Group Decision Making with Uncertain Outcomes: Unpacking Child-Parent Choice of the High School Track*

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Abstract

Predicting multilateral decisions with uncertain outcomes involves the empirically difficult task of separating individual decision makers' prior beliefs and utilities from the group's decision rule. This paper presents and estimates a simple behavioral model of child-parent choice of the high school track with subjective risk and heterogeneous decision rules, in which the basic identification problem is addressed by combining standard data on actual choices with novel information about children's and parents' self-reported: choice-based probabilities of outcomes, individual preferences over choices, and family decision rule. Counterfactual analysis indicates that identity of policy recipients–whether children, parents, or both–matters for enrollment response, and underscores the importance of incorporating information on beliefs and decision rules when modeling interactive decisions with uncertain outcomes and evaluating policies.

[*JEL codes*: C25, C35, C50, C71, C81, C83, D19, D81, D84, I29, J24.]

[*Key words*: Choice under Uncertainty, Multilateral Choice, Heterogeneous Decision Rules, Curricular Tracking, Curriculum Choice, Child-Parent Decision Making, Subjective Probabilities, Stated and Revealed Preferences, Choice-Based Sampling.]

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"I chose this school for its training [in foreign languages,] *and because I would like to study Law in college. But assume that something happens to me,* [with this diploma] *I can still find a job in a travel agency... I am not lost. It* [this curriculum] *will provide me with several job opportunities."* (A girl attending a vocational curriculum for tourism) (Istituto IARD, 2001, p.38)[1]

"As for her high school track, she decided what to study. She chose the type of school, but only after talking together. Her father, for instance, preferred a different [type of] *school and, perhaps, I hoped for yet a different one. But she made her own choice in the end, after a series of discussions we had together."* (A mother) (Istituto IARD, 2001, p.39)

1 Introduction

Social researchers and policy makers have long been interested in analyzing and predicting important real-life decisions with uncertain outcomes and multiple decision makers. The choice of a board of directors to manufacture a new product, the decision of a criminal gang to raid a bank, a couple's choice of the contraceptive method are just but a few prominent examples. These decisions, however, are inherently characterized by subjective uncertainty, raising conceptual and practical challenges for modeling and prediction (Gilboa et al. (2008), Manski (2000)). One such a challenge for empirical policy analysis involves disentangling decision makers' prior beliefs, utilities, and decision rules, since several configurations of the latter may be compatible with the same observed choice while carrying different policy implications.

This paper introduces uncertainty, in the form of subjective risk, and heterogeneous rules of child-parent decision making with no strategic interaction in a simple behavioral model of family choice of the high school track with curricular stratification. And it brings novel data to bear on the question of how children's and parents' beliefs, utilities, and decision rule drive curriculum choice, thereby informing modeling, identification, and prediction of this choice.[2]

A recognized crux of the standard economic framework for modeling decisions with subjective uncertainty is its silence about formation and aggregation of prior beliefs and utilities by decision makers conforming to Savage (1954)'s theory.[3] Additional difficulties involve lack of a clear distinction between states of the world and consequences of choice (outcomes), and an unrealistic complexity of the relevant state space for most realistic choice situations (see Machina (2003) and Karni (2006)). Substantial progress, however, has been recently made in the development of more behavioral-sound theories of subjective expected utility that do not rely on the state space (e.g., Karni (2006, 2007)).

This paper uses a simple Bayesian framework of group decision making with uncertain outcomes featuring two innovations. First, individual preferences of family members are repre-

[1] From the Istituto IARD (2001)'s sociological study. My translation from Italian.

[2] By "subjective risk" I mean that the analysis is restricted to a framework in which, although agents are allowed to hold fully subjective and, in fact, arbitrary beliefs over realization of the uncertainties, they are nonetheless assumed to act upon their beliefs as if probabilities were known to them. This excludes any role for higher moments of the beliefs' distribution or "ambiguity."

[3] See discussions and examples in Machina (2003), Gilboa et al. (2008), Dietrich (2010), and Nehring (2007), among others. Indeed, understanding belief formation stands rightly at the forefront of both the decision-theoretic and empirical literatures of economic decision making (see Gilboa et al. (2008) and Hurd (2009)).

sented by linear subjective expected utilities such that children and parents directly assess the likelihood of different outcomes conditional on each possible choice, and use their utilities of outcomes to make trade-offs among the latter in a compensatory fashion. Hence, the diverse bundle of outcomes encompassed by the empirical analysis–i.e., child's enjoyment, effort, and achievement while in school, as well as opportunities and choices after graduation–is interpreted as a set of subjective criteria against which the quality of the match between the child and each curriculum is evaluated. This specification builds on recent evidence from education and labor economics suggesting that academic achievement and monetary returns may not be the only or the most important drivers of educational choices (e.g., Jacob and Lefgren (2007) and Wiswall and Zafar (2011)).

Second, families are allowed to employ one of a small set of decision rules. That is, either family members make the choice interactively by aggregating their utilities and/or beliefs, or one of them make a unilateral decision. This corresponds with recent theory and evidence from household economics supporting heterogenous decision roles of adolescent children and parents both across families and decision domains (Lundberg et al., 2009*a*,*b*).[4]

Within this simple framework, I address the identification problem facing a researcher who observes a distribution of choices and tries to make inference on the underlying distributions of probabilities, utilities, and decision rules. While existence of this problem has been long recognized in the decision-theoretic literature (Hylland and Zeckhauser, 1979), my paper makes the point that telling decision makers' beliefs, utilities, and rules apart is fundamental for policy analysis. First, expectation-driven choices may be affected by provision of information about curriculum-specific outcomes; whereas utility-driven choices may require a different policy (e.g., no policy). Second, identifying the best target–whether children, parents, or both–of a policy aiming at affecting curriculum enrollment, and assessing the potential effectiveness of such a policy via counterfactual analysis, require uncovering the decision role of each family member.[5]

Insufficient prior knowledge and lack of adequate data on how individuals and groups make decisions with uncertain outcomes, however, have thus far rendered this identification problem hard to tackle empirically (Manski, 2000, 2004). My work addresses this issue directly by collecting new data on usually unobserved components of families' schooling decisions, and by using such data to separately identify and estimate parameters capturing how children

[4]Existing applied examples of outcome-dependent expected utility with interactive decision making under uncertainty and no conflict of interest are Karni (2009)'s and Karni (2011)'s prescriptive models of patient-physician choice of medical treatment. The physician provides a diagnosis, a set of alternative treatments, and the probabilities of the outcomes associated with the latter. The patient provides his personal characteristics and preferences over outcome realizations. The problem is one of integration of the private information of the two parties. Because my application concerns child-parent decision making and is descriptive rather than prescriptive in nature, it does not seem appropriate to assume a specific form of specialization of decision roles *a priori*. Instead, exploiting information on family decision rules in my data, I specify and estimate a small number of curriculum choice models, each one describing a different process.

[5]Recent evidence from Dinkelman and Martinez (2011)'s field experiment in Chilean middle schools corroborates this argument. Specifically, the authors find that providing information about financial aid for post-secondary education to both 8th graders and their parents ("family treatment"), while significantly increasing both children's and parents' knowledge about financial aid, did not induce differential response in college-preparatory high school enrollment relative to informing children only ("student treatment").

and parents individually make trade-offs among outcomes ("utility weights") and parameters describing different types of child-parent decision making ("decision weights").[6]

Specifically, I designed a survey and collected the following data from a sample of families in Northern Italy:

(D1) Children's and parents' probabilistic expectations before the final choice over several in-high-school and post-graduation outcomes, elicited on a 0-100 scale;

(D2) Children's and parents' self-reported rankings over curricula before the final choice, or *stated preferences* (SP);

(D3) Families' actual choices, or *revealed preferences* (RP);

(D4) Self-reported family decision rules among
- **(R1)** Unilateral decision by child,[a]
- **(R2)** Choice by child after listening to the parent (child),[b] and
- **(R3)** Child-parent joint decision;[c]

(D5) Orientation suggestions provided by junior high school teachers;

(D6) Children's and families' background characteristics.

[a]Holding that the child maximizes a subjective expected utility made of his own beliefs and utilities over outcomes.

[b]Holding that the child maximizes a subjective expected utility made of his own utilities and of beliefs updated to account for parental beliefs.

[c]Holding that child and parent jointly maximize a linear combination of their expected utilities.

In the standard case of unilateral decision making (or "unitary families" (Becker, 1981)), identification of utility weights from observed choices **(D3)** simply relies on heterogeneous expectations across decision makers (or families) **(D1)**. To separately identify utility and decision weights governing multilateral decisions, instead, I further combine data **(D3)** and **(D1)** with stated choice preferences of individual family members **(D2)**, within a stated preference-revealed preference (SP-RP) joint framework (Ben-Akiva et al., 1994). That is, given data on child and parent preferences over choice alternatives, their utility parameters are respectively identified by heterogenous beliefs of children and parents across families; whereas decision parameters are identified by within-family differences between choice preferences of individual members and the family's actual choice. Information on family members' decision role **(D4)** is used to directly identify families' decision-making rule or type.

Methodologically, the paper bridges an emerging literature in economics employing right-hand-side probabilistic expectations in discrete choice models under uncertainty to identify preference parameters (e.g., Delavande (2008), Arcidiacono et al. (2012), and Wiswall and Zafar (2011) among others)[7] with a literature, originated in transportation engineering (Morikawa,

[6]I am able to focus on the demand side of the problem because the Italian secondary system features open enrollment. That is, lack of selectivity on the school side eliminates potential identification problems from the interplay of demand and supply in producing observed choices.

[7]Other recent papers have used expectations data as equilibrium outcomes in discrete choice with social interactions (Li and Lee, 2009), as a response variable for choice experiments under incomplete scenarios (Blass et al., 2010) or analysis of decision processes over time (Stinebrickner and Stinebrickner, 2011), and as a tool to improve estimation efficiency (van der Klaauw, 2011) and identify unobserved heterogeneity in dynamic settings (Pantano and Zheng, 2010).

1994), that combines SP and RP data to identify preference parameters that RP data alone could not identify and/or to improve estimation efficiency (Hensher et al., 1999). Both literatures, however, have focused on analysis of individual decision making, and, to the best of my knowledge, the SP-RP approach has been never employed for analysis of decision making under uncertainty.[8]

Substantively, the paper addresses the following questions about curriculum choice:

(Q1) What are the most valued outcomes (or outputs) of curriculum choice among children's enjoyment, effort, and achievement while in school, as well as their opportunities and choices after graduation?

(Q2) To what extent do parental beliefs and utility values affect children's final choice, *conditional on* an interactive child-parent decision?

(Q3) How does curriculum enrollment respond to hypothetical policy-induced changes of families' beliefs? And, in particular, does accounting for heterogeneous family decision rules of matter for prediction and counterfactual analysis of curriculum enrollment?

I find that child's taste for subjects is systematically the most valued factor by both children and parents, and across families using different decision rules. Whereas importance of other in-high-school outcomes relative to post-diploma ones (e.g., school achievement and effort relative to flexible college-vs.-work and college major choices) is heterogeneous across groups **(Q1)**. Estimates of the model with heterogeneous decision rules reveal that parental beliefs affect curriculum choice differentially through different outcomes **(Q2, R2)**. For instance, parental opinion regarding children's future achievement in school matters more than children's own opinion. Whereas, the opposite is true with regard to the flexibility that different curricula will provide children with in face of the subsequent choice of field in college. Decision parameters for families making a joint decision imply a predominant influence of parental preferences, with weights of approximately (1/3, 2/3) on child and parent expected utility respectively **(Q2, R3)**.

I simulate counterfactual scenarios in which awareness campaigns, publication of education statistics, and policies altering curricular specialization and standards are hypothesized to induce fixed changes in family members' beliefs and, thus, affect curriculum enrollment **(Q3)**. For instance, simulation of a 10-point increase in students' percent chances of enjoying math in the general scientific curriculum suggests that the large utility weight families attach to the child taste for subjects may yield fairly large impacts on curriculum enrollment with relatively small movements in beliefs. Anchoring access to university to one's graduation track in high school also produces a large impact on curriculum enrollment, as opposed to providing information on population graduation rates and college enrollment by high school track, suggesting that those beliefs are likely on target.

[8] As a partial exception, Dosman and Adamowicz (2006) use SP-RP methods to examine household vacation site choice with inter-spouses bargaining, but their setting does not feature uncertainty nor heterogeneous decision processes.

The unitary-family benchmark and the proposed model with heterogeneous rules generate intuitive predictions that are qualitatively similar but quantitatively different from each other. For instance, assuming a unitary model with parents as representative decision makers overestimates the magnitude of enrollment response to awareness and desensitization campaigns implied by the heterogenous model. Moreover, counterfactual enrollment responses decomposed by decision rule and by targeted group suggest that publication of education statistics would have the largest impact on children reporting unilateral decision by self, and that if parents alone were informed about policies changing institutional features of curricular tracking, the impact of such policies might be much smaller than if children, too, were informed.

While direct observation of family members' probabilistic beliefs and decision rules makes modeling expectations and assuming a particular decision-making unit unnecessary–a main strength of my analysis–my approach does not mean to nor can eliminate the need of assumptions altogether. First, counterfactual results hold as long as family decision rules are correctly specified, and remain unchanged following the hypothesized policies. In the empirical section, I provide some evidence about the ability of self-reported measures of child and parent decision-making roles to discriminate among different family rules. However, neither alternative modes of group behavior (e.g., strategic interaction) nor family selection into decision rules are addressed in this paper. Second, my paper maintains the basic agnosticism of Bayesian subjective expected utility theory regarding belief formation and the role of Knightian uncertainty (Knight, 1921). In particular, only the mean of the distributions of decision makers' beliefs enters (linearly) their expected utilities, ruling out any role of beliefs' precision and its potential heterogeneity within and across families.

The paper is organized as follows. Section 2 conceptualizes child, parent, and family choice problems, and illustrate the main identification and policy issues through an idealized example. Section 3 covers the study design and describes the samples used in the empirical analysis of section 4. Section 5 presents the counterfactual policy exercises. Section 6 relates the paper to the relevant literature. Conclusions follow.

2 The Identification Problem, Idealized

2.1 A Simple Framework of Curriculum Choice under Uncertainty

Setup. The environment is populated by dyadic families, indexed by $f = 1, ..., F$. Each family is formed by one child, $c = c(f)$, and one parent, $p = p(f)$.[9] Families face the compulsory choice of high school curriculum over a common set of alternatives, $j = 1, ..., J \in \mathcal{J}$, and wish to select

[9]The assumption of dyadic families is maintained because data on beliefs and stated preferences are available for one parent only. Theoretically, this is equivalent to assuming that parental role in the choice can be represented through primitives of a single parent, the "representative" or "relevant" parent. However, if the key data were available for both parents, the analysis could be easily adapted to handle more decision participants.

the alternative that maximizes the quality of the match between the child and the available curricula, $\max_{j \in \mathcal{J}} \theta_{cj}$.[10] Values of $\{\theta_{cj}\}_{j=1}^{J}$, however, are generally not known by families at the time of decision, as they depend on outcomes whose uncertainty will resolve, for the chosen alternative only, during or after high school. Uncertainty is represented as a separable set of choice-dependent binary outcomes, $\mathcal{B} = \{b_{nj}\}$ with $n = 1, ..., N$ and $j = 1, ..., J$. For instance, let us say that $b_{1j} = 1$ denotes "the child likes the core subjects of curriculum j," then $b_{1j} = 0$ denotes its complement. Each family member $i \in \{c, p\}$ holds subjective probabilistic beliefs, $P_i(b_{nj} \in \{0, 1\})$, over possible outcome realizations, and assigns utility values to them, $u_i(b_{nj})$. These beliefs and utilities are then combined into a vector of linear subjective expected utilities $\{EU_{ij}\}_{j=1}^{J}$ to form estimates of $\{\theta_{cj}\}_{j=1}^{J}$.[11] Notice that family members' estimates of each θ_{cj} need not but may coincide with its true value, and they need not but may be equal between members. In fact, such estimates constitute potential inputs into the final decision, depending on the elected family decision rule.[12]

Families approach the choice in two stages. In the first stage, child and parent may initially develop and refine a common understanding of the decision problem (e.g., by establishing a decision frame, gathering and exchanging information, discussing alternatives, comparing probabilities and utilities), which in general would lead to some convergence. Then, whether or not this interaction has occurred, each member individually evaluates the alternatives from the perspective of what (s)he thinks would be best for the child. If a systematic interaction does not take place in stage 1, one of the two members (the child, in my data) make a unilateral decision **(R1)**. On the other hand, when the preliminary interaction occurs, in stage 2 child and parent make a final choice according to one of two interactive decision rules. Specifically, child and parent may engage in pooling of their possibly still heterogenous beliefs, similar to the typical Bayesian expert problem (e.g., Dietrich (2010)), while the child's trade-offs among outcomes are being accepted as child-exclusive inputs in the choice **(R2)**. Alternatively, child and parent may use a non-dictatorial pair of weights to aggregate their preferences over alternatives and, thus, single out the best curriculum for the child according to Keeney and Nau (2011)'s model of Bayesian group decisions **(R3)**.

The following diagram represents the two stages. The subsequent example with 2 family members, 2 alternatives, 2 outcomes, and 2 decision rules illustrates the setup and is expanded throughout the section to discuss identification and policy implications.

[10] The supply side is characterized by curricular tracking with physically separate curricula, and by open enrollment based on family choice. The latter justifies the paper's focus on the demand side. The assumption of a common universal choice set is partly dictated by the study's design, as family-specific consideration sets were not elicited, and the main alternatives were listed in the questions eliciting expectations and stated preferences. This rules out heterogeneous non-compensatory processes of choice set formation, that is, an additional channel through which parents and teachers may affect children's choice.

[11] This representation of uncertainty is dictated by feasibility of data collection so that, for each family member $i \in \{c, p\}$, only $\{P_i(b_{nj} = 1)\}$ need to be elicited instead of the more complicated objects $\{P_i(b_{11}, ..., b_{nj}, ..., b_{NJ})\}$, with $n = 1, ..., N$ and $j = 1, ..., J$. Also, if multiple discrete or continuous outcomes were included, multiple points of respondents' distributions of beliefs would need to be elicited for each outcome and alternative.

[12] To be precise, family members form subjective estimates of probabilities, while utilities are interpreted as an "outcomes aggregating device." As previously mentioned, precision of subjective beliefs does not play any role in the analyzed framework.

Stage 1 Time before the final decision

(1a) Do child and parent systematically develop a common decision framework?

NO: After **(1b)**, they go to decision rule **(R1)**.

YES: After **(1b)**, they go to decision rule **(R2)** or **(R3)**.

(1b) Child and parent individually evaluate each alternative.

Stage 2 Final decision

(R1) Child chooses unilaterally on the basis of his own beliefs and utilities.

(R2) Child and parent pool their opinions, outcome by outcome, into "family beliefs." Choice is based on family beliefs and the child's own utilities.

(R3) Choice is based on a family expected utility aggregating child and parent choice preferences.

