College Choice as a Collective Decision*

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Abstract

Although the choice between colleges can be thought of as being made by a family, models of educational choice almost universally portray the decision as made by the student alone. I suggest that both students and parents have agency and estimate a collective decision function using a conjoint choice experiment. Students have more influence than parents over the decision and care more about class experience, social life, and future earnings than do parents. Ignoring the dual-agent nature of the decision can bias indirect utility estimates and lead to poor predictions and poorly-targeted policy designs.

JEL Codes: I21, J24, D13

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1 Introduction

College attendance is an important determinant of human capital. The choices of whether or not to attend college and which college to attend both affect a 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 Jacob et al. 2016 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. It is broadly acknowledged that parental characteristics influence choice over college options. 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, which we might expect if the parent exerts financial control over the decision or if the student is otherwise incentivized to compromise with them (e.g., the “rotten kid theorem” of Becker, 1974). 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), and a general acknowledgment of dual-agent choice concerning intergenerational transfer. There is room for improvement in the model by more fully integrating the interaction between student and parent preferences in the model.

In the domain of educational choice, there is a small amount of previous work on collective student/parent decision making. Kalenkoski (2008) presents a model of Nash bargaining between parents and students for the decision of how much post-secondary education to attain. Using data from the United States, Kalenkoski rejects that decisions are made as a unitary household and that parents have altruistic preferences. 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. Both mother and student expectations 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 high schools in Florida. 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 “unitary” model and one in which multiple agents with different preferences come together to make a decision. Work in other areas shows that this is not a trivial distinction. In particular, the literature on intra-household decision making between husbands and wives generally rejects the unitary model of 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).

The 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 the 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, the value of this approach to college choice 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 dif-
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. A household’s decision function is a weighted average of student and parent utilities. Student and parent indirect utility functions are identified separately using a conjoint analysis choice experiment. These separately identified indirect utility functions can be combined with a weighting parameter, also estimated in the experiment, to form a household decision function. In choice-based conjoint experiments, respondents are presented with a choice between hypothetical products with attributes varied by the researcher.\(^1\) I repeatedly 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. Student and parent indirect utility functions are determined by the choice responses.

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 assigned, estimates are not based on the uncertainty inherent in the educational choice process, in which the outcomes of different educational options are unknown. In the presence of such uncertainty, strong assumptions about beliefs, or data on those beliefs, are necessary to identify preferences (Manski, 2004). The random assignment of college attributes also sidesteps the “choice set” problem. In the study of demand for college attributes, detailed and hard-to-obtain data on each step of the college application process are necessary to distinguish between a college not chosen because it is not preferred and a college not chosen because it was not in the choice set, since the student was not accepted or did not consider it as a possibility.

In a data set of 964 online participants, variation in respondent age and assigned respondent role allow me to compare indirect utility parameters across groups. Student and parent priorities are significantly different. In particular, students respond more strongly, relative to parents, to how enjoyable the classes are, the quality of social life, and future earnings. Parents

\(^1\)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., 2010). However, in the broader literature the term “conjoint analysis” is commonly used in this way, and I will continue to do so.
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 so 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.

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 \( C \). They make this decision collectively, maximizing a combination of student and parent utilities over two periods. The first period covers the time spent in college, 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).

\[
\begin{align*}
\max_{c,z_1^s,z_2^s,z_1^p,z_2^p} & \quad [U^s(x_c,z_1^s) + \delta^s U^s(0,z_2^s) + \mu[U^p(x_c,z_1^p) + \delta^p U^p(0,z_2^p)]] \\
\text{s.t.} & \quad t_c + z_1^s + z_1^p = Y_1^s + Y_1^p + L \\
& \quad z_2^s + (1 + r)L \leq Y_2^s + B \\
& \quad z_2^p + B \leq Y_2^p
\end{align*}
\]

\(^{2}C\) also includes the option to not attend college at all.
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 paternalistic (Pollak, 1988) or 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 $(z^s_1, z^s_2)$ and the parent $(z^p_1, z^p_2)$ in the first and second period.

Tuition and other goods are paid for using student and parent income $Y^s_1, Y^s_2, Y^p_1,$ and $Y^p_2$, and student loans $L$ that must be repaid at an interest rate $r$.$^3$ Second-period student income $Y^s_2$ depends on the college chosen in the first period due to differences in networking opportunities and human capital accumulation across colleges. While the student and parent do not share budget constraints in the second period, they may make transfers $B$ between each other. If the parent is responsible for repaying student loans, $B \geq (1 + r)L$.

Reflecting the process of choosing among a static and limited set of colleges, and the fact that tuition is unlikely to be determined competitively, there is no assumption that colleges are priced hedonically. That is, college attributes $x_c$ and $Y^s_2$ are not a direct function of price $t_c$. Rather than choosing a college with optimal levels of $x_c$ and $Y^s_2$ given a price for each attribute, the family chooses $c$ from available attribute baskets $C$ given a set price $t_c$ for each basket.

