for particular levels of education. Second, I produce estimates of influence designed to be comparable to the consumption value simulations.

Elasticities and cross-elasticities of planned educational level with respect to changes in wages specific to each education level are in Table 3.4. I increase the wage of each level of schooling in turn by 10% and simulate the change in the proportion of students who plan to have each level of schooling. I find that own-wage and cross-wage elasticities are very low, especially in response to wage changes for higher levels of education.

There is a limited response to direct positive manipulations of perceived wages. The strongest response is to an increase in the high school wage, suggesting that the margin at

Table 3.4: Elasticity of Educational Demand With Respect to Wage

		Elasticity of demand for this schooling level...				
		HS	Some Coll.	2-Year	4-Year	Advanced
with respect to the wage of this schooling level	$S =$ HS	.089	-.029	-.020	-.014	-.013
	Some Coll.	-.012	.084	.003	-.002	-.003
	2-Year	-.024	-.011	.048	-.003	-.003
	4-Year	0	-.030	-.033	.041	-.044
	Advanced	0	-.000	-.000	-.021	.033

which financial returns are the most influential is the margin between no higher education and some. However, even this response is inelastic, with an elasticity of .089. Other elasticities are lower, around .04. The limited response to changes in perceived wages casts doubt on policies that aim to increase or correct perceptions of the wage benefits associated with college. These policies will be addressed more directly in the next section.

Other papers, using longitudinal and geographic variation in the wage premium, also find small responses (Acemoglu and Pischke, 2001; Jacob, 2002)<sup>30</sup> although exact estimates vary by sample and by demographics. Results in Jacob (2002) suggest elasticities of .117 for men and .160 for women.<sup>31</sup> There is evidence that responsiveness is higher for students with high socioeconomic status (Beattie, 2002). In Appendix C I also find that men and students with high socioeconomic status have stronger responses.<sup>32</sup> The elasticities in Table 3.4 are also similar to the low elasticities calculated for the response of college major choice to wages.

<sup>30</sup>Notably, these other papers examine the response of actual attainment. If parents or colleges are able to respond to wage changes by encouraging more schooling in their child, then we may expect that behavioral response will be greater than a response derived solely from student preferences.

<sup>31</sup>Elasticity estimates are calculated from published results in Jacob (2002) using average levels of college attendance and published coefficients from regressions of college attendance on the college wage premium and controls. Similar results can be derived from Acemoglu and Pischke (2001) or Beattie (2002).

<sup>32</sup>There is also the potential for preference heterogeneity by race, but the number of students in each racial minority is too small to estimate these differences precisely.

Beffy et al. (2012) find an elasticity of about .1, depending on major, in response to econometrically derived wage expectations. Wiswall and Zafar (2015) use earnings expectations derived from subjective expectations and find elasticities of about .04.

Elasticity estimates are difficult to compare to the influence of consumption value, since it is unintuitive to imagine a certain percentage increase in a consumption value input. For consumption value inputs, I simulate the effect on schooling plans of a one-unit increase in each consumption value input.<sup>33</sup> I also report the simulated response to a .1 increase in the expected graduation rate (with a maximum possible graduation rate of 1). Table 3.5 Panel A reports the increase in the planned number of years of higher education, or the increase of the proportion of students planning to attain college degrees (two-year, four-year, or advanced), in response to a one-unit increase in consumption value incentives. The increase in the number of years of higher education gives a better sense of the importance of that input in the model, since it allows for improvement at all margins. The increase in the proportion of students planning for a college degree, which is already predicted to be .821 before any simulated changes, may be a more realistic measure of student behavioral response since it focuses on the margin that is most immediately relevant for students.

For some inputs, such as race variables, it is not obvious how to interpret the meaning of a one-unit increase. As mentioned in Section 3.4.1, these results do not indicate that these minority groups are necessarily expected to attain more schooling. Since the model already controls for perceived wages and the probability of graduation, these controls can be interpreted as demographic differences in the flow utility gained from college education in addition to income differences. In these cases, the consumption value counterfactuals being considered are the result of giving the entire sample the additional consumption value enjoyed by that group. These values do not offer a policy lever, as race is immutable, but still tell us about the reduced form influence of these inputs on choice.

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<sup>33</sup>For binary variables, outcomes when the variable is equal to 1 for all students are compared to outcomes when the variable is equal to 0 for all students. For non-binary variables, the simulated effect is the change due to an increase in the variable by one unit. In each case, only one variable is altered at a time.

Table 3.5: Educational Influence of Inputs

Panel A: Single input changes					
Association between a one-unit increase and additional average years of school ( $S_i$ ) or proportion of degree attainers (Degree)					
$F_i^E$ (Expectations):	$S_i$	Degree	$F_i^B$ (Background):	$S_i$	Degree
Family to College	.065	.006	FRPL	.109	.011
Friends to College	.093	.009	Female	.083	.008
Parent has BA	.035	.003	Black	.372	.034
College is Important	.375	.038	Asian	.211	.020
			Hispanic	.178	.017
$T_i$ (Tastes):	$S_i$	Degree		$S_i$	Degree
Enjoy Academics	.245	.032	Expect Easy	.130	.023
Enjoy Non-academics	-.104	.007	HS GPA	.725	.098
Other:	$S_i$	Degree			
Grad. Rate (.1 increase)	.079	.005			
Panel B: Aggregate changes					
Additional years of school ( $S_i$ ) or proportion of degree attainers (Degree) associated with a one standard deviation increase in the index					
Variable Group:				$S_i$	Degree
Family Encouragement ( $F_i^E$ )				.248	.023
Background ( $F_i^B$ )				.195	.018
College Experience ( $T_i$ )				.685	.087
Net Earnings with any Degree				.008	.005
Labor Market Utility with any Degree				.002	.016

For a number of consumption value inputs, the predicted increase in average educational level is fairly high. One-unit increases in Enjoy Academics or Expect Easy are predicted to increase the number of students attempting college degrees by 3.2 and 2.3 percentage points, respectively. College is Important is similarly influential. Perhaps unsurprisingly, if students received the college consumption value of those with a high school GPA one unit higher, they would attain a much higher educational level.

The variables in  $T_i$  are particularly influential. Enjoyment of non-academics leads to an overall simulated decrease in years of education, but most of this is along the margin of those who would have gone to graduate school instead entering the labor market with only a bachelor's degree; more students go to college overall in this simulation. The effects of all the variables in  $T_i$  are concentrated among the choice between no college and the different undergraduate options; these incentives are less influential in the decision of whether to pursue an advanced degree. In the  $F_i^E$  vector, variables outside of College is Important have relatively little effect.

Some of the estimated effects of consumption value inputs may be driven towards zero by correlation with other consumption value inputs. In particular, the coefficient on parental educational attainment is surprisingly low, which may be driven by strong correlation with other inputs in  $F_i^E$  such as Family to College and College is Important. I address this in Panel B by simulating the response to a one standard deviation increase in indices of the variables and estimated parameters in the taste ( $T_i$ , including academic enjoyment, non-academic enjoyment, expected ease, and high school GPA), family expectations ( $F_i^E$ , including the proportion of family and friends that went to college, whether any parent has a bachelor's degree, and whether a parent thinks college is the most important thing to do after high school) and background ( $F_i^B$ , including gender, race, ethnicity, and eligibility for free or reduced price lunch) vectors.<sup>34</sup> By simulating a change to the index, overlap between

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<sup>34</sup>To calculate these increases, estimated coefficients are used to generate a measure of the amount of indirect utility contributed by those variables. The standard deviation of this total is taken over all students, and an amount of utility equal to the standard deviation is added to the college flow utility for each student. For example, to simulate the response to  $F_i^E$ , the sum  $\hat{\gamma}_4^s F_i^E$  is calculated for each

correlated variables is accounted for. This allows a comparison between the characterized *types* of consumption value inputs in terms of how they are valued as a group and how they relate to education options.

In Panel B, the direct experience index generated from  $T_i$  dominates. A one standard deviation increase in this index raises the proportion of students planning to attempt degrees from .821 to .908. If the influence of the  $T_i$  index is calculated while leaving out HS GPA, it is still predicted to increase planned years of schooling by .395 years per student and the proportion of degrees by .041. This effect is much larger than estimated from the other two indices. The importance of  $T_i$  is especially notable given that the interpretation of the coefficients in  $T_i$  as working through consumption value is stronger than the interpretation for  $F_i^E$  and  $F_i^B$ , for which the reduced form influence is still strong but which also represent a family income effect. All three types of consumption value have considerable influence, although direct experience and the expectation of ease seem to dominate, with family normalization and encouragement of college coming out somewhat ahead of background.

The influence of consumption value inputs can be compared to the influence of financial incentives. In Panel B I also simulate the response to standard-deviation increases in net earnings with any degree and to increases in total labor market utility with any degree, which also includes job-education level match. A one standard deviation increase in the expected wages for two-year, four-year, and advanced degrees translates into an average simulated increase of only .008 years of education, or a half-percentage point increase in the number of students planning to attempt degrees (see Panel B). To put these numbers into perspective, a standard-deviation change in discounted lifetime net earnings is about 50% of discounted lifetime net earnings for each level of schooling. This can be compared to a one standard deviation increase in the index of family encouragement and norms ( $F_i^E$ ), which leads to a simulated increase of 2.3 percentage points more degrees, almost five times as much.

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student (see equations 3.11-3.12), where  $\hat{\gamma}_4^s$  is the vector of estimated coefficients on the variables in  $F_i^E$ . Each student then has the standard deviation of  $\hat{\gamma}_4^s F_i^E$  added to college flow utility, and their response is simulated.

A standard-deviation increase in discounted lifetime net earnings, which is about 50% of lifetime earnings, leads to an increase in the attainment rate of planned degrees by .5 percentage points. This effect size is extremely small, especially compared to the consumption value inputs. For example, a one standard deviation increase in the index of family encouragement and norms ( $F_i^E$ ), which leads to a simulated increase of 2.3 percentage points in the planned attainment rate, almost five times as much.

I emphasize the low response of college enrollment to financial incentives for two reasons. First, the small student response to wage returns, backed up by similar results in the literature, casts doubt on the use of a model of college choice that relies entirely or largely on finances. Second, this small response also offers one explanation for why the financial return to college education has persisted over time and has not been wiped out by general equilibrium effects. Third, the small wage response serves as a contrast to the much larger influence of consumption value inputs. Even if the response to net earnings were four or five times larger, the effect of a rather large change in earnings would be comparable to a one standard deviation increase in family normalization or background, but still would not match direct experience, or consumption value as a whole.

The estimates in Table 3.5 show that, although financial returns to education do play a part in educational plans, they are dwarfed by the pursuit of consumption value, and the variation there drives educational planning. Additionally, this table shows that direct experiential consumption value ( $T_i$ ) is the most valued and appears to have more to do with plans than background, norms, and encouragement. Policy makers interested in influencing student planning for college should consider their capacity to alter these consumption value inputs.

#### 3.4.4 Policy Simulation

In this section I simulate changes in certain policy-malleable inputs to the education decision and how student plans change in response. In each case I use the multiple-type parameters from Table 3.3. Holding these parameters and other data constant, it is straightforward to

estimate how manipulations of the input data change the predicted plans.

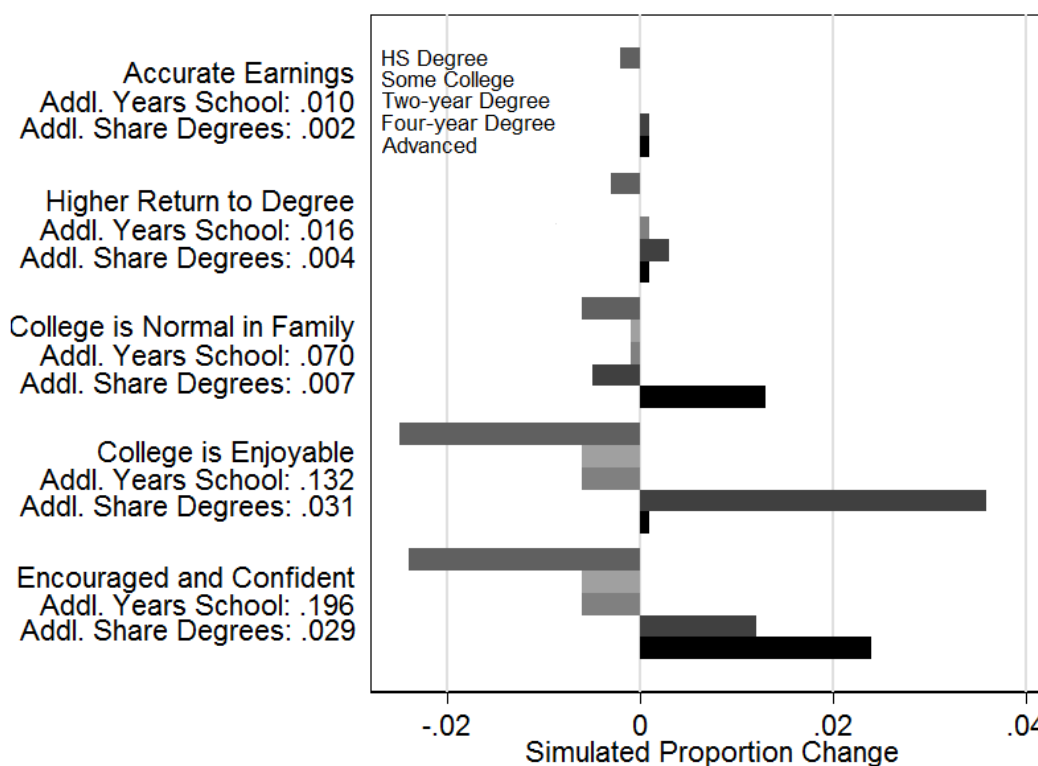
A fair amount of recent policy and research attention has been given to interventions that aim to correct student perceptions of labor market outcomes (Wiswall and Zafar, 2011; Oreopoulos and Dunn, 2013) or available financial aid (Hoxby and Turner, 2013). Recent proposals by the Obama administration aim to make this sort of information more available to students in the form of “scorecards” for colleges. While part of the administration’s goal is to use these scorecards to make funding decisions, the scorecards are also intended to guide student choice (College Affordability and Transparency Center, 2014). Wage information-provision interventions are popular because they are low-cost ways of addressing student misperceptions thought to lead to less education. However, in terms of actual behavioral change, results are mixed. Some, such as Hoxby and Turner (2013) and Jensen (2010) find large positive effects on behavior. Other laboratory and intervention studies (Wiswall and Zafar, 2011; Oreopoulos and Dunn, 2013; Bettinger et al., 2012; Fryer, 2013; Kerr et al., 2014) find small or no behavioral effects of information-only interventions, even when perceptions are changed, or when the combination of information with other interventions are effective, (as in Bettinger et al., 2012).

The top two sections of Figure 3.3 show the response of student plans to manipulations of perceived labor market returns to college. In the top section, “Accurate Earnings,” market wages and employment levels projected using observed data are substituted for student estimations, mimicking a policy that teaches students about labor market premia.<sup>35</sup> The observed data exhibits a lower wage return to education and a higher overall probability of employment than does the subjective data. The second, “Higher Return to Degree” policy shows how student plans respond to perceptions of a higher (rather than corrected) return to a generalized college degree; the perceived wage associated with each level of education is

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<sup>35</sup>I run regression models using Washington residents ages 25-35 in the 2008-2010 American Community Survey to generate predicted log wages (OLS) and employment probability (logit). I run a separate model for each level of education, regressing labor market outcomes on gender, race, and ethnicity. This predictive model does not correct for selection or ability, but the proposed “scorecards” and many other similar proposed interventions that the simulation approximates do not perform such a correction either.

Figure 3.3: Simulated Response to Policy Interventions



increased by a successive 10%.

Responses are very modest. Given parameters estimated using subjective expectations, correcting wage expectations to match observed data increases the average planned number of years of higher education attained by only .010, and only increases the share of students planning to attempt a degree by .2 percentage points. Attempts to ‘correct’ student perceptions of the financial benefits education are unlikely to significantly increase attainment through changes in student plans; any effect would have to operate through an alternative mechanism such as parental behavior or the relaxation of credit constraints. Encouraging higher perceived returns to college degrees has similarly small effects, keeping with prior estimates of responsiveness to wage.

Also in Figure 3.3 are predicted educational plans resulting from manipulations of a few

select aspects of consumption value. Here the simulations address alternative consumption value-based interventions and policy levers proposed in the literature. Ideally, the policies simulated here would be scaled so that the reported effect would have a budget equivalent to accurate-earnings policy. However, there is little literature showing the cost-effectiveness of consumption value-targeted interventions or policies that target student perceptions of wages, so estimating the budget-equivalent effect size is not feasible. Instead, I present the response to an arbitrary, conservative increase in the relevant inputs. The difference in effect sizes between wage- and consumption value- based policies is very large, and a very small change in consumption value inputs would generate the same effect, for example, as the .002 share increase in the number of students planning to attempt a college degree generated by the Accurate Earnings policy. If the hypothetical budget-equivalent consumption value-based policy would raise inputs by a greater amount, then the consumption value-based policy has a greater effect.