A 2×2×2×2 Example. An adolescent named *Adolo* (A) and his parent *Parenta* (P) face the choice between art and math–the *Michelangelo* (M) and *Galileo* (G) curricula. The family elects to judge the uncertain quality of the match between the child and each curriculum by weighing an "Adolo likes the subjects" criterion (L)–based on whether the child would enjoy the core subjects of each track–and a "Flexibility" criterion (W)–based on whether the training of each track would provide him with a wide range of education and work opportunities after graduation **(stage 1a)**. While not disliking math, Adolo has a distinct taste for art. Hence, he actually faces 95 and 70 percent chances of enjoying M and G respectively. On the other hand, Michelangelo's training is somewhat narrow and most suitable for majoring or working in the area of figurative arts. Hence, Adolo's actual probability of facing flexible college and work choices after graduation from M is substantially lower than if he were to graduate from G, 30 and 90 respectively.

Child and parent form their subjective assessments, $\{(P_{iML}, P_{iMW}); (P_{iGL}, P_{iGW})\}$ with $i \in \{A, P\}$, of the actual probabilities, $\{(95, 30); (70, 90)\}$, and assign choice-independent utility values to the outcomes, $\{(\Delta u_{iL}, \Delta u_{iW}); (\Delta u_{iL}, \Delta u_{iW})\}$ **(stage 1b)**. Then, either the child makes curriculum choice individually **(stage 2, R1)**, or the family makes a joint decision **(stage 2, R3)**. However, as it is commonly true for observational data on choice behavior, only the final choice of Michelangelo is publicly observed. Table 1 summarizes the example.

2.2 Individual Decision Making: Separating Utilities and Beliefs

The Child Problem. When individually evaluating the alternatives **(stage 1b)** or unilaterally choosing the best curriculum **(stage 2, R1)**, the child solves

$$EU_{cj} = \sum_{n=1}^{N} \sum_{b_{nj} \in \{0,1\}} P_c(b_{nj}) \cdot u_c(b_{nj}) + x'_{cj}\delta + \varepsilon_{cj} = \sum_{n=1}^{N} P_{cjn} \cdot \Delta u_{cjn} + \bar{U}_{cj} + x'_{cj}\delta_c + \varepsilon_{cj}, \quad (1)$$

which is a function of the vector of uncertain outcomes, $b_j = (b_{1j}, ..., b_{Nj})$, of a vector of child-

Table 1: Child-Parent Choice of the High School Track with Uncertain Outcomes: A 2×2×2×2 Example

		Binary Outcome 1 ($b_1 \in \{L = \text{Likes}, D = \text{Doesn't L.}\}$)		**Binary Outcome 2** ($b_2 \in \{W = \text{Wide}, N = \text{Narrow}\}$)		**Subjective Expected Utility** (EU_{ij})	**Individual Choice Preference** (Stated Pref.)	**Family Decision Rule** (Γ_f)	**Family Actual Choice** (Revealed Pref.)
		Subjective Probability	**Utility Value**	**Subjective Probability**	**Utility Value**				
Adolo ($i = A$)	**Michel.** ($j = M$)	P_{AML}; $1 - P_{AML}$	$\Delta u_{AL} =$ $= u_A(L) - u_A(D)$	P_{AMW}; $1 - P_{AMW}$	$\Delta u_{AW} =$ $= u_A(W) - u_A(N)$	$P_{AML} \cdot \Delta u_{AL} +$ $+ P_{AMW} \cdot \Delta u_{AW}$	$M \cdot$ $\cdot 1\{EU_{AM} \geq EU_{AG}\} +$ $+ G \cdot$ $\cdot 1\{EU_{AM} < EU_{AG}\}$	$\Gamma_{fj} =$ $= \phi_A \cdot EU_{Aj} +$ $+ \phi_P \cdot EU_{Pj}$, $j \in \{M, G\}$	$M \cdot$ $\cdot 1\{\Gamma_{fM} \geq \Gamma_{fG}\} +$ $+ G \cdot$ $\cdot 1\{\Gamma_{fM} < \Gamma_{fG}\}$
	Galileo ($j = G$)	P_{AGL}; $1 - P_{AGL}$	$\Delta u_{AL} =$ $= u_A(L) - u_A(D)$	P_{AGW}; $1 - P_{AGW}$	$\Delta u_{AW} =$ $= u_A(W) - u_A(N)$	$P_{AGL} \cdot \Delta u_{AL} +$ $+ P_{AGW} \cdot \Delta u_{AW}$			
Parenta ($i = P$)	**Michel.** ($j = M$)	P_{PML}; $1 - P_{PML}$	$\Delta u_{PL} =$ $= u_P(L) - u_P(D)$	P_{PMW}; $1 - P_{PMW}$	$\Delta u_{PW} =$ $= u_P(W) - u_P(N)$	$P_{PML} \cdot \Delta u_{PL} +$ $+ P_{PMW} \cdot \Delta u_{PW}$	$M \cdot$ $\cdot 1\{EU_{PM} \geq EU_{PG}\} +$ $+ G \cdot$ $\cdot 1\{EU_{PM} < EU_{PG}\}$		
	Galileo ($j = G$)	P_{PGL}; $1 - P_{PGL}$	$\Delta u_{PL} =$ $= u_P(L) - u_P(D)$	P_{PGW}; $1 - P_{PGW}$	$\Delta u_{PW} =$ $= u_P(W) - u_P(N)$	$P_{PGL} \cdot \Delta u_{PL} +$ $+ P_{PGL} \cdot \Delta u_{PL}$			

Table 2: The Paper's Language for Preferences

Language for preferences with respect to decision makers' utility structure	
(1) Individual preferences over alternatives (E.g., $M \cdot 1\{EU_{iM} \geq EU_{iG}\} + G \cdot 1\{EU_{iM} < EU_{iG}\}$, with $i \in \{C, P\}$)	Represented by decision makers' subjective expected utility incorporating both subjective beliefs and utility values of outcomes. It is used to operationalize decision makers' perception of the quality of the match between the child and each available curriculum.
(2) Utility values of outcomes (E.g., $\{u_i(b_2)\}$, with $b_2 \in \{W, N\}$ and $i \in \{C, P\}$)	Utility values that decision makers assign to future realizations of the uncertainties. They are assumed to be (i) known by agents at all times, (ii) time consistent, and (iii) not manipulable by policy.
(3) Child's taste for school subjects ($b_1 \in \{L, D\}$)	A specific component of decision makers' preferences over curricula. This is uncertain at the moment of choice, and decision makers hold subjective prob. beliefs about its future realization ($\{P_{ijL}\}$ with $i \in \{C, P\}$ and $j \in \{M, G\}$).
Language for preferences with respect to measurement	
(1) Stated choice preferences	Respondents' individually most preferred curriculum, i.e., net of any family interactions.
(2) Reveled preferences	Observed (actual) choices, made by families according to the employed family decision rule.

and curriculum-specific attributes not subject to uncertainty, $x_{cj} = (x_{cj1}, ..., x_{cjM})'$, and of a random term unobservable to the econometrician, ε_{cj}.

Each utility weight, $\Delta u_{cnj} = u_c(b_{nj} = 1) - u_c(b_{nj} = 0)$, is the difference in utility that the child derives from occurrence of outcome n (i.e., $b_{nj} = 1$) relative to its non-occurrence (i.e., $b_{nj} = 0$). These parameters represent child c's preferences over outcomes at the time of choice.[13] In the empirical analysis, however, heterogeneity of utility parameters is restricted to differences between the populations of children and parents and across families using different decision rules. Additionally, utility weights are assumed to be constant across alternatives, as it is customary in econometric analysis of random utility models. Hence, in place of Δu_{cnj} I will use Δu_n^c, with the convention that superscript c indicates that the parameter refers to the population of children rather than to a specific child, and j has been dropped to indicate that utility parameters are not choice dependent. The latter implies also that $\bar{U}_{cj} = \sum_{n=1}^{N} u_c(b_{nj} = 0)$, too, is constant across j and, hence, drops out of the choice.

As a final note, a child's preferences over outcomes (the utility weights) should not be confused with his preferences over alternatives (represented by his expected utility), nor with his preference or taste for curriculum-specific subjects (the first argument of his utility function), which the child may not know perfectly beforehand and holds subjective beliefs about. Table 2 clarifies the different concepts of and language for preference used in the paper.

The Identification Problem. Let us temporarily assume that Adolo is observed to make curriculum choice unilaterally according to $\underset{j \in \{M,G\}}{Max}\ EU_{Aj} = P_{AjL} \cdot \Delta u_{AL} + P_{AjW} \cdot \Delta u_{AW}$. A researcher interested in making inference on Adolo's choice is faced with multiple competing explanations consistent with choice of Michelangelo. The following two scenarios illustrate the identification problem and its relevance for policy.

- **(S1) Utility-driven choice.** Adolo holds rational expectations, i.e., $\{(P_{AML}, P_{AMW}); (P_{AGL}, P_{AGW})\} = \{(95, 30); (70, 90)\}$, but he only cares about enjoying curriculum's content, e.g., $\{\Delta u_{AL}, \Delta u_{AW}\} = \{10, 0\}$. This configuration of beliefs and utilities implies $EU_{AM} = 95 \cdot 10 + 30 \cdot 0 > EU_{AG} = 70 \cdot 10 + 90 \cdot 0$.
- **(S2) Expectation-driven choice.** Adolo holds rational expectations on his taste for subjects, but he erroneously perceives the two alternatives as providing the same flexibility, e.g., $\{(P_{AML}, P_{AMW}); (P_{AGL}, P_{AGW})\} = \{(95, 90); (70, 90)\}$. Moreover, he equally cares about enjoying curriculum's content and about post-graduation flexibility, e.g., $\{\Delta u_{AL}, \Delta u_{AW}\} = \{5, 5\}$. This yields $EU_{AM} = 95 \cdot 5 + 90 \cdot 5 > EU_{AG} = 70 \cdot 5 + 90 \cdot 5$.

[13] Preferences for outcomes realizing far ahead in time may feature discounting and/or time inconsistency. However, I do not incorporate these aspects in the model, since my data would not enable me to identify the corresponding parameters. On the other hand, Mahajan and Tarozzi (2011) use expectations data to identify time preferences with heterogeneous agent types.

Under the standard assumption that utilities are "hardwired" and cannot be manipulated, **(S1)** and **(S2)** carry different policy implications. Specifically, if a policy maker were to intervene by providing the child with the correct information, her policy would be potentially effective only under the second scenario. That is, if the now informed decision maker of **(S2)** were to use the disclosed objective realization probabilities, he would switch to choice of G (since $95 \cdot 5 + 30 \cdot 5 < 70 \cdot 5 + 90 \cdot 5$).[14] Under **(S1)**, instead, the decision maker would choose M even without holding rational expectations, as long as he does not value flexibility and he perceives M as an alternative whose core subjects are more appealing to him.

The Parent Problem. Parents put themselves in their children's shoes–meaning that they solve the same problem as children do–but do it through through their own lenses–i.e., through their prior beliefs and utilities. This implies that the parent problem can be formalized as in (1), with c replaced by p.

2.3 Group Decision Making: Separating Utilities, Beliefs, and Rules

The Family Problem. Family members are assumed to use one of the following decision rules observed in the data.

(R1) Child chooses individually. When a child chooses without any major interactions with his parents, the family objective function (Γ_f) and the child expected utility (eq. 1) coincide.

(R2) Child chooses after listening to the parent. Families following this process maximize an expected utility function based on

(i) Child's utility weights, i.e., $\{\Delta u_n^c\}_{n=1}^N$ and $\{\delta_m^c\}_{m=1}^M$;

(ii) Family beliefs constructed by linear aggregation of individual members' prior beliefs with weights $\{w_n^c, w_n^p\}_{n=1}^N$ such that $w_n^p = 1 - w_n^c$ for all n.

This decision rule is a version of the basic Bayesian model of group decision making (e.g., Hylland and Zeckhauser (1979)), with children's utilities accepted by their families and with linear pooling of child's and parent's opinions. Choice of the latter to capture decision makers' aggregation of beliefs at the time of the final decision (i.e., after information has been shared and jointly processed in stage 1) corresponds with the literature's view of linear pooling as a suitable way to model reconciliation of different interpretations of the same shared body of information rather than reconciliation of differences in information (Dietrich, 2010).

[14] In reality, a policy maker will generally not know the stochastic process faced by single individuals. However, she may know current and past population realizations. This information, may induce decision makers to revise their subjective self-beliefs (e.g., see Wiswall and Zafar (2011) in the context of college major choice). In fact, a broader interpretation of beliefs suggests that the latter may be adjusted not only upon arrival of new substantive information, possibly in form of relative frequencies, but also upon changes in how relevant evidence should be interpreted and summarized (e.g., Dietrich (2010)).

(R3) Child and parent make a joint decision. This decision rule implements Keeney and Nau (2011)'s model of Bayesian group decision making with aggregation weights $\{\phi^c, \phi^p\}$ such that $\phi^p = 1 - \phi^c$ and $\phi^c, \phi^p \geq 0$, which must be determined collectively by the family. It is worth noticing that, different form the basic Bayesian model in which separate aggregation of probabilities and utilities does not guarantee Pareto optimality of the group decision (e.g., Hylland and Zeckhauser (1979)), this model is consistent with Pareto optimality.

These family processes can be also related to existing models of belief and preference transmission from parents to children (see Saez-Marti and Zilibotti (2008)'s review). In "non-paternalistic models," parents make costly investments and choose their children's preferences to maximize children's well-being, but without necessarily trying to install their own cultural variant (e.g., Doepke and Zilibotti (2008)). Whereas in "paternalistic models" parents use their own preferences to evaluate children's utility and, with some effort, seek to transmit their cultural trait to the latter (e.g., Bisin and Verdier (2001)). My framework incorporates both non-paternalistic and paternalistic features. On the one hand, children and parents share the common goal of choosing the curriculum that suits the child best, accounting for both near- and later-future consequences of curriculum choice (same objective function). And, with this very purpose, parents may try to affect children's current choices (and, thus, future paths) via the channel of beliefs **(R2)**, or both beliefs and utilities **(R3)**. On the other hand, parental role in the choice is based on parents' own beliefs and utilities, which may differ from those of their children. The latter echoes Bisin and Verdier (2001)'s assumption of parental "imperfect empathy."

While a more precise behavioral interpretation of these rules is not possible absent an explicit model of family rule selection and/or additional data (e.g., decision weights may depend on a number of individual and family characteristics, such as parenting style, see Bisin et al. (2004) and references therein), the following example shows how information about family members' decision roles is important for policy analysis.[15]

The Identification Problem (Continued). Let us assume that Adolo and Parenta make a joint decision,

$$\max_{j \in \{M,G\}} \phi_A \cdot [P_{AjL} \cdot \Delta u_{AL} + P_{AjW} \cdot \Delta u_{AW}] + \phi_P \cdot [P_{PjL} \cdot \Delta u_{PL} + P_{PjW} \cdot \Delta u_{PW}] \, .$$

[15] A link may be also drawn with the literature on efficient group (household) behavior (see Chiappori and Ekeland (2009) and reference therein). However, my framework differs from the latter in several ways. For example, on the one hand, I exploit information from my data on family members' decision roles to specify detailed rules of child-parent decision making; whereas the approach described by Chiappori and Ekeland (2009) relies uniquely on the assumption of Pareto efficiency. On the other hand, I allow families to use heterogenous decision rules, only one of which is consistent with Pareto optimality. Moreover, I explicitly focus on the aspect of subjective uncertainty characterizing curriculum choice within a Bayesian framework, while I do not address some of the focal issues in household's models of consumption and saving under uncertainty, such as risk sharing.

It is easy to concoct a third scenario in which child and parent select once again M.

(S-III) : **Family-driven choice.** Parenta has more say than Adolo, e.g., $\{\phi_A, \phi_P\} = \{1/3, 2/3\}$. They both care equally about Adolo's preference for subjects and post-graduation flexibility, e.g., $\{\Delta u_{AL}, \Delta u_{AW}\} \equiv \{\Delta u_{PL}, \Delta u_{AW}\} = \{5, 5\}$. Adolo holds rational expectations, i.e., $\{(P_{AML}, P_{AMW}); (P_{AGL}, P_{AGW})\} = \{(95, 30); (70, 90)\}$, while Parenta erroneously perceives M and G as providing the same flexibility, e.g., $\{(P_{PML}, P_{PMW}); (P_{PGL}, P_{PGW})\} = \{(95, 90); (70, 90)\}$. Together these imply

$$EU_{fM} = \frac{1}{3}\left[95 \cdot 5 + 30 \cdot 5\right] + \frac{2}{3}\left[95 \cdot 5 + 90 \cdot 5\right] > EU_{fG} = \frac{1}{3}\left[70 \cdot 5 + 90 \cdot 5\right] + \frac{1}{3}\left[70 \cdot 5 + 90 \cdot 5\right].$$

In this case, information provision should target the parent. Moreover, assessing whether disclosing information would be at all effective, and to what extent, requires knowledge of decision makers' roles and preferences. For instance, in scenario **(S-III)** decision and utility weights are such that disclosure of actual probabilities on flexibility, if feasible, may effectively induce a change in behavior, since $1/3\left[95 \cdot 5 + 30 \cdot 5\right] + 2/3\left[95 \cdot 5 + 30 \cdot 5\right] < 1/3\left[70 \cdot 5 + 90 \cdot 5\right] + 2/3\left[70 \cdot 5 + 90 \cdot 5\right]$. But this need not be the case in general.

Let us finally consider a scenario in which family members' preferences are perfectly aligned.

(S-IV) **Perfect alignment.** Both Adolo and Parenta prefer M based on the wrong perception that it provides the same degree of flexibility as G does, i.e., $\{\Delta u_{AL}, \Delta u_{AW}\} \equiv \{\Delta u_{PL}, \Delta u_{PW}\} = \{5, 5\}$ and $\{(P_{AML}, P_{AMW}); (P_{AGL}, P_{AGW})\} \equiv \{(P_{PML}, P_{PMW}); (P_{PGL}, P_{PGW})\} = \{(95, 90); (70, 90)\}$.

Child and parent should be now "indifferent" among different decision rules, since any rule linearly combining members' expected utilities, including $\{0, 1\}$ and $\{1, 0\}$, would result in choice of M. Nevertheless, knowing which rule is employed will be important for policy makers. For example, under the family decision process of scenario (**S-II**), providing the correct information may be useful. Whereas under the family rule of scenario (**S-III**), targeting the child alone would not be effective, since $1/3\left[95 \cdot 5 + 30 \cdot 5\right] + 2/3\left[95 \cdot 5 + 90 \cdot 5\right] > 1/3\left[70 \cdot 5 + 90 \cdot 5\right] + 2/3\left[70 \cdot 5 + 90 \cdot 5\right]$; however, targeting the parent alone or both may be, e.g., $1/3\left[95 \cdot 5 + 90 \cdot 5\right] + 2/3\left[95 \cdot 5 + 30 \cdot 5\right] < 1/3\left[70 \cdot 5 + 90 \cdot 5\right] + 2/3\left[70 \cdot 5 + 90 \cdot 5\right]$.