Then, for each college $c \in C$, there is an optimal allocation $(z^s_1, z^s_2, z^p_1, z^p_2, L^*, B^*|c)$ found using first-order conditions from Equation 1 and the constraints in Equations 2-5. The goods allocation is a function of fixed parameters $r, Y^s_1, Y^p_2$.

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$^3$ $L$ 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 any results of interest here. Additionally, under the assumption that the second period represents all further periods, the second period budget constraints will bind, allowing them to be substituted into the first period budget constraint.
and $Y^p_s$ and college-specific variables $t_c$, $Y_{c2}^s$, and $x_c$. The household’s objective function given a specific college $c$ can then be based on indirect utility functions $V^s$ and $V^p$:

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

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

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

s.t. $c \in C$

Aggregating utility over both periods gives the lifetime indirect utility functions $\bar{V}^s$ and $\bar{V}^p$ as shown in Equation 7. Equation 7 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 $\varepsilon^s_c$ and $\varepsilon^p_c$ to student and parent total utility, respectively, the experiment identifies up to a scale parameter the empirical indirect utility functions $\hat{V}^s$ and $\hat{V}^p$ that determine the choice of $c$ from the set $C$ (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:

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

4In 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, 2009). In work available from the author, I show that results are robust to the use of the nonparametric Hainmueller et al. (2014) estimator.

5Not represented here is the model-implied linear relationship between $\partial \bar{V}^i/\partial t_c$ and $\partial \bar{V}^s/\partial Y_{c2}^s$, since they enter together into the budget constraint as $Y_{c2}^s - (1+r)t_c$. 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.
\[
\frac{\partial \hat{V}^s}{\partial V_p^*} \left( \frac{\partial \hat{V}_p}{\partial V_s^*} \right)^{-1} = \mu
\]

Equation 10

There are several important features of the analysis to point out here. First, indirect utility parameters are not identified separately from time preference ($\delta^s$ and $\delta^p$). Second, Equation 10 is constructed based on the derivatives of Equation 7 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 estimate of the bargaining parameter $\mu$.\(^6\)

Equations 9-10 illustrate how different empirical responses to college attributes can be related directly to a mix of indirect utility and discounting. In addition, the estimate of the bargaining parameter $\mu$ tells us about the college decision-making process. The decision is guided mostly by student preferences $\mu < 1$, 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 student choice model anyway would bias estimates depends both on the value of $\mu$ and how large the differences between student and parent preferences are.

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 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 (Orme, 2006).

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\(^6\)This estimate gives incorrect results if $\partial \hat{V}^s / \partial \bar{V}_p^* < 0$ or $\partial \hat{V}_p / \partial \bar{V}^s < 0$. However, if either of these inequalities is true, this can be taken as a rejection of the cooperative model.
separate experiment to estimate the value of each attribute separately and simply assuming independence between attributes.

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 1.

FIGURE 1 ABOUT HERE

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 annual tuition charged, and (5) The opinion of one’s parents. 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: 7

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

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

7To avoid order effects where the first attribute listed is more heavily weighted in the decision (see Chrzan, 1994), the experiment uses five different orderings of the attributes, with each of the five attributes listed first in one of the orderings and the other attributes ordered randomly. Each subject is assigned randomly to one of the five orderings.

8I emphasize “enjoyability,” a direct measure of consumption value, rather than the more generic “quality” of classes, which could also indicate academic rigor. This approach lends to 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.
See Appendix B for the full instrument and instructions. The earnings and tuition levels chosen for inclusion in the experiment are necessarily somewhat arbitrary, but are chosen to represent realistic ranges for the earnings of college graduates and tuition.

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 warm-up question is given first; this response is discarded. Most results use groups that are best representative of parents and students: college-age respondents in the student role 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”).

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 $C_j$ for each individual decision $j$ to be made.

I estimate indirect utility functions using a conditional logit model (McFadden, 1973). Conditional logit models are a standard means of identifying indirect utility functions from discrete choice data, and carry a random utility interpretation.

With the conditional logit specification, the probability of choosing a particular alternative $c$ from the choice set $C_j$ is

$$p_c = \frac{\exp(F(A_c, \beta))}{\sum_{c' \in C_j} \exp(F(A_{c'}, \beta))}$$  \hspace{1cm} (11)

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 $\beta$. $\sum_{c' \in C_j}$ sums over all colleges in the choice set the respondent faces. The specification of $F(A_c, \beta)$ is flexible. Since attributes are fully random-
ized, $\beta$ is identified even if interaction terms 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 Rossi et al., 2005; Sawtooth Software, 2009; Sermas, 2014). Rather than estimating population average indirect utility parameters $\beta$, HB generates individual-level coefficients $\beta_i$ with a Markov chain Monte Carlo algorithm.\footnote{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. Interacted models instead use 100,000 iterations. Convergence logs and images are available from the author.} The HB estimator assumes that each coefficient in the logit model follows a joint normal distribution

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

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. $\beta_i$ 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 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 in standard conditional logit analysis (McFadden and Train, 2000).