The first simulation examines the effects of further family normalization of college. The relationship between parental and family educational attainment and student attainment is well known and can explain persistent trends in attainment (Perna and Titus, 2005). How would increasing attainment persist between generations through student choice? By setting all students to have a parent with a bachelor's degree and increasing the share of the extended family that went to college (by one unit on a five unit scale, unless they already reported the maximum), the planned number of years of education increases by .070, and the share of students planning to attempt a degree increases by .007. This reduced-form effect, which captures both consumption value and an income effect, is not monumental but is quite large compared to perceived-earnings manipulations.

The second simulation increases the perceived enjoyability of college. I increase the perceived enjoyment of both the academic and non-academic aspects of a college education by one unit on a five-unit scale, unless they already reported the maximum. A policy with these effects would increase planned attainment by .132 years, with a share of planned degrees .031 higher.

The final simulation examines parental encouragement and student confidence. Socialization and encouragement from those around the student significantly shapes plans (Bozick et al., 2010). Policy may target student expectations of their ability to succeed in college or target parents to improve the encouragement given to students. This simulation increases the ease with which students expect to get good grades by one unit on a five-unit scale, unless they already responded with the maximum, and sets all students to have parents who suggest that college is the most important thing to do after high school. A policy with these effects would be predicted to increase average planned attainment by .196 years, with the share of students planning a degree increasing by .029. With encouragement alone, and no manipulation of perceived ease, the average planned attainment increases by .077 years, or .009 more planned degrees.

Correcting or improving perceptions of financial costs or benefits has relatively little impact compared to manipulations of more “soft” variables such as perceptions of college difficulty.<sup>36</sup> These simulations suggest the further development of policies that target consumption value.

One potential concern about policies that target consumption value is that they cannot be effective since consumption value is immutable. However, this does not appear to be the case; there are already policies that target perceived and actual consumption value. A plan to develop further policies along this line would benefit by taking a closer look at what already exists. Some of these policies, like the amenity-building mentioned in Jacob et al. (2013), directly increase the actual academic and non-academic enjoyability of college. Others, like Hoxby and Turner (2013), combine a financial information intervention with information about the availability and experience of certain economic programs, to great success. There is a long history of outreach programs that work to increase parental encouragement as well as work directly with students to familiarize them with the college experience and build

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<sup>36</sup>The scale of impact can be observed in another way. The .002 increase in planned degrees achieved as a result of the Accurate Earnings policy could also be achieved by approximately a .08 unit increase instead of a unit increase, for each of the consumption value policies. In each case a .08 unit increase is also about .08 of a standard deviation.

confidence in their ability to perform well in college (Swail and Perna, 2002).

Relatively small changes in consumption value inputs are capable of generating large changes in student plans. There is clear value in understanding this relationship, and in designing and increasing emphasis on policy that takes advantage of it.

### **3.5 Discussion**

Using a model of educational choice estimated with stated preference and expectations data, I find that consumption value is an important determinant of educational choice. Consumption value explains more than differences in earnings expectations. Researchers and policymakers intending to understand student choice must look at student attitudes towards education and other non-financial incentives in order to understand more than a small amount of the variation in educational choice.

Several individual elements of consumption value, such as the expectation of ease (both directly elicited and proxied by high school GPA), the encouragement of parents, and the stated enjoyment of academics, are important predictors of educational plans, and variation in these predictors drives those plans. In general, direct experiential components of consumption value (taste for educational experience and psychic costs) are the most valuable and relevant aspects of consumption value; family encouragement and background are also valuable, but less so. Consumption value matters more for decisions regarding the educational levels below graduate school, but is still highly valued in high school students' current perceptions of the decision of whether or not to attempt an advanced degree.

These results pertain to our understanding of choice in higher education, and thus our understanding of labor supply. While some results on major choice already show that the consumption value of education has a very large monetary equivalent (Alstadsæter, 2011; Beffy et al., 2012; Wiswall and Zafar, 2015), this study shows that it is possible to break down that value into individual observed or reported components and compare them. This adds important detail to the generalized high valuation of consumption value.

There are several limitations to the validity and usefulness of these results. First, while the

use of subjective expectations data is well-supported, the use of stated preference data is less robustly supported. However, without the use of stated preference variables, other schooling utility variables still make the case for the importance of consumption value. Second, I focus on student plans, but parents and school officials may have control over some part of the choice, or as suggested by the model, may be able to influence the student through encouragement. The variable for parental encouragement in the model may represent an avenue for future earnings or other incentives to influence students indirectly. It is also possible that credit constraints affect choice in a manner that students may not take into account in their reported data. If parents or schools respond more strongly to financial incentives than students do, or if changes in financial incentives ease credit constraints in a way not anticipated by the student, then actual behavior will deviate from plans. Third, it is difficult to reconcile the low response to net earnings with the financial aid literature that finds stronger responses of college enrollment to tuition and grants (Dynarski, 2003). The APCAB data is not well-suited to attempt to replicate these results, since behavioral response to college cost is likely highly dependent on parental preference. As such, I acknowledge that the use of a general response to financial incentives, rather than allowing costs and benefits to enter separately, may understate the response to costs. I leave further detail on this to future research.

Despite these limitations, the general qualitative result that the influence of consumption value outweighs that of financial incentives is both reflected in other studies and so overwhelmingly supported here that the estimates would need to be seriously changed to suggest an alternate interpretation. Consumption value must be carefully considered in the study of educational choice. Models that omit student-varying consumption value are likely to mispredict student plans, and in this paper are found to significantly overestimate the degree of student response to financial incentives. Accordingly, policies based on these models are likely to misunderstand what motivates students and what they will respond to.

Attempts to increase educational plans among students should focus on improving the perception of the college experience or the social rewards to attending. Interventions and

policies along these lines exist, and deserve attention (Swail and Perna, 2002). A manipulation of, for example, the perception of psychic costs is likely to have larger effects than changes in perceptions of financial reward. Making the actual educational experience more enjoyable is likely to significantly affect student plans (Alter and Reback, 2014). The colleges themselves are already aware of this, and in Jacob et al. (2013) are found to compete for students along these lines. In terms of competition between colleges, the student response to consumption value can lead to an inefficient amenities arms race between colleges (like the example given in Carey, 2015). However, it is possible instead for policymakers to harness this student response with an aim to increase attainment. Even if incentives such as the college experience do not directly contribute to social welfare, they may be worthwhile targets for policy as an incentive to encourage students to earn a degree that improves the stock of human capital in the economy.

Influenced by the human capital model, much economic research on educational choice has focused largely on the labor market returns to education. Students nominally agree with this research agenda: in the APCAB sample used in this paper, “getting a good paying job” was the most popular reason to attend college: 79.0% of respondents listed it as *a* good reason to go to college, and 24.9% of those who picked a *most important* reason chose “getting a good paying job.”<sup>37</sup> However, despite the clear presence and importance of financial motivation, it appears that for high school students, the decision of how far to go in school is more driven by elements of the choice that have little to do with money.

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<sup>37</sup>Other options were “getting an enjoyable job,” “meeting other students,” “discovering myself,” “learning,” and “because my family wants me to.” Choosing good reasons to go to college was not exclusive. Choosing most important reasons was exclusive, and only 57.9% of all respondents chose a favorite.

## Chapter 4

# A DUAL-AGENT MODEL OF COLLEGE CHOICE: IDENTIFICATION FROM A CONJOINT CHOICE EXPERIMENT

### 4.1 Introduction

College attendance is a major determinant of human capital. The choices of whether or not to attend college and which college to attend both affect that student's performance in the labor market. Aggregated, these choices determine much of the supply of skilled labor.

A large literature addresses the determinants of educational choice. Many modern applications of the human capital model consider a wide range of influences on choice (e.g. Altonji et al. 2012 on uncertainty, Stinebrickner and Stinebrickner 2014 on field-specific skills, and Chapter 3 on consumption value). However, college choice is nearly always presented as the choice of *a student*, or in the case of educational decisions for children at a younger age, the choice is that of *a parent*.

In household settings, both students and parents have an interest in the student's educational plans and both have some agency in the decision. A dual-agent model is likely to provide a better description of educational choice. In the case of choice at the college level, where choices are typically assumed to be made by the student alone, it is broadly acknowledged that parental characteristics influence educational choice. However, in modeling it is assumed that parental characteristics have an influence on what is fundamentally a student's choice, for example by including a variable for parental education or encouragement as a predictor, rather than allowing for direct parental agency in a dual-agent decision. There is room for improvement in the model by more fully integrating the interaction between student and parent preferences in the model.

Collective choice between students and their parents is generally ignored, despite evidence that children do have a say in household decisions (Dauphin et al., 2011). In the specific domain of educational choice, there is a small amount of previous work on collective student/parent decision making. Results from this work show that a dual-agent model is appropriate. Giustinelli (2010) looks at parent-child interactions in the choice of high school curriculum in Italy, allowing for uncertainty in both parents' and children's beliefs. She finds that students tend to lead decision-making. A child's preference for a particular type of curriculum is the most important predictive factor in choice. While there is heterogeneity across families, in general children are more likely to get their way. Attanasio and Kaufmann (2009, 2014) use data from Mexico to look at the influence of both student and mother labor market expectations on the choice of whether to attend high school and whether to attend college. Results differ between the two Attanasio & Kaufmann papers, but both mother and student expectations seem to matter. Student expectations may matter less for girls and for the high school decision, as opposed to the college decision. Long and Conger (2013) look at the choice between different public schools in the United States. They find evidence that public school choices depend on student gender. They examine differences in student and parent preferences in determining high school choice, and find that gender differences in student preferences are responsible for gender differences in high school choice.

The slim literature on student/parent educational decisions makes a distinction between the standard model and one in which multiple agents with different preferences come together to make a decision. Work in other areas suggests that this is not a trivial distinction. In particular, this work descends from a much wider literature on collective intra-household decision making in which husbands and wives make decisions together. The intra-household literature generally rejects the unitary approach to household choice in which household preferences can be described by a shared utility function (see Fortin and Lacroix 1997 or Ermisch 2003 for a review), and underlines the research and policy implications of these modeling choices.

For example, a unitary model implies that the effects of a transfer policy should be

invariant to which person in the household receives the funds. However, in Thomas (1990), unearned income has differential effects on family health and nutritional status for daughters and sons depending on whether the funds go to fathers or mothers. In Lundberg et al. (1997), the goods bought using funds from a child allowance in the United Kingdom are different depending on whether the funds are sent to the husband or wife. In Duflo (2003), pensions received specifically by women have significant impacts on the health of girls in the household, rather than boys. Educational policy, similarly, may have differing effects depending on who in the household is targeted by the intervention. Without a study of intra-household educational choice, there is no way to take advantage of this difference or to be aware of the implications of policy targeting.

Just as dual-agent models of intra-household bargaining have added significant insights to the study of labor supply and transfer policy, there is a clear value in further work on the dual-agent nature of college choice. The value of this approach is clear as long as the collective model is appropriate, and student and parent preferences over college attributes differ. The latter point is supported by work by Broekemier and Seshadri (2000) in which stated importance ratings for college criteria were significantly different between students and parents. Students rated social life, friends, and athletic programs more strongly, while parents favored academic and facility quality as well as campus safety.

In this paper, I develop a model of intra-household choice of colleges, based on their attributes. This model identifies the household objective function by separately identifying indirect utility functions for students and parents as well as a bargaining parameter. The bargaining parameter shows how heavily each side's preferences are weighted in the decision. Student and parent indirect utility functions are identified separately using a conjoint analysis choice experiment. Choice-based conjoint experiments are a tool that are heavily used to estimate demand functions in the field of marketing, in which respondents are presented with a choice between hypothetical products with attributes varied by the researcher.<sup>1</sup> In

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<sup>1</sup>It is worth noting that the use of the term "conjoint analysis" to describe a discrete choice experiment based on random utility theory, as is done in this paper, has met with some opposition (Louviere et al.,

this paper, I present subjects with four hypothetical colleges, each with randomly determined levels of five attributes: future earnings, enjoyability of classes, social life, the opinion of their parent/child, and annual tuition. Because college attributes are randomly assigned, indirect utility parameters can be easily identified. Student and parent indirect utility functions are determined by the choice response to the earnings, enjoyability, social life, and tuition attributes. Bargaining power is determined by the choice response to the other agent's opinion about the hypothetical college.

There is some history in using conjoint analysis to study family decision-making (Krishnamurthi, 1988), and the tool offers a particularly useful means of analyzing the educational choice decision. Since college attributes are randomly assigned, estimates are not based on the uncertainty inherent in the educational choice process, in which the outcomes of different educational options are unknown. Strong assumptions about beliefs, or data on those beliefs, are necessary to identify preferences (Manski, 2004). Such uncertainty motivated the collection of subjective expectations data in both Giustinelli (2010) and Attanasio and Kaufmann (2009, 2014). The random assignment of college attributes also sidesteps the “choice set” problem of estimating college demand. In the study of demand for college attributes, without detailed and hard-to-obtain data on each step of the college choice process, it is difficult to distinguish between a college not chosen because it is not preferred and a college not chosen because the student was not accepted or did not consider it a realistic possibility.

I use a novel data set of 864 online participants and estimate individual-level indirect utility parameters. Variation in respondent age and assigned respondent role allow me to compare indirect utility parameters across groups. The model has strong out-of-sample validity: in the model specification with attribute interactions, the average probability assigned to the out-of-sample option that the subject actually selects is .886. Student and parent priorities are significantly different. Students have stronger preferences over college attributes in general. In particular students respond more strongly, relative to parents, to how enjoyable

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2010). However, in the broader literature the term “conjoint analysis” is commonly used in this way, and I will continue to do so.

the classes are, the quality of social life, and future earnings. Parents respond strongly to their child's opinion, and so the weight of bargaining power falls to the students. Differences in the relative importance of different college attributes appear to be mostly between the assigned student and parent roles, rather than over respondent age. Respondent priorities are then based on role (parents do not directly experience enjoyable classes) rather than changing priorities over the life cycle (parents are more mature and care less about enjoyable classes), although age and cohort effects cannot be distinguished.

I reject the single-agent model of college choice. The dual-agent model outperforms the single-agent model in terms of predictive power, and coefficients estimated from a model that omits parent's opinion are biased estimates of student indirect utility parameters.

## 4.2 Model

In this section I present a collective model of college choice along the lines of Chiappori (1992) and show how certain parameters of that model can be identified experimentally. This section is intended to show how experimental estimates relate to an underlying model of collective choice.

Parents ( $p$ ) and their student children ( $s$ ) must choose a college option  $c$  from the set of available colleges  $\mathbb{C}$ .<sup>2</sup> They make this decision collectively, maximizing a combination of student and parent utilities over two periods. The first period covers the in-college period, and the second covers time in the post-college labor market. This formulation of the decision process follows from the standard cooperative model of intra-household allocation and assumes that the decision process is Pareto efficient but otherwise does not impose a particular model of bargaining on choice (Chiappori, 1992; Ermisch, 2003).

$$\max_{c, z_1^s, z_1^p, z_2^s, z_2^p} [U^s(x_c, z_1^s) + \delta^s U^s(0, z_2^s) + \mu[U^p(x_c, z_1^p) + \delta^p U^p(0, z_2^p)]] \quad (4.1)$$

$$\text{s.t. } t_c + z_1^s + z_1^p = Y_1^s + Y_1^p + L \quad (4.2)$$

$$z_2^s + z_2^p + (1 + r)L \leq Y_{c2}^s + Y_2^p \quad (4.3)$$

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<sup>2</sup> $\mathbb{C}$  also includes the option to not attend college at all.

$$c \in \mathbb{C} \tag{4.4}$$

where  $U^s$  and  $U^p$  are student and parent utility functions, respectively,  $\mu$  is the weight of parental utility relative to student utility in the decision-making process, and  $\delta^s$  and  $\delta^p$  are student and parent discount factors, respectively.

Each college option  $c$  offers consumption value attributes  $x_c$  at a tuition cost of  $t_c$ , both of which only apply in the first period. College attributes  $x_c$  act here as public goods preferred by both students and parents. Parent utility over college attributes may be partially an example of altruistic preferences, as many aspects of consumption value, such as the enjoyment of classes, will not be experienced directly by the parent. In addition to tuition payments, parents and children must pay for and distribute other goods  $z$  to the student  $(z_1^s, z_2^s)$  and the parent  $(z_1^p, z_2^p)$  in the first and second period.

Tuition and other goods are paid for using student and parental income  $Y_1^s$ ,  $Y_{c2}^s$ ,  $Y_1^p$ , and  $Y_2^p$ , and student loans  $L$  that must be repaid at an interest rate  $r$ .<sup>3</sup> Second-period student income  $Y_{c2}^s$  depends on the college chosen in the first period due to differences in networking opportunities and human capital accumulation across colleges.<sup>4</sup> Reflecting the process of choosing among a static and limited set of colleges, there is no assumption that colleges are priced hedonically. That is, college attributes  $x_c$  and  $Y_{c2}^s$  are not linked to their price  $t_c$  in a deterministic way. Rather than choosing a college with optimal levels of  $x_c$  and  $Y_{c2}^s$  given a price for each attribute, the family chooses  $c$  from available attribute baskets  $\mathbb{C}$  given a set price  $t_c$  for each basket.

In order to put the above model into a reduced form, I further assume that  $z$  enters into

<sup>3</sup> $L$  may be negative to indicate savings, which forces the first-period budget constraint to bind. The student loan interest rate is assumed equal to the interest rate on savings, which simplifies the model but does not change qualitative results. Additionally, under the assumption that the second period represents all further periods, the second period budget equation will bind, allowing it to be substituted into the first period budget constraint.