3 Survey and Data

3.1 Study Design and Sample Characteristics

Sample. Families were sampled with a choice-based design (i.e., at random within choices)[16] from the population of all 9th graders entering any public high school of the Municipality of

[16] See Manski and McFadden (1981) for a definition and for an introduction on the econometrics of different sampling schemes.

Verona, Italy in September 2007 (4,189 in total) and their parents. Children's participation reached almost 100% of the targeted sample (1,215 in total). Albeit lower ($\approx$ 60%), parents' participation was good for this type of surveys.[17] In the empirical analysis, I focus on the 1,029 families whose children were attending 9th grade for the first time. Tables 3 and 4 show the 2007-2008 distributions of curriculum enrollment in the population and in the estimation samples and basic break-downs by children's and parents' characteristics.

Design. The survey took place during the first 10 days of school, and questions were posed retrospectively with reference to the time of the final choice.[18] Children completed a 50-minute paper-and-pencil questionnaire during class, assisted by an interviewer. Parent questionnaire, instead, was self administered at home during the following 7-10 days, and returned in a sealed envelope for collection.

Two important features of the study are collection of field (as opposed to experimental) data and use of a retrospective (as opposed to a prospective) approach. Choice of the former was motivated by the high-stakes and once-and-for-all nature of the analyzed choice that may not be easily simulated or manipulated experimentally (Dosman and Adamowicz, 2006). The latter appeared to be the most sensible choice within the context of a one-time data collection. First and foremost, actual choices were observed by design and could thus be combined with expectations data. Second, respondents could provide their probabilistic expectations and stated choice preferences with reference to a point in time–a relatively recent past before the final decision was made–which is likely to vary across families and would be hard to capture for everybody within a prospective non-longitudinal framework. The obvious downside is that this approach relies on respondents' capability to unbiasedly report their expectations and choice preferences before the choice, that is, net of family interactions during the final decision.

3.2 Subjective Data

Family Decision Rule. Child and parent perception of the family decision rule was elicited by means of the following question (here worded for the child).[19]

Which one of the following statements best describe the WAY in which CHOICE of the high school curriculum for you was made in your family? Please mark one only.

[17]Average participation masks some differences across family decision rules, with lowest participation among parents of children reporting unilateral decision by self. As long as decision rule selection and curriculum choice are separable, this is not particulary problematic for the current analysis, since parental beliefs and choice preferences are only used for estimation of models (R2) and (R3), whose subsamples have the highest parental participation (up to 80%).

[18]Questions were preceded by the following introduction: "The next set of questions will ask you about YOUR attitude toward choice of the high school curriculum for you [your child] and YOUR opinion about each curriculum available to you [your child] with reference to the period PRECEDING the final choice. Therefore, while answering the ENTIRE set of questions of this section, please, try to think about the LAST SCHOOL YEAR when your family had NOT yet CHOSEN the curriculum, NOR had it HAD the MAIN/FINAL DISCUSSION(S) about it."

[19]In the survey, the battery of questions pertaining family decision making was placed after the expectations and stated preferences battery, in order to minimize any risk that the former would influence the latter.

(A) We realized pretty soon that in our family we had the SAME IDEA	○
(B) We DISCUSSED within our family till we reached a COMMON DECISION based on some COMPROMISE	○
ONLY ONE PERSON took the final decision, AFTER RECEIVING INFORMATION from the others and/or AFTER LISTENING to their OPINIONS	
Indicate who decided:	
(C) Myself	○
(D) My father	○
(E) My mother	○
(F) Other person, specify:	○
ONLY ONE PERSON made the final decision, WITHOUT discussing or exchanging OPINIONS with others	
Indicate who decided:	
(G) Myself	○
(H) My father	○
(I) My mother	○
(L) Other person, specify:	○

Answers to this question and to a follow-up question eliciting identities of all persons the decision maker talked to were used to classify reported family decision rules into the three processes previously described.[20] Table 3 shows the sample distribution of family decision rules reported by children: child chooses unilaterally ($\approx 27\%$), child chooses after listening to his parent(s) ($\approx 35\%$), and child and parent made a joint decision ($\approx 38\%$). The fraction of families for which no rule or a different rule was reported was below 5% and dropped from the sample.[21]

Insofar as parents are generally thought to play a substantial role in curriculum choice, these numbers may look surprising. However, a comparison of child and parent stated preferences with the actual family's choice reveals that only 14% of children did not have their own way versus 40% of parents (see tables 6 and 7). And a further comparison of child and parent knowledge of each other preferences in table 5 suggests that, while parents know their children's preferences better than viceversa on average, **(R1)** parents are less knowledgeable of their

[20] "Child chooses unilaterally" **(R1)** includes the case in which the child talked to any person different from his parents and, hence, it groups part of **(C)** and all **(G)**. "Child chooses after listening to the parent" **(R2)** covers part of **(C)**. "Child and parent make a joint decision" **(R3)** includes **(A)** and **(B)**. "Parent chooses after listening to the child" and "parent chooses unilaterally" were constructed symmetrically, but not used in the empirical analysis. Additionally, when either **(A)** or **(B)** was selected, respondents were asked a follow-up question eliciting identity of the decision maker in the counterfactual situation in which no agreement or compromise would be reached. Answers to this question and other information were used to define the "relevant" or "representative" parent.

[21] Following existing studies of parenting in developmental psychology and economics (e.g., Bumpus et al. (2001) and Cosconati (2011)), I use children's reports of the family decision rule. This choice is particularly warranted by the fact that administration of the student questionnaire was assisted by trained interviewers (instead of being self administered) and avoids issues related to selection in parental participation.

children's preferences.[22]

Stated Preferences and School Counseling. Choice preferences were elicited by means of the following question.

Try and think about your [your child's] situation last year, when you were [he was] still in your [his] third year of junior high school. [In the common introductory paragraph to expectations and stated preference questions.] ***Please, RANK the following curricula from the one YOU like BEST to the one you like the LEAST for yourself [your child], considering the criteria YOU considered important for choosing among them. Start by assigning 1 to YOUR FAVORITE curriculum, then proceed by increments of 1 till YOUR LEAST preferred one. The same number may not be assigned to two different schools.***

Curriculum (either standard or laboratory)	**Rank**
Vocational - Commerce	
Vocational - Industrial	
Technical - Commerce or Social	
Technical - Industrial	
Technical - Surveyors	
Artistic Education	
General - Humanities	
General - Languages	
General - Learning or Social Sciences	
General - Math and Sciences	

Hence, the question task for an **(R2)** child, for example, required him to report his probabilistic beliefs and curriculum ranking (corresponding to those beliefs) at the time before the final choice was made, that is, between stage 1 and stage 2 of the model described in the previous section. Notice that this is a weaker and more plausible requirement than asking respondents to report their beliefs before stage 1.[23]

Child and parent stated preferences will generally not coincide with the family's actual choice due to child-parent interactive decision making. Table 6 shows that the proportion of families in which the chosen curriculum does not coincide with the child's stated preferred alternative is approximately 13-14% (columns 1 and 2). This figure is intuitively smallest among families whose children reported making a unilateral decision (column 3), and it increases slightly among families employing multilateral decisions (columns 4 and 5). On the other hand, actual choices and parents' stated choice preferences do not coincide in 40% of families (table

[22] This pattern concords with recent independent evidence on family participation in adolescents' lives. For instance, in the 2006 survey of "Adolescents' Habits and Life Styles" (Tucci, 2006) conducted by the Italian Society of Pediatrics on a sample of 1,251 children between 12 and 14, only between 34% and 40% of children reported that parents influenced their choice of the high school curriculum. Whereas, more that 50% of them believed that, independently of what applied to their own family, parents should provide an input in children's high school choice.

[23] Necessary validity conditions are (i) that respondents do not display forms of cognitive dissonance or ex-post rationalization in reporting their beliefs and stated preferences, and (ii) that no additional relevant information about curricula, especially the chosen one, has arrived since the choice was made, or (ii') that, if such information has arrived, it does not bias respondents' reports. Reassuringly, neither Zafar (2011) nor Arcidiacono et al. (2012) find evidence of cognitive dissonance among U.S. college students choosing their majors. I discuss this issue further in appendix B.2.1.

7). This percentage is intuitively highest among families in which children reported making a unilateral choice and decreases conditional on more interacted decision rules.

Family's actual choice and child's stated preferred alternative, however, do not coincide even for 11% of families whose children reported unilateral decision by self (see table 6). Taking reported decision rules at face value, this pattern may be explained by existence of some factors or constraints that affected the actual decision but were not factored in the stated preference reports. For instance, figures in table 8 show that in about 60% of cases in which child's SP and RP do not coincide, the latter does coincide with the orientation suggestion provided by the child's teachers. Hence, one possibility is that, children reported their choice preferences net of the influence that teachers' suggestions had in their choice. In the empirical analysis of section 4 I explore this possibility.

A separate interesting question is whether **(R3)** families select non-dominated alternatives, given individual members' choice preferences. Table 9 shows that these families fail to select an non-dominated alternative in less than 5% of cases in my sample, thereby supporting the Pareto principle implicit in Keeney and Nau (2011)'s model.

Probabilistic Expectations. Respondents were asked to report the percent chances with which they thought a list of outcomes would realize should the child attend each of the available curricula (i.e., both the curriculum that was eventually chosen and the counterfactual ones). The outcomes, reported below, were identical in child and parent questionnaires, with the exception of the last one (b_{11}: "making parents happy"). The list was constructed from existing qualitative evidence on curriculum choice (Istituto IARD, 2001, 2005), and includes (i) the main components of achievement during high school, (ii) opportunity, choices, and returns after graduation, and (iii) aspects of child-parent interdependent preferences and peers' interdependent choices.

Outcome	**Description**
$b_{j1} = 1$	**Taste:** The child enjoys curriculum j-specific subjects.
$b_{j2} = 1$	**Effort:** In curriculum j the child spends $\geq$ 2.5h a day studying or doing homework.
$b_{j3} = 1$	**Performance I:** The child graduates from curriculum j in any length of time.
$b_{j4} = 1$	**Performance II:** The child graduates from curriculum j in the regular time.
$b_{j5} = 1$	**Performance III:** The child graduates from curriculum j in the regular time *and* with a yearly GPA $\geq$ 7.5.
$b_{j6} = 1$	**College vs. Work:** Curriculum j provides the training needed for either some university field(s) or for work in some liked occupation(s).
$b_{j7} = 1$	**College enroll.:** The child enrolls in college after graduating from curriculum j.
$b_{j8} = 1$	**College fields:** Attending curriculum j enables the child to choose among a wide range of fields in college.
$b_{j9} = 1$	**Liked jobs:** The child finds a liked job after graduating from curriculum j.

Outcome	**Description** (continued)
e_{j1}	**Expected earnings I:** The child's expected earnings at 30 with a diploma from curriculum j and no college.
e_{j2}	**Expected earnings II:** The child's expected earnings at 30 with a diploma from curriculum j *and* a college degree.
$b_{j10} = 1$	**Peers:** Attending curr. j enables the child to be in school with his best friend(s).
$b_{j11} = 1$	**Parent(s):** The child makes his parent(s) happy by attending curriculum j.

School achievement can be thought of as the output of a human capital production technology such that combination of innate ability, effort, and previously acquired skills–as a minimal set of inputs–produce new skills over time (e.g., Todd and Wolpin (2003)). In general, study effort is costly. On the other hand, interest or taste for studying (in the current application, for specific subjects) may mediate the disutility of effort and affect skill production. It is therefore interesting to look at respondents' expectations about children's interest, effort, and performance (as a measure of achievement) in different curricula. Figure 1, for instance, shows the average beliefs about realizations of outcomes $\{\{b_{jn} = 1\}_{j\in\mathcal{J}}\}_{n=1}^{5}$ in students' and parents' samples, unconditional on the attended curriculum. Children and parents have similar perceptions of children's taste for subjects. However, parents appear to be more optimistic concerning their children's performance than children are, consistent with findings elsewhere (e.g., Fischhoff et al. (2000), Dominitz et al. (2001), and Attanasio and Kaufmann (2010)). Moreover, on average, parents anticipate smaller differences in children's effort and performance across curricula.

Children may believe that they would exert lower effort in curricula whose subjects they are less likely to enjoy and/or they are less good at. Alternatively, children may think they would study at least as much in those curricula–e.g., because they value school performance in general (as found by Stinebrickner and Stinebrickner (2011)), or because they are ability constrained. Figure 1 shows that while effort and interest for subjects do indeed tend to move together across curricula, the observed increase in the probability of a high study and homework effort–as one moves from vocational to technical to general curricula (with a big jump up for the latter)– and the corresponding decrease in the probability of a regular/high academic performance suggest that at least some children are likely to feel ability constrained with respect to general curricula. In turn, figures 4, 3, and 2 support this hypothesis, since only children from technical and vocational curricula (fig. 3 and 2) display the above dip in their hypothesized performance should they attend a general curriculum. On the other hand, children from general curricula (especially math and humanities) hold a higher probability of exerting high effort in those curricula–which they both like better and find more challenging–but without any substantial drop in performance.

Motivated by evidence suggesting that some families prefer curricula that, they believe, will enable children to hedge current uncertainty about future college and work choices (i.e., to postpone those choices), the survey elicited respondents' perception of the flexibility each curriculum would likely offer in the future college and work choices (outcomes $\{\{b_{jn} = 1\}_{j \in \mathcal{J}}\}_{n \in \{6,8\}}$).[24] In Giustinelli (2010), for instance, I find that respondents' beliefs about outcome b_8 and enrollment statistics from AlmaDiploma (2007*b*) for different fields by graduation curriculum concord in identifying the general math curriculum and the technology-oriented curricula (independent of the track) as the curricula providing greatest flexibility in the choice of field in college.[25] To capture this aspect and mitigate the assumption of risk neutrality implied by linear expected utility, the empirical specification of child and parent expected utilities incorporates, albeit in a somewhat reduced-form fashion, the two flexibility outcomes.[26]

Finally, the survey attempted to elicit children's expected earnings at the age of 30 under the two alternative scenarios of obtaining a high school diploma from each curriculum and of obtaining a college degree following graduation from each curriculum. However, item non-response for these questions was very high, especially among children ($\approx 65\%$). Most of them did admit that they had no sense whatsoever of the order of magnitude of a monthly salary. While a minority reported either the information received during orientation activities in junior high school or their parents' earnings. In turn, a number of parents left written notes on the survey instrument explaining that, beyond the difficulty of providing any meaningful forecast, they did not regard such a factor as particularly important for this choice. Be as it may, such low response rates prevented inclusion of expected earnings in the empirical specification of family members' expected utility.

4 Empirical Analysis

4.1 The "Unitary Family" Benchmark

Econometric Model. I use actual choices (RP data) together with children's and, alternatively, parents' probabilistic expectations to estimate two versions of a "unitary family" model of curriculum choice, which I take as a benchmark for the models accounting for heterogenous decision rules. In the first version, children are assumed to be the representative or relevant decision makers (i.e., $i \equiv c(f)$); in the second, such a role is played by parents (i.e., $i \equiv p(f)$).

Assuming i.i.d. type-I extreme value random terms, the probability of observing child c from

[24] *"I knew I would go to college and I could do well in any type of general high school. Then, they* [the parents] *said 'A scientific curriculum is better because you will have more options afterwards.' That is, this school will enable me to choose among a large number of fields in college."* (a boy attending a general math and science curriculum) (Istituto IARD, 2001, p.39)

[25] AlmaLaurea/AlmaDiploma is a consortium that collects data on attainment, college, and labor market outcomes of high school graduates in Italy with the aims of providing them with college orientation services and of facilitating matching of labor demand and labor supply for high school graduates (see http://www.almalaurea.it for details).

[26] Economic theory has shown that risk aversion can generate preference for flexibility both in presence and in absence of learning over time (Ficco and Karamychev, 2009).

family f attending curriculum $\tilde{j}$ is

$$P\left(\tilde{j}|\{\{P_{ijn}\}_{n=1}^{N}\}_{j=1}^{10};\{\{\alpha_j^i\}_{j=1}^{9},\{\Delta u_n^i\}_{n=1}^{N}\}\right)=\frac{exp\left(\mu^i\left[\alpha_{\tilde{j}}^i+\sum_{n=1}^{N}P_{i\tilde{j}n}\cdot\Delta u_n^i\right]\right)}{\sum_{j=1}^{10}exp\left(\mu^i\left[\alpha_j^i+\sum_{n=1}^{N}P_{ijn}\cdot\Delta u_n^i\right]\right)},\quad(2)$$

where α_j^i is an alternative-specific constant measuring the average effect of all unincluded factors and μ^i is the scale parameter inversely related to the variance of the error terms. Given the parametric assumptions for the random terms and after setting $\alpha_{10}^i = 0$ as a location normalization, the model's coefficients, $\{\alpha_j^i\}_{j=1}^{9}$ and $\{\Delta u_n^i\}_{n=1}^{N}$ with $i \in \{c, p\}$, are identified up to the scale factor, μ^i.

In practice, statistical identification of utility parameters relies on heterogeneity of decision makers' beliefs, which function as alternative- and individual-specific attributes of the conditional logit. It is therefore important to notice that under the commonly made assumption of homogeneous beliefs ("common priors") it would not be possible to identify and estimate utility weights of outcomes. Moreover, given observed heterogeneity in respondents' beliefs, using population probabilities rather than individual beliefs to explain choice would amount to model misspecification. Finally, it is worth clarifying that my approach does not provide a test for the other commonly made assumption of rational expectations. Indeed, my analysis is fully consistent with a scenario in which all agents hold rational expectations while facing fully heterogenous stochastic processes.[27]

Estimation of (2) from actual choices requires taking choice-based sampling into account. I use Manski and Lerman (1977)'s weighted exogenous sampling maximum likelihood (WESML) estimator (described in appendix A), on the ground that it is computationally tractable and provides a constrained best predictor of the discrete response even when the logit assumption is not correct (Xie and Manski, 1989). This approach, however, requires knowledge of the population enrollment shares for the school year 2007-2008 to calculate weights that make the likelihood function behave asymptotically as under random sampling. I obtained this information from the Provincial Agency for Education of Verona.

I additionally estimate (2) using child and parent stated choice preferences (SP data) as response variables, and I compare the estimates thus obtained with those from actual choices.[28] In this case the sampling scheme can be thought of as equivalent to one of "intercept-&-follow" with choice-based recruitment or interception. McFadden (1996) shows that for the

[27] See Delavande (2008), Hurd (2009), and Pantano and Zheng (2010) for further discussion and examples.

[28] Estimates from the SP model should not necessarily be interpreted as strictly providing trade-offs children and parents (would) make under unilateral decision making, since this would require that members of families employing multilateral decision rules (and non-decision makers of families using a unilateral rule) be presented with a *counterfactual* stated choice scenario explicitly worded in terms of individual decision making. And it would additionally require that decision makers of families employing a unilateral decision rule be presented with a stated choice scenario making explicit reference to the actual choice situation. Yet, since respondents were asked to report their beliefs and preferences before the final discussion(s) and choice took place within their family, SP data will contain useful information on individual preference structures of children and parents over outcome realizations.

basic case without persistent heterogeneity across choice situations and for the sole purpose of parameter estimation–as opposed to recovery of other population quantities which would still require re-weighting–data from choice situations other than the interception can be treated as if sampling were random. This will naturally apply also to the joint SP-RP models presented later, as made transparent by the formal framework for choice-based sampling with multiple data sources presented in appendix A.