HB allows takes advantage of full-sample choice behavior to inform individual-
level estimates. HB is capable of effectively and accurately estimating individual-level heterogeneity in indirect utility parameters even with relatively few choice observations per respondent (Lenk et al., 1996; Sawtooth Software, 2009). In a Monte Carlo analysis, HB performed similarly to the use of finite mixture distributions in model fit and the retrieval of individual preference parameters, and both outperformed completely aggregate models and estimating each subject separately, even under the violation of certain model assumptions (Andrews et al., 2002). HB is chosen here over the use of a finite mixture distribution because it directly models heterogeneity at the individual level and is designed to produce point estimates of indirect utility parameters at the individual level.

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 Data

4.1 Sample Information

Data collection occurred on the survey administration website SocialSci.com. SocialSci is a private firm that has access to a recruited pool of online survey takers.\textsuperscript{10} While participation in the survey pool and the survey is voluntary, SocialSci works to actively recruit respondents in demographic groups underrepresented in the pool. All subjects are given a small amount of compensation (less than $5) for their participation.

There are 964 survey participants. Each respondent answers thirteen college choice questions, twelve of which are used, for a total of 11,568 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. At the end of the survey, each respondent gives a self-report of their age, gender, non-exclusive race and ethnicity, completed education level, and self-reported academic ability.

\textsuperscript{10}The protocol detailing pool recruitment and subject treatment is available on the website: https://research.socialsci.com/docs/categories/17-using_our_participant_pool. SocialSci has given notice that it is shutting down. If this link is no longer active, please contact the author for a backed up version.
Demographic information about the respondents is shown in Table 1. Relative to the United States population, women and white people are over-represented. Also, in line with the use of an internet sample, the sample appears to select for respondents with higher levels of education than the population: more than 60% of the sample has a Bachelor’s degree or above. 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, with 83% of the sample “above average.” 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 pool. 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.

With minor exception, choices seem to be made with attention paid to the task. The median completion time for the entire survey is 7 minutes and 49 seconds, with a median time of 22 seconds spent on each choice task disregarding the warm-up task. 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 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.
4.2 Generalizing From the Sample

One concern about the data used in this study is the extent to which it will allow results to be generalized to a broader real-world context. Two issues in particular arise: the use of an online survey sample, and the use of a broad group of respondents to represent “students” and “parents.”

Internet-based survey data has a good record of providing data that are, when adjusted for respondent characteristics, similar to those collected offline. 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; Gosling et al., 2004; Sethuraman et al., 2005). In this study, college-educated respondents are overrepresented in the sample relative to the population, and there is no explicit control to correct for this. In the context of this study, this means that the sample is focused towards the type of respondents who would actually be likely to be considering college options.

The issue of using a broad group to represent “students” and “parents” may be of more concern. In this paper, respondents aged 18-25 who are responding in the assigned role of “student” are assumed to represent actual students making decisions about colleges, and respondents aged 39-47 responding in the assigned role of “parent” are assumed to represent actual parents. 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. Further, respondents are surveyed individually rather than in matched pairs of actual 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 equivalence between the sample and those actually making these decisions is likely the strongest assumption in the analysis. This issue speaks to a more general concern about representativeness in laboratory experiments in the social sciences (Henrich et al., 2010).

In the absence of this equivalence assumption, the primary contribution of the paper is methodological. However, there are two pieces of evidence in favor of the assumption, which may alleviate concerns if not eliminate them. Both pieces of evidence draw on general results that will be explained in more detail in the next section. First, the general relative importance for students of consumption value, cost, and earnings in college choice mimics results from studies that use data on actual students (e.g. Wiswall and Zafar,
Second, and perhaps more important, I find that respondents taking the student or parent roles give similar answers regardless of age, and in many cases education. Extrapolating from this result we may expect that respondents who are younger still (16-17) would be likely to give similar answers as well, allowing the results to generalize to that population.

5 Results

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. The hierarchical Bayes method draws individual indirect utility coefficients for each respondent.

The model has 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. 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, 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 .907 is assigned to the option chosen, and the true positive rate is 91.3%. For simplicity of presentation I show the uninteracted model here and in Section 5.2 and return to the interacted model in Section 5.3. Cross-group comparisons at the mean college profile are similar using the interacted model.

In Figure 2a I show the average indirect utility coefficients over the whole sample, estimated using all choice tasks rather than leaving the last one out as in the validation exercise. In Figure 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 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. These groups are the age-matched students and parents, respectively.

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 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; Huntington-Klein, 2015), 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), 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. This suggests a rather high discount rate, 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

Deriving a model-based discount rate from these results would require strong assumptions about loan burdens, transfers, and base earnings. Intuitively, the fact that $24,000 over the next four years has a similar impact as about $6,000 per year starting in five years and every year thereafter implies a high discount rate. The simplest calculation produces an annual discount rate of .18, 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.
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.12

A useful feature of the mean indirect utility parameters in Figures 2a-2c is that 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 means and standard deviations of the linear coefficients are shown in Table 2.