<sup>4</sup>An alternative formulation would suggest separate budget constraints in the second period, so that parents do not repay student loans and increased second-period income for the student does not lead to increased parental consumption. The use of separate budget constraints leads to similar empirical implications if parental utility includes altruistic preferences for student consumption and student-parent transfers are allowed.

both utility functions in a linearly separable manner. This assumption means that the choice of non-college goods  $z_1^s$  and  $z_1^p$  is not contingent on the particular mix of college attributes  $x_c$  chosen.<sup>5</sup> The choice of college attributes only interacts with the choice of other goods through the budget constraints, which involve only  $t_c$  and  $Y_{c2}$ , not  $x_c$ .

Then, for each college  $c \in \mathbb{C}$ , it is straightforward to find optimal goods allocation  $(z_1^{s*}, z_2^{s*}, z_1^{p*}, z_2^{p*} | c)$  using first-order conditions from Equation 4.1 and the constraints in Equations 4.2-4.4. The goods allocation is a function of fixed parameters  $r, Y_1^s, Y_1^p$ , and  $Y_2^p$  as well as college-specific variables  $t_c$  and  $Y_{c2}^s$ , but not  $x_c$ . The household's objective function given a specific college  $c$  can then be based on indirect utility functions  $V^s$  and  $V^p$ :

$$\max_c [V^s(x_c, z_1^{s*}(t_c, Y_{c2}^s)) + \delta^s V^s(0, z_2^{s*}(t_c, Y_{c2}^s)) + \mu [V^p(x_c, z_1^{p*}(t_c, Y_{c2}^s)) + \delta^p V^p(0, z_2^{p*}(t_c, Y_{c2}^s))] ] \quad (4.5)$$

$$\equiv \max_c [\bar{V}^s(x_c, t_c, Y_{c2}^s) + \mu \bar{V}^p(x_c, t_c, Y_{c2}^s)] \quad (4.6)$$

$$\text{s.t. } c \in \mathbb{C} \quad (4.7)$$

Aggregating utility over both periods gives the lifetime indirect utility functions  $\bar{V}^s$  and  $\bar{V}^p$  as shown in Equation 4.6. Equation 4.6 can be linked to the experimental results. In the experiment, subjects are presented with random variation in  $x_c, t_c, Y_{c2}^s$ , and either  $\bar{V}^p$  or  $\bar{V}^s$  depending on whether they are choosing as a student or a parent.

Given this random variation as well as the addition of random taste shifters  $\varepsilon_c^s$  and  $\varepsilon_c^p$  to student and parent total utility, respectively,<sup>6</sup> the experiment identifies up to a scale parameter the latent indirect utility functions  $\hat{V}^s(x_c, t_c, Y_{c2}^s, \bar{V}^{p*})$  and  $\hat{V}^p(x_c, t_c, Y_{c2}^s, \bar{V}^{s*})$  that

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<sup>5</sup>When  $z_1^s$  and  $z_1^p$  are linearly separable, they are chosen by  $\partial U^s(x_c, z_1^s) / \partial z_1^s = \mu \partial U^p(x_c, z_1^p) / \partial z_1^p$ , which does not depend on  $x_c$ , although it must be chosen given the budget constraint that depends on  $t_c$  and  $Y_{c2}^s$ . This assumption allows for a simple reduced form solution and simplifies the interpretation of the derivatives in Equations 4.8-4.11. Similar, but more complex, qualitative implications can be drawn without this assumption.

<sup>6</sup>In this paper, these taste shifters are assumed to follow a parametric Type I Generalized Extreme Value distribution, but the model can be identified using other error distributions or nonparametrically (Berry and Haile, 2010). As shown in Appendix E, primary results are robust to the use of one form of nonparametric estimation.

determine the choice of  $c$  from the set  $\mathbb{C}$  (Orme, 2006; Raghavarao et al., 2011). The estimated function  $\hat{V}^s$  is equivalent to the theoretical lifetime indirect utility function  $\bar{V}^s + \mu\bar{V}^{p*}$  in which  $\bar{V}^{p*}$  is exogenous rather than a function of college attributes. Similarly,  $\hat{V}^p$  is equivalent to  $\bar{V}^{s*} + \mu\bar{V}^p$ . Then, the estimated latent indirect utility functions  $\hat{V}^s$  and  $\hat{V}^p$  are linked to the theoretical indirect lifetime utility functions  $\bar{V}^s$  and  $\bar{V}^p$  through the first derivatives:

$$\frac{\partial \hat{V}^i}{\partial x_c} = \frac{\partial \bar{V}^i}{\partial x_c} \quad \forall i \in \{s, p\} \quad (4.8)$$

$$\frac{\partial \hat{V}^i}{\partial t_c} = \frac{\partial \bar{V}^i}{\partial t_c} = \frac{\partial V^i}{\partial z_1^{i*}} \frac{\partial z_1^{i*}}{\partial t_c} + \delta^i \frac{\partial V^i}{\partial z_2^{i*}} \frac{\partial z_2^{i*}}{\partial t_c} \quad \forall i \in \{s, p\} \quad (4.9)$$

$$\frac{\partial \hat{V}^i}{\partial Y_{c2}^s} = \frac{\partial \bar{V}^i}{\partial Y_{c2}^s} = \frac{\partial V^i}{\partial z_1^{i*}} \frac{\partial z_1^{i*}}{\partial Y_{c2}^s} + \delta^i \frac{\partial V^i}{\partial z_2^{i*}} \frac{\partial z_2^{i*}}{\partial Y_{c2}^s} \quad \forall i \in \{s, p\} \quad (4.10)$$

$$\frac{\partial \hat{V}^s}{\partial \bar{V}^{p*}} \left( \frac{\partial \hat{V}^p}{\partial \bar{V}^{s*}} \right)^{-1} = \mu \quad (4.11)$$

There are several important features of the analysis to point out here. First, since the experiment holds the “other” person’s utility constant when varying college attributes (as signified by the use of  $\bar{V}^{p*}$  and  $\bar{V}^{s*}$  rather than  $\bar{V}^p$  and  $\bar{V}^s$ ), the effect of a college attribute on the other person’s utility does not factor into Equations 4.8-4.10. Second, both preferences for consumption and time preference ( $\delta^s$  and  $\delta^p$ ) make up the theoretical interpretation of the derivative of indirect utility with respect to  $t_c$  and  $Y_{c2}^s$ .<sup>7</sup>

Third, Equation 4.11 is derived on the basis of the derivative of Equation 4.5 with respect to the total utility of the parent and child, in turn. Strictly, the derivative of the household objective function with respect to  $V^p$  is  $\mu$  and the derivative with respect to  $V^s$  is 1. However, given that logit coefficients are identified only up to a scale parameter, I use the ratio as an

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<sup>7</sup>The model suggests a linear relationship between  $\partial \bar{V}^i / \partial t_c$  and  $\partial \bar{V}^i / \partial Y_{c2}^s$ , since they enter together into the budget constraint as  $Y_{c2}^s - (1+r)t_c$  and thus both should affect goods allocation in a proportional manner. However, enforcing this restriction empirically may make the results unduly sensitive to the fact that the model assumes a lack of credit constraints and does not include an aversion to borrowing (Cunningham and Santiago, 2008; Dynarski and Scott-Clayton, 2013). In practice, since  $\delta^s$  and  $\delta^p$  are unknown and  $r$  may be uncertain on the part of the family, the restriction does not affect analysis.

estimate of the bargaining parameter  $\mu$ .<sup>8</sup>

Equations 4.8-4.11 illustrate the relationship between the experimental results and an intra-household model of educational choice. Different empirical responses to college attributes can be related directly to indirect utility and discounting. In addition, the estimate of the bargaining parameter  $\mu$  tells us about the college decision-making process. If  $\mu < 1$ , then the decision is guided mostly by student preferences, and by parental preferences if  $\mu > 1$ . In any case where  $\mu > 0$  and  $\bar{V}^s \neq \bar{V}^p$ , a model of educational choice that allows only for student agency is rejected. How heavily the use of a single-agent model anyway would bias estimates depends both on the value of  $\mu$  and how large are the differences in partial derivatives in Equations 4.8-4.10 between student preferences  $i = s$  and parent preferences  $i = p$ .

### 4.3 *Experimental Method and Estimation*

In order to identify the latent functions of indirect utility from the previous section ( $\hat{V}^s$  and  $\hat{V}^p$ ), I perform a choice-based conjoint analysis. Conjoint analysis is a method commonly used in marketing studies in which subjects demonstrate their preferences for different products on the basis of their qualities, brands, and prices (Orme, 2006). Conjoint analysis allows the researcher to estimate subject willingness-to-pay for different product qualities relative to each other using subjective choice tasks that force respondents to make tradeoffs.

The central approach of a choice-based conjoint analysis is to present subjects with a choice set of goods. Subjects choose their preferred option. Since the attributes of the goods are varied by the researcher, it is straightforward to identify a subject's indirect utility as a function of the different attributes. This experimental approach allows for many attributes to be varied at once, and allows for interactions between those attributes, rather than requiring a separate experiment to estimate the value of each attribute separately and simply assuming independence between attributes.

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<sup>8</sup>This estimate gives incorrect results if  $\frac{\partial \hat{V}^s}{\partial V^{p*}} < 0$  or  $\frac{\partial \hat{V}^p}{\partial V^{s*}} < 0$ . However, if either of these inequalities is true, this can be taken as a rejection of the cooperative model.

Figure 4.1: Example Question

- You could enjoy classes “not a lot,” “a little,” “fairly,” or “very”
- You could rate the social life as “poor,” “okay,” “good,” or “great”
- Your parents’ opinion of a school can be “really dislike” “dislike” “like” or “love”

<p>College A</p> <p>Earn <b>\$48,000</b> per year at age 25            You rate social life as <b>okay</b>            You rate classes <b>a little</b> enjoyable            Your parents <b>love</b> this school            Annual tuition of <b>\$15,000</b></p>	<p>College B</p> <p>Earn <b>\$54,000</b> per year at age 25            You rate social life as <b>good</b>            You rate classes <b>fairly</b> enjoyable            Your parents <b>dislike</b> this school            Annual tuition of <b>\$20,000</b></p>
<p>College C</p> <p>Earn <b>\$66,000</b> per year at age 25            You rate social life as <b>poor</b>            You rate classes <b>fairly</b> enjoyable            Your parents <b>like</b> this school            Annual tuition of <b>\$15,000</b></p>	<p>College D</p> <p>Earn <b>\$60,000</b> per year at age 25            You rate social life as <b>okay</b>            You rate classes <b>fairly</b> enjoyable            Your parents <b>love</b> this school            Annual tuition of <b>\$20,000</b></p>

**Please choose:**  
**As a high school student about to go to college, which college would you choose to go to? \***

College A  
 College B  
 College C  
 College D  
 If these were my only options, I would not go to college.

**If you do not go to college, assume you will earn \$30,000 per year at age 25.**

For this paper, the central task presented to subjects is to choose between four hypothetical colleges, each with five attributes. The subject may also choose a “no college” option if they would rather select no college at all than one of the options. An example question is presented in Figure 4.1.

The example question shown is a “student” question in which the subject is told to imagine that they are a student about to go off to college, and are instructed to choose one of the presented options. The subject has the ability to compare the colleges on the basis of (1) The earnings associated with a degree from this college, (2) How enjoyable the classes at the college are, (3) The quality of the social life at the college, (4) The opinion of one’s

parents, and (5) The annual tuition charged. There is an alternate “parent” form of the question in which the subject is told to imagine that they are a parent with a child who is about to go off to college, and are instructed to choose for the child. In the parent form of the question, “The opinion of one’s parents” is replaced with “The opinion of the child.” Each of these attributes varies at four levels:

- Earnings at age 25: \$48,000, \$54,000, \$60,000, \$66,000
- Enjoyability of classes:<sup>9</sup> not a lot, a little, fairly, very
- Social life: poor, okay, good, great
- Parents’/child’s opinion: hate, dislike, like, love
- Annual tuition: \$5,000, \$10,000, \$15,000, \$20,000

for a total of  $4^5 = 1,024$  different possible college profiles. As in Figure 4.1, these colleges are grouped into sets of four and the subject chooses between them.

Subjects are presented with a total of thirteen choice tasks, which is likely not so many as to cause fatigue in respondents (Johnson and Orme, 1996). In six of these tasks, they are shown “student” questions and told to choose as though they were a student. In another six, they are shown “parent” questions and told to choose as though they are a parent. An additional question is given first and is a warm-up question so that the subject can get familiarized with the task; this response is discarded.<sup>10</sup> Most results use groups that are best representative of parents and students: college-age respondents in the student role

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<sup>9</sup>I emphasize “enjoyability,” a direct measure of consumption value, rather than the more generic “quality” of classes, which could also indicate academic rigor. This approach aids in the specificity of the results. Also, in trial runs of the experiment that did include “quality” of classes, respondents were confused by colleges featuring high-quality classes that led to low earnings.

<sup>10</sup>The use of “warm-up” tasks is encouraged in some parts of the conjoint choice literature (Huber et al., 1993, e.g.) although it is not always found to be necessary (Johnson and Orme, 1996; Jaeger et al., 2001, e.g.).

and parent-of-college-student-age respondents in the parent role. By giving both forms of questions to all applicants, it is possible to distinguish preference differences that arise from aging (“as I get older, I start to think that a college’s social life is less important”) from differences that arise from role (“I care about my own social life but less about my child’s, and so I wouldn’t pick their college on the basis of its social life”).

A subject participating in the experiment is handled using the following procedure:

1. The subject indicates whether they are at or above age 40 or under age 40.<sup>11</sup>
2. The subject is shown the instructions (see Appendix D for full wordings).
3. The subject is randomly assigned to answer “student” questions first or “parent” questions first.
4. To average out order effects (see Chrzan, 1994), the order of the traits is randomly assigned.<sup>12</sup>
5. The subject is given seven random choice tasks of the type they were assigned to answer first in step (3). The first of these is discarded.
6. The subject is shown the instructions for the second choice task type.
7. The subject is given six random choice tasks of the second type.
8. The subject is asked questions about their demographic and educational background.

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<sup>11</sup>This step is performed to ensure an acceptable number of over-40 respondents, since the sample pool over-represents young people. After a quota of under-40 participants take the experiment, further under-40 participants are prohibited. The survey website performs quality checks to ensure that respondents do not lie about their age at this step. Website procedures are detailed further in the next section.

<sup>12</sup>In practice, due to technical limitations, five orders were determined beforehand and subjects were randomly assigned to one of the five. Each trait is first in one of the five orders, and the other four attributes were randomly ordered.

The above procedure results in a data set with twelve observations per subject, six of which are from the assumed role of a student and six of which are from the assumed role of a parent. Each observation details a discrete choice between four randomly determined hypothetical colleges, with the addition of a “no college” option. These five options form the choice set  $\mathbb{C}_j$  for each individual decision  $j$  to be made.

I estimate an indirect utility function using a conditional logit model. The conditional logit model is commonly used for estimating models of discrete choice, and describes indirect utility functions assuming that choices are made by utility maximization and that there are random taste shifters on subject utility that carry an Extreme Value distribution (McFadden, 1973). In Appendix E I additionally present results estimated using a nonparametric discrete choice model and find similar results.

With the conditional logit specification, the probability of choosing a particular alternative  $c$  from the choice set  $\mathbb{C}_j$  is

$$p_c = \frac{\exp(F(A_c, \beta))}{\sum_{c' \in \mathbb{C}_j} \exp(F(A_{c'}, \beta))} \quad (4.12)$$

where  $F(A_c, \beta)$  is a function of  $A_c$ , which contains the four college attributes and the other person’s opinion, and the total indirect utility parameters  $\beta$ .  $\sum_{c' \in \mathbb{C}_j}$  sums over all colleges in the choice set the respondent faces. The function  $F(A_c, \beta)$  may be parameterized flexibly in  $A_c$ .  $F(A_c, \beta)$  may in the simplest case be linear in each of the elements of  $A_c$ , or may take any functional form of the attributes, including a fully saturated model (with binary indicators for each level of each attribute) or a model with interactions between the attributes. Since attributes are fully randomized,  $\beta$  is identified even if interactions are included (Hainmueller et al., 2014).

Those who choose the “no college” option do not experience the college attributes. Indirect utility from the no college option is then constant with respect to  $A_c$ , such that  $F(A_{c^*}, \beta) = \gamma_{NONE} \forall \beta$ , where  $c^*$  is the “no college” option.  $\gamma_{NONE}$  may indicate a preference for no college over lower-quality colleges.

The model is estimated using the hierarchical Bayes (HB) algorithm (see Sawtooth Software, 2009) as implemented in the ChoiceModelR package (Rossi et al., 2005; Sermas, 2014; R Core Team, 2014). Rather than estimating population average indirect utility parameters  $\beta$ , HB generates individual-level coefficients  $\beta_i$  with a Markov Chain Monte Carlo algorithm.<sup>13</sup> The HB estimator assumes that each coefficient in the logit model follows a joint normal distribution

$$\beta_i \sim N(\alpha, \Sigma) \quad (4.13)$$

where  $\beta_i$  is a vector of model coefficients for individual  $i$ ,  $\alpha$  is a vector of the mean for each coefficient, and  $\Sigma$  is a variance-covariance matrix of the coefficients. The  $\beta_i$  values are estimated iteratively.  $\beta_i$  parameters are updated each iteration of the Markov chain with a random-walk Metropolis-Hastings algorithm in two steps: first, candidate  $\beta_i$  draws are obtained by adding to the current parameter vector a normal draw with mean zero and covariance equal to the current estimate of the covariance matrix  $\Sigma$ . The likelihood of the data based on these parameter draws determines the probability that the new coefficient draw will be accepted. Second, these draws are used to update  $\alpha$  and  $\Sigma$ . The algorithm is outlined in more detail in Rossi, Allenby, & McCulloch (Appendix A, 2005).