Revealed Preferences. Table 10 shows estimates of utility parameters of the basic benchmark model from actual choices. Significance levels are based on robust asymptotic standard errors derived by Manski and Lerman (1977) (see robustness discussion in appendix B.1). All specifications include alternative-specific constants (estimates not shown for reasons of space), whose overall significance is confirmed by a Likelihood Ratio (LR) test. The adjusted LR index reported in the bottom row of the table measures the percent increase in the value of the log-likelihood calculated at parameter estimates relative to its value under equal chances (i.e., no model), and it should neither be interpreted as the R^2 of a linear regression nor be used to compare specifications that are not estimated on the same sample of data.

Estimates from children's subjective expectations (columns 2-5) display the expected (positive) signs, perhaps with the exception of the effort outcome (b_2), whose utility coefficient would be rather hypothesized to be negative. The most important outcome is taste for subjects (b_1), whose coefficient is approximately 2.5 times larger than that of facing a flexible college field's choice (b_8), 3.5 times larger than that of graduating in the regular time (b_4), and approximately 5 times larger than those of finding a liked job after graduation (b_9), attending college (b_7), and facing a flexible college-work choice (b_6). Utility parameters for these outcomes are all significant at 1%, as opposed to that for being in school with friends (b_{10}) which, somewhat surprisingly, is barely significant.

Qualitative results do not change when pleasing one's parents (b_{11}) is introduced in column 3, although this outcome turns out to be the third most important one after child preference for core subjects and facing a flexible college field choice. Similarly, inclusion of a dummy capturing the orientation suggestion by teachers (columns 4 and 5) induces only marginal changes in the estimates, mostly by making the coefficient of effort not significant.[29] However, the corresponding utility coefficient is significant and approximately 4 times smaller in magnitude than that of preference for subjects. This is true despite the fact that the information content of teachers' suggestions should be already incorporated in individual expectations. It is therefore possible that teachers' counseling affects curriculum choice through additional channels–e.g.,

[29]The orientation dummy is equal to 0 both when no suggestion was provided *and* when a track was suggested but no curriculum was specified, and is equal to 1 otherwise. A specification constraining utility coefficient of the suggestion indicator to 0 when the child (parent) received a suggestion but declared it was not considered in the choice produced identical results. Sample size of columns 4 and 5 is lower than that of columns 2 and 3 because of item non-response to the orientation question.

by suggesting a specific consideration set and/or "appropriate" weighting of outcomes.[30]

Columns 6-7 display estimates from analogous specifications based on parental expectations. The implied similarity of preference ranking over outcomes to that obtained from children's expectations confirms the similarity of children's and parents' beliefs documented in a preliminary descriptive analysis (Giustinelli, 2010, Chpt. 2). To ease comparison between children's and parents' utility weights, columns 8-13 display estimates from the same specifications as in columns 2-7 but obtained from families in which expectations were available for both child and parent. Because estimated coefficients measure the product of utility weights, $\{\Delta u_n^i\}_{n=1}^N$, and scale parameter, μ^i, a quick way to check whether size of utility weights, as well, is similar between children and parents is to compare ratios (between pairs of outcomes) of coefficients estimated from each group, since such ratios are scale free.[31] Overall, children's expectations appear to have more explanatory power on actual choices than those of their parents, consistent with the descriptive evidence presented in subsection 3.2 that children have a more important role in the choice.[32]

Stated Preferences. Table 11 shows estimates from SP data.[33] A comparison with RP estimates (e.g., columns 5 of tables 10 and 11) reveals that the relative importance of different outcomes implied by children's stated choices and by actual choices differ somewhat. For instance, outcomes related to future opportunities and choices, such as finding a liked job after graduation and attending college, play a relatively more important role in explaining stated preferences than actual choices, while the opposite is true for some of the in-high-school outcomes, like graduating in the regular time. Moreover, the model based on SP data detects positive preferences for being in school with friends, but implies smaller weights on pleasing one's parents and on teachers' suggestion. Parents, too, assign higher importance to their children finding a liked job upon graduation and facing a flexible college-work choice based on stated preferences (e.g., columns 7 of tables 11 and 10), while the opposite is true about teachers' suggestion. The effort coefficient is now intuitively negative, but only among parents (though not statistically significant). Moreover, parents do not seem to assign a significantly positive weight on their children being in school with friends based on their stated preferences.

These differences in utility coefficients across data sources seem consistent with descriptive

[30]In fact, if teachers' suggestion is delivered in the form of one or more specific alternatives a child may successfully pursue but lacks detailed supporting motivations, families will face an inferential problem similar to that faced by an econometrician trying to recover decision makers' beliefs and utilities from choices.

[31]Estimates of utility parameters may be also evaluated and compared in terms of the change they imply in predicted choice probabilities when expectations for specific outcomes and alternatives change marginally. These calculations are not shown for reasons of space, but are available upon request. Unfortunately, the high item non-response prevented me from including expected earnings and, thus, deriving willingness-to-pay calculations.

[32]In fact, the higher level of significance of children's expectations for almost all outcomes may also suggest greater underlying heterogeneity in preferences among children.

[33]Existing evidence from stated ranking data supports significant differences across rank levels with decreasing stability of ranking information as the rank of an alternative decreases (BenAkiva et al., 1991). I therefore estimate the SP models using the highest ranked curriculum rather than the complete ranking of alternatives.

evidence from interest, effort, and performance expectations shown in section 3.2 suggesting that at least some fraction of children are likely to feel ability constrained with respect to the most challenging curricula. Hence, while part of this may be coming in through teachers' suggestions as well, children and parents may not have fully accounted for these "constraints" when reporting their stated preferences.[34]

I next pool RP and SP data together, and I exploit their distinct information contents together with information on family decision rules to separately identify family decision weights from child and parent utility weights (subsection 4.2). Specifically, I estimate a distinct discrete choice model for each observed family decision rule, thereby making the conceptual framework presented in subsection 2.3 operational.

Heterogeneity. While I do necessarily impose restrictions on utility and decision parameters between SP and RP models *within* family decision rules, I do not impose any restriction *across* models describing different decision processes. This is because child and parent preference structures are likely to vary across families employing different decision rules, as suggested by raw correlations between observed family rules and actual choices in the data.[35]

Utilities' heterogeneity between children and parents and across decision rules are the only forms of systematic or observed heterogeneity I explore in this paper. It is of course possible that utilities of outcomes may vary with decision makers' characteristics, such as gender and family background, and even with their beliefs. While there would be neither conceptual nor computational difficulties in introducing systematic heterogeneity by specifying a functional form for how individual characteristics enter utility parameters, because of the relatively small sample sizes available for estimation of the rule-specific models relative to the already large number of estimated parameters, I prefer not to pursue this line. This notwithstanding, given the correlation pattern existing between family decision rules, actual choices, and background characteristics, allowing for heterogeneous family rules will itself provide indirect evidence about utilities' heterogeneity across the latter.[36]

[34] In appendix B.2.1 I discuss possible biases of stated preference data and how they are dealt with in the literature. Notice, however, that different from data on subjective expectations and family decision rules, stated preference data are not taken at face value, and are naturally treated within a latent-variable framework.

[35] Imposing homogeneous utility weights of children and parents across decision rules would actually strengthen identification, and would potentially enable me to estimate more general models of interactive child-parent decision with distinct aggregation weights for beliefs and utilities.

[36] A discrete choice model may additionally feature forms of unobserved heterogeneity that, if present, will generate correlation across alternatives' random utility components and cause the i.i.d. assumption to fail. In appendix B.2.2 I discuss one potential source of unobserved heterogeneity specific of SP-RP (and repeated SP and other logitudinal) settings, i.e., unobservable persistence across data sources. On the other hand, current works on choice modeling both within and outside economics stress the importance of analyzing alternative sources of heterogeneity, beyond heterogeneity in utility parameters, such as heterogeneity in choice sets and choice rules across decision makers (Adamowicz et al., 2008).

4.2 Heterogeneous Decision Rules

4.2.1 Econometric Models

Child Chooses Unilaterally (R1). Taking the information about family decision rules at the face value, if a child reports making curriculum choice without any major interaction with his parents, only his expectations and utilities should be relevant for the final choice. Hence, a first natural approach is to estimate children's utility weights from their subjective expectations and actual (or stated) choices, as follows.

- **Model with One Data Source.** This model is formally equivalent to the unitary benchmark in (2), with $i \equiv c(f)$, but is estimated on the subsample of children that reported making a unilateral choice. That is,

$$\max_{j\in\mathcal{J}} \Gamma^1_{fj} \equiv EU^{t,1}_{cj} = \alpha^{t,1}_j + \sum_{n=1}^{N} P_{cjn} \cdot \Delta u^{c,t,1}_n + \varepsilon^{t,1}_{cj}, \tag{3}$$

  where Γ^1_{fj} denotes family f's decision rule under unilateral decision making by child **(R1)** and $\varepsilon^{t,1}_{cj}$ is assumed i.i.d. type-I extreme value, with scale parameters $\mu^{t,1}$ and $t \in \{\text{RP}, \text{SP}\}$.

Alternatively, SP and RP data can be combined to increase estimation precision while gaining insight on possible differences between the two data generating processes.

- **SP-RP Joint Model.** The model is

$$\begin{cases} (RP,1): \quad \Gamma^1_{fj} = \alpha^{RP,1}_j + \sum_{n=1}^{N} P_{cjn} \cdot \Delta u^{c,1}_n + \varepsilon^{RP,1}_{fj} \\ (SP,1): \quad EU^{SP,1}_{cy} = \alpha^{SP,1}_y + \sum_{n=1}^{N} P_{cyn} \cdot \Delta u^{c,1}_n + \varepsilon^{SP,1}_{cy}, \end{cases} \tag{4}$$

  where j indexes actual choices (RP) and y indexes stated preferences (SP), with $j, y \in \mathcal{J}$. $\varepsilon^{RP,1}_{fj}$ and $\varepsilon^{SP,1}_{cy}$ are assumed i.i.d. type-I extreme value, with scale parameters $\mu^{RP,1}$ and $\mu^{c,SP,1}$ respectively. With no serial correlation between SP and RP error components, the resulting log-likelihood of observing the RP-SP pair (j, y) is the sum of the log-likelihoods of j and y, the former corrected for choice-based sampling (see appendix A).

The main difference between (4) and (3) is that the common component of the systematic portion of RP and SP expected utilities (i.e., $\sum_n P_{cjn} \cdot \Delta u^{c,1}_n$) enables identification and estimation of the SP/RP scale ratio, $\mu^1 = \mu^{c,SP,1}/\mu^{RP,1}$. Specifically, because $\text{Var}(\varepsilon^{RP,1}_{fj}) = (\mu^1)^2 \cdot \text{Var}(\varepsilon^{SP,1}_{cy})$, estimate of μ^1 can be used to investigate whether the two sources of data have approximately the same amount of random noise by testing $\mu^1 = 1$. In turn, testing equality of the RP and SP alternative-specific constants provides additional information on the relationship between RP and SP unobservables, since they capture the average effects of all unobserved factors.

Child Chooses After Listening to the Parent (R2). The system of latent expected utilities is

$$\begin{cases} (RP,2): \quad \Gamma^2_{fj} = \alpha^{RP,2}_j + \sum_{n=1}^N \Big[(1-w^{p,2}_n)\cdot P_{cjn} + w^{p,2}_n \cdot P_{pjn}\Big] \cdot \Delta u^{c,2}_n + \varepsilon^{RP,2}_{fj} \\ (c\text{-}SP,2): \quad EU^{SP,2}_{cy} = \alpha^{c,SP,2}_y + \sum_{n=1}^N P_{cyn}\cdot \Delta u^{c,2}_n + \varepsilon^{SP,2}_{cy}, \end{cases} \tag{5}$$

with $j, y \in \mathcal{J}$, and where $\varepsilon^{RP,2}_{fj}$ and $\varepsilon^{SP,2}_{cy}$ are i.i.d. type-I extreme value with scale parameters $\mu^{RP,2}$ and $\mu^{c,SP,2}$ and no serial correlation between SP and RP. Parent's utilities, instead, are estimated from a standard SP model,

$$(p\text{-}SP,2): EU^{SP,2}_{ph} = \alpha^{c,SP,2}_h + \sum_{n=1}^N P_{phn}\cdot \Delta u^{p,2}_n + \varepsilon^{SP,2}_{ph}, h \in \mathcal{J}. \tag{6}$$

Utility weights, $\{\Delta u^{c,2}_n\}_{n=1}^N$, are identified from heterogeneity in children's expectations, through the SP component of model (c-SP,2). The equality constraints on utility parameters between (c-SP,2) and (RP,2) and the add-to-one restrictions on the decision weights for each outcome makes it possible to back up the latter, $\{w^{p,2}_n\}_{n=1}^N$, from the RP model.[37] Being able to pin these weights down with some precision, however, will generally depend on how much variability exists in within-family differences in beliefs, and between child's stated choice and the family's actual choice across families. Once again, combination of SP and RP data yields identification of the SP-RP relative scale, μ^2.

Child and Parent Make a Joint Decision (R3). The model is

$$\begin{cases} (RP,3): \quad \Gamma^3_{fj} = \alpha^{RP,3}_j + \phi^{c,3}\sum_{n=1}^N \Big[P_{cjn}\cdot \Delta u^{c,3}_n\Big] + (1-\phi^{c,3})\sum_{n=1}^N \Big[P_{pjn}\cdot \Delta u^{p,3}_n\Big] + \varepsilon^{RP,3}_{fj} \\ (c\text{-}SP,3): \quad EU^{SP,3}_{cy} = \alpha^{c,SP,3}_y + \sum_{n=1}^N P_{cyn}\cdot \Delta u^{c,3}_n + \varepsilon^{SP,3}_{cy} \\ (p\text{-}SP,3): \quad EU^{SP,3}_{ph} = \alpha^{p,SP,3}_h + \sum_{n=1}^N P_{phn}\cdot \Delta u^{p,3}_n + \varepsilon^{SP,3}_{ph}, \end{cases} \tag{7}$$

with $j, y, h \in \mathcal{J}$. $\varepsilon^{RP,3}_{fj}$, $\varepsilon^{SP,3}_{cy}$ and $\varepsilon^{SP,3}_{ph}$ are i.i.d. type-I extreme value with scale parameters $\mu^{RP,3}$, $\mu^{c,SP,3}$, and $\mu^{p,SP,3}$ and no serial correlation across data sources. The identification argument for (7) is analogous to that of (5), but it requires the additional restriction of equal relative scales for (c-SP,3) and (p-SP,3).

4.2.2 Estimation Results

Utility weights. Estimates of children's utility parameters are displayed by family decision rule in tables 12, 13, and 15, which also include estimates of decision weights described below.

[37] Taking ratios of SP and RP utility coefficients separates $\{w^{p,2}_n \cdot \mu^2\}_{n=1}^N$ and $\{(1-w^{p,2}_n)\cdot\mu^2\}_{n=1}^N$ from $\{\Delta u^{c,2}_n\}_{n=1}^N$. Further taking ratios between $\{w^{p,2}_n \cdot \mu^2\}_{n=1}^N$ and $\{(1-w^{p,2}_n)\cdot\mu^2\}_{n=1}^N$ for each outcome isolates $\{w^{p,2}_n\}_{n=1}^N$.

Whereas parents' utility parameters, shown in tables 14 and 15, are estimated for groups **(R2)** and **(R3)** only, because of low participation of **(R1)** parents.

Taste for subjects is confirmed to be the most valued outcome by both children and parents, as well as across families using different decision rules and across data sources. The difference in utility generated by the prospect of having to study and do homework for at least 2.5 hours daily versus not having to is negative for the **(R1)** children and positive, but not significant, for the other two groups. This coefficient is negative also for **(R2)** and **(R3)** parents, but it is not significant. Because the **(R1)** subsample is mostly populated by boys attending curricula with less homework and home study and more manual laboratory classes (e.g., vocational and technical industrial curricula and artistic track), this pattern is suggestive of differential disutility of academic effort among these groups.

The importance rank of graduating in the regular time, between 3rd and 5th among all outcomes, is fairly stable across models; however, its relative magnitude (with respect to taste for subjects) is highest in the **(R2)** group and lowest in the **(R1)** group. Again, this may be capturing differential preferences for a regular path among high ability students and girls, more represented in the former group (see table 4). On the contrary, this outcome does not appear to be particularly important for parents, since its coefficient is not significantly different from 0 in all specifications and groups.

As far as being in school with friends is concerned, its utility weight is positive among children and negative among parents for most specifications, but never significant. Finally, when the the possibility of making parents happy is introduced, qualitative results do not change and, similar to the benchmark model, the coefficient for this outcome is always positive and usually significant. Its relative importance, however, vary across decision rules, being substantially higher among **(R1)** children. Hence, to the extent that children have some knowledge, albeit imperfect, of their parents' choice preferences, this finding suggests that even **(R1)** parents are likely to play a role in their children's choice, perhaps more indirectly.

Moving to post-graduation outcomes, **(R2)** children display a relatively strong preference for being able to make a flexible college field choice, second most important outcome to them after enjoying the subjects, followed by finding a liked job after graduation and making a flexible college-work choice. **(R3)** children, too, place a high preference on making a flexible college field choice, whose coefficient is comparable in magnitude to that of attending college. This pattern is intuitive given that these two groups are made of relatively high ability and high socio-economic background students, more concentrated in general curricula (see table 4). Less intuitive is the fact that parents assign higher importance ranks and relatively higher weights to finding a liked job immediately after graduation and to making a flexible college-work choice than to making a flexible college field choice and to attending college, respectively.

The picture for **(R1)** children is somewhat more complex. On the one hand, their SPs imply a strong and intuitive preference for finding a liked job immediately after graduation. On the other hand, estimates obtained from RP data generate significant utility weights on attending college, followed by making a flexible college-work choice, and a non-significant coefficient for finding a liked job immediately after graduation. To shed light on some of these differences I combine RP and SP data and let preference coefficients vary across data sources one outcome at the time. I generally cannot reject the null hypothesis of equal SP and RP coefficients based on an LR test, with the exceptions of making a flexible college field choice and finding a liked job after graduation. Hence, in columns 11 and 13 of table 12 (specifications S5 and S6 respectively) I allow coefficients of the those two outcomes to vary between (RP,1) and (SP,1), while constraining the remaining ones to be equal in the two models. A LR test rejects the fully constrained specifications S2 and S4 in favor of S5 and S6.[38]

Another difference between RP and SP for group **(R1)** concerns teachers' orientation. As previously hypothesized, the RP model implies a stronger role for the orientation dummy, whose coefficient is approximately twice as large as that implied by the SP data. And even larger differences are observed for the other two groups, **(R2)** and **(R3)**, where the orientation dummy is usually not significantly different from 0 in the SP component of the model. Because the same expectations data are used to estimate the SP and RP utility parameters, this finding suggests existence of an additional channel, beyond that of expectations, through which teachers affect actual choices but not stated preferences.[39] This channel could be utility parameters directly and/or families' consideration set. The former may occur if, for instance, teachers were to publicize institutionally-sound criteria of curriculum choice (e.g., by saying that children should focus on their attitudes instead of letting themselves being influenced by their friends' choices), thereby offering second-order preferences that children may adopt through a process of alignment of their first-order preferences to the former.[40] The latter may occur if teachers' opinions and recommendations were to affect choice sets used by families, thereby by inducing them to consider alternatives that they would not consider otherwise or, viceversa, to drop alternatives that they would seriously consider otherwise.