TABLE 2 ABOUT HERE

The mean coefficients in Table 2 largely reiterate the results from Figures 2b-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 the sample (with the exception of the “no college” parameter) in Figure 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 that the cooperative model is incorrect for a portion of the population, and a single-agent or noncooperative bargaining model would be more appropriate. 7.0% of the sample, including 6.3% of age-matched students and 7.9% of age-matched parents, have a negative parent/child’s opinion coefficient.

FIGURE 3 ABOUT HERE

These linear estimates allow for straightforward calculation of the structural parameters in Equations 9-10 in Section 2. In particular, average esti-

12The phenomenon of less precise decision-making conditional on the observed characteristics is referred to as a difference of “scale” in the categorical choice literature.
mates of $\partial \hat{V}^i / \partial x_c$, $\partial \hat{V}^i / \partial t_c$, and $\partial \hat{V}^i / \partial Y_{s2} \forall i \in \{s, p\}$ as in Equation 9 are the mean values reported in rows 1-4 of Table 2. Average $\mu$, as in Equation 10, is $0.819/1.077 = 0.740$, 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.

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. The standard error of the mean is roughly about .04 for each attribute, rather than the .5 as shown in Table 2, which is the standard deviation of the distribution. As one might expect from Table 2, 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 driven partially by differences in scale: students have stronger preferences in general over college attributes than do parents. However, 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.

5.2 Relative Importance of Attributes

Direct comparisons of coefficients, as in the previous section, 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 scale of the logit model affect estimates in Table 2. 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 $\beta_i$.

---

13 The use of significance testing with a Bayesian model may seem odd. Recall here that the individual indirect utility parameters are estimated using the hierarchical Bayes method, but these parameters are then analyzed using frequentist methods, and it is in this context that group comparisons are made.
\[ R_{\beta_i(j')} = \sum_j I(|\beta_i(j')| > |\beta_i(j)|) \] (13)

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. 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 3 mimics Table 2 by comparing ranks between Age-Matched Students and Age-Matched Parents, with Age-Matched Student as the excluded category. I also include mismatched groups: young respondents acting in the assumed role of parents (Age-Mismatched Parents) and older respondents acting in the assumed role of students (Age-Mismatched 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.

TABLE 3 ABOUT HERE.

Coefficients in Table 3 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 respondents 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; the only significant difference (at the 5% level) is that older respondents report caring more about their parents’ opinion in the student role than young respondents do.

Coefficient rankings are significantly different between age-matched parents and age-mismatched parents only for the attributes of child’s opinion. Rankings are different between older parents and older students at the 10% level or better for every attribute except salary and tuition.

Differences between roles tend to dominate differences in attribute rankings rather than differences over the life cycle (or cohort). With the exception of parent/student’s opinion, differences in the relative importance of college attributes are largely determined by the role of the decision-maker, suggest-
ing 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. Consider the parable of the student driven by a desire to study a subject they will enjoy, while their parents discourage such behavior. This may come down to the fact that the student gets to enjoy those classes while their parents don’t, rather than a shift in priorities as one ages.

A further study of relative coefficient rankings can reveal how preferences relate to background. In Jacob et al. (2016), for example, respondents with a strong academic background 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.

Table 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 18-25 or 39-47 age groups above), with an additional control for assigned role.14

**TABLE 4 ABOUT HERE**

Consistent with previous analyses, those answering in the parent role put more emphasis on the student’s opinion than those in the student role put on parent’s opinion, to the detriment of all other attributes, with the smallest difference for tuition. Also, there are no significant differences relating to the age of the respondent.

Several demographic differences stand out. Women put less emphasis on salary and tuition and more on the enjoyability of classes and other’s opinion than do men. Compared to white respondents, black respondents put more emphasis on tuition and less on the enjoyability of classes, while Asian respondents put more emphasis on salary and less on social life and tuition. Hispanic students are not significantly different from white students.

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14 All demographic controls are included at once in Table 4, 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. An alternate approach to the Table 4 analysis is to perform a cluster analysis on the ranks and relate those clusters to background characteristics. This produces roughly similar results, although it does not allow for relationships between background characteristics and individual college attributes.
for any attribute.

Self-reported academic quality is related to a stronger emphasis on earnings and other's opinion. Consistent with Jacob et al. (2016), these respondents also place less emphasis on social life and more on classes (keeping in mind that Jacobs et al.’s measure of classes is closer to class quality than enjoyability). There are relatively few significant differences across educational attainment levels compared to those with at most a high school degree, although small group sizes for some levels may mask true effects. Those with 1-2 year degrees care less about other’s opinion, while those with a Bachelor’s put more emphasis on tuition. Those with different kinds of graduate degrees disagree which benefits are worth choosing a college over - those with master’s degrees or doctorates put less emphasis on salary, while those with professional degrees put less emphasis on class enjoyability.