The HB estimator for the logit model allows for heterogeneity in preferences by assigning a random distribution (a “mixture distribution”) to each of the indirect utility parameters. The use of a random distribution relaxes the assumption that all respondents within a particular group have the same preferences for the different college attributes, and sidesteps biases arising from the independence of irrelevant alternatives (IIA) assumption inherent in conditional logit analysis (McFadden and Train, 2000).

HB goes further than most mixture distribution methods. It allows for point estimates of indirect utility parameters at the individual level by taking advantage of full-sample choice behavior to inform individual-level estimates. HB is capable of effectively and accurately

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<sup>13</sup>For most models I use 8,000 Markov chain iterations to allow coefficient values to converge, and then another 2,000 draws to generate average coefficient values.

estimating individual-level heterogeneity in indirect utility parameters even with relatively few choice observations per respondent (Lenk et al., 1996; Sawtooth Software, 2009).

I take the individual-level coefficients  $\beta_i$  generated by the HB algorithm and compare these coefficients across respondent groups and roles. These comparisons comprise the main results of the paper.

#### **4.4 Data**

Data collection occurred between July 12 and November 18, 2014 on the survey administration site SocialSci.com.<sup>14</sup> SocialSci is a private firm that has access to a recruited pool of online survey takers. While participation in the survey pool and the survey is voluntary, SocialSci works to actively recruit respondents in demographic groups underrepresented in the pool. Additionally, the site deters false answers by checking for consistency in standard questions (such as gender and age) across different surveys. The protocol detailing pool recruitment and subject treatment is available on the website.<sup>15</sup> All subjects are given a small amount of compensation (less than \$5) for their participation. Data collected using SocialSci has been published in top journals in psychology, human ecology, and anthropology (Cogsdill et al., 2014; Lee et al., 2014; Pepper and Nettle, 2014). Conjoint analysis results are commonly found to be consistent across data collection methods, and the reliability of results collected online is comparable to results from offline data collection (Melles et al., 2000; Sethuraman et al., 2005).

There are 864 survey participants. 534 of these respondents are between the ages of 17 and 40 (non-inclusive), and the other 330 are 40 or above. The median completion time for the entire survey is 7 minutes and 47 seconds, with a median time of 22 seconds spent on each choice task disregarding the discarded warm-up task. Each respondent gives a self-report of

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<sup>14</sup>Data collection is ongoing for respondents 40 or older; current data includes the first 330 of an eventual 500 respondents age 40 or older. As of this writing (April 6, 2015), 440 respondents age 40 or older have completed the choice tasks. The paper will not be rewritten with new data until all 500 have completed the task.

<sup>15</sup>[https://research.socialsci.com/docs/categories/17-using\\_our\\_participant\\_pool](https://research.socialsci.com/docs/categories/17-using_our_participant_pool)

their age, gender,<sup>16</sup> race and ethnicity, completed education level, and self-reported academic ability.

Respondents are allowed to fill in their own race and ethnicity without restriction. These responses are grouped non-exclusively into white (636 respondents), black (73), Asian (83), Hispanic (53), and “Other/Unspecified Mixed/Don’t Know or Won’t Report” (35). The sample appears to select for respondents with slightly higher levels of education than the population: options for completed education level are “Less than a high school degree” (3), “High school degree or GED” (70), “Some college but no degree” (190), “One- or two-year college degree or certification” (72), “Bachelor’s degree” (321), “Master’s degree” (144), “Professional degree” (31), or “Doctorate” (33). Self-reported academic ability is elicited relative to an undefined “average person.” Consistent with selection for those with higher levels of academic attainment but also consistent with the tendency of averages of self-reports of ability to be above-average, self-reported academic ability is biased upwards: respondents could rate their academic ability as “far less than average” (0), “much less than average” (5) “a little less than average” (13), “average” (125), “a little more than average” (268), “much more than average” (342), or “far more than average” (111). Self-reported academic ability is used to get a sense of academic confidence and affiliation, which may interact with opinion about college attributes, rather than as an objective measure of ability.

Young respondents are over-represented in the SocialSci sample. To ensure that there were older respondents in the sample, I implemented an age quota in data collection, capping the number of young respondents. The SocialSci system allows age quotas only for the groups “under 40” and “40 or above,” and so data collection is split at age 40. Conveniently, the over-representation of young respondents combined with a split at 40 ensures a lot of people around the ages of 18-24, roughly the age of actual college students, and a lot of people around 40-46, the age of many parents who see college coming soon for their children.

Each respondent answers thirteen college choice questions, twelve of which are used, for a

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<sup>16</sup>Respondents are allowed to indicate male (369 respondents), female (486), or if they prefer neither. 9 respondents choose neither male nor female.

total of 10,368 choice observations. In each observation, the respondent chooses between four randomly determined sets of college attributes and a “no college” option. The “no college” option is relatively unpopular, and is chosen in only about 3% of cases.

With minor exception, choices seem to be made in a consistent and attentive manner. There is the potential in these sorts of experiments for subjects to choose a “strictly dominated” option - a college for which every attribute is worse than another available option. This may indicate a negative response to one or more of the attributes (or a positive response to tuition), but can also indicate inattention to the task. Strictly dominated options appear in 7.4% of choice tasks, but are only chosen in .3% of choice tasks. Similarly, weakly dominated colleges (worse or equal to another option for all attributes) are available in 64.7% of choice tasks, but respondents only choose a weakly dominated option in 4.2% of choice tasks. Another small discrepancy in choice comes from the random placement of colleges in the option list: there seems to be a slight bias against college D. Colleges A, B, and C are chosen 24.5%, 25.7%, and 24.0% of the time, which are statistically different at the 5% level from the 22.7% rate at which D is selected. However, since attributes are uncorrelated with placement, this is not of concern for the results.

## 4.5 Results

### 4.5.1 Indirect Utility Parameters

I first estimate the model as fully saturated and without any interaction terms: each attribute enters  $F(A_c, \beta)$  as a series of dummies for each of the four levels of the attribute. The coefficient on the lowest level of the attribute is constrained to be zero, and the coefficient on each other level can be interpreted as the difference in indirect utility between two otherwise identical colleges with the given level of that attribute as compared to the lowest level. Given the model estimates and random effects, the hierarchical Bayes method draws individual indirect utility coefficients for each respondent.

These individual estimates provide important information about the decision structure,

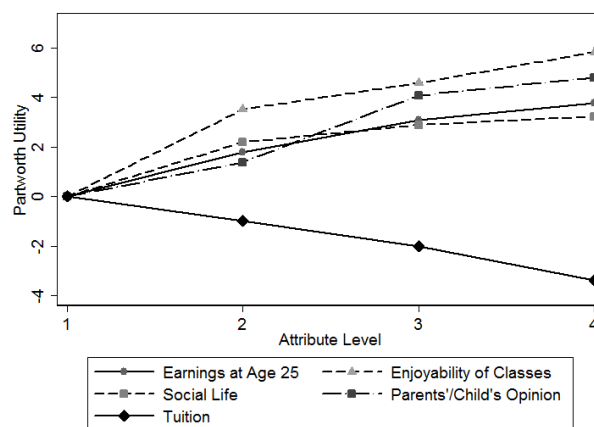
and have considerable predictive power. I first estimate the model while “leaving out” the final choice task for each respondent and role, using estimates from only the first five observations to predict the sixth, out-of-sample observation. One measure of out-of-sample fit is the choice probability assigned to the option that is actually chosen. On average, the model assigns a choice probability of .570 to the option that is actually chosen, as compared to .236 as would be achieved by simply using the average popularity of the different options (the “no college” option prevents this from being .25). In 60.2% of cases the option with the highest assigned probability is actually chosen, or the “true positive” rate, as compared to 25.7% using average popularity. A linear model with a full set of second-level interaction terms between attributes has higher out-of-sample predictive power: an average probability of .886 is assigned to the option chosen, and the true positive rate is 89.0%. However, for simplicity of presentation I show the uninteracted model here and in Section 4.5.2 and return to the interacted model in Section 4.5.3. Cross-group comparisons at the mean college profile are similar using the interacted model.

In Figure 4.2a I show the average indirect utility coefficients over the whole sample, estimated using all choice tasks rather than leaving one out as in the validation exercise. The convergence of the model over the 8,000 Markov chain steps is shown in Appendix A Figure A.2. In Figure 4.2b I show coefficient averages over the responses that best represent students: those performed from the point of view of the student by a respondent aged 25 or under. In Figure 4.2c I show coefficient averages over the responses that best represent parents: those performed from the point of view of the parent by a respondent aged 39-47. The age range of 39-47 is chosen because the 25th and 75th percentiles of mother’s age for an 18-year-old are 39 and 47, respectively, in the National Longitudinal Survey of Youth 1997 cohort.

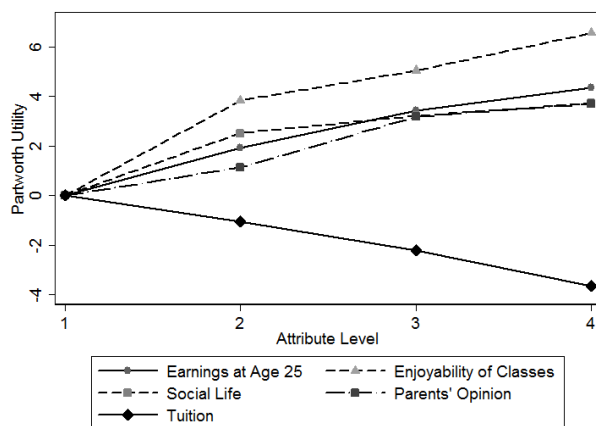
Student and parent average coefficients have some notable similarities. In both cases, higher tuition is negatively regarded while all other attributes are positively regarded, implying that improvements in each attribute increase the willingness to pay for college. Also in both cases, the enjoyability of classes ranks as one of the most important attributes, and

Figure 4.2: Indirect Utility Coefficients in Saturated Model

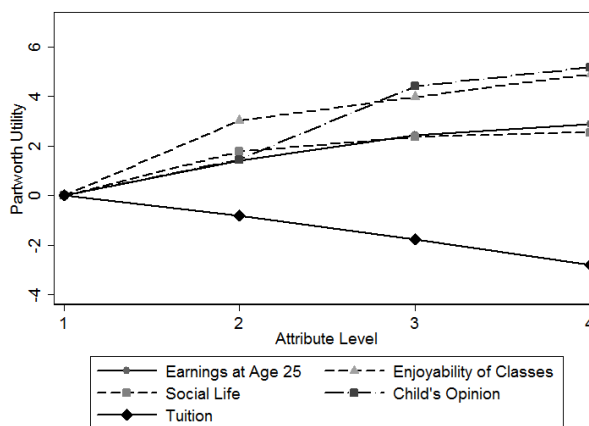
(a) All Responses



(b) Responding as Student



(c) Responding as Parent



earnings and social life are ranked very similarly to each other. Consistent with other work on the relative influence of consumption value and earnings (Alstadsæter 2011; Wiswall and Zafar 2015, Chapter 3), the consumption value inputs of the enjoyability of classes and social life receive a particularly strong weight as compared to earnings. A one-unit increase in the enjoyability of classes (e.g. going from “a little enjoyable” to “fairly enjoyable”) has more influence on choice than a rather large \$6,000 annual raise or \$5,000 annual tuition increase. Consistent with literature on financial aid (Dynarski, 2002, e.g.), responses to tuition are strong relative to earnings. A decrease of \$5,000 in tuition has, for both students and parents, a similar influence on the decision as an increase of \$6,000 in annual earnings. The \$6,000 in annual earnings has a much larger effect on lifetime earnings than the \$5,000 in annual tuition. If wages are perceived to be at all persistent, this suggests a rather high discount rate,<sup>17</sup> or an aversion to debt (Cunningham and Santiago, 2008; Dynarski and Scott-Clayton, 2013) unaccounted for in the model in the previous section.

There are differences between students and parents as well. Parents place a large weight on the child’s opinion, giving it influence similar to that of the enjoyability of classes, while students do not place as much weight on the parent’s opinion, giving it influence similar to earnings and social life. Students have stronger preferences over college attributes in general. Choices change more rapidly in response to changes in attributes for students than for parents. Parents are either more ambivalent to these attributes (which would not be surprising given that most are experienced indirectly) or they exhibit less precision in their decision process.<sup>18</sup>

A useful feature of the mean indirect utility parameters in Figures 4.2a-4.2c is that

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<sup>17</sup>Deriving a model-based discount rate from these results would require strong assumptions about loan burdens, transfers, and base earnings. Intuitively, the fact that \$6,000 over the next four years has a similar impact as about \$5,000 per year starting in five years and every year thereafter implies a high discount rate. The simplest calculation produces a discount rate of .20, using utility linear in earnings, retirement at age 65, and assuming that the earnings increase represents a level shift and does not affect earnings growth.

<sup>18</sup>The phenomenon of less precise decision-making conditional on the observed characteristics is referred to as a difference of “scale” in the categorical choice literature.

Table 4.1: Linear Coefficient Means

College Attribute	Mean	SD	Mean	SD
	Young Students		Older Parents	
Earnings at Age 25	.873	(.504)	.578	(.513)
Enjoyability of Classes	1.160	(.511)	.875	(.582)
Social Life	.673	(.319)	.483	(.350)
Parent/Child's Opinion	.818	(.500)	1.090	(.732)
Tuition	-.741	(.508)	-.588	(.591)
"No College"	-3.808	(1.302)	-3.307	(1.892)

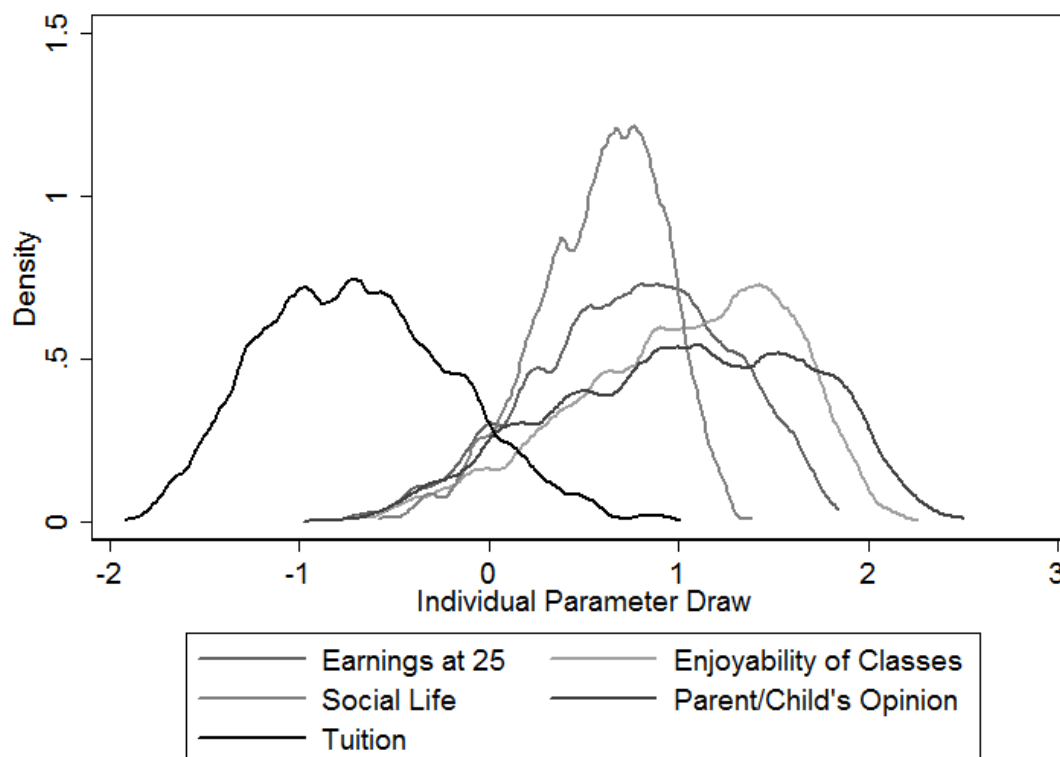
"Young" is age 18-25; "Older" is age 39-47. Standard deviations shown are standard deviations of the distribution of coefficients over the sample, not standard deviations of the estimate of the mean.

coefficient means appear to be relatively linear in the attributes. None of the coefficient means are strictly linear, in particular parent/child's opinion deviates from linearity. However, each of the coefficient means could be reasonably approximated by a straight line. I re-estimate the model using a linear specification for each of the attributes, which greatly simplifies the presentation of results, and allows for more straightforward comparisons between groups. The convergence of the model is shown in Appendix A Figure A.3, and the means and standard deviations of the linear coefficients are shown in Table 4.1.