Differences between SP and RP data generating processes can be further investigated by inspecting the SP/RP scale parameter and the alternative-specific constants. For the **(R1)** group I cannot reject the hypothesis that $\mu^1 = 1$, nor a model with the RP and SP constants

[38]A possible explanation is what the SP literature calls "prominence," i.e., respondents' tendency to focus only on few most important attributes or not to consider situational constraints when responding stated choice questions. While prominence would seem more likely to occur in stated choice tasks with hypothetical scenarios or in the kinds of SP-off-RP experiments analyzed by Train and Wilson (2008), here it would imply that SPs and RPs do not coincide in more cases than they should. Hence, if present, this type of response bias would go in the opposite direction of the "inertia or justification bias" generated, e.g., by mechanisms of ex-post rationalization discussed in appendix B.2.1.

[39]Endogeneity of the orientation dummy may be an alternative or additional explanation. However, if SP data are measured with sufficient accuracy the endogeneity effect should show up also in the SP model, which does not seem to be the case, at least for the **(R2)** and **(R3)** groups.

[40]Of course this would require relaxing the assumption, maintained by this paper, that individuals' utility structures are hardwired and cannot be manipulated via policies enacted by socialization agents. See Karniol (2010) for a theory of socialization that develops this idea.

constrained to be equal to one another by alternative. These findings indicate that for the group of children that reported making a unilateral decision the unobservable processes underlying RP and SP are reassuringly similar. On the other hand, μ^2 and μ^3 are significantly different from 1 in all specifications, and range from 0.45 to 0.65, meaning that the variance of the unobserved components of the SP model is between 2.5 and 5 times larger than the variance of the RP model. A larger SP variance is a common finding in the SP-RP empirical literature (Morikawa, 1994). This is not surprising, since SP data are usually elicited from stated choice experiments under hypothetical scenarios in which respondents generally have only a subset of the information they would have in actual choice situations. Hence, as pointed out by Manski (1999), stated choice experiments tend to elicit preferences mixed with individual expectations of events that may affect choice behavior and are not included in the proposed scenario. While in my setting the SP task in one of recall and not one of hypothetical choice, it is possible that the additional noise is indeed related to the mental process of recollection and abstraction respondents were required to perform.

Decision weights. Inspection of table 13 (top panel) reveals that variability in child-parent expectation differences pins down decision weights, $\{\widehat{w_n^{p,2}}\}_{n=1}^N$, with some precision only for few outcomes. For instance, parents' opinion about their children's performance in school receives a higher weight than children's own opinion. The estimated weight on parental belief for this outcome ranges from 0.626 to 1.120, depending on the specification; however, all values between 0.5 and 1 are compatible with the estimates, and for some specifications even a weight of 0 cannot be rejected. The weight on parents' belief about their child's preference for subjects is estimated precisely and lies between 0.411 and 0.457. The hypothesis of equal weights cannot be rejected, while 0 and 1 are rejected for all specifications. The weight on facing a flexible college field choice, instead, favors children's opinion, and values above 0.5 can generally be rejected. As for the remaining outcomes, weights are estimated imprecisely and are, therefore, compatible with any value between 0 and 1. Despite this, a model with equal weights across outcomes is rejected for all specifications.

In the top panel of table 15, weights on the child expected utility, $\{\widehat{\phi_n^{c,3}}\}_{n=1}^N$, for **(R3)** families range between 0.295 and 0.370, and are precisely estimated; both 0 and values of 0.5 or above are rejected. This confirm the important explicit role of the **(R3)** parents in their children's curriculum choice.

Of course, these estimates rely on the decision-making unit and decision process being correctly specified. To shed some light on potential misspecification, I test the multilateral decision models, **(R2)** and **(R3)**, against the unilateral model **(R1)** and against one another. Since the unilateral model is nested in both of the multilateral models, I perform an LR test for whether all weights on parental beliefs are equal 0 in table 13, and for whether the child weight is equal

1 in table 15. The null hypothesis is rejected in both cases.

I finally estimate the **(R2)** model on the **(R3)** subsample, and I compare it with the child-parent joint decision model, and viceversa for the **(R2)** subsample. Since the two models are not nested, I use Ben-Akiva and Lerman (1985, p. 171-174) test comparing the adjusted LR indeces of the two models being tested, i.e., $P\left(\bar{\rho}_B^2 - \bar{\rho}_A^2 > z\right) \geq \Phi\{-[2 \cdot N \cdot z \cdot ln(J) + (K_B - K_A)]^{1/2}\}$ with $z > 0$, where all N observations in the sample have all J alternatives and K_A and K_B are the number of parameters of the two models. Based on this test, the **(R2)** specification in which the child chooses after listening to the parent is found to be statistically superior for both **(R2)** and **(R3)** groups. On the other hand, an alternative specification of the joint decision model featuring outcome-specific weights (not shown for reasons of space) is rejected in favor of the basic model with a unique weight.

5 Counterfactual Analysis

Galileo and Michelangelo, Resumed. In this paper I maintain the standard assumption that utilities of outcomes are "hardwired" and cannot be manipulated by policies. On the other end, preference for subjects are uncertain in the model, and individuals hold subjective beliefs about them. It is therefore possible that "awareness" or "desensitization" campaigns may influence choice behavior by affecting beliefs on taste. Hence, in table 16 I simulate two scenarios in which family members' beliefs about whether the child would enjoy the subjects of specific curricula change by a fixed amount. Specifically, in the top panel I calculate the percent change in predicted enrollment shares following a 10-point increase in reported percent chances (by children, parents, and both) that the child would enjoy the core subjects of the math-and-science curriculum **(policy 1)**. Whereas, in the bottom panel I report the corresponding changes following a 10-point drop in the percent chances that the child would like subjects of the artistic curriculum **(policy 2)**. Calculations are done separately for the pooled samples (unitary models) and for families using different decision rules.

These hypothetical policies generate, for all groups and models, an intuitive increase of the probability of enrolling in the math-and-science curriculum and a drop of the art enrollment probability. Choice probabilities of all other curricula display the opposite pattern. Such changes, however, are heterogeneous across models and targeted recipients, suggesting that family decision rule and identity of the targeted group(s) matters. For instance, assuming a unitary model with parents as representative decision makers sizeably overestimates the magnitude of enrollment response to awareness and desensitization campaigns implied by the heterogenous model (+18.93 vs. +12.07 for math-and-science awareness, and -18.91% vs. -13.28% for art desensitization). Whereas a unitary model based on children's expectations generates much closer predictions (+11.16% vs. +12.07 and -13.77% vs. -13.28%, respectively).

Publication of Education Statistics. I then simulate policies that make curriculum-specific statistics available to families.[41] Specifically, in the top panel of table 17 I calculate the percent changes in predicted enrollment probabilities following publication of the 2006 graduation rates (conditional on a regular path) by curriculum, based on AlmaDiploma (2007*a*)'s statistics **(policy 3)**. Instead, in the bottom panel I show percent changes in predicted enrollment probabilities following disclosure of the AlmaDiploma (2007*b*)'s statistics on 2006 college enrollment by graduation curriculum **(policy 4)**. These statistics are the most recent ones that could have been made available to families of my sample, whose children entered high school in Fall 2007.

Both **policy 3** and **policy 4** generate an intuitive though moderate increase in predicted enrollment for general curricula, especially the humanities and math, and a corresponding drop in predicted enrollment for vocational and artistic curricula. In turn, decomposition of counterfactual enrollment response by family decision rule shows that publication of education statistics would have a larger impact on children reporting unilateral decision by self. While this cannot be taken as an unambiguous sign that these children have less precise beliefs, this would indeed be one possible explanation. For example, families in which parents have a greater involvement in their children's choice may be relying more on statistics and on other "hard" information from teachers, schools, and orientation in stage 1.

An obvious shortcut of these calculations is their reliance on the assumption that, if given such information, families would use these statistics at the face value. That is, even though families would likely update their beliefs, there is no reason to believe that they would slavishly adopt population probabilities in place of individual-specific ones, as confirmed by evidence from experiments with U.S. college students (Wiswall and Zafar, 2011). In fact, an alternative interpretation of these counterfactuals may be that they provide estimates of the prediction error made by an econometrician assuming common prior beliefs across (and within) families for these outcomes.

Institutional Policies. In table 18, I simulate the effects of changes in families' beliefs generated by two institutional-type policies. **Policy 5** lowers educational standards and equalizes them across curricula by guaranteeing all students to pass all grades on the first try.[42] In practice, I assume that under this scenario family members would change their subjective probabilities that the child would follow a regular school path to 1 for all curricula, keeping expectations for the other outcomes constant.

[41] Recent field experiments in both developed and developing countries study the effect on education choices and related outcomes of disclosing information about school-specific test scores, returns to schooling, financial aid opportunities, etc. (see Hastings and Weinstein (2008), Jensen (2010), and Dinkelman and Martinez (2011) among others). Indeed, most high schools in Verona, and Italy more generally, publish on their web pages school-level statistics (e.g., passing rates between grades) and post-graduation outcomes (e.g., college enrollment by field and job placement by sector) of older cohorts.

[42] While taken literally this policy may appear unrealistic and certainly not desirable, its dynamics are similar to those generated by the introduction of "educational debits" or "fail credits" by the Law 425-1997, subsequently modified by the Law 1-2007. *De facto* this system enabled children with grades below the passing level in one or more subjects to progress through school grades by contracting "educational debits" that could be (easily) cleared at some later time.

Policy 6, instead, strengthens specialization by preventing access to university following any diploma of the vocational type, similar to the Italian secondary system before the 1969 reform that opened university access to students graduating from technical and vocational schools. In the simulation I assume that, under this scenario, individuals would change their subjective probabilities of going to college, of facing a flexible college-work choice, and of facing a flexible choice of field in college to 0 following graduation from any vocational curriculum.

As expected, the first intervention busts enrollment in general curricula and in some technical curricula while depressing enrollment in vocational and artistic curricula. Responses, however, do not seem large. Once again the pattern is attenuated, and in some cases reversed, among **(R2)** children who are likely to be the least ability constrained. The second intervention, instead, induces a huge drop in vocational enrollment, mostly in favor of technical schools. The result is intuitive: children who value the possibility of going to college after graduation, but would enroll in a vocational curriculum if the restriction were not in place, would now switch to curricula of the "lowest" track ensuring eligibility for enrolling in college. Finally, decomposition by decision rule shows that if parents only were aware of policies changing institutional features of tracking, the impact of such policies may be smaller than it would be if children, too, were informed.

6 Relationship with Existing Research

6.1 Curricular Stratification, Intergenerational Transmission, and Career Decisions under Uncertainty

Most schooling systems feature some form of stratification or tracking, which can be by ability (e.g., in the U.S.), curricular, or a combination of the two (e.g., most European countries). The distinctive purpose of the latter forms is to provide educational specialization so that children with different aptitudes and aspirations may pursue careers in different areas and requiring different types of expertise. Yet, significant cross-country variation exists in how stratification is implemented, depending on its time, the allocation mechanism of children into tracks, and the extent of specialization and separation of different tracks.[43] In turn, these variables are the main determinants of the (form and degree of) uncertainty faced by families regarding their children's education paths and future outcomes: On the one hand, the earlier a child's age at tracking the longer the future he must anticipate and the less the accumulated history of past

[43] A sizeable literature in economics of education studies how institutional features of a stratified schooling system affects its efficiency (e.g., Ariga et al. (2012)) and equity (e.g., Brunello and Checchi (2007)). Prominent issues are the tension between breadth and depth of education and the determination of the optimal time of tracking (e.g., Brunello et al. (2007)). For example, in the OECD group children's age of first tracking ranges between 10 in Austria and Germany to 18 in Canada and the U.S., and 15 and 16 are modal (Brunello and Checchi, 2007). As for sorting, typical mechanism are testing (e.g., in Germany) and family choice (e.g., in Italy). Finally, as far as rigidity is concerned, a fully rigid stratification (e.g., Germany) is characterized by the impossibility of switching between tracks during compulsory education and by barriers to college enrollment following graduation from lower vocational-type tracks.

school performance he can use to form expectations on his tastes, ability, and future outcomes; on the other hand, the stronger and more rigid is specialization, the more difficult are wrong choices to be costlessly corrected or corrected at all.

The Italian system is characterized by a relatively early age of tracking (at high school entry) mitigated, at least in principle, by family choice as a sorting device, and by flexibility mechanisms enabling both track switching during high school (*passerelle* or "bridges") and enrollment in university following any 5-year diploma from any track. Anecdotal and sociological evidence (Istituto IARD, 2001, 2005), however, suggests that Italian families, especially children, believe that a wrong training in high school will generally carry a cost in the form of an inadequate preparation for college (or work), and unfavorably perceive track switching as likely yielding a longer time to graduation. Hence, these flexibility mechanisms do not appear to unambiguously reduce the uncertainty accompanying an early curricular stratification.

Tracking during compulsory education thus renders curriculum choice a (early) career decision which, as such, requires a large investment in training and is *per se* characterized by uncertainty on individual ability and investment returns (e.g., Altonji (1993)). My work contributes to existing empirical studies of curriculum choice with early curricular stratification (e.g., Checchi and Flabbi (2007)) by modeling uncertainty explicitly, but without imposing strong assumptions on how youths and their parents form expectations on future choice-dependent outcomes (see Manski (1993) and references therein).

Some scholars have further claimed that track choice by families (as opposed to testing) ultimately translates into a greater dependence of children's paths on family background, thereby hampering intergenerational mobility (Checchi and Flabbi, 2007). According to this view, curriculum choice may be a channel through which parents end up creating children in their own image (*à la* Bisin and Verdier (2001)), rather than improving their children's condition (as in Doepke and Zilibotti (2008)). However, while intergenerational transmission of preferences and beliefs from parents to children is commonly considered to be the main vehicle for either possibilities, very little is known in practice of how children and parents perceive uncertain dimensions of curriculum choice and of what roles children and parents play in it. Hence, a second contribution of the data collection and the empirical analysis carried by this work is to provide new evidence on some these issues.

6.2 Parenting and Decision Making by Children

The literature on curriculum choice posits a crucial role of family background (e.g., Checchi and Flabbi (2007) and Giuliano (2008)). To the best of my knowledge, however, no existing study has explicitly modeled the roles played by children and parents in this choice. Kalenkoski (2008) and Attanasio and Kaufmann (2010) are partial exceptions. Kalenkoski (2008) rejects the unitary preference model in favor of a bargaining model of youths' post-secondary education decision in which child and parent disagree on the level and parental financing of education. However, her model does not feature uncertainty. Attanasio and Kaufmann (2010) analyze high school and college enrollment decisions in rural Mexico with data from *Progresa* and find that both children's and parents' expectations matter for the former, while only youths' expectations are relevant for the latter. However, they do not model the child-parent decision process explicitly.

In truth, identification of a proper decision-making unit for this type of choice is not at all unambiguous. The main difficulty is that, on the one hand, adolescents undergo development of their preferences and capabilities for communication, formal reasoning, and independent action; on the other hand, they still rely on parental guidance and support. In particular, while adolescents appear old enough to play an active role in their schooling decisions, their level and rate of autonomy acquisition will generally vary with their traits, ability, environment, as well as parental preferences, resources, and parenting style (Lundberg et al., 2009*a*,*b*). It seems, therefore, natural to hypothesize existence of heterogeneous decision rules across families, ranging from unilateral to more interactive processes.

This notwithstanding, to date only a recent handful of studies have challenged the unitary view of household behavior (Becker, 1981) in the context of educational choices of children and adolescents. Usually, these works develop non-cooperative models of child-parent interactions with moral hazard motivating empirical applications of children's school attendance (or achievement) using data from field experiments in developing countries. For instance, Bursztyn and Coffman (Forthcoming) study adolescents' school attendance in Brazilian *favelas*, and provide evidence that child-parent conflicts play an important role via the parents' difficulty of monitoring their children's actions. Whereas Berry (2012) tests whether identity of recipients (i.e., children or parents) of cash incentives for school achievement (e.g., enrollment and attendance) in India affects their effectiveness.[44]

My paper contributes to this stream of works by analyzing a different schooling choice margin (i.e., the "type" rather than "quantity" of human capital, though the two are clearly related in presence of curricular stratification) and by explicitly modeling heterogeneous rules of child-parent decision making with no strategic interaction. The latter choice is justified by the fact that in my setting children and parents are assumed to solve the same problem. That is, even though in this paper I do not model family selection into decision rules, which I take as given, the underlying idea is that interactive decisions may occur whenever communication of opinions, information, and preferences can improve quality of choice.

[44] These papers and mine fit in with an emerging literature studying child-parent interactions and decision-making, and their consequences on children's outcomes (e.g., Weinberg (2001), Burton et al. (2002), Hao et al. (2008), Cosconati (2011), etc.). These studies model child-parent interactions as non-cooperative games for, under the influence of earlier works exploring limitations of Becker (1981)'s Rotten Kid Theorem (e.g., Bergstrom (1989)), they consider the standard assumption of (inter-spouses) bargaining (that binding, costlessly enforceable agreements can support an efficient solution) not plausible in the child-parent context (see Lundberg et al. (2009*a*) for a discussion).

7 Conclusions

This paper introduces subjective risk and heterogeneous rules of child-parent decision making in a simple behavioral model of family choice of the high school track. Its main contribution lies in the original combination of novel data on self-reported probabilistic beliefs, choice preferences, and decision roles of children and parents with standard data on actual choices to recover parameters capturing how children and parents individually make trade-offs among uncertain choice outcomes and parameters describing different rules of child-parent decision making.

The general message of the paper is that disentangling beliefs and utilities of individual decision makers from the decision process through which those beliefs and utilities are combined is fundamental for prediction and for policy analysis. Within the current application, descriptive analysis and counterfactuals suggest that the economics of the family needs to provide a formal accommodation of adolescent decision making, and that the economics of education needs to take into account the channels through (and extent to) which parents affect children's human capital decisions–whether because they want to make their children in their own image or, on the contrary, because they wish to help them face better opportunities and make better choices.

Inevitably, this work relies on simplifications and assumptions concerning both the theoretical framework and the data. Future efforts should be devoted to modeling and analysis of selection into family decision processes. There are several reasons why families may tackle important decisions concerning their children's future heterogeneously. Excellent longitudinal data on youths' choices and outcomes, background characteristics, and social context have been collected for decades by large representative surveys, such as the PSID, NLSY, and ADDH. To help furthering our understanding of why families employ certain decision styles and ultimately make the choices we observe about children's human capital, it would be fruitful to couple current data with better information on individual family members' choice preferences, beliefs and information, and the incentives and constraints they pose to each other.