5.3 The Implications of Model Choice

The above results present a difference between students or parents in preferences over college attributes. These results make it possible to estimate functions of the model parameters in Section 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. However, it is possible that students and parents 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.\textsuperscript{15} So, for example, earnings enters five times: by itself, and multiplied by each of the other four traits. Coefficients on all interaction terms are identified since every attribute is randomized independently. Average coefficients are in Appendix C Table 5. These interacted coefficients exhibit

\textsuperscript{15}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.
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 which parent’s opinion and its interactions are left out. Student coefficients from this single-agent model represent indirect utility parameters that result from not considering parental opinion as an input to choice.

I compare these models in two ways. First, I estimate whether the omission of parental 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 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. Priorities, as examined in Section 5.2, change as well. Future earnings, the enjoyability of classes, and social life are all affected similarly, with an average rank about .3 higher in the single-agent model than in the dual-agent model. The average rank of tuition drops by .85.

The mismatch in parameter estimates suggests problems in policy design that rely on the single agent model, especially if they elicit preferences directly from students. Policies concerning changes in tuition, or advertising changes in tuition, may not be pursued because the student response to tuition changes is underestimated. Conversely, student response to policies targeting earnings or consumption value may be lower than expected. Further, policies based on behavioral data may target the wrong member of the household since the preferences of unmodeled parents may be attributed to
their children. This, too, would lead to smaller responses than expected.

There are also predictive differences between 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 5.1, the dual-agent interacted model has strong out-of-sample predictive power, assigning a probability of .913 to the option that is actually chosen. The comparable in-sample figure is .935. In contrast, lacking information on parental opinion, the single-agent model assigns on average a probability of .700 to the option that is chosen. An in-sample predictive validity of .700 is still strong. 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 (omitting parental opinion as a predictor), 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. These links are made by either pairing students and parents randomly or by Gale and Shapley (1962) matching, where students and parents both want to minimize a noise-augmented Mahalanobis (1936) distance between their indirect utility parameters and their partner’s. The Gale-Shapley matching allows for the possibility that parents are likely to have and raise children with preferences similar to their own.

The matching 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 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. After matching each student to a parent, I then average over each of the correlations like the one in Figure 4a. The student-parent pairing is performed 10,000 times using completely random matching, and another 10,000 times using Gale-Shapley matching.

The distribution of the average correlation over all replications is in Figure 4b. Over all iterations, the average correlation between the single-agent and dual-agent preference rankings when matching randomly has an average of .444 with a standard deviation of .016. When using positive matching, the average is .506 with a standard deviation of .012.

FIGURES 4a-4b ABOUT HERE

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. 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 show that the differences between the single-agent and dual-agent models are not trivial.

6 Discussion

In this paper I use a conjoint choice experiment to identify a collective household objective function guiding the choice between colleges as a function of their attributes. Students place significantly different amounts of weight on certain college attributes than do parents. Students have stronger responses to college attributes in general, and in particular students rank future earnings and educational consumption value 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 parameter estimates as well as different (and more accurate) predictions of behavior in the choice tasks.

Aside from the representativeness concerns mentioned in Section 4.2, 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 homoge-
neous parents, rather than modeling two 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 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 subjects 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 earnings” 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.

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. 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. Many, if not most, choices are made to some degree collectively but are modeled as single-agent. While demand functions estimated using conjoint analysis do face some of the concerns mentioned above, they allow for a straightforward identification of the
collective model, which typically relies on very detailed in-house consumption data or convenient natural experiment. Conjoint analysis has allowed this paper to sidestep issues of choice set construction in college choice. Also, the conjoint experiment has made it possible to separate differences in preferences that result from age from differences in preferences that result from role, which to my knowledge is novel.

These methodological possibilities allow for improved policy recommendations. Without expensive full-scale policy experiments, this study provides useful implications for the design of educational choice policy. Individual colleges looking to market themselves to students (as in Jacob et al., 2016) could gain from these results, as could governmental agencies interested in guiding choice between different types of colleges (such as public vs. private college) 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; Huntington-Klein, 2015). This study affirms that policymakers should 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. The previous single-agent literature has not greatly overstated the importance of consumption value, although the results here may shade the interpretation: it may be the case that analyses that do not take into account parental preference may overstate the relationship between student preference for consumption value and behavioral response to consumption value incentives.

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., 2016), 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 rests with the student.
References


College Affordability and Transparency Center. 2014. College Scorecard.


Huntington-Klein, Nick. 2015. Consumption Value and the Demand for College Education.