The mean coefficients in Table 4.1 largely reiterate the results from Figures 4.2b-4.2c. Parents put a stronger weight on the child's opinion than vice versa, enjoyability of classes ranks highest among the other attributes, and students have stronger preferences over college attributes than do parents.

Presenting the coefficient means, which are estimated at the individual level, hides a fair deal of heterogeneity in the parameters. I present the distribution of each coefficient over

Figure 4.3: Individual Linear Coefficient Distributions



the sample (with the exception of the “no college” parameter) in Figure 4.3. Individual coefficients vary widely. Indeed, a nonzero portion of the population has coefficients of an unintuitive sign, with either a positive coefficient on tuition or a negative coefficient on any of the other attributes. These tail coefficients may represent actual negative preference for those attributes, or may be indicators that some respondents tried to think outside the choice task, for example taking high tuition as a signal of quality.

In the case of parent/child’s opinion, a negative coefficient means means that the cooperative model is incorrect for a portion of the population, and a single-agent or noncooperative bargaining model would be more appropriate. 7.6% of the sample, including 5.5% of young students and 10.3% of older parents, has a negative parent/child’s opinion coefficient.

These linear estimates allow for straightforward calculation of the structural parameters

in Equations 4.8-4.11 in Section 4.2. In particular, average estimates of  $\partial \hat{V}^i / \partial x_c$ ,  $\partial \hat{V}^i / \partial t_c$ , and  $\partial \hat{V}^i / \partial Y_{c2}^s \forall i \in \{s, p\}$  as in Equations 4.8-4.10 are the mean values reported in rows 1, 2, 3, and 5 of Table 4.1. Average  $\mu$ , as in Equation 4.11 is  $.818/1.090 = .750$ , which is significantly lower than 1 at the 1% level. On average, student preferences are weighted more heavily in the decision process than parental preferences.<sup>19</sup>

The necessity of the bargaining model as opposed to the single-agent model depends on differences in coefficients between students and parents, and so I test for these differences at the group means. First, it is straightforward to test for mean differences between groups. The standard error of the mean is roughly about .04 for each attribute, rather than the .5 as shown in Table 4.1, which is the standard deviation of the distribution. As one might expect from Table 4.1, students and parent coefficients are significantly different at the 1% level for all attributes.

Importantly, as mentioned above, these results suggest statistical differences over both age and role. These differences are in raw coefficient estimates. These differences are driven partially by differences in scale: students have stronger preferences in general over college attributes than do parents. Using these results to infer differences in priorities, then, is very difficult. One should not be tempted to use these results to answer the natural question of “are parent and student priorities different?” To further study how these preferences relate to respondent age and role, as well as other respondent attributes, it is necessary to scale these coefficients so that they can be taken as relative to each other, which I do in the next section.

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<sup>19</sup>It is also straightforward to calculate elasticities with respect to earnings and tuition here. Given estimated parameters, the elasticity of demand with respect to earnings at age 25 is .154 for the average student and .102 for the average parent, and with respect to tuition is -.131 for the average student and -.104 for the average parent. I do not highlight these results because they are likely to be sensitive to the particular choice of \$6,000 gaps in earnings and \$5,000 gaps in tuition between attribute levels.

#### 4.5.2 *Relative Importance of Attributes*

In the previous section I examined how indirect utility parameters vary over respondent age and assigned role. Mean coefficient estimates vary significantly between students and parents. However, I also found that students tend to hold stronger preferences for college attributes in general, or have a more precise decision process, as compared to parents. Direct comparisons of coefficients, then, are informative about the decision process but do not answer the question of how the relative importance of different attributes varies over respondent characteristics. The previous section only partially addresses the question of “do students care more about earnings than parents?” since both the response to earnings relative to other attributes and the strength of preference overall affect estimates in Table 4.1. For this reason, I generate an individual ranking  $R_{\beta_i(j)}$  of the relative strength of each attribute for each individual  $i$  and attribute  $j$  of the coefficient vector  $\beta_i$ .

$$R_{\beta_i(j')} = \sum_j I(|\beta_i(j')| > |\beta_i(j)|) \quad (4.14)$$

In other words: for an individual  $i$ , if the absolute value of the coefficient for earnings is highest and the absolute value of the coefficient for tuition is second highest, then earnings would be ranked 5 for individual  $i$  and tuition would be ranked 4, where higher numbers indicate a higher ranking. This ranking process discards some information, such as the size of any difference between coefficients. However, the ranking does allow for a consistent comparison of attribute types across respondents and across respondent characteristics. Table 4.2 demonstrates such a comparison, mimicking Table 4.1 by comparing ranks between young students and older parents, with young student as an excluded category. I also include mismatched groups: young respondents acting in the assumed role of parents (young parents) and older respondents acting in the assumed role of students (older students). These comparison groups allow me to distinguish differences due to age or cohort from differences due to role. I use an ordered logit model relating the coefficient rankings for each attribute to indicators for being in the four groups, essentially comparing the average rankings across the

Table 4.2: Ranked Linear Coefficients Group Differences

Group	Earnings	Classes	Soc. Life
Older Parents	-.571*** (.173)	-.807*** (.176)	-.265 (.176)
Older Students	-.199 (.171)	-.267 (.182)	.068 (.173)
Young Parents	-.376** (.158)	-.951*** (.163)	-.390** (.160)
Group	Other's Opinion	Tuition	
Older Parents	1.322*** (.180)	.089 (.172)	
Older Students	.265 (.171)	.042 (.173)	
Young Parents	1.851*** (.169)	-.294* (.157)	

“Young” is age 18-25; “Older” is age 39-47. Standard errors in parentheses. \*/\*\*/\*\* indicates statistical significance at the 10%/5%/1% level, respectively.

groups.

Coefficients in Table 4.2 compare rankings to those of younger respondents in the role of student. Differences between young respondents in the student role and in the parent role are all significant at the 10% level or better. Priorities for young students in the parental role, relative to the student role, favor the child’s opinion (by nearly a full two ranks out of five) at the expense of all other characteristics, in particular the enjoyability of classes. In contrast, older and younger respondents rank the attributes similarly when responding as students; none of these differences are significant.

Coefficient rankings are significantly different between older parents and younger parents only for the attributes of child's opinion and tuition. Rankings are different between older parents and older students at the 10% level or better for every attribute except tuition.

Differences between roles tend to dominate differences in attribute rankings rather than differences over the life cycle (or cohort). Differences in the relative importance of college attributes are largely determined by the role of the decision-maker, suggesting that students and parents see eye-to-eye on what college attributes they should be paying attention to, but are also aware of the differences in whether they will be receiving the benefits of those attributes directly or indirectly. Tension between parents and students is a difference in incentive structure, not a difference in priorities. Making an analogy to educational choice in a different domain, there is a common perception that students are driven by a desire to study a subject they will enjoy, while parents discourage such behavior. This may come down to the fact that students get to enjoy those classes while parents don't, rather than a shift in priorities as one ages.

A further study of relative coefficient rankings can reveal how respondents of differing backgrounds favor different college attributes. In Jacob et al. (2013), for example, respondents with a strong academic background will especially favor class quality. Correlates of income, such as racial background, may relate to the shadow value of money or (as in Hahn and Price, 2008) the degree of debt aversion and as such change how respondents weight earnings or tuition. Tables 4.3 and 4.4 show coefficients from an ordered logit of coefficient rankings on all collected respondent background characteristics over the entire sample (not just limited to those in the "young"/"old" groups above), by student and parent role, respectively. The models estimated for Tables 4.3 and 4.4 include all demographic controls at once, introducing the possibility for coefficients to be affected by multicollinearity, but results are similar if models for each type of background characteristic (age, gender, race, etc.) are estimated separately.

Table 4.3: Ranked Linear Coefficients by Background - Student Role

Group	Earnings	Classes	Soc. Life	Parent's Opinion	Tuition
Age	.017 (.032)	-.006 (.032)	.020 (.032)	-.029 (.031)	-.018 (.031)
Age <sup>2</sup>	-.000 (.000)	.000 (.000)	-.000 (.000)	.001 (.000)	.000 (.000)
Female	-.262** (.125)	.298** (.128)	-.130 (.126)	.094 (.124)	-.036 (.123)
Neither Gender	-.647 (.548)	.091 (.612)	-.148 (.649)	.084 (.611)	.442 (.609)
Black	.118 (.220)	-.388* (.227)	-.329 (.230)	-.007 (.226)	.482** (.228)
Hispanic	-.394 (.263)	.109 (.263)	.522** (.256)	-.072 (.260)	-.129 (.261)
Asian	.342 (.221)	.013 (.215)	-.479** (.219)	.432** (.210)	-.395* (.211)
Other Race	.029 (.312)	-.396 (.332)	.013 (.320)	.078 (.323)	.314 (.316)
Acad. Ability (Self-Report)	.258*** (.068)	.036 (.070)	-.178*** (.069)	-.104 (.069)	-.058 (.068)
Some College	.140 (.249)	-.271 (.258)	-.315 (.248)	-.105 (.248)	.459* (.254)
1-2 Yr. Degree	-.005 (.308)	-.527* (.312)	.426 (.306)	-.110 (.304)	.231 (.306)
Bachelor's	.006 (.241)	-.342 (.251)	-.073 (.240)	-.184 (.243)	.534** (.246)

Master's	-.354 (.272)	.079 (.286)	.231 (.272)	-.287 (.278)	.526* (.279)
Professional	.161 (.408)	-.928** (.404)	.542 (.402)	-.325 (.400)	.593 (.413)
Doctorate	-.105 (.386)	-.145 (.416)	.151 (.396)	-.449 (.422)	.670* (.392)

“Young” is age 18-25; “Older” is age 39-47. Standard errors in parentheses.

\*/\*\*/\*\* indicates statistical significance at the 10%/5%/1% level, respectively.

Table 4.4: Ranked Linear Coefficients by Background - Parent Role

Group	Earnings	Classes	Soc. Life	Student's Opinion	Tuition
Age	.021 (.032)	.006 (.032)	.034 (.032)	-.110*** (.035)	.035 (.031)
Age <sup>2</sup>	-.000 (.000)	-.000 (.000)	-.000 (.000)	.001*** (.000)	-.000 (.000)
Female	-.265** (.125)	.345*** (.127)	-.256** (.128)	.398*** (.134)	-.258** (.124)
Neither Gender	-1.915*** (.641)	1.275* (.661)	.965 (.599)	.208 (.595)	-.277 (.597)
Black	.032 (.214)	-.192 (.228)	.221 (.235)	-.320 (.237)	.262 (.232)
Hispanic	-.091 (.260)	-.336 (.255)	.210 (.266)	.537* (.293)	-.329 (.256)
Asian	.492** (.215)	-.167 (.217)	-.230 (.222)	.076 (.232)	-.210 (.206)

Other Race	.017	-.276	.732**	-.619**	.031
	(.318)	(.349)	(.322)	(.314)	(.335)
Acad. Ability	.117*	.061	-.052	-.119	-.068
(Self-Report)	(.069)	(.071)	(.070)	(.073)	(.068)
Some Colege	-.243	.299	-.049	.002	.053
	(.253)	(.252)	(.258)	(.275)	(.251)
1-2 Yr. Degree	-.223	.197	.236	-.459	.217
	(.312)	(.312)	(.314)	(.324)	(.309)
Bachelor's	-.204	.093	.021	-.010	.109
	(.245)	(.246)	(.250)	(.266)	(.242)
Master's	-.474*	.358	.139	.334	-.195
	(.278)	(.280)	(.283)	(.303)	(.276)
Professional	.304	-.588	.130	-.322	.530
	(.414)	(.416)	(.398)	(.418)	(.395)
Doctorate	-.695*	.711*	-.383	.308	.048
	(.388)	(.420)	(.413)	(.413)	(.396)

“Young” is age 18-25; “Older” is age 39-47. Standard errors in parentheses.

\*/\*\*/\*\* indicates statistical significance at the 10%/5%/1% level, respectively.

Several ranking differences stand out. Beginning with rankings in the student role, women put less emphasis on earnings and more emphasis on the enjoyability of classes than do men, but there are no other significant gender differences. Black respondents put more weight on tuition and earnings and less on consumption value compared to white respondents (although not all of these differences are significant), whereas Hispanic respondents are the opposite. Asian respondents place more weight on parental opinion and less on social life or tuition, relative to white students.

Self-reported academic quality is related to a stronger emphasis on earnings. Consistent with Jacob et al. (2013), these respondents also place less emphasis on social life. The finding of no relationship between self-reported academic ability and enjoyability of classes may seem to contradict Jacob et al., but the attributes they focused on may be considered closer to rigor of classes rather than enjoyability, and so these results are not directly comparable. There are few significant differences across educational attainment levels, although small group sizes for some levels may mask true effects. However, those with professional degrees or 1-2 year degrees respond much less strongly to the enjoyability of classes than do high school graduates (consistent with a stereotype of a preference for pragmatic education among those who pursue these degrees). Higher levels of education in general are related to a stronger response to tuition as compared to those with only a high school education, perhaps developed as a result of familiarity with the repayment of student loans.

Concerning rankings in the parental role, there are in general fewer significant differences in rankings between groups, indicating that people are more likely to disagree on the attributes they would like for their own college experience, but are more similar when considering their child's college experience. There are significant differences over gender. Women's emphasis on the enjoyability of classes over earnings as compared to men holds here, and those who selected Neither Gender concur. In addition, for parental coefficients women place more weight on the child's opinion, and less on social life and tuition relative to men. These differences were all present in the student rankings, but they were not statistically significant.

#### *4.5.3 The Implications of Model Choice*

The above results focus on whether or not there is a difference between the indirect utility parameters of those whose role and age makes them representative of students or parents in the college choice decision. It appears that these differences exist, both in terms of which attributes are most valued, and how strong preferences are in general. These results also make it possible to estimate the parameters of the collective model outlined in Section 4.2. The bargaining parameter is significantly different from 0, meaning that the single-agent

student-only model can be formally rejected for the average respondent, although for some of the sample with low or negative regard for their parent/child's opinion, the collective dual-agent model can be rejected. While there are important differences between student and parent indirect utility functions, it is possible that they are not so drastically different that the choice of a single-agent or dual-agent model matters much. In this section I evaluate the consequences of choosing a single-agent model over a dual-agent model of college choice.

Since an intuitive interpretation of slope estimates is not as important here, I use a model that includes second-level interactions between attributes. Each attribute enters linearly by itself and multiplied with each other attribute.<sup>20</sup> So, for example, earnings enters five times: by itself, multiplied by enjoyability of classes, multiplied by quality of social life, multiplied by parent/child's opinion, and multiplied by tuition. Coefficients on all interaction terms are identified since every attribute is randomized independently. The convergence of this model over 100,000 Markov chain iterations is shown in Appendix A Figure A.4. Average coefficients are in Appendix A Table A.3. These interacted coefficients exhibit a considerably more variance over the sample than in the uninteracted models. Interaction terms are consistently in the same direction as the product of the coefficients for the attributes that make them up. In other words, at a college with a particularly poor (rich) level of one attribute, other attributes become less (more) capable of influencing choice.

I compare the predictions of two separate models. The first is the standard collective model, with all interaction terms, as just described. The second represents a single-agent model of student choice. In this model, parent's opinion and its interactions are left out of the data and all other coefficients are estimated. Student coefficients from this single-agent model represent indirect utility parameters estimated by approaching the problem without considering parental opinion as an input to choice.

I compare these models in two ways. First, I estimate whether the omission of parental

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<sup>20</sup>Squared terms and higher-order interactions are omitted. Models with these terms show a similar relationship between the single-agent and dual-agent model, but are not used to avoid including too many parameters, and because they do not appreciably increase the fit of the model.

opinion from the model is likely to bias estimates of student indirect utility parameters. Second, I determine the predictive implications of the removal of parental opinion, by creating student/parent pairs and determining how much the predicted preference ordering of colleges changes when parental opinion is omitted from the model.

The single-agent model produces significantly different average coefficient estimates than the model with parent's opinion included. I compare relative ranked student coefficients as estimated in the two models (like in Section 4.5.2), evaluated at attribute means of 2.5, leaving out parent's opinion from the ranking in the dual-agent model to make the ranks comparable. Estimates from the single-agent model imply that the average student puts less weight on tuition, and more on future earnings, the enjoyability of classes, and social life, relative to estimates from the dual-agent model. All differences are significant at the 1% level. Future earnings, the enjoyability of classes, and social life are all affected similarly, with an average rank about .2 higher in the single-agent model than in the dual-agent model. The average rank of tuition drops by about .6.

In addition to the question of whether estimates from the single-agent model are biased, I am also interested in the predictive differences of the two models. Differences in prediction are important to help determine whether the single-agent model is an effective model of educational choice in which the parameters are simply mischaracterized as student preferences, or if the model as a whole is actually weaker. Since the single-agent model has fewer predictors, it will necessarily have worse fit. However, the difference may be small or large. As mentioned in Section 4.5.1, the dual-agent interacted model has strong out-of-sample predictive power, assigning a probability of .886 to the option that is actually chosen. The comparable in-sample figure is .927. In contrast, lacking information on parental opinion, the single-agent model assigns on average a probability of .714 to the option that is chosen. An in-sample predictive validity of .714 is still strong, however. In the absence of information on parental opinion a detailed single-agent model may well be "good enough." However, in observational studies where predictive power is likely to be lower, the loss of predictive power may be of stronger concern.