Table 3: Observed Choices and Family Decision Rules

Curriculum	**Population**[a] (%)[b]	**"Unitary"**[c] **Model All**	**"Unitary"**[d] **Model Matched**	**Rule 1**[c] **Reported by Child**	**Rule 2**[e] **Reported by Child**	**Rule 3**[f] **Reported by Child**
Vocational - Commerce	320 (7.64)	86 (8.62)	36 (6.25)	14 (8.23)	13 (5.94)	12 (5.04)
Vocational - Industrial	311 (7.43)	51 (5.11)	17 (2.95)	11 (6.47)	3 (1.37)	7 (2.94)
Total Vocational	631 (15)	137 (13.73)	53 (9.20)	25 (14.70)	16 (7.31)	19 (7.98)
Technical - Commerce-Social	742 (17.72)	100 (10.02)	57 (9.90)	17 (10)	17 (7.76)	26 (10.92)
Technical - Industrial	521 (12.44)	85 (8.52)	55 (9.55)	25 (14.70)	13 (5.94)	28 (11.76)
Technical - Surveyors	285 (6.81)	96 (9.62)	67 (11.63)	23 (13.53)	18 (8.22)	29 (12.18)
Total Technical	1548 (36.9)	281 (28.16)	179 (31.08)	65 (38.23)	48 (21.92)	83 (34.86)
Total Artistic	177 (4.2)	76 (7.62)	15 (2.60)	18 (10.59)	5 (2.28)	5 (2.10)
General - Humanities	395 (9.43)	172 (17.23)	123 (21.35)	16 (9.41)	52 (23.74)	52 (21.85)
General - Languages	168 (4.01)	59 (5.91)	33 (5.73)	6 (3.53)	22 (10.05)	8 (3.36)
General - Education-Social Scie.	330 (7.89)	100 (10.02)	57 (9.90)	18 (10.59)	29 (13.24)	21 (8.82)
General - Math and Science	940 (22.43)	173 (17.33)	116 (20.14)	22 (12.94)	47 (21.46)	50 (21.01)
Total General	1833 (43.8)	504 (50.49)	329 (57.12)	62 (36.47)	150 (68.49)	131 (55.04)
Total	4189 (100)	998 (100)	576 (100)	170 (100)	219 (100)	238 (100)
Family Decision Rule				170 (27.11)	219 (34.93)	238 (37.96)
Total				627 (100)	627 (100)	627 (100)

[a] Source: Provincial Agency for Education of Verona (Italy).

[b]: Percentages in parentheses.

[c]: After dropping families with item non-response to any child's expectation questions.

[d]: After dropping families with item non-response to any expectation questions.

[e]: After dropping families with item non-response to any expectation questions, child did not report his stated preferred curriculum, or responding parent is different from relevant parent.

[f]: After dropping families with item non-response to any expectation questions, child and/or parent did not report his/her/their stated preferred curriculum/a, or responding parent is different from relevant parent.

Table 4: Background Characteristics

Background Characteristics	Unitary Model Sample	Rule 1 Sample	Rule 2 Sample	Rule 3 Sample
Gender				
Male	433 (43.39)	92 (54.12)	72 (32.88)	115 (48.32)
Female	561 (56.21)	78 (45.88)	147 (67.12)	123 (51.68)
Non-response	4 (0.40)	0 (0)	0 (0)	0 (0)
Child's country of Birth				
Italy	907 (90.88)	153 (90.00)	211 (96.35)	229 (96.22)
Foreign Country	86 (8.62)	16 (9.41)	8 (3.65)	9 (3.78)
Non-response	5 (0.50)	1 (0.59)	0 (0)	0 (0)
Father's Country of Origin				
Italy	846 (84.77)	137 (80.59)	203 (92.69)	220 (92.44)
Foreign Country	79 (7.92)	17 (10.00)	10 (4.57)	9 (3.78)
Non-response	73 (7.31)	16 (9.41)	6 (2.74)	9 (3.78)
Mother's Country of Origin				
Italy	830 (83.17)	137 (80.59)	201 (91.78)	220 (92.44)
Foreign Country	116 (11.62)	24 (14.12)	15 (6.85)	15 (6.30)
Non-response	52 (5.21)	9 (5.29)	3 (1.37)	3 (1.26)
Father's Education				
Junior high school or less	246 (24.65)	55 (32.35)	51 (23.29)	53 (22.27)
High school	372 (37.27)	54 (31.76)	95 (43.38)	107 (44.96)
College or more	192 (19.24)	29 (17.06)	46 (21.00)	48 (20.17)
Non-response	188 (18.84)	32 (18.82)	27 (12.33)	30 (12.61)
Mother's Education				
Junior high school or less	250 (25.05)	50 (29.41)	53 (24.20)	59 (24.79)
High school	448 (44.89)	73 (42.94)	119 (54.34)	116 (48.74)
College or more	173 (17.33)	25 (14.71)	41 (18.72)	51 (21.43)
Non-response	127 (12.73)	22 (12.94)	6 (2.74)	12 (5.04)
Child's Graduation Grade from Junior High School				
Excellent	190 (19.04)	17 (10.00)	74 (33.79)	61 (25.63)
Distinction	235 (23.55)	39 (22.94)	63 (28.77)	57 (23.95)
Good	291 (29.16)	49 (28.82)	47 (21.46)	73 (30.67)
Pass	249 (24.95)	62 (36.47)	28 (12.79)	43 (18.07)
Non-response	33 (3.31)	3 (1.76)	7 (3.20)	4 (1.68)
Total	998 (100)	170 (100)	219 (100)	238 (100)

Table 5: Child and Parent Knowledge of Each Other Choice Preferences

	Rule 1	**Rule 2**	**Rule 3**
Child reports his parent's preferred curriculum correctly	41.90%[a]	39.25%	45.61%
Parent reports her child's preferred curriculum correctly	48.71%[a]	60.34%	63.13%
Child says he doesn't know his parent's preferred curriculum/ Doesn't respond	31.82%[b]	28.51%	13.85%
Parent says she doesn't know her child's preferred curriculum/ Doesn't respond	18.14%[b]	12.68%	14.23%
Sample size	81	219	238

Matched sample. Family rule reported by child. Weighted data. [a] are likely upper bounds and [b] lower bounds of the population fraction due to high non-participation of **(R1)** parents.

Table 6: Family Revealed Preference (RP) and Child Stated Preference (C's SP)

	Unitary Model All	**Unitary Model Matched**	**Rule 1 Reported by Child**	**Rule 2 Reported by Child**	**Rule 3 Reported by Child**	**Total (1+2+3)**
RP $\equiv$ C's SP	836 (86.09)	475 (87.16)	151 (88.82)	194 (88.58)	207 (86.97)	552 (88.04)
RP $\neq$ C's SP	135 (13.91)	70 (12.84)	19 (11.18)	25 (11.42)	31 (13.03)	75 (11.96)
Total	971 (100)	545 (100)	170 (100)	219 (100)	238 (100)	627 (100)

Percentages in parentheses.

Table 7: Family Revealed Preference (RP) and Parent Stated Preference (P's SP)

	Unitary Model Matched	**Protocol 1 Reported by Child**	**Protocol 2 Reported by Child**	**Protocol 3 Reported by Child**	**Total (1+2+3)**
RP $\equiv$ P's SP	327 (60)	44 (54.32)	127 (59.07)	150 (63.03)	321 (60.11)
RP $\neq$ P's SP	218 (40)	37 (45.68)	88 (40.93)	88 (36.97)	213 (39.89)
Total	545 (100)	81* (100)	215* (100)	238 (100)	534 (100)

Percentages in parentheses.
*: Smaller size for these groups than in corresponding cells of table 6 is due to higher item non-response rates to the SP question among parents.

Table 8: Family Choice, Child SP, and Junior High School Suggestion - R1 Families

	RP ≡ JH	**RP ≠ JH**	**Marginals**
RP ≡ Child's SP	68 (55.74)	37 (30.33)	105 (86.07)
RP ≠ Child's SP	10 (8.20)	7 (5.74)	17 (13.93)
Marginals	78 (63.93)	44 (36.07)	122 (100)

Percentages in parentheses.

Table 9: "Group Rationality" - R3 Families

	RP P.O.	**RP ¬P.O.**	**Marginals**
RP≡C's SP≡P's SP	138 (57.98)	0 (0)	138 (57.98)
RP≡C's SP≠P's SP	69 (28.99)	0 (0)	69 (28.99)
RP≡P's SP≠C's SP	12 (5.04)	0 (0)	12 (5.04)
RP≠C's SP&P's SP	7 (2.94)	12 (5.04)	19 (7.98)
Marginals	226 (94.96)	12 (5.04)	238 (100)

Percentages in parentheses.

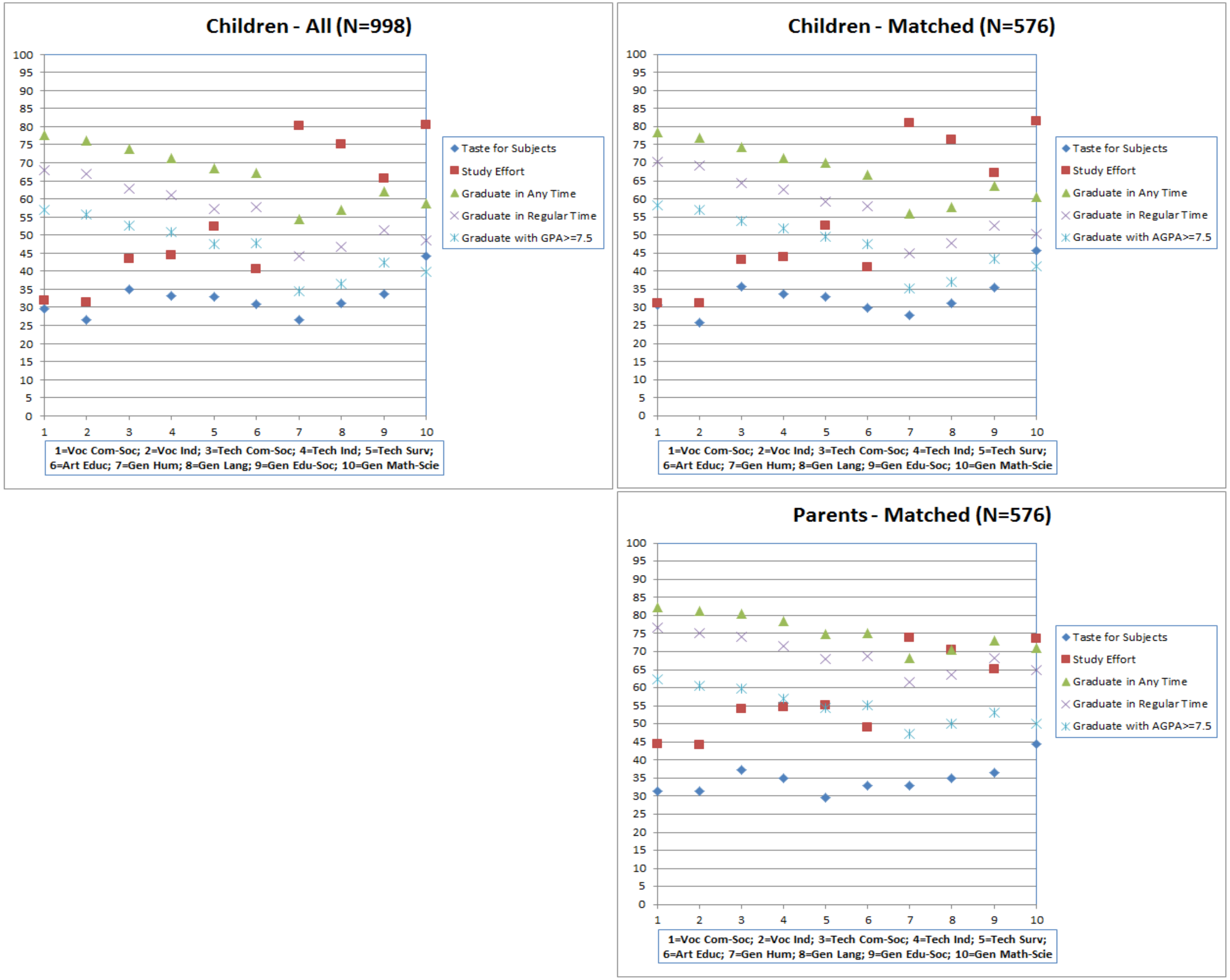

Figure 1: Children's and parents' average beliefs about taste for subjects, effort, and performance across curricula.

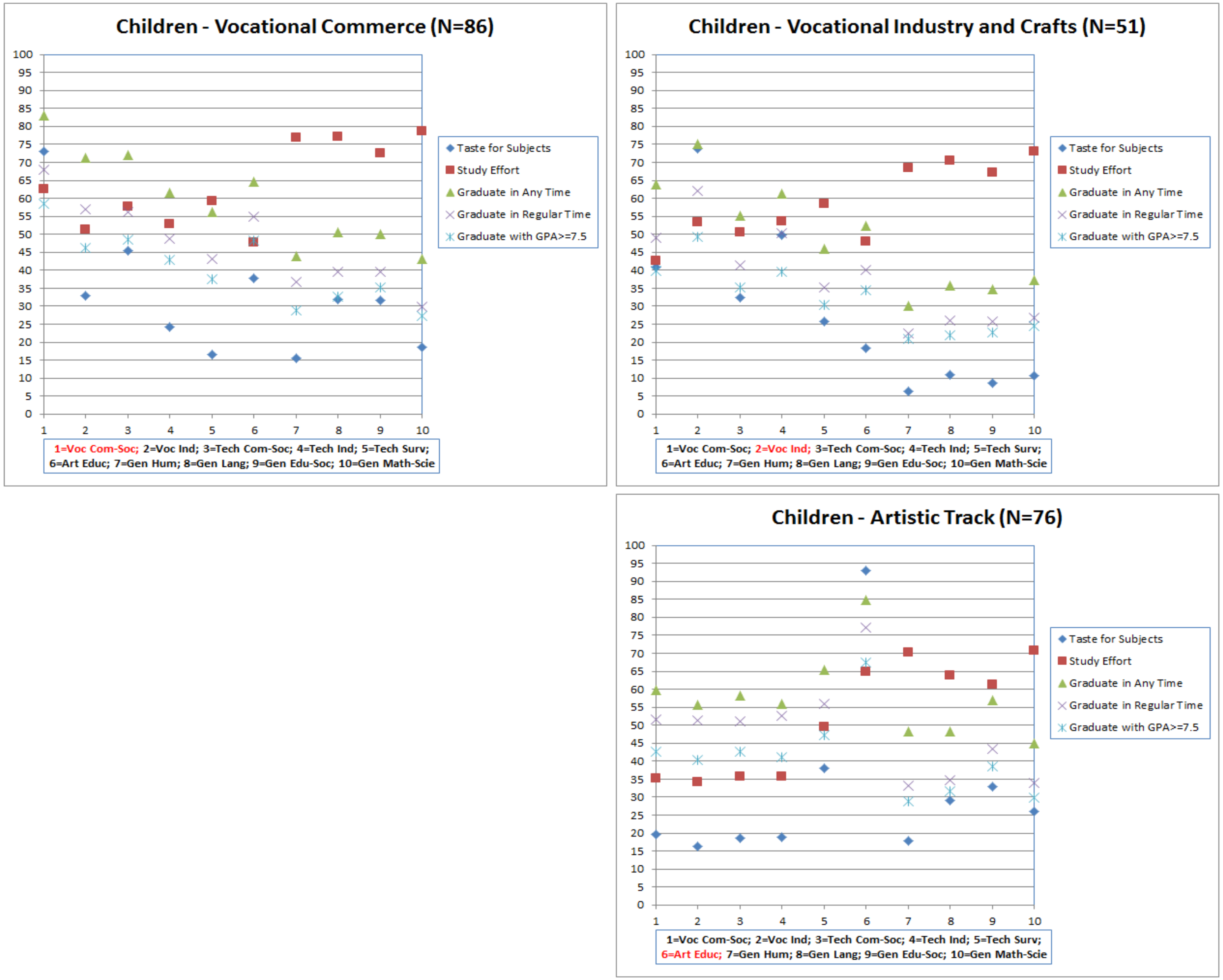

Figure 2: Average beliefs about taste, effort, and performance across curricula among children attending curricula of the vocational track.

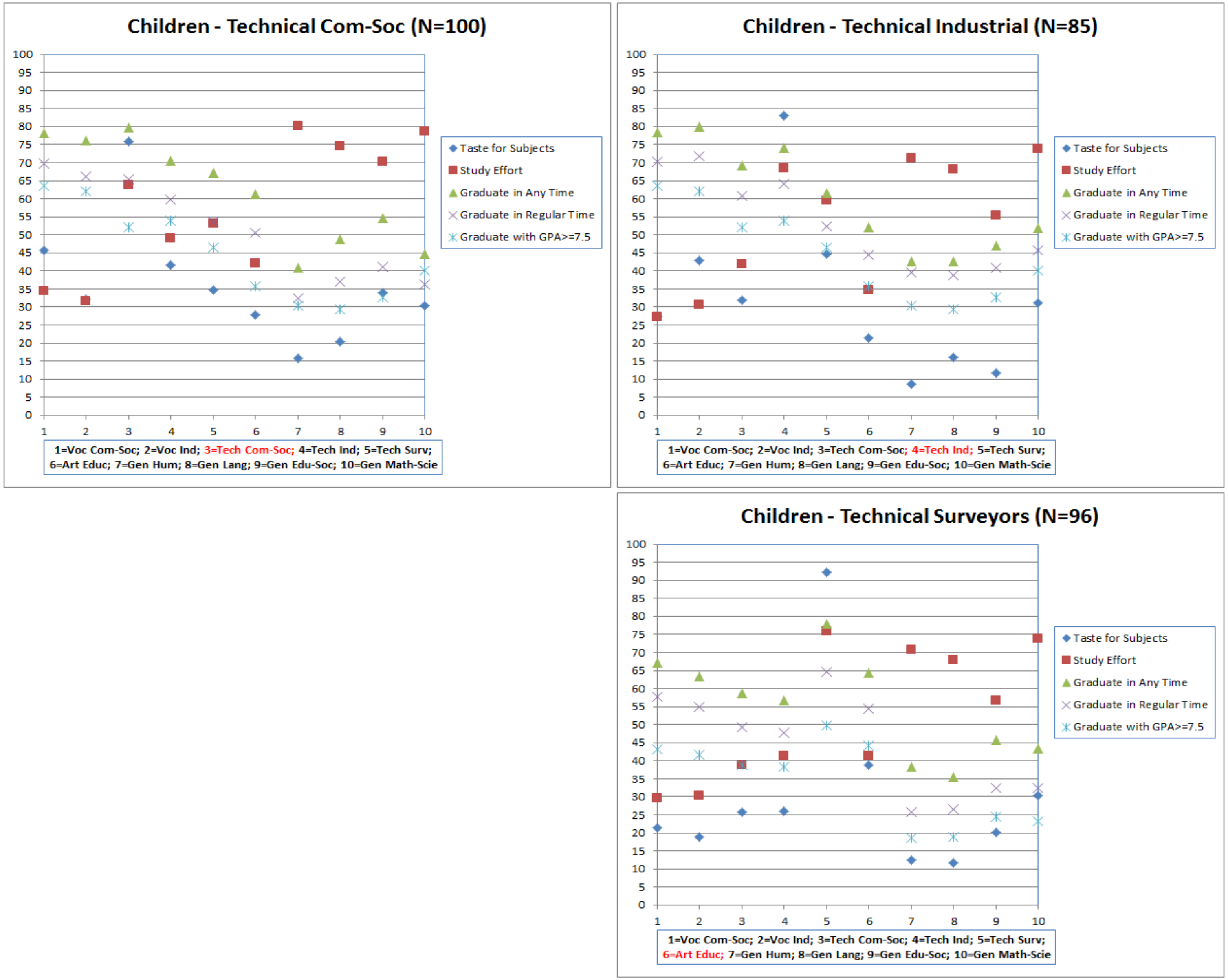

Figure 3: Average beliefs about taste, effort, and performance across curricula among children attending curricula of the technical track.