Appendix A Figures and Tables

Figure 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"

<table>
<thead>
<tr>
<th>College A</th>
<th>College B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Earn $48,000 per year at age 25</td>
<td>Earn $54,000 per year at age 25</td>
</tr>
<tr>
<td>You rate social life as <strong>okay</strong></td>
<td>You rate social life as <strong>good</strong></td>
</tr>
<tr>
<td>You rate classes <strong>a little</strong> enjoyable</td>
<td>You rate classes <strong>fairly</strong> enjoyable</td>
</tr>
<tr>
<td>Your parents love this school</td>
<td>Your parents dislike this school</td>
</tr>
<tr>
<td>Annual tuition of <strong>$15,000</strong></td>
<td>Annual tuition of <strong>$20,000</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>College C</th>
<th>College D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Earn $66,000 per year at age 25</td>
<td>Earn $60,000 per year at age 25</td>
</tr>
<tr>
<td>You rate social life as <strong>poor</strong></td>
<td>You rate social life as <strong>okay</strong></td>
</tr>
<tr>
<td>You rate classes <strong>fairly</strong> enjoyable</td>
<td>You rate classes <strong>fairly</strong> enjoyable</td>
</tr>
<tr>
<td>Your parents like this school</td>
<td>Your parents love this school</td>
</tr>
<tr>
<td>Annual tuition of <strong>$15,000</strong></td>
<td>Annual tuition of <strong>$20,000</strong></td>
</tr>
</tbody>
</table>

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.
Table 1: Respondent Background Information

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Mean</th>
<th>Attribute</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>.418</td>
<td>Less than HS Degree</td>
<td>.004</td>
</tr>
<tr>
<td>Female</td>
<td>.549</td>
<td>HS Degree/GED</td>
<td>.081</td>
</tr>
<tr>
<td>Neither Gender</td>
<td>.009</td>
<td>Some College, No Degree</td>
<td>.217</td>
</tr>
<tr>
<td>White</td>
<td>.733</td>
<td>1-2 Yr. Degree or Cert.</td>
<td>.088</td>
</tr>
<tr>
<td>Black</td>
<td>.087</td>
<td>Bachelor’s Degree</td>
<td>.360</td>
</tr>
<tr>
<td>Asian</td>
<td>.090</td>
<td>Master’s Degree</td>
<td>.177</td>
</tr>
<tr>
<td>Hispanic</td>
<td>.070</td>
<td>Professional Degree</td>
<td>.033</td>
</tr>
<tr>
<td>Other</td>
<td>.038</td>
<td>Doctorate</td>
<td>.039</td>
</tr>
<tr>
<td>Age</td>
<td>36.791</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Self-Reported Academic Ability

| Far Less than Average      | .003  | A Little More than Average   | .322  |
| Much Less than Average     | .005  | Much More than Average       | .378  |
| A Little Less than Average | .024  | Far More than Average        | .131  |
| Average                    | .138  |                              |       |

Race was filled in without restriction and grouped into the above non-exclusive categories by the researcher. “Other” includes unlisted races, respondents who wrote “mixed” but did not specify which races were mixed, and those who reported “don’t know” or would not report.
Figure 2: Indirect Utility Coefficients in Saturated Model

(a) All Responses

(b) Age-Matched Students

(c) Age-Matched Parents
Table 2: Linear Coefficient Means

<table>
<thead>
<tr>
<th>College Attribute</th>
<th>Mean</th>
<th>SD</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age-Matched Students</td>
<td>Age-Matched Parents</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Earnings at Age 25</td>
<td>.853</td>
<td>(.490)</td>
<td>.599</td>
<td>(.498)</td>
</tr>
<tr>
<td>Enjoyability of Classes</td>
<td>1.143</td>
<td>(.503)</td>
<td>.879</td>
<td>(.585)</td>
</tr>
<tr>
<td>Social Life</td>
<td>.648</td>
<td>(.320)</td>
<td>.450</td>
<td>(.341)</td>
</tr>
<tr>
<td>Tuition</td>
<td>-.724</td>
<td>(.490)</td>
<td>-.590</td>
<td>(.549)</td>
</tr>
<tr>
<td>Parent/Child’s Opinion</td>
<td>.819</td>
<td>(.486)</td>
<td>1.077</td>
<td>(.693)</td>
</tr>
<tr>
<td>“No College”</td>
<td>-4.107</td>
<td>(1.412)</td>
<td>-3.594</td>
<td>(1.992)</td>
</tr>
</tbody>
</table>

Age-matched students are respondents aged 18-25 responding as students; Age-matched parents are respondents aged 39-47 responding as parents. Standard deviations shown are standard deviations of the coefficient distributions over the sample, not standard errors.
Figure 3: Individual Linear Coefficient Distributions
Table 3: Ranked Linear Coefficients Group Differences

<table>
<thead>
<tr>
<th>Group</th>
<th>Earnings</th>
<th>Classes</th>
<th>Soc. Life</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age-Matched Students</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Reference)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age-Matched Parents</td>
<td>-0.421***</td>
<td>-0.750***</td>
<td>-0.339**</td>
</tr>
<tr>
<td></td>
<td>(0.163)</td>
<td>(0.167)</td>
<td>(0.166)</td>
</tr>
<tr>
<td>Age-Mismatched Students</td>
<td>-0.167</td>
<td>-0.229</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.162)</td>
<td>(0.171)</td>
<td>(0.165)</td>
</tr>
<tr>
<td>Age-Mismatched Parents</td>
<td>-0.354**</td>
<td>-0.933***</td>
<td>-0.386**</td>
</tr>
<tr>
<td></td>
<td>(0.160)</td>
<td>(0.162)</td>
<td>(0.158)</td>
</tr>
<tr>
<td>Age-Matched Students</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Reference)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age-Matched Parents</td>
<td>-0.049</td>
<td>1.375***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.162)</td>
<td>(0.170)</td>
<td></td>
</tr>
<tr>
<td>Age-Mismatched Students</td>
<td>-0.071</td>
<td>0.367**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.163)</td>
<td>(0.160)</td>
<td></td>
</tr>
<tr>
<td>Age-Mismatched Parents</td>
<td>-0.299*</td>
<td>1.849***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.157)</td>
<td>(0.169)</td>
<td></td>
</tr>
</tbody>
</table>