The estimate of model fit obscures differences in predictive power that would come about due to the heterogeneity in parental coefficients across the sample. To assess this, I compare the preference ordering of all colleges for each student under the two different models. In the single-agent model, this is simply a ranking of the student's indirect utility based on college attributes across all  $4^4 = 256$  college profiles, plus the "no college" option, ignoring the parent/child's opinion attribute. This ranking is compared to a similar complete preference ordering as determined by the dual-agent model, linking a single student to a single parent, using the following process:

1. Match each parent to a student. There will be some students left over since there are more students than parents. Matching is either performed either completely at random, or by the following positive matching method:
  - (a) As a measure of how similar each parent is to each student, calculate the Mahalanobis (1936) distance between each parent and each student using individual indirect utility parameters.
  - (b) Add noise  $\epsilon \sim N(0, \sigma_\epsilon^2)$  to the unsquared Mahalanobis distance, where  $\sigma_\epsilon$  is one fourth of the standard deviation of the unsquared Mahalanobis distance in the sample.
  - (c) Use the Gale and Shapley (1962) matching algorithm to pair parents and students, with parents as proposers and with both parents and students attempting to find the match with the lowest noisy Mahalanobis distance.
2. For each college profile, calculate the indirect utility of students  $\hat{V}^s$  and parents  $\hat{V}^p$  for that college, using only college attributes and momentarily leaving out the other's opinion as a determinant of  $\hat{V}^s$  and  $\hat{V}^p$ .
3. For each college profile, calculate the student's and parent's marginal valuation of the

other's opinion.<sup>21</sup>

4. Calculate the bargaining parameter  $\hat{\mu}$  using Equation 4.11 and the marginal valuations from the previous step.
5. As in Equation 4.5, use  $\hat{V}^s$ ,  $\hat{V}^p$ , and  $\hat{\mu}$  from steps 2 and 4 to create the household objective function  $\hat{V}^s + \hat{\mu}\hat{V}^p$ . Generate preference rankings over all colleges using the objective function.
6. For each matched student, calculate the correlation between the collective preference ranking and the preference ranking derived from the single-agent model.
7. Average those correlations over all students and store the result.

In other words, the above process pairs a student to a parent, and compares the preference ranking over all possible college attribute mixes using estimates from the single-agent model and the dual-agent model. Figure 4.4a gives an example of one of these comparisons, choosing one student-parent pairing at random. The ranking generated by the single-agent model is along the x-axis, and the ranking generated by the dual-agent model is along the y-axis. I then average over each of the correlations like the one in Figure 4.4a.

The student-parent pairing is performed 10,000 times using completely random matching, and another 10,000 times using positive matching, on the assumption that students and parents are likely to have correlated indirect utility parameters. The distribution of the average correlation over all replications is in Figure 4.4b. Over all iterations, the average correlation between the single-agent and dual-agent preference rankings when matching randomly has an average of .437 with a standard deviation of .020. When using positive matching, the average is .544 with a standard deviation of .013.

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<sup>21</sup>As outlined in Section 4.5.1, for about 10% of the sample the collective model is not appropriate since respondents put negative weight on the other side's opinion (and in the interacted model, this may be the case for some college profiles but not others). These responses are dropped at this step.

The rankings from the single-agent and dual-agent models are related, as we might expect given that student preferences are determinants of both, and since parental coefficients are not wildly different from those of students, especially when students and parents are positively matched. However, there are still large differences in the predictions of the two models. The relatively small differences in average coefficients hide the meaningful differences between the two models implied by the combination of cross-sample preference heterogeneity and the fact that students and parents are matched in the true model. The results in this section imply that the differences between the single-agent and dual-agent models are not trivial.

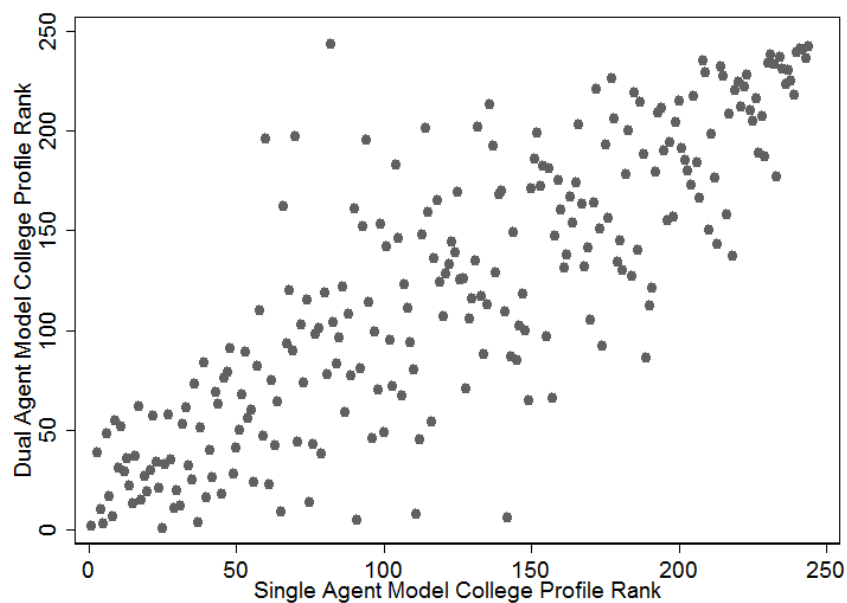
#### **4.6 Discussion**

In this paper I use a conjoint choice experiment to identify a collective student/parent objective function guiding the choice between colleges as a function of their attributes. Younger respondents in the role of students receive significantly different amounts of indirect utility from college attributes than do older respondents in the role of parents. Students have stronger responses to college attributes in general, and in particular students rank future earnings and the enjoyability of classes more highly than parents. Parents place a much higher emphasis on the student's opinion than students place on the parent's opinion, giving students a stronger bargaining position in the choice. Compared to a single-agent model, a dual-agent collective choice model leads to significantly different student indirect utility parameter estimates as well as significantly different (and more accurate) predictions of behavior in the choice tasks.

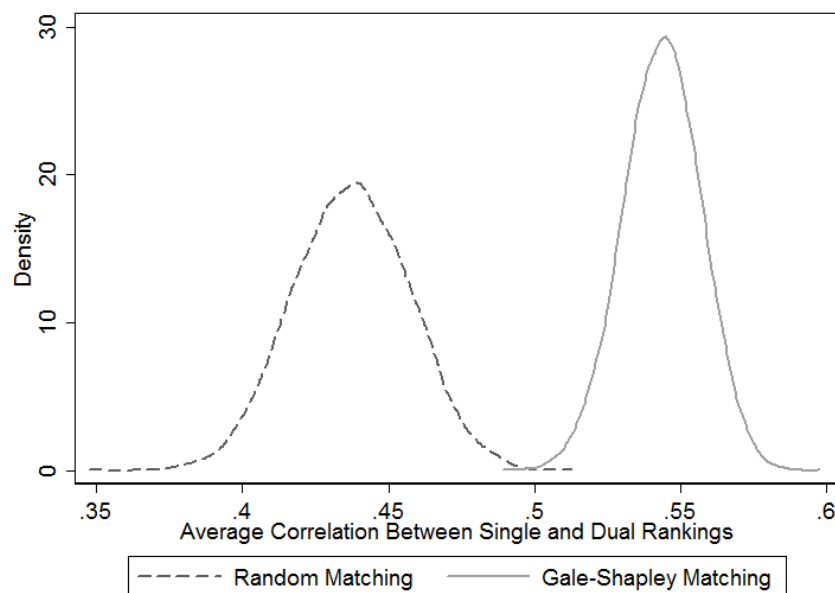
There are several caveats to the analysis that restrict a broad application of the results and invite further study. First, while I add a second agent to the choice model, I implicitly assume a single parent or a pair of homogenous parents, rather than modeling both parents separately. Second, I do not consider credit constraints in the model. It is a strong assumption that credit constraints never matter. However, it is likely that in the United States credit constraints are not a dominant factor in college choice (Dynarski, 2002; Carneiro and

Figure 4.4: Predictive Differences between Single-Agent and Dual-Agent Models

(a) Single-Agent and Dual-Agent Profile Rankings from a Single Randomly Chosen Student/Parent Pairing



(b) Simulated Correlation between Single-Agent and Dual-Agent Profile Rankings



Heckman, 2002). Importantly, in the experiment, subjects are instructed to consider the possibility of taking on loans but to assume that sufficient loans are available to cover tuition. Still, coefficients may be biased by unconsidered shadow prices arising from credit constraints.

Third, the hypothetical nature of the choice tasks removes them from the real task of choosing a college. While conjoint analysis is typically able to predict real-world market shares well (Orme, 2006) and experimental economists routinely draw policy and real-world implications from laboratory choice tasks, the implicitly false nature of the setting is always of a concern. Fourth, the need to simplify the myriad and complex attributes of colleges to several easily-labeled factors may be reductive or have introduced confusion on some level. While “annual tuition” may be easy to understand, the concept of a particular amount of annual earnings being linked to a college option may be less so. Similarly, “enjoyability of classes” as a college trait is more abstract than the qualities that are typically attached to product profiles in conjoint analyses. In a trial version of the study in this paper, respondents did not report difficulty in understanding the attributes, and in describing them gave answers consistent with the theoretical framework presented here. However, usually conjoint analyses use traits that are more concrete than the ones in this paper.

Perhaps the most important caveat is that the sample used in the study is of respondents of a wide range of ages under different hypothetical roles, and is drawn from a voluntary sample pool, rather than randomly sampled actual pairs of parents and students. This approach simplifies data collection and analysis, and allows for a distinction between priority differences that are due to role and those that are due to age. However, the inclusion of “parent” respondents who do not actually have college-age children or “student” respondents who may have never made a college choice makes the results less representative. This issue speaks to a more general concern about representativeness in laboratory experiments in the social sciences (Henrich et al., 2010). The generally strong alignment of coefficients by role, across different respondent groups, alleviates this concern somewhat but does not eliminate it.

These weaknesses represent some of the downsides of using a conjoint choice method to study major life choices and intra-household choices such as the decision of which college to attend (in particular the latter three weaknesses apply more broadly to such attempts, while the first two could be overcome in other studies). However, conjoint analysis offers a useful tool for estimating demand or indirect utility functions without needing to find a source of naturally occurring exogenous variation.

Choice-based conjoint analysis has seen some use in agricultural, environmental, and health economics, as well as in academic and commercial marketing applications. It may have further use in labor and education economics in addressing questions that have thus far been difficult to answer. The potential for further work in intra-household decision-making and in choice over educational options (both college and otherwise, in the case of K-12 school choice) is made clear by this study. To offer a further example, in labor economics the study of compensating differentials has been limited by the difficulty in finding exogenous variation in a wide range of job characteristics separate from worker identity or preferences. Such a task would be straightforward in a conjoint analysis setting. While demand functions estimated using conjoint analysis do face some of the concerns mentioned above, they compensate by allowing for counterfactual predictions about topics like demand for education without relying as heavily on quasi-experimental analysis, which can in some cases be assumption-heavy or require serendipitous circumstances, and without requiring expensive full-scale policy experiments.

Without quasi-experimental analysis or expensive full-scale policy experiments, this study provides useful implications for the design of educational choice policy on behalf of individual colleges looking to market themselves to students (as in Jacob et al., 2013) or broad governmental agencies interested in guiding choice between different types of colleges or making college more attractive relative to not attending.

This study provides results consistent with a growing literature on consumption value incentives that decisions seem to be sensitive to expectations of experience at college (here the enjoyability of classes and social life) to a degree that is difficult to match with realistic

variation in financial rewards (Alstadsæter 2011; Wiswall and Zafar 2015, Chapter 3). This study affirms that policymakers should emphasize policies that target these experiential expectations. In addition to results about which attributes are heavily valued, this study adds the result that while students favor these variables more than parents do, parents also weight these aspects strongly, and the single-agent nature of the previous literature has not greatly overstated the importance of consumption value.

Further, in line with policy prescriptions from the wider husband/wife household choice literature, there is the opportunity for policy targeting. In addition to college-specific policy that reaches out to potential students in an attempt to entice them away from competitors (Jacob et al., 2013), there is a wide range of potential and existing informational and persuasive outreach policies that attempt to sway student and parent choice about whether or not to go to college and occasionally where to go (Swail and Perna, 2002; Domina, 2009; Jensen, 2010; Hoxby and Turner, 2013; College Affordability and Transparency Center, 2014). These policies can maximize their effectiveness by targeting students more often than parents. Parental choice does matter, but I estimate that the weight of the decision appears to rest with the student. Also, student preferences over college attributes are in general stronger, so any changes to perceptions of college attributes are more likely to lead to a change in behavior if the student is targeted.

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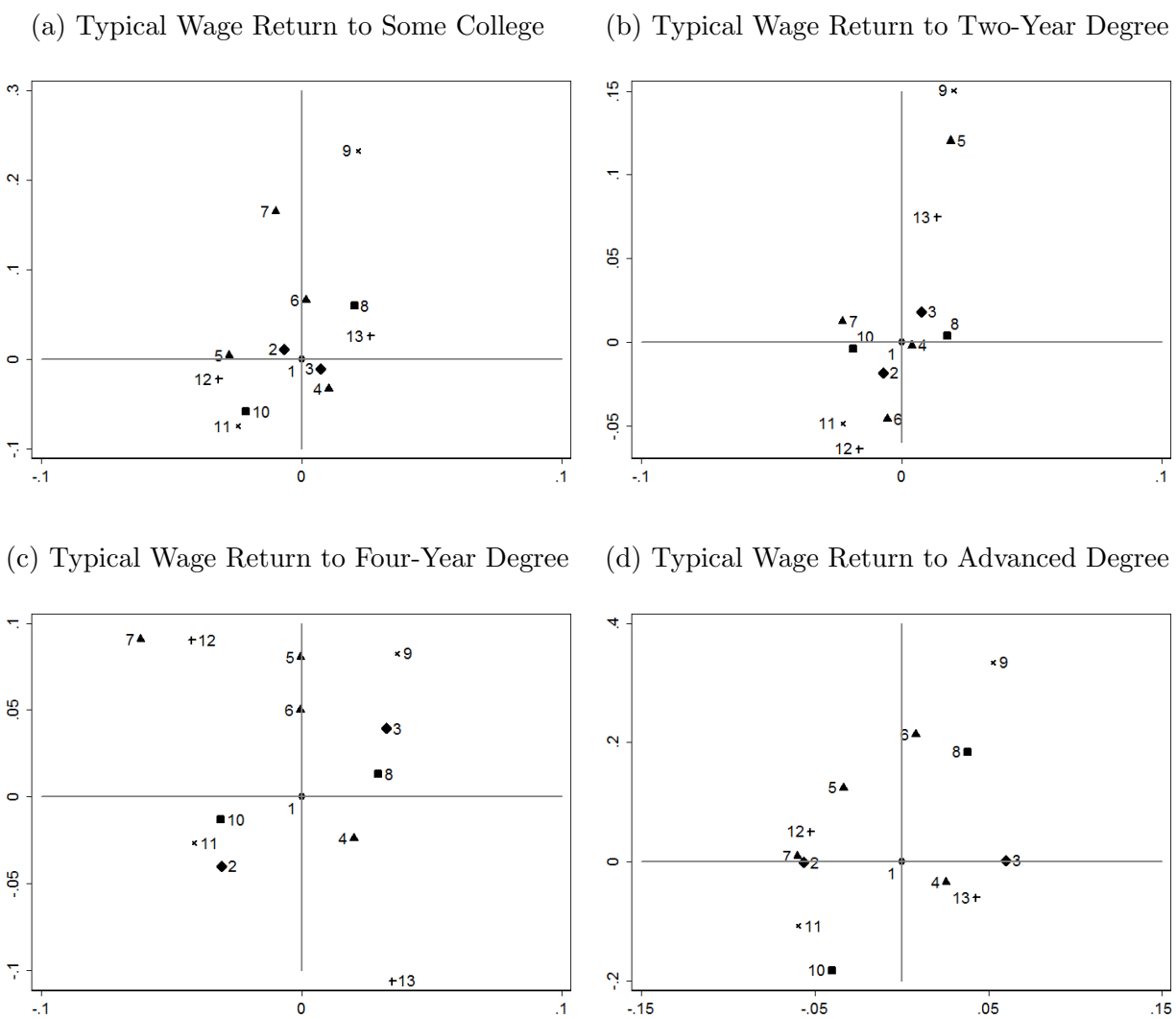
## ADDITIONAL RESULTS

Table A.1: Subjective Wages and Non-employment Rates Relative to HS Degree

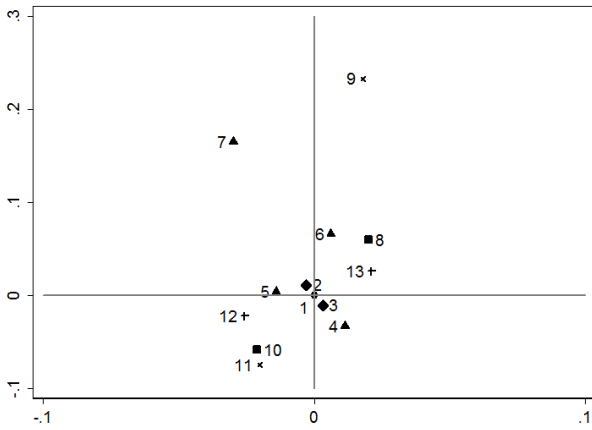
Panel A: Ratio of Annual Full-Time Salary to Salary with HS Degree								
	APCAB (Self)			APCAB (Typical)			ACS (WA)	
	Mean	Median	SD	Mean	Median	SD	Mean	Median
No HS Degree	.968	.786	.890	.907	.750	.891	.813	.683
HS Degree	1	1	0	1	1	0	1	1
Some College	1.294	1.222	.510	1.323	1.212	.731	1.156	1.067
2-Year Degree	1.649	1.517	.717	1.663	1.538	.741	1.213	1.183
4-Year Degree	2.244	2.050	1.155	2.312	2.083	1.229	1.622	1.547
Advanced	3.051	2.714	1.726	3.257	2.889	1.816	1.965	1.737
Panel B: Non-employment Rates								
	APCAB (Typical)			ACS (WA)				
	Mean	Median	SD	Mean	Mean			
No HS Degree	.056	.060	.185	.056	.081			
HS Degree	0	0	0	0	0			
Some College	-.056	-.050	.143	-.056	-.080			
2-Year Degree	-.103	-.100	.218	-.103	-.129			
4-Year Degree	-.157	-.180	.277	-.157	-.159			
Advanced	-.228	-.230	.327	-.228	-.222			

Standard deviations are omitted for the ACS results since these comparisons are not calculated at the individual level.