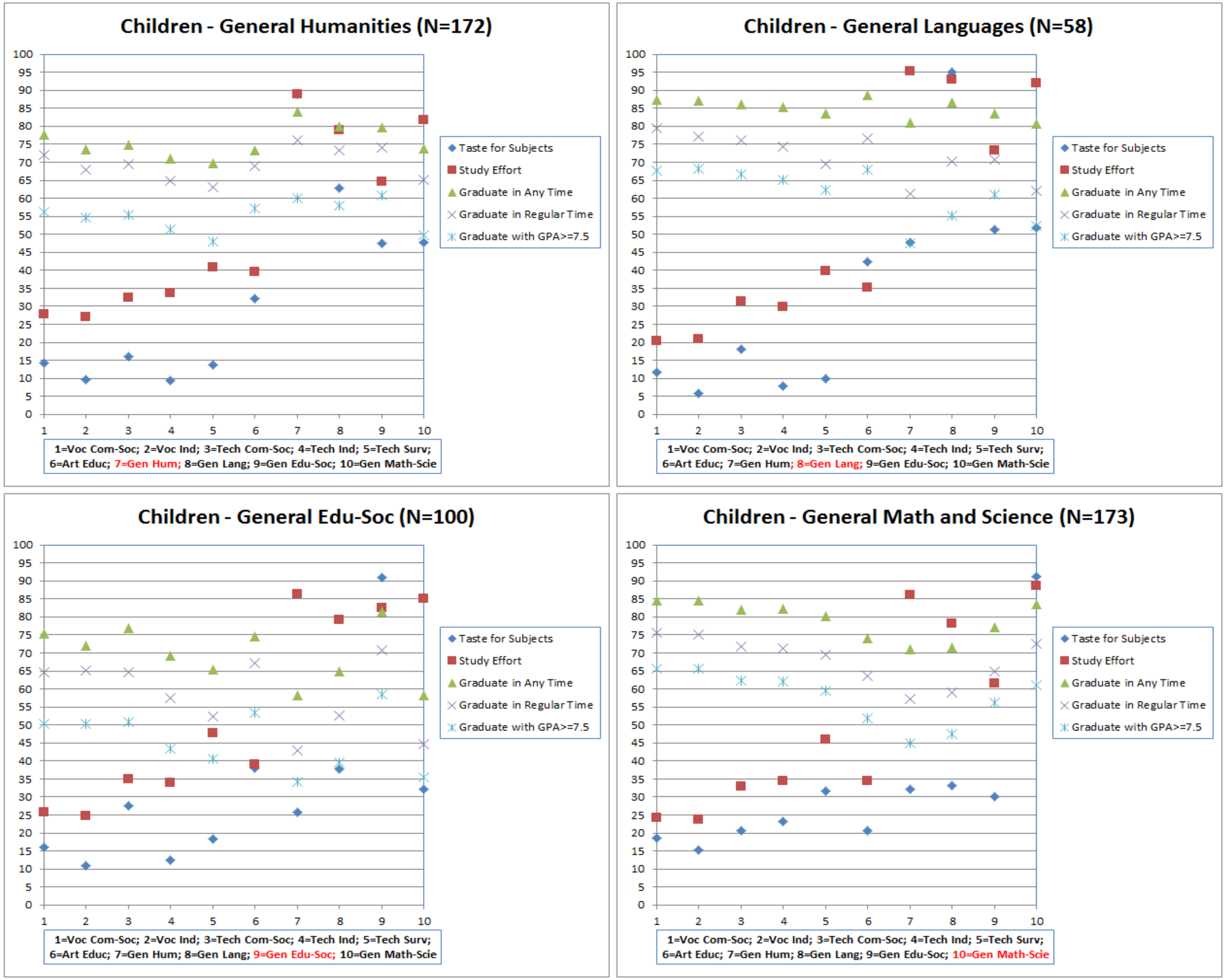

Figure 4: Average beliefs about taste, effort, and performance across curricula among children attending curricula of the general track.

Table 10: Unitary Benchmark with RP Data

	All Children and Parents						Matched Children and Parents					
	Children				Parents		Children				Parents	
Variables	**(S1)**	**(S2)**	**(S3)**	**(S4)**	**(S1)**	**(S3)**	**(S1)**	**(S2)**	**(S3)**	**(S4)**	**(S1)**	**(S3)**
Like Subjects (b_1)	5.94^{***} (0.41)	5.58^{***} (0.41)	6.05^{***} (0.50)	5.75^{***} (0.50)	8.14^{***} (0.64)	7.45^{***} (0.64)	6.12^{***} (0.57)	5.64^{***} (0.59)	5.79^{***} (0.63)	5.40^{***} (0.65)	8.10^{***} (0.63)	7.44^{***} (0.64)
Daily Homework $\geq$ 2.5h (b_2)	1.07^{***} (0.40)	0.91^{**} (0.42)	0.80 (0.49)	0.58 (0.51)	0.97 (0.61)	0.89 (0.69)	1.01 (0.66)	0.71 (0.66)	0.69 (0.75)	0.41 (0.75)	0.96 (0.61)	0.87 (0.68)
Graduate in Regular Time (b_4)	1.62^{***} (0.46)	1.59^{***} (0.46)	1.41^{***} (0.49)	1.45^{***} (0.49)	1.68^{**} (0.82)	1.68^{*} (0.87)	2.27^{***} (0.52)	2.30^{***} (0.55)	1.98^{***} (0.61)	1.98^{***} (0.64)	1.58^{*} (0.83)	1.54^{*} (0.88)
In School with Friend(s) (b_{10})	0.36 (0.24)	0.11 (0.25)	0.20 (0.28)	−0.05 (0.29)	0.69 (0.42)	0.69 (0.49)	0.33 (0.37)	0.02 (0.39)	0.13 (0.40)	−0.13 (0.41)	0.71^{*} (0.43)	0.70 (0.50)
Flexible College-Work Choice (b_6)	1.05^{***} (0.32)	0.96^{***} (0.32)	1.36^{***} (0.37)	1.21^{***} (0.39)	0.87^{*} (0.45)	0.99^{*} (0.53)	1.74^{***} (0.46)	1.49^{***} (0.49)	1.84^{***} (0.47)	1.65^{***} (0.50)	0.89^{**} (0.45)	1.03^{*} (0.53)
Attend College (b_7)	1.13^{***} (0.43)	0.92^{**} (0.46)	1.31^{**} (0.52)	1.22^{**} (0.56)	0.70 (0.65)	1.14 (0.78)	1.13^{*} (0.61)	0.90 (0.64)	0.74 (0.65)	0.52 (0.71)	0.70 (0.65)	1.13 (0.79)
Flexible College Field Choice (b_8)	2.40^{***} (0.47)	2.11^{***} (0.48)	2.58^{***} (0.64)	2.19^{***} (0.67)	2.64^{***} (0.62)	1.94^{***} (0.75)	3.59^{***} (0.77)	3.27^{***} (0.78)	3.84^{***} (0.87)	3.45^{***} (0.89)	2.59^{***} (0.63)	1.87^{**} (0.75)
Liked Job after Graduation (b_9)	1.16^{***} (0.30)	1.05^{***} (0.31)	1.09^{***} (0.36)	0.98^{***} (0.37)	1.18^{***} (0.47)	1.16^{**} (0.50)	1.13^{**} (0.45)	1.13^{***} (0.46)	1.01^{**} (0.47)	1.02^{**} (0.49)	1.19^{**} (0.47)	1.14^{**} (0.50)
Parent Happy (b_{11})	–	1.74^{***} (0.39)	–	1.74^{***} (0.49)	–	–	–	2.19^{***} (0.72)	–	2.01^{**} (0.78)	–	–
Teachers' Suggestion	–	–	1.59^{***} (0.19)	1.49^{***} (0.20)	–	1.90^{***} (0.21)	–	–	1.54^{***} (0.25)	1.43^{***} (0.24)	–	1.91^{***} (0.21)
Constants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood ($LL(\hat{\theta})$)	-630.358	-612.273	-442.091	-429.431	-455.437	-379.272	-339.832	-326.477	-281.294	-271.957	-449.725	-373.192
Adjusted Likelihood Ratio Index ($\bar{\rho}^2$)	0.718	0.726	0.767	0.773	0.651	0.686	0.731	0.740	0.758	0.765	0.648	0.684
Sample Size	998		857		588	550	576		537		576	537

***: significant at 1%, **: significant at 5%, *: significant at 10%. Manski and Lerman (1977)'s asymptotic robust standard errors for Weighted Exogenous ML in parentheses. $\bar{\rho}^2 = 1 - [LL(\hat{\theta}) - K]/LL(0)$, where $LL(\hat{\theta})$ is the value of the log-likelihood at the parameter estimates, K is the number of the estimated parameters, and $LL(0)$ is the value of the log-likelihood under no model (Ben-Akiva and Lerman, 1985). Optimization performed in Matlab.

Table 11: Child and Parent Preferences from SP Data

	All Children and Parents						Matched Children and Parents					
	Children				Parents		Children				Parents	
Variables	**(S1)**	**(S2)**	**(S3)**	**(S4)**	**(S1)**	**(S3)**	**(S1)**	**(S2)**	**(S3)**	**(S4)**	**(S1)**	**(S3)**
Like Subjects (b_1)	7.11*** (0.53)	6.71*** (0.53)	7.22*** (0.62)	6.89*** (0.64)	4.08*** (0.29)	3.79*** (0.31)	7.06*** (0.65)	6.64*** (0.66)	7.05*** (0.74)	6.70*** (0.76)	4.06*** (0.30)	3.78*** (0.31)
Daily Homework (b_2)	0.79* (0.46)	0.64 (0.47)	0.50 (0.50)	0.32 (0.52)	-0.21 (0.42)	-0.20 (0.43)	0.20 (0.59)	0.08 (0.59)	2.18×10^{-3} (0.66)	-0.14 (0.67)	-0.19 (0.43)	-0.17 (0.44)
Graduate in Regular Time (b_4)	1.66*** (0.47)	1.54*** (0.48)	1.33** (0.52)	1.25** (0.53)	-0.12 (0.45)	-0.18 (0.48)	1.19** (0.60)	1.08* (0.60)	0.94 (0.62)	0.85 (0.62)	-0.19 (0.46)	-0.24 (0.48)
In School with Friend(s) (b_{10})	0.64*** (0.22)	0.49** (0.24)	0.66*** (0.23)	0.52** (0.25)	0.09 (0.31)	-0.02 (0.33)	0.74** (0.30)	0.61* (0.32)	0.78** (0.30)	0.64** (0.32)	0.09 (0.31)	-0.01 (0.34)
Flexible College-Work Choice (b_6)	0.70* (0.38)	0.55 (0.38)	0.57 (0.37)	0.42 (0.38)	1.05*** (0.35)	1.13*** (0.38)	0.69 (0.44)	0.51 (0.46)	0.64 (0.44)	0.52 (0.47)	0.97*** (0.35)	1.04*** (0.38)
Attend College (b_7)	2.01*** (0.46)	1.95*** (0.48)	1.58*** (0.47)	1.57*** (0.49)	0.37 (0.38)	0.39 (0.40)	1.36** (0.60)	1.16* (0.60)	1.03 (0.63)	0.87 (0.62)	0.37 (0.38)	0.39 (0.40)
Flexible College Field Choice (b_8)	2.52*** (0.52)	2.29*** (0.52)	2.35*** (0.54)	2.15*** (0.54)	1.29*** (0.46)	1.22*** (0.47)	2.81*** (0.71)	2.63*** (0.71)	2.53*** (0.71)	2.37*** (0.70)	1.26*** (0.46)	1.20** (0.47)
Liked Job after Graduation (b_9)	2.26*** (0.34)	2.30*** (0.35)	2.23*** (0.37)	2.26*** (0.38)	1.87*** (0.34)	1.94*** (0.37)	2.52*** (0.47)	2.57*** (0.47)	2.57*** (0.48)	2.61*** (0.49)	1.90*** (0.35)	1.97*** (0.37)
Parent Happy (b_{11})	–	1.57*** (0.41)	–	1.32*** (0.42)	–	–	–	1.46*** (0.54)	–	1.38** (0.55)	–	–
Teachers' Suggestion	–	–	0.38** (0.15)	0.31** (0.16)	–	0.64*** (0.16)	–	–	0.35* (0.19)	0.27 (0.18)	–	0.63*** (0.16)
Constants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood ($LL(\hat{\theta})$)	-515.229	-503.288	-433.089	-426.189	-709.581	-646.179	-300.042	-294.457	-276.285	-271.808	-696.524	-633.629
Adjusted Likelihood Ratio Index ($\bar{\rho}^2$)	0.762	0.767	0.766	0.769	0.433	0.447	0.747	0.751	0.749	0.752	0.431	0.445
Sample Size	971		836		557	522	545		510		545	510

***: significant at 1%, **: significant at 5%, *: significant at 10%. Asymptotic robust standard errors in parentheses. $\bar{\rho}^2 = 1 - [LL(\hat{\theta}) - K]/LL(0)$, where $LL(\hat{\theta})$ is the value of the log-likelihood at the parameter estimates, K is the number of the estimated parameters, and $LL(0)$ is the value of the log-likelihood under no model (Ben-Akiva and Lerman, 1985). Optimization performed in Matlab.

Table 12: "Child Chooses Unilaterally" (R1)

	RP Model				SP Model				SP-RP Model			
Variables	**(S1)**	**(S2)**	**(S3)**	**(S4)**	**(S1)**	**(S2)**	**(S3)**	**(S4)**	**(S2)**	**(S5)**	**(S4)**	**(S6)**
Like Subjects (b_1)	6.76*** (1.16)	6.46*** (1.08)	6.30*** (1.38)	6.40*** (1.17)	6.16*** (1.02)	5.65*** (1.04)	5.86*** (1.13)	5.69*** (1.13)	5.98*** (1.13)	6.55*** (1.13)	5.72*** (1.19)	6.57*** (1.23)
Daily Homework $\geq$ 2.5h (b_2)	−0.05 (0.74)	−1.20 (0.82)	−1.18 (0.78)	−2.80*** (1.01)	0.57 (1.01)	−0.06 (1.01)	−0.04 (1.04)	−0.96 (1.11)	−0.66 (0.84)	−0.73 (0.89)	−1.77* (1.04)	−2.06* (1.12)
Graduate in Regular Time (b_4)	2.60*** (0.85)	2.91*** (0.87)	1.78* (0.99)	2.60** (1.11)	1.77* (0.98)	1.91* (1.03)	1.21 (1.03)	1.70 (1.10)	2.30*** (0.78)	2.59*** (0.85)	1.89** (0.87)	2.21** (1.00)
In School with Friend(s) (b_{10})	0.98* (0.51)	0.48 (0.54)	0.87 (0.61)	0.53 (0.62)	0.81 (0.55)	0.31 (0.58)	0.67 (0.59)	0.24 (0.70)	0.35 (0.46)	0.42 (0.50)	0.36 (0.59)	0.48 (0.64)
Flexible College-Work Choice (b_6)	1.66** (0.80)	1.55* (0.84)	2.94*** (0.98)	2.89*** (0.90)	0.75 (0.80)	0.43 (0.83)	1.14 (0.85)	0.92 (0.94)	0.95 (0.71)	1.14 (0.77)	1.74** (0.87)	2.08** (0.94)
Attend College (b_7)	3.87*** (1.02)	3.95*** (1.16)	4.68*** (1.49)	5.24*** (2.01)	2.37** (1.02)	2.53** (1.08)	2.30** (1.11)	2.37** (1.18)	3.20*** (0.92)	3.49*** (1.01)	3.48** (1.39)	4.02** (1.59)
Flexible College Field Choice (b_8) **RP**	0.47 (0.85)	0.32 (0.95)	−0.45 (1.02)	−1.22*** (0.89)	–	–	–	–	1.36 (0.88)	0.42 (0.97)	0.34 (0.82)	−1.08 (0.96)
Flexible College Field Choice (b_8) **SP**	–	–	–	–	2.52** (1.23)	2.41** (1.11)	1.51 (1.15)	1.46 (1.06)	–	2.87** (1.41)	–	1.65 (1.28)
Liked Job after Graduation (b_{10}) **RP**	0.86 (0.73)	0.88 (0.74)	1.30* (0.77)	1.47* (0.79)	–	–	–	–	1.81*** (0.69)	0.87 (0.77)	2.28*** (0.72)	1.23 (0.89)
Liked Job after Graduation (b_{10}) **SP**	–	–	–	–	2.84*** (0.81)	3.13*** (0.92)	3.13*** (0.80)	3.55*** (0.94)	–	3.55*** (1.12)	–	4.14*** (1.12)
Parent Happy (b_{11})	–	3.23*** (1.02)	–	3.52*** (1.13)	–	2.77** (1.22)	–	3.38** (1.37)	2.84*** (1.09)	3.22*** (1.18)	3.08*** (1.13)	3.65*** (1.28)
Teachers' Suggestion RP	–	–	2.38*** (0.64)	2.32*** (0.64)	–	–	–	–	–	–	2.33*** (0.64)	2.26*** (0.63)
Teachers' Suggestion SP	–	–	–	–	–	–	1.26*** (0.45)	1.14*** (0.44)	–	–	1.11** (0.48)	1.50** (0.61)
SP/RP Scale	–	–	–	–	–	–	–	–	1.008*** (0.120)	0.845*** (0.096)	1.010*** (0.134)	0.813*** (0.103)
Constants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood ($LL(\hat{\theta})$)	-92.110	-85.159	-61.820	-56.210	-92.839	-88.230	-74.944	-69.626	-178.309	-174.317	-131.176	-127.823
Adjusted Likelihood Ratio Index ($\bar{\rho}^2$)	0.721	0.736	0.759	0.773	0.719	0.729	0.720	0.733	0.736	0.739	0.757	0.759
Sample Size	170		144		170		144		170		144	

***: significant at 1%, **: significant at 5%, *: significant at 10%. Asymptotic robust standard errors in parentheses. $\bar{\rho}^2 = 1 - [LL(\hat{\theta}) - K]/LL(0)$, where $LL(\hat{\theta})$ is the value of the log-likelihood at the parameter estimates, K is the number of the estimated parameters, and $LL(0)$ is the value of the log-likelihood under no model (Ben-Akiva and Lerman, 1985). Optimization performed in Matlab.