Those responding in student role are age-matched if age 18-25 or age-mismatched if age 39-47, and the reverse for those responding in the parent role. Standard errors in parentheses. */**/*** indicates statistical significance at the 10%/5%/1% level, respectively. Coefficients are from an ordered logit regression of trait rank on age/role combination dummies.
Table 4: Ranked Linear Coefficients by Background

<table>
<thead>
<tr>
<th>Variable</th>
<th>Earnings</th>
<th>Classes</th>
<th>Soc. Life</th>
<th>Tuition</th>
<th>Parent’s Opinion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parent Role</td>
<td>-0.327***</td>
<td>-0.662***</td>
<td>-0.420***</td>
<td>-0.190**</td>
<td>1.454***</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.084)</td>
<td>(0.083)</td>
<td>(0.081)</td>
<td>(0.088)</td>
</tr>
<tr>
<td>Age</td>
<td>0.011</td>
<td>0.007</td>
<td>0.016</td>
<td>-0.016</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.021)</td>
<td>(0.021)</td>
<td>(0.020)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Age$^2$</td>
<td>-0.000</td>
<td>-0.000</td>
<td>-0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Female</td>
<td>-0.266***</td>
<td>0.299***</td>
<td>-0.125</td>
<td>-0.150*</td>
<td>0.251***</td>
</tr>
<tr>
<td></td>
<td>(0.084)</td>
<td>(0.086)</td>
<td>(0.085)</td>
<td>(0.083)</td>
<td>(0.086)</td>
</tr>
<tr>
<td>Other Gender</td>
<td>-0.997**</td>
<td>0.445</td>
<td>0.555</td>
<td>0.038</td>
<td>0.213</td>
</tr>
<tr>
<td></td>
<td>(0.409)</td>
<td>(0.447)</td>
<td>(0.456)</td>
<td>(0.424)</td>
<td>(0.434)</td>
</tr>
<tr>
<td>Black</td>
<td>0.032</td>
<td>-0.307**</td>
<td>0.115</td>
<td>0.365**</td>
<td>-0.238</td>
</tr>
<tr>
<td></td>
<td>(0.144)</td>
<td>(0.150)</td>
<td>(0.150)</td>
<td>(0.149)</td>
<td>(0.154)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.262</td>
<td>-0.124</td>
<td>0.210</td>
<td>-0.081</td>
<td>0.270</td>
</tr>
<tr>
<td></td>
<td>(0.164)</td>
<td>(0.162)</td>
<td>(0.164)</td>
<td>(0.160)</td>
<td>(0.170)</td>
</tr>
<tr>
<td>Asian</td>
<td>0.446***</td>
<td>-0.081</td>
<td>-0.279*</td>
<td>-0.302**</td>
<td>0.199</td>
</tr>
<tr>
<td></td>
<td>(0.149)</td>
<td>(0.149)</td>
<td>(0.152)</td>
<td>(0.143)</td>
<td>(0.152)</td>
</tr>
<tr>
<td>Other Race</td>
<td>-0.110</td>
<td>-0.474**</td>
<td>0.695***</td>
<td>0.200</td>
<td>-0.303</td>
</tr>
<tr>
<td></td>
<td>(0.219)</td>
<td>(0.234)</td>
<td>(0.214)</td>
<td>(0.228)</td>
<td>(0.221)</td>
</tr>
<tr>
<td>Acad. Ability (Self-Report)</td>
<td>0.148***</td>
<td>0.089*</td>
<td>-0.111**</td>
<td>-0.072</td>
<td>-0.101**</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.046)</td>
<td>(0.046)</td>
<td>(0.045)</td>
<td>(0.047)</td>
</tr>
<tr>
<td>Some College</td>
<td>-0.112</td>
<td>0.069</td>
<td>-0.058</td>
<td>0.256</td>
<td>-0.172</td>
</tr>
<tr>
<td></td>
<td>(0.167)</td>
<td>(0.167)</td>
<td>(0.166)</td>
<td>(0.163)</td>
<td>(0.174)</td>
</tr>
<tr>
<td>1-2 Yr. Degree</td>
<td>-0.033</td>
<td>-0.041</td>
<td>0.211</td>
<td>0.168</td>
<td>-0.418**</td>
</tr>
<tr>
<td></td>
<td>(0.202)</td>
<td>(0.201)</td>
<td>(0.202)</td>
<td>(0.199)</td>
<td>(0.206)</td>
</tr>
<tr>
<td>Bachelor’s</td>
<td>-0.047</td>
<td>-0.059</td>
<td>-0.062</td>
<td>0.295*</td>
<td>-0.217</td>
</tr>
<tr>
<td></td>
<td>(0.162)</td>
<td>(0.162)</td>
<td>(0.161)</td>
<td>(0.157)</td>
<td>(0.170)</td>
</tr>
<tr>
<td>Master’s</td>
<td>-0.358**</td>
<td>0.269</td>
<td>0.066</td>
<td>0.105</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>(0.180)</td>
<td>(0.183)</td>
<td>(0.181)</td>
<td>(0.177)</td>
<td>(0.192)</td>
</tr>
<tr>
<td>Professional</td>
<td>0.242</td>
<td>-0.514*</td>
<td>0.250</td>
<td>0.390</td>
<td>-0.439</td>
</tr>
<tr>
<td></td>
<td>(0.282)</td>
<td>(0.275)</td>
<td>(0.271)</td>
<td>(0.283)</td>
<td>(0.285)</td>
</tr>
<tr>
<td>Doctorate</td>
<td>-0.426*</td>
<td>0.328</td>
<td>0.020</td>
<td>0.175</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>(0.257)</td>
<td>(0.270)</td>
<td>(0.264)</td>
<td>(0.259)</td>
<td>(0.275)</td>
</tr>
</tbody>
</table>