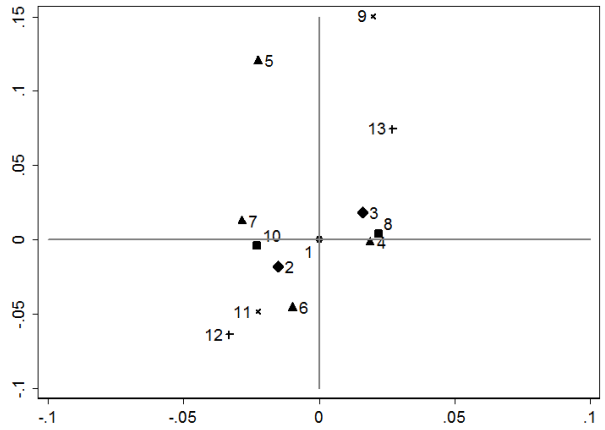
Figure A.1: All Subsample Analyses



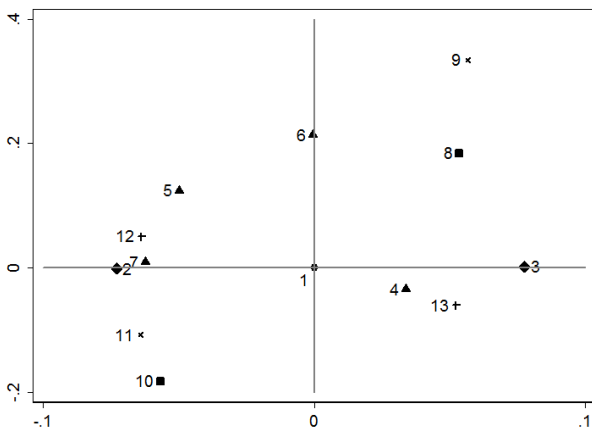
(e) Self Wage Return to Some College



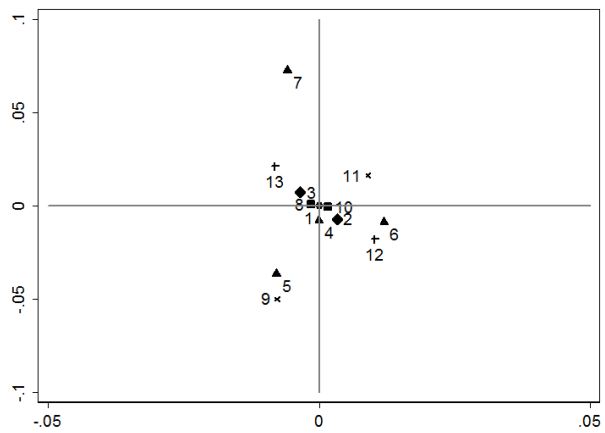
(f) Self Wage Return to Two-Year Degree



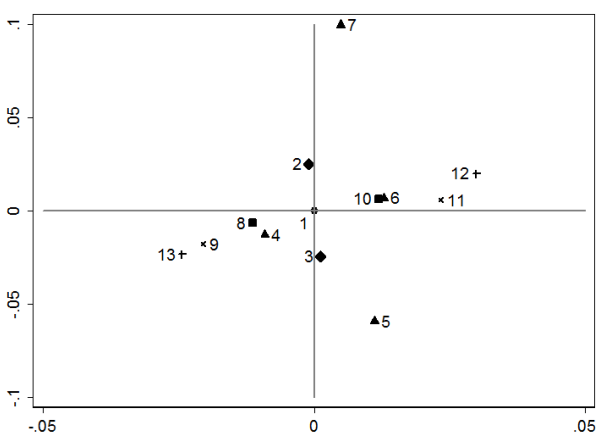
(g) Self Wage Return to Advanced Degree



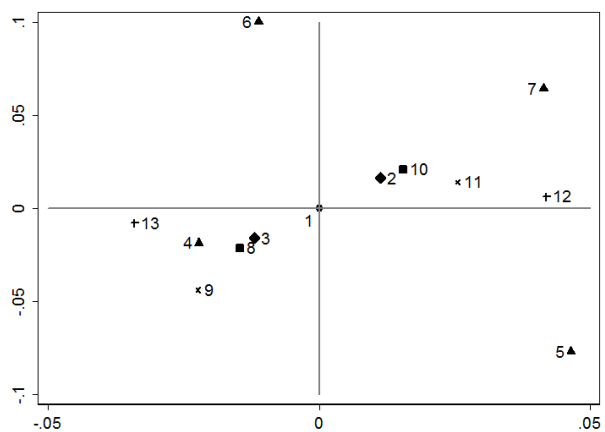
(h) Non-employment Rate Return to Some College



(j) Non-employment Rate Return to Two-Year Degree



(k) Self Wage Return to Advanced Degree



Legend: 1 Origin, 2 Male, 3 Female, 4 White, 5 Black, 6 Asian, 7 Hispanic, 8 GPA above Median, 9 Parent has BA, 10 GPA below Median, 11 No Parent has BA, 12 FRPL, 13 No FRPL

Table A.2: Multiple-Type Preference Vectors

	Type 4 ( $\gamma^4$ )	Type 5 ( $\gamma^5$ )	Type 6 ( $\gamma^6$ )
Type weight:	.024	.717	.259
	Coef.	Coef	Coef
Discount Rate ( $\delta$ )	.878	.880	.882
Log Lifetime Net Earnings ( $\gamma_w^2$ )	.124	.126	.127
Ed. Level at Work ( $\gamma_w^1$ )	.109	.129	.149
Pay Own Tuition	.007	.032	.057
$F_i^E$ : Family Expectations and Norms			
Family to College	.043	.034	.026
Friends to College	.056	.048	.040
Parent has BA	.007	.016	.024
College is Important	.189	.189	.189
$F_i^B$ : Background			
FRPL	.066	.057	.048
Female	.020	.038	.055
Black	.180	.185	.190
Asian	.072	.099	.126
Hispanic	.055	.083	.111

Parameters in the  $T_i$  vector and intercept not shown because they are not allowed to vary across types. Types 1-3 and 7-9 are not shown because they are estimated to have zero weight. As described in Section 3.2.4,  $\gamma^5$  is identical to the single-type results. Each parameter is of uniform distance from the parameter in the next vector; that distance is determined by the variance/covariance matrix from the one-type model.

Figure A.2: Convergence of Saturated Model

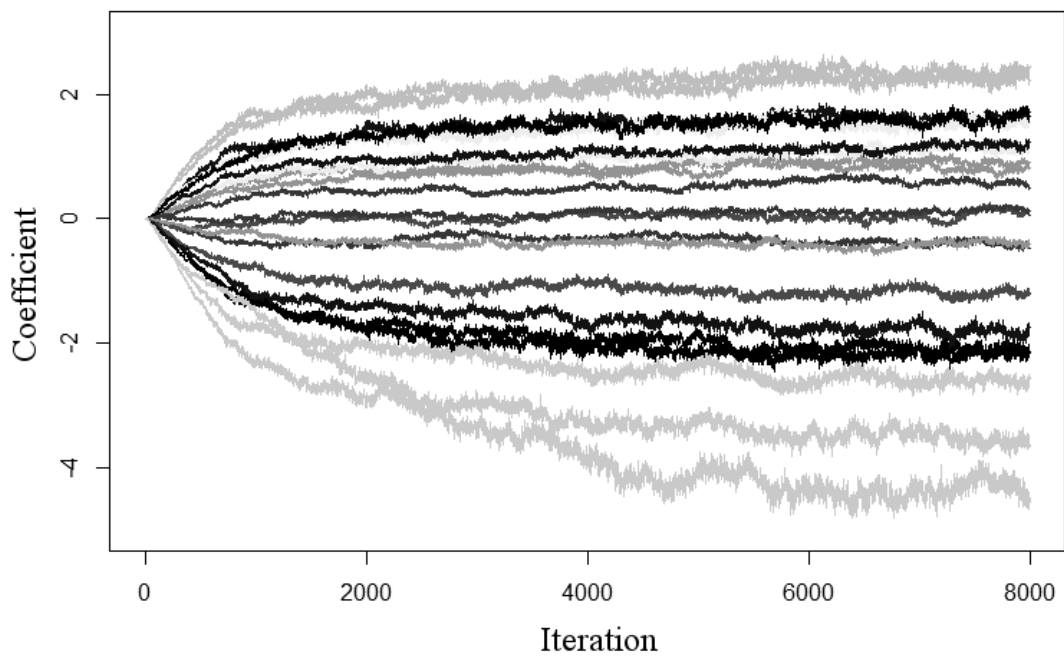


Figure A.3: Convergence of Linear Model

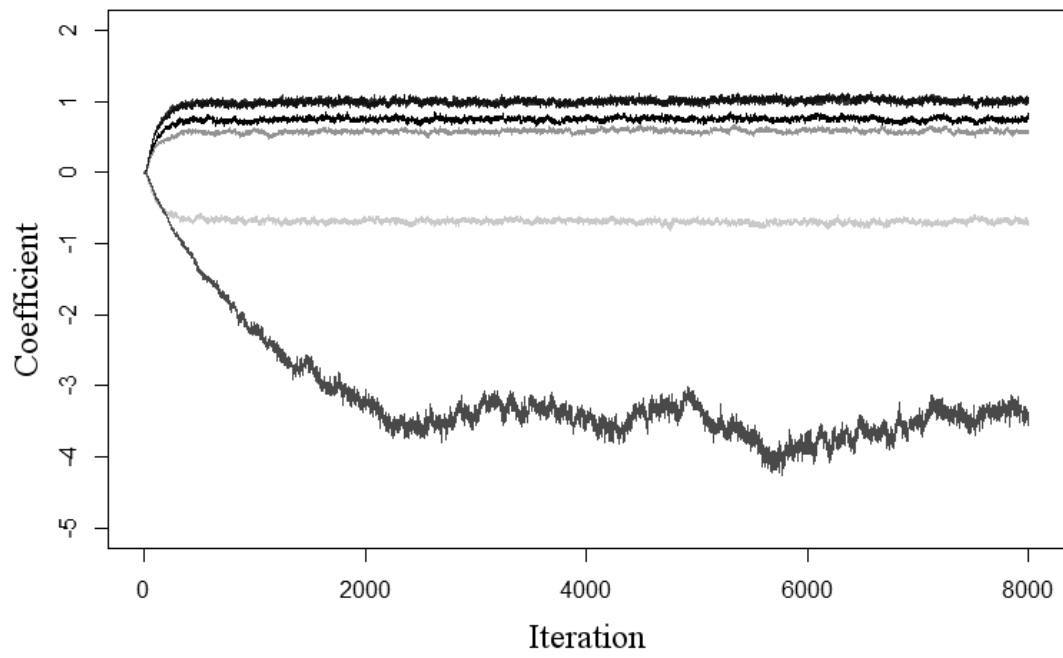


Figure A.4: Convergence of Interacted Linear Model

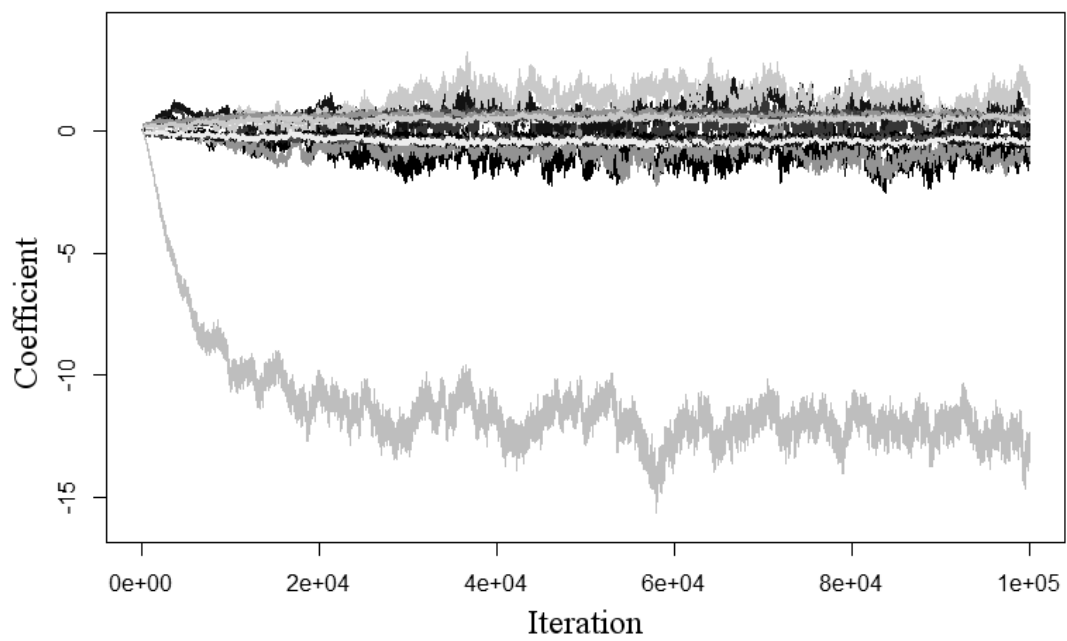


Table A.3: Interacted Coefficient Distribution for Matched Age/Role

College Attribute	Mean	SD	Mean	SD
	Young Students		Older Parents	
Earnings at Age 25	-1.254	(3.702)	-.719	(3.946)
Enjoyability of Classes	.455	(2.731)	.154	(3.346)
Social Life	-.870	(2.078)	-1.123	(2.050)
Parent/Child's Opinion	.420	(3.043)	.901	(3.215)
Tuition	1.152	(3.578)	2.060	(3.953)
"No College"	-14.208	(5.553)	-11.247	(7.679)
Earnings $\times$ Enjoyability	.952	(.794)	.372	(.959)
Earnings $\times$ Social Life	.656	(.807)	.390	(.810)
Earnings $\times$ Opinion	.433	(.869)	.524	(.959)
Earnings $\times$ Tuition	-.194	(1.068)	-.198	(1.175)
Enjoyability $\times$ Social	.757	(.917)	.514	(.835)
Enjoyability $\times$ Opinion	.477	(.892)	.828	(1.055)
Enjoyability $\times$ Tuition	-.585	(.661)	-.580	(.818)
Social Life $\times$ Opinion	.443	(.640)	.479	(.802)
Social Life $\times$ Tuition	-.488	(.786)	-.384	(.848)
Opinion $\times$ Tuition	-.317	(.887)	-.493	(.953)

"Young" is age 18-25; "Older" is age 39-47. Standard deviations shown are standard deviations of the distribution of coefficients over the sample, not standard deviations of the estimate of the mean.

## Appendix B

### APCAB SURVEY WORDINGS

The APCAB survey was administered at thirteen high schools in three districts in King County, Washington. The surveyed schools varied in socioeconomic status of the student body, urbanicity, and enrollment size, from fewer than 90 juniors and seniors at the smallest school to over 1,000 at the largest. The survey was voluntary and was offered to a subset of the students at each school in non-purposively selected school periods and classrooms. Students were offered a \$5 gift card in exchange for their participation. The survey was administered using paper and pencil, and there was always a representative available to answer student questions about the survey. Wage expectations were elicited using a method similar to that used by Betts (1996). Students were informed of what was meant by “annual salary” and the structure of the question. Then, for each level of education, they were presented with a line of 39 numbers, representing \$12,000 per year to \$120,000 per year in increments of \$3,000 per year, with the additional options “Less than \$12,000” and “More than \$120,000.” Students were also allowed to indicate that their answer was between two listed numbers. In analysis, these intermediate estimates were coded as being halfway between the circled numbers, “Less than \$12,000” was coded as \$9,000, and “More than \$120,000” was coded as \$123,000.<sup>1</sup>

The introduction for the two questions reads:

Now I want you to think about **ANNUAL SALARIES**. For this survey, an annual salary is defined as the amount of money someone would make in a **year**

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<sup>1</sup>For the Typical salary, fewer than .1% of respondents were subject to these cutoffs for any education level other than “No HS Degree” and “Advanced Degree.” The same number for the Self salary is fewer than .38% of respondents. For both Self and Typical, about 1.5% of respondents experienced a cutoff for the “No HS Degree” option, 1.75% for the “Advanced Degree” option.

from all of their employment if they worked full-time (at least 35 hours per week) and full-year (at least 50 weeks of the year). For all of the following questions, think about someone who is 30 years old and is working full time and full year (at least 35 hours per week, 50 weeks of the year). Please answer **ALL** of the following, even if you are unsure. To give a sense of perspective, a person who earns \$15 per hour and works full-time and full-year will have an annual salary of about \$27,000.

For each question, circle the annual salary closest to what you think it is. If you think the answer is between two of the listed salaries, circle both of those salaries. All listed numbers are in thousands of dollars.

For example, if you want to answer “\$30,000,” circle “30.” If you want to answer “\$31,000,” circle both “30” and “33.” **Raise your hand if you are not sure how to write your answers to this question.**

The two questions for the Typical person and the Self had additional specifying instructions:

What do you think the **annual salary** is for an **average 30-year-old** full-time, full-year worker in Washington...

What do you think **YOUR** annual salary would be at **age 30** if you had a full-time, full-year job...

The sentence concludes in six different ways for the six types of education: “who does not have a high school degree?” / “without having a high school degree?” for no high school degree, and then “who has” / “with a” “high school degree but without going to college?” “some college experience but no degree?” “an associate’s or technical degree (two-year college degree)?” “a bachelor’s degree (four-year college degree)?” or “a Master’s degree, PhD, MD (Doctor), or JD (Lawyer)?”

The question relating to the non-employment rate in Chapter 2 and the employment rate in Chapter 3 was worded similarly. Students were encouraged to think about 100 typical 30-year-old Washington residents with the specified level of education and asked to estimate how many of those 100 residents might be unemployed. This method of asking for frequency counts rather than eliciting an actual non-employment rate follows from the psychological literature suggesting that this method of asking about rates is more likely to generate realistic responses (Gigerenzer and Hoffrage, 1995). The exact wording is:

For each question, imagine 100 people in Washington who are 30 years old with the given level of education. How many of these 100 people would you expect to be **unemployed** today...

The sentence concludes again in six different ways with “among 100 people who” have the given levels of education, described in the same way as for the wage questions.

The remainder of the variables described here are used in Chapter 3 but not Chapter 2 and are described in terms of the notation of Chapter 3.

The graduation rate ( $P_i$ ) is elicited in a manner similar to the employment probability question, asking “Out of 100 students who attend a four-year college, how many do you think receive a bachelor’s degree within six years after they begin college?” and allowing the student to fill in a number out of 100.

Students are asked to fill in “What job do you think you will have at age 30?” The follow up question is used for  $JobEd_i$ : “How much education do you think the typical person with that job has?” with the education levels and “I don’t know” as options. On the survey, for  $JobEd_i$ , labor market outcomes, and educational plans, “Less than a high school degree” is also an education level option. Respondents are mostly nearly high school graduates and rarely choose “Less than a high school degree” as their educational plan or as the level of education in their workplace. “Less than a high school degree” answers for these questions are grouped in with “high school degree.”

Enjoy Academics and Enjoy Non-academics, questions relating to enjoyment of the academic and non-academic parts of the college experience, ask “How much do you think you would enjoy attending college classes?” and “How much do you think you would enjoy the non-academic part of the college experience, for example the social environment?” and give five options: “I would (hate it/dislike it/neither like it nor dislike it/like it/love it).”

The Expect Easy variable is framed in terms of the expected difficulty of performing well in college, and then reversed for analysis. The question asks “Compared to the average college student, how difficult do you think it would be for you to get good grades in college?” The options are “Much easier for me,” “A little easier for me,” “About the same,” “A little more difficult for me,” and “Much more difficult for me.”

The Family to College and Friends to College variables refer to the portion of family members and friends who had gone or are going to college. They ask, respectively, “Think about the members of your extended family who you know. How many of the adults in your extended family attended college at some point in their life?” and “Think about your friends. How many of your friends have already attended, or do you think will attend, college?” with the options “None,” “Some, but less than half,” “About half,” “More than half,” and “All.”

## Appendix C

### ALTERNATE ASSUMPTIONS AND SPECIFICATIONS

In this appendix I evaluate the sensitivity of the results in Chapter 3 to certain modeling choices and assumptions. These tests are chosen with the intent of contradicting the result that consumption value inputs drive student plans more than financial rewards. For that reason, I will focus on changes to the coefficient on future net earnings.

(1) I first attempt several alterations to the specification for labor market utility. I estimate the model (1A) without  $I(JobEd_i = S_i)$ , (1B) without student loans, (1C) with different student loan interest rates, and (1D) with a wider distribution of preference types for future net earnings.

(1A) I remove  $I(JobEd_i = S_i)$ , the indicator equal to one when the student's educational level is equal to the education they expect others to have in their workplace, from labor market utility. This indicator is correlated with expected wages and thus may depress the coefficient on future net earnings. Removing this variable actually leads the coefficient on future net earnings to drop, but the estimated discount rate to rise. Holding the discount rate at the .880 estimated in the main model, the coefficient on future net earnings increases to .168, but this is not a large enough change to contradict the paper's main findings.

(1B) I eliminate student loans from the analysis, setting  $L_i = 0$  for all students. This robustness check is motivated by the possibility that the data on expected loans may be less trustworthy than the other data, given the lower item response rate, and because expected loans were calculated using expected loans at particular colleges, which may not apply to students who do not expect to attend those colleges. This alternate model implicitly assumes that variation in actual expected loans is uncorrelated with earnings variables, which allows the average effect of student debt on workplace utility to be absorbed by the intercept, and

the variation in expected loan burden between students to be absorbed by the error term. The coefficient on future net earnings rises slightly to .129. This does not significantly change any presented results.

(1C) I estimate the model using different student loan interest rates. In the paper, the annual interest rate  $\Psi$  is set at .05, as per Perkins loan terms. However, many student loans are taken out at different rates. Without going into the variety of private loans available, I look at the interest rate of .068 set by federal Stafford loans at the time of the survey. I also estimate the model allowing only students who qualify for Free or Reduced Price Lunch to get loans at the Perkins rate of .05, while everyone else has .068. In neither case do results change significantly. When all students face a rate of .068, the coefficient on future income drops slightly to .110. When only non-FRPL students face the Stafford rate, the coefficient increases slightly to .129. In neither case is the main result affected.

(1D) I allow for a different heterogeneous preference structure than the nine types determined by the variance-covariance matrix discussed in Section 3.2.4. While in the main specification weights on extreme preferences are zero, the use of the variance/covariance matrix to generate preference vectors may not allow tightly-estimated parameters, such as the coefficient on future income, enough variance such that extremely high preferences can be accounted for. Here I allow for 51 different preference types, between which only the coefficient on future net earnings varies. I allow the coefficient to take values uniformly from .02 to 1.02. There is some evidence for subgroups with high coefficients on future net earnings. The highest group (with a coefficient of 1.02) has a weight of .012. There is also a total weight of about .099 given to the coefficients between .62 and .72. However, nearly all other groups with very high coefficients are given a weight of zero. Most of the distribution weight is grouped near the single-type coefficient or below. The average coefficient on future net earnings in this analysis actually shrinks to .093.

(2) Second, I look for heterogeneity in preference in other ways. As mentioned in Section 3.4.3, I look for differences in response by gender and socioeconomic status. I estimate the model (2A) separately for the sample of men and women, and then (2B) separately for

students who do and do not qualify for Free or Reduced-Price Lunch. These models are estimated as two-type, allowing for differences by the listed groups but no further preference heterogeneity.

(2A) There is evidence of significant difference between men and women. As is found in Jacob (2002), women's college enrollment elasticity with respect to net earnings is higher than for men. The coefficient on future income is .178 for women and .060 for men, with elasticities between .016 and .189 for women, and between .004 and .052 for men. The general result of the paper holds for both men and women. There are other differences between men and women. Women have a discount rate of .956, as opposed to .872 for men. Men respond more strongly to job-education match than women and have a larger coefficient on FRPL eligibility, but coefficients on GPA and race are larger for women. Other coefficients are similar between the genders.

(2B) There is also evidence of significant difference between low- and high-income students. Students who are eligible for FRPL have a lower response to net future earnings (coefficient of .082 and elasticities between .004 and .071) than students who are not eligible (coefficient of .163 and elasticities between .016 and .174). The main qualitative result holds for both groups. Most other coefficients are similar, although FRPL students respond more strongly to parental encouragement, and non-FRPL students put more weight on expected ease.

(3) Third, I make more significant alterations to the model. I (3A) change the approach to discounting to allow for time-inconsistent hyperbolic discounting, (3B) remove advanced education from the model, and (3C) relax the linearity assumption on the variables rated 1-5.

(3A) The model in this paper assumes an exponential discount rate, which implies a consistent time preference. However, evidence on time discounting suggests that a hyperbolic discounting approach better fits the data (Frederick et al., 2002; Laibson et al., 2007). Hyperbolic discounting allows for a "present bias" in which the discount rate between today and tomorrow is much steeper than the discount rate between a year from now and a year

and a day from now. In the case of this study, all decisions are prospective - even the choice between the first year of college and entering the labor market will not actually come for at least several months for the seniors in the study, and more than a year for juniors. This suggests that present bias is not likely to affect results.

To check, I estimate the model allowing for time-inconsistent preferences. I use beta-delta discounting, a tractable form of hyperbolic discounting, in which the standard exponential discount rate  $\delta$  is used, but an additional discount of  $\beta$  is applied to discount between “now” and all other times. So, an immediate payout is not discounted, a payout one period later is discounted by  $\beta\delta$ , a payout two periods later is discounted by  $\beta\delta^2$ , and so on. I treat the first year of payoffs - the utility received during the first year after high school, as “now.” As expected, I find no evidence for present bias.  $\beta$  is .978, very close to 1, and the exponential discount rate  $\delta$  rises only slightly to .903.

(3B) I remove the decision of whether or not to continue on to graduate school. This test follows from the possibility that, since the decision takes place so far in the future, high school students may not be seriously considering the question of whether or not to continue on to graduate school after attaining a bachelor’s degree. All students who reported planning to attempt an advanced degree were reassigned to only attempt a four-year degree. The model then has only two decisions - whether to continue on to college, and which degree to attempt. This does increase the size of the coefficient on future net earnings from .126 to .188. Net income becomes somewhat more influential, but not by enough to contradict the main result of the paper. The elasticity of high school-only attainment with respect to high school wage is .136, and the according figures for some college, two-year, and four-year degrees are .136, .067, and .012.

(3C) A final alternate specification relaxes the linearity assumption for all variables rated 1-5 (Enjoy Academics, Enjoy Non-academics, Expect Easy, Family to College, and Friends to College). In the current model, each of these variables is treated linearly. I relax this by instead including a set of dummies for each level of the consumption value input, leaving out the lowest rating. The estimated model suggests that linearity is restrictive for some

of these inputs; for example, the coefficients on Enjoy Academics for undergraduate utility are  $-.211$ ,  $.107$ ,  $.293$ , and  $.412$  on dummies indicating a value of 2, 3, 4, and 5, respectively, relative to a value of 1. In this case, the negative coefficient on 2 reveals a somewhat non-monotonic relationship where students reporting a 1 have higher consumption value than those reporting a 2. However, the coefficient on future net earnings decreases slightly to  $.117$  and consumption value inputs do not become less influential. The general result of the paper holds. The interpretation of the influence of these particular variables becomes more complex, but in general these results hold as well.

(4) One final test checks for the possibility of reverse causality in the results, as mentioned in the Data section. It is possible that students alter their reported beliefs and preferences after making educational decisions so as to rationalize the choice they have already made. I follow the argument of Attanasio and Kaufmann (2014): in the presence of ex-post rationalization, stated beliefs and preferences should be more extreme for seniors than for juniors. For a given distribution of beliefs or stated preferences for juniors, seniors who then choose more education should shift their beliefs and preferences in favor of education, and seniors who choose less education should shift their beliefs and preferences in favor of less education. This should produce a distribution for seniors with less weight in the middle and more weight towards the sides.

To test for reverse causality, I calculate the senior to junior variance ratio for each wage and employment belief variable, as well as the stated preference variables Enjoy Academics, Enjoy Non-academics, and Expect Ease. I generate the null distribution of this ratio by randomly reassigning students to be juniors or seniors and calculating the ratio 1,000 times. The ratio of senior variance to junior variance was 1.08 for expected employment probability with an advanced degree. In every other case, senior beliefs and preferences actually had lower variance than juniors. In no case was the ratio unlikely to have occurred under the null distribution - the lowest p-value for rejecting the null would be greater than .3. I fail to find significant evidence in favor of reverse causality.

## Appendix D

### EXPERIMENTAL INSTRUMENT

In this section I detail the exact wording and steps used as the experimental instrument referenced in Chapter 4. Respondents in the sample pool are shown the opportunity to take the survey. Those who select it are shown a standard disclaimer provided by the institutional review board before beginning. The experiment is presented as a series of slides. On each slide the participant is given a set of instructions or a choice task. In this section I list the exact wording used on each slide.

#### *Slide 1*

In this survey, you will choose between hypothetical colleges for yourself or for your child.

For each question, you will be shown the profiles of four colleges. The profiles will list a few things about each college. Assume that for everything not mentioned, the colleges are identical. When choosing a college, you will have to make trade-offs. One college may be better than another at one thing (perhaps it has lower tuition) but worse at another (perhaps the classes are not enjoyable). Try to think about which mix of attributes you would prefer most. It is important that you try to choose the college that you would actually select if presented with the decision in real life.

#### *Slide 2*

[An example of a hypothetical college is shown here with the below-listed attributes]

Here is an example of a college. In the college described above, if you attend College A:

- You will earn a salary of \$60,000 per year at age 25
- Your parents would like for you to go to this school
- You would not enjoy the classes at all

- You would rate the social life as poor
- You would pay \$15,000 in tuition per year (or take on loans to cover what you can't afford)

*Slide 3*

[This slide is shown first to those who are randomized into the “perform choice tasks as student first” version. Otherwise, the parental version (here slide 11) is shown first.]

Imagine that you are just finishing high school. You can choose which college to go to and you are trying to decide which college to choose (or no college at all). Assume that for all attributes not listed, the colleges are exactly the same. If the tuition is too high for you and/or your parents to afford, assume the rest can be covered by student loans.

*Slides 4-10*

[These seven slides show the choice tasks where the respondent plays the role of a student.]

*Slide 11*

Imagine that your child is just finishing high school. You can choose which college to send them to and you are trying to decide which college to choose (or no college at all). Assume that for all attributes not listed, the colleges are exactly the same. If the tuition is too high for you and/or your child to afford, assume the rest can be covered by student loans.

*Slides 12-17*

[These six slides show the choice tasks where the respondent plays the role of a parent.]

*Slide 18*

[This slide shows the demographic questions, as outlined in Section [4.4](#).]

## Appendix E

### NONPARAMETRIC ESTIMATION

In this section, I estimate indirect utility coefficients for the analysis in Chapter 4 using the nonparametric estimator of Hainmueller et al. (2014), hereafter HYH. The intent of this section is to show that the results of the analysis are not simply a result of the error term distribution assumption inherent in multinomial logit analysis. HYH show that, when attributes are totally randomized as in this study, the Average Marginal Component Effect (AMCE, that is, the causal impact of a change of an attribute on the probability of choosing a particular option) can be calculated nonparametrically. This nonparametric estimator is calculated by performing an OLS regression of binary choice outcomes on a set of dummies (and interaction terms if desired) for each attribute. A linear regression approach to estimating coefficient values is standard in ratings-based conjoint analysis, but HYH show that this approach gives causal estimates for choice-based conjoint as well.

I do not use this estimator for the main analysis because it is explicitly designed to avoid relying on a utility-based choice representation, and so the relationship between the HYH empirical results and those from the model in Section 4.2 is strained. Additionally, the HYH estimator does not translate as easily into individual coefficient estimates and does not take advantage of the likely useful information on the choice set - which colleges are compared when choices are made. However, in practice the HYH approach is very similar to the use of marginal effects from a conditional logit, at least for the purpose of estimating mean marginal effects. These approaches largely vary in terms of the strength of assumptions about the error term and whether or not they take advantage of information about the choice set.

I calculate AMCE estimates using the HYH estimator first on a sample of “young student” respondents and then on a sample of “older parent” respondents. I compare these to average

marginal effects estimates for the same groups from the saturated model in Section 4.5.1. Average marginal effects are calculated by comparing for each option the probability of selecting that option with a given binary indicator set to one against the probability with that indicator set to zero, and then averaging over the appropriate group.

There are some differences between main model estimates and the HYH estimates, but they are not large. Over the 15 estimated parameters (five attributes with three levels each to be compared to the base level), the mean absolute difference between the main model average marginal effect and the HYH AMCE is .012 for young students and .012 for older parents. The largest differences are .045 for young students on the highest level of parent's opinion, and .027 for older parents on the highest level of social life. In each of these cases the main model estimated a stronger effect than the HYH AMCE.

Overall, the differences between mean marginal effects in the saturated model as estimated using hierarchical Bayes and the HYH nonparametric estimator are small. Qualitative results do not change when using the HYH estimator.