$N = 1,928$, sample includes all subjects twice, once in parent role and once in student role. Coefficients are from an ordered logit regression of trait rank on respondent background. Standard errors in parentheses. */**/*** indicates statistical significance at the 10%/5%/1% level, respectively.
Figure 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
Appendix B   Experimental Instrument

Respondents in the sample pool are shown the opportunity to take the survey. Those who opt in 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 questions about respondent background, including gender, age, and educational attainment.]
### Appendix C  Additional Results

Table 5: Interacted Coefficient Distribution for Matched Age/Role

<table>
<thead>
<tr>
<th>College Attribute</th>
<th>Mean</th>
<th>SD</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Age-Matched Students</td>
<td></td>
<td>Age-Matched Parents</td>
</tr>
<tr>
<td>Earnings at Age 25</td>
<td>-.123</td>
<td>(3.221)</td>
<td>-.825</td>
<td>(3.590)</td>
</tr>
<tr>
<td>Enjoyability of Classes</td>
<td>.596</td>
<td>(3.563)</td>
<td>.061</td>
<td>(3.993)</td>
</tr>
<tr>
<td>Social Life</td>
<td>-.846</td>
<td>(3.082)</td>
<td>-.289</td>
<td>(3.350)</td>
</tr>
<tr>
<td>Tuition</td>
<td>.876</td>
<td>(2.995)</td>
<td>1.898</td>
<td>(3.143)</td>
</tr>
<tr>
<td>Parent/Child’s Opinion</td>
<td>.039</td>
<td>(2.883)</td>
<td>1.138</td>
<td>(2.834)</td>
</tr>
<tr>
<td>“No College”</td>
<td>-13.877</td>
<td>(5.576)</td>
<td>-10.792</td>
<td>(7.076)</td>
</tr>
<tr>
<td>Earnings × Classes</td>
<td>.890</td>
<td>(.779)</td>
<td>.421</td>
<td>(.889)</td>
</tr>
<tr>
<td>Earnings × Social</td>
<td>.622</td>
<td>(.716)</td>
<td>.324</td>
<td>(.665)</td>
</tr>
<tr>
<td>Earnings × Tuition</td>
<td>-.270</td>
<td>(.897)</td>
<td>-.187</td>
<td>(.916)</td>
</tr>
<tr>
<td>Earnings × Opinion</td>
<td>.509</td>
<td>(.915)</td>
<td>.519</td>
<td>(1.039)</td>
</tr>
<tr>
<td>Classes × Social</td>
<td>.601</td>
<td>(.903)</td>
<td>.367</td>
<td>(.865)</td>
</tr>
<tr>
<td>Classes × Tuition</td>
<td>-.477</td>
<td>(.682)</td>
<td>-.495</td>
<td>(.782)</td>
</tr>
<tr>
<td>Classes × Opinion</td>
<td>.471</td>
<td>(.839)</td>
<td>.839</td>
<td>(.972)</td>
</tr>
<tr>
<td>Social × Tuition</td>
<td>-.402</td>
<td>(.749)</td>
<td>-.370</td>
<td>(.837)</td>
</tr>
<tr>
<td>Social × Opinion</td>
<td>.472</td>
<td>(.767)</td>
<td>.359</td>
<td>(.895)</td>
</tr>
<tr>
<td>Opinion × Tuition</td>
<td>-.311</td>
<td>(.888)</td>
<td>-.522</td>
<td>(.919)</td>
</tr>
</tbody>
</table>

Age-matched students are respondents aged 18-25 responding as students; Age-matched parents are respondents aged 39-47 responding as parents. Standard deviations shown are standard deviations of the coefficient distributions over the sample, not standard errors.