Table 13: "Child Chooses After Listening to the Parent" (R2)–Family Model

Variables	(S1)	(S2)	(S2d)	(S3)	(S4)	(S4d)
Weights on Parent Beliefs						
Like Subjects (b_1)	0.433*** (0.047)	0.450*** (0.051)	0.457*** (0.056)	0.411*** (0.056)	0.434*** (0.059)	0.448*** (0.060)
Daily Homework $\geq$ 2.5h (b_2)	1.282 (2.534)	1.440 (2.470)	0.962 (1.106)	−0.073 (3.248)	−0.984 (13.953)	−1.930 (28.146)
Graduate in Regular Time (b_4)	0.626 (0.481)	0.669 (0.534)	0.698* (0.399)	1.021*** (0.343)	1.120** (0.447)	1.028*** (0.231)
In School with Friend(s) (b_{10})	−0.167 (1.141)	0.057 (1.174)	−0.474 (3.304)	0.113 (1.167)	0.710 (1.088)	0.386 (1.354)
Flexible College-Work Choice (b_6)	−0.113 (0.484)	0.099 (0.430)	0.181 (0.362)	0.047 (0.526)	0.296 (0.470)	0.373 (0.289)
Attend College (b_7)	−0.403 (1.905)	16.132 (37.568)	−1.919 (13.161)	2.180 (7.317)	1.131 (2.058)	0.702 (0.921)
Flexible College Field Choice (b_8)	0.204 (0.174)	0.249 (0.173)	0.187 (0.196)	0.231 (0.178)	0.229 (0.159)	0.204 (0.169)
Liked Job after Graduation (b_9)	0.545* (0.247)	0.494** (0.245)	0.503* (0.263)	0.411 (0.304)	0.281 (0.371)	0.218 (0.361)
Child Preferences						
Like Subjects (b_1)	12.64*** (2.24)	12.43*** (2.36)	12.20*** (2.32)	15.16*** (3.05)	15.38*** (3.56)	16.50*** (3.39)
Daily Homework $\geq$ 2.5h (b_2)	0.80 (1.54)	0.90 (1.57)	1.72 (2.04)	0.72 (2.05)	0.30 (2.12)	0.33 (3.16)
Graduate in Regular Time (b_4)	3.33** (1.57)	2.94* (1.53)	4.06* (2.30)	4.29** (2.05)	3.52* (1.79)	6.58** (2.57)
In School with Friend(s) (b_{10})	0.81 (0.84)	0.68 (0.90)	0.54 (1.33)	1.04 (0.91)	0.86 (0.94)	1.03 (1.45)
Flexible College-Work Choice (b_6)	2.44** (1.32)	2.66** (1.31)	3.60*** (1.28)	3.41** (1.59)	3.67* (1.87)	6.00** (2.42)
Attend College (b_7)	0.78 (1.68)	−0.08 (1.77)	0.36 (2.08)	−0.59 (1.67)	−1.42 (1.74)	−2.54 (1.96)
Flexible College Field Choice (b_8)	7.70*** (1.83)	7.88*** (2.01)	6.97*** (2.09)	9.23*** (2.47)	9.12*** (2.63)	8.43*** (2.56)
Liked Job after Graduation (b_9)	3.40*** (1.01)	3.25*** (1.01)	3.55*** (1.24)	3.83*** (1.39)	3.58** (1.40)	2.10 (1.89)
Parent Happy (b_{11})	–	2.53** (1.10)	2.32** (1.04)	–	3.43** (1.54)	3.66** (1.69)
Teachers' Suggestion RP	–	–	–	3.13*** (3.05)	3.08 (2.12)	3.30 (3.16)
Teachers' Suggestion SP	–	–	–	0.51 (2.05)	0.35* (0.179)	−4.33** (2.57)
RP Dummies	No	No	Yes	No	No	Yes
SP/RP Scale	0.608*** (0.122)	0.586*** (0.124)	0.348*** (0.089)	0.511*** (0.120)	0.488*** (0.126)	0.272*** (0.073)
Constants	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood ($LL(\hat{\theta})$)	-161.119	-156.909	-116.437	-132.824	-128.487	-93.125
Adjusted Likelihood Ratio Index ($\bar{\rho}^2$)	0.806	0.807	0.839	0.820	0.824	0.851
Sample Size		219			205	

***: significant at 1%, **: significant at 5%, *: significant at 10%. Asymptotic robust standard errors in parentheses. $\bar{\rho}^2 = 1 - [LL(\hat{\theta}) - K]/LL(0)$, where $LL(\hat{\theta})$ is the value of the log-likelihood at the parameter estimates, K is the number of the estimated parameters, and $LL(0)$ is the value of the log-likelihood under no model (Ben-Akiva and Lerman, 1985). Optimization performed in Matlab.

Table 14: "Child Chooses After Listening to the Parent" (R2)–Parent Preferences

Variables	(S1)	(S1d)	(S3)	(S3d)
Like Subjects (b_1)	4.07*** (0.49)	2.76*** (0.49)	4.02*** (0.53)	2.96*** (0.51)
Daily Homework $\geq$ 2.5h (b_2)	−0.65 (0.74)	−0.80 (0.68)	−0.45 (0.78)	−0.48 (0.73)
Graduate in Regular Time (b_4)	−0.32 (0.76)	−0.64 (0.71)	−0.39 (0.77)	−0.43 (0.71)
In School with Friend(s) (b_{10})	0.03 (0.44)	0.04 (0.42)	−0.15 (0.48)	−0.12 (0.41)
Flexible College-Work Choice (b_6)	1.37** (0.55)	1.34** (0.55)	1.50*** (0.57)	1.56*** (0.56)
Attend College (b_7)	0.20 (0.64)	−0.06 (0.59)	0.22 (0.66)	−0.16 (0.62)
Flexible College Field Choice (b_8)	1.56** (0.75)	1.55** (0.72)	1.52** (0.73)	1.47** (0.71)
Liked Job after Graduation (b_9)	2.34*** (0.58)	2.35*** (0.58)	2.33*** (0.61)	2.30*** (0.60)
Teachers' Suggestion	–	–	0.42* (0.23)	0.02 (0.29)
RP Dummies	No	Yes	No	Yes
Constants	Yes	Yes	Yes	Yes
Log-likelihood ($LL(\hat{\theta})$)	-268.705	-244.849	-244.111	-221.891
Adjusted Likelihood Ratio Index ($\bar{\rho}^2$)	0.433	0.461	0.445	0.471
Sample Size	219		205	

***: significant at 1%, **: significant at 5%, *: significant at 10%. Asymptotic robust standard errors in parentheses. $\bar{\rho}^2 = 1 - [LL(\hat{\theta}) - K]/LL(0)$, where $LL(\hat{\theta})$ is the value of the log-likelihood at the parameter estimates, K is the number of the estimated parameters, and $LL(0)$ is the value of the log-likelihood under no model (Ben-Akiva and Lerman, 1985). Optimization performed in Matlab.

Table 15: "Child and Parent Make a Joint Decision" (R3)

Variables	(S1)	(S2)	(S2d)	(S3)	(S4)	(S4d)
Child's Weight	0.344^{***} (0.085)	0.357^{***} (0.078)	0.370^{***} (0.107)	0.295^{***} (0.075)	0.307^{***} (0.069)	0.311^{***} (0.080)
Child's Preferences						
Like Subjects (b_1)	13.33^{***} (3.09)	12.13^{***} (2.79)	11.49^{***} (4.87)	14.90^{***} (3.97)	13.58^{***} (3.58)	13.23^{***} (4.26)
Daily Homework $\geq$ 2.5h (b_2)	1.48 (1.88)	1.86 (1.77)	2.30 (2.47)	1.18 (2.38)	1.60 (2.30)	2.04 (2.84)
Graduate in Regular Time (b_4)	4.27^{**} (2.47)	3.88^{**} (2.35)	3.81 (3.05)	3.37^{*} (2.25)	3.10^{*} (2.09)	2.33 (2.40)
In School with Friend(s) (b_{10})	1.11 (1.07)	0.52 (1.13)	0.31 (1.66)	1.65^{*} (1.16)	1.10 (1.16)	0.69 (1.68)
Flexible College-Work Choice (b_6)	1.48^{*} (1.14)	1.04 (1.26)	1.15 (1.92)	1.12 (1.27)	0.86 (1.42)	1.20 (2.05)
Attend College (b_7)	3.27^{**} (1.61)	2.88^{**} (1.46)	2.67^{*} (1.84)	2.83^{*} (1.81)	2.71^{*} (1.68)	2.48 (1.96)
Flexible College Field Choice (b_8)	6.37^{***} (2.44)	5.49^{***} (2.26)	6.02^{*} (3.85)	6.00^{**} (2.84)	5.18^{**} (2.56)	5.29^{**} (3.13)
Liked Job after Graduation (b_9)	3.74^{***} (1.53)	3.98^{***} (1.61)	4.15^{**} (2.19)	4.56^{**} (2.13)	4.72^{**} (2.19)	5.91^{**} (3.19)
Parent Happy (b_{11})	–	3.56^{**} (1.67)	4.05^{*} (2.65)	–	4.18^{**} (2.03)	5.22^{**} (2.92)
Teachers' Suggestion RP	–	–	–	1.20^{***} (0.45)	1.13^{***} (0.45)	1.15^{***} (0.47)
Teachers' Suggestion SP	–	–	–	0.17 (0.56)	−0.04 (0.55)	-2.61^{**} (1.41)
Parent's Preferences						
Like Subjects (b_1)	8.49^{***} (1.54)	8.46^{***} (1.56)	8.99^{***} (3.59)	7.94^{***} (1.66)	7.97^{***} (1.68)	8.12^{***} (1.71)
Daily Homework $\geq$ 2.5h (b_2)	−1.39 (1.17)	−1.31 (1.16)	−2.12 (1.95)	−1.33 (1.23)	−1.23 (1.22)	−1.63 (1.44)
Graduate in Regular Time (b_4)	2.52 (2.10)	2.35 (1.98)	3.32 (2.86)	3.34^{*} (2.27)	3.18^{*} (2.16)	4.23^{**} (2.32)
In School with Friend(s) (b_{10})	−0.37 (0.86)	−0.38 (0.86)	−0.94 (1.15)	−0.70 (0.97)	−0.73 (0.97)	−1.25 (1.09)
Flexible College-Work Choice (b_6)	2.14^{**} (1.09)	2.20^{**} (1.12)	2.68^{**} (1.59)	2.04^{**} (1.12)	2.15^{**} (1.15)	2.36^{**} (1.22)
Attend College (b_7)	0.92 (1.06)	0.88 (1.07)	0.48 (1.43)	0.84 (1.13)	0.81 (1.14)	0.69 (1.45)
Flexible College Field Choice (b_8)	2.99^{***} (1.19)	2.96^{***} (1.21)	3.75^{**} (2.11)	2.98^{***} (1.21)	2.96^{***} (1.23)	3.46^{***} (1.41)
Liked Job after Graduation (b_9)	1.74^{**} (0.99)	1.84^{**} (0.96)	1.70^{*} (1.26)	1.66^{*} (1.04)	1.78^{**} (1.03)	1.58 (1.24)
Teachers' Suggestion SP	–	–	–	2.00^{***} (0.70)	2.01^{***} (0.71)	2.06^{***} (0.93)
RP Dummies	No	No	Yes	No	No	Yes
SP/RP Scale (Child≡Par)	0.523^{***} (0.093)	0.524^{***} (0.093)	0.329^{**} (0.195)	0.488^{***} (0.103)	0.486^{***} (0.102)	0.329^{***} (0.076)
Constants	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood ($LL(\hat{\theta})$)	-507.4697	-501.9089	-445.5068	-463.1923	-457.8141	-407.4601
Adjusted LR Index ($\bar{\rho}^2$)	0.664	0.667	0.689	0.668	0.671	0.690
Sample Size		238			223	

***: significant at 1%, **: significant at 5%, *: significant at 10%. Asymptotic robust standard errors in parentheses. $\bar{\rho}^2 = 1 - [LL(\hat{\theta}) - K]/LL(0)$, where $LL(\hat{\theta})$ is the value of the log-likelihood at the parameter estimates, K is the number of the estimated parameters, and $LL(0)$ is the value of the log-likelihood under no model (Ben-Akiva and Lerman, 1985). Optimization performed in Matlab.

Table 16: Counterfactuals 1 and 2: Awareness Campaigns on Curriculum Subjects

	Voc Com-Soc ($j=1$)	**Voc Ind** ($j=2$)	**Tech Com-Soc** ($j=3$)	**Tech Ind** ($j=4$)	**Tech Surv** ($j=5$)	**Artistic Educ** ($j=6$)	**Gen Hum** ($j=7$)	**Gen Lang** ($j=8$)	**Gen Edu-Soc** ($j=9$)	**Gen Math-Scie** ($j=10$)
	Initial Predicted Probabilities of Choosing Curriculum j									
	7.64	7.42	17.71	12.44	6.80	4.23	9.43	4.01	7.88	22.44
	% Change in Predicted Probabilities of Choosing Curriculum j Following									
Policy 1–Math&Scie "Awareness" Campaign	**An Increase in Percent Chances that "Child Likes the Subjects" in General Math-Scie by 10**									
Unitary Model (All)–Children's Expectations	-1.29	-1.73	-1.38	-2.27	-3.97	-1.99	-8.40	-7.61	-3.78	+11.16
Unitary Model (All)–Parents' Expectations	-2.53	-3.05	-3.50	-5.04	-4.63	-3.47	-11.58	-12.36	-6.76	+18.93
Rule 1 (SP-RP)–Children's Expectations	-1.28	-0.84	-0.26	-1.76	-3.51	-2.01	-4.78	-1.58	-4.02	+7.04
Rule 2–Children's Expectations	-0.30	-0.14	-1.09	-3.64	-1.42	-0.20	-5.44	-3.93	-0.71	+6.74
Rule 2–Parents' Expectations	-0.23	-0.10	-0.83	-2.71	-1.02	-0.18	-4.17	-2.90	-0.50	+5.06
Rule 2–Children's and Parents' Exp.	-0.50	-0.24	-2.02	-6.95	-3.16	-0.28	-9.63	-7.99	-1.58	+12.73
Rule 3–Children's Expectations	-0.73	-0.54	-0.40	-0.76	-1.12	-2.93	-4.94	-7.33	-2.75	+6.41
Rule 3–Parents' Expectations	-0.94	-0.73	-0.55	-0.98	-1.43	-3.85	-6.61	-9.71	-3.67	+8.50
Rule 3–Children's and Parents' Exp.	-1.49	-1.34	-1.00	-1.68	-2.29	-6.62	-11.89	-17.20	-6.66	+15.03
Policy 2–Arts "Desensitization" Campaign	**A Decrease in Percent Chances that "Child Likes the Subjects" in Artistic Educ by 10**									
Unitary Model (All)–Children's Expectations	+0.86	+0.41	+0.45	+0.21	+1.53	-13.77	+0.46	+1.20	+1.50	+0.29
Unitary Model (All)–Parents' Expectations	+0.88	+0.72	+0.57	+0.59	+1.79	-18.91	+1.17	+2.02	+0.92	+0.54
Rule 1 (SP-RP)–Children's Expectations	+0.48	+0.83	+0.17	+0.14	+0.95	-15.33	+0.93	+2.61	+2.24	+0.31
Rule 2–Children's Expectations	+0.01	+0.06	+0.06	-0.02	+0.13	-6.20	+1.80	+0.23	+0.80	-0.01
Rule 2–Parents' Expectations	+0.00	+0.06	+0.06	-0.03	+0.11	-4.70	+1.33	+0.16	+0.64	-0.01
Rule 2–Children's and Parents' Exp.	+0.01	+0.07	+0.07	-0.02	+0.19	-11.43	+3.58	+0.57	+1.21	-0.01
Rule 3–Children's Expectations	+0.12	+0.11	+0.12	+0.01	+0.72	-6.13	+0.31	+0.31	+0.18	+0.52
Rule 3–Parents' Expectations	+0.17	+0.12	+0.13	+0.02	+0.94	-7.86	+0.39	+0.43	+0.21	+0.67
Rule 3–Children's and Parents' Exp.	+0.37	+0.20	+0.20	+0.06	+1.51	-13.53	+0.66	+0.86	+0.40	+1.14

Table 17: Counterfactuals 3 and 4: Publication of Education Statistics

	Voc Com-Soc ($j=1$)	Voc Ind ($j=2$)	Tech Com-Soc ($j=3$)	Tech Ind ($j=4$)	Tech Surv ($j=5$)	Artistic Educ ($j=6$)	Gen Hum ($j=7$)	Gen Lang ($j=8$)	Gen Edu-Soc ($j=9$)	Gen Math-Scie ($j=10$)
	Initial Predicted Probabilities of Choosing Curriculum j									
	7.64	7.42	17.71	12.44	6.80	4.23	9.43	4.01	7.88	22.44
	% Change in Predicted Probabilities of Choosing Curriculum j if									
Policy 3–Info Provision on Difficulty	**Individual Percent Chances that "Child Graduates in the Regular Time" Coincide with Realized Frequencies in a Previous Cohort[a] for All Curricula**									
Unitary Model (All)–Children's Expectations	-2.15	-3.42	+0.35	-1.72	-4.09	-7.37	+4.03	+0.43	-0.65	+3.63
Unitary Model (All)–Parents' Expectations	-4.47	-5.23	+0.15	-3.83	-0.67	-5.11	+5.94	+2.62	-1.56	+4.00
Rule 1 (SP-RP)–Children's Expectations	-0.94	-6.32	+0.34	-4.09	-3.51	-9.81	+3.70	+4.12	-1.23	+5.46
Rule 2–Children's Expectations	-1.73	-0.17	-0.50	+0.38	+0.16	+0.41	-0.85	+0.12	+0.27	-0.23
Rule 2–Parents' Expectations	-4.30	-0.12	+1.06	-2.94	-2.23	-5.10	+3.93	+4.12	+0.64	+1.32
Rule 2–Children's and Parents' Exp.	-3.07	-0.32	+0.73	-2.39	-2.05	-4.32	+2.86	+4.30	+1.07	+0.99
Rule 3–Children's Expectations	-2.48	-2.88	+0.22	+1.47	-1.89	-3.39	+1.28	-2.63	+0.79	+1.68
Rule 3–Parents' Expectations	-5.74	-4.57	+0.09	+0.75	-1.19	-3.64	+2.86	-0.70	+1.80	+2.31
Rule 3–Children's and Parents' Exp.	-7.53	-6.94	+0.10	+1.87	-2.89	-7.21	+4.15	-3.14	+2.38	+3.96
Policy 4–Info Provision of College Enrollment Stats.	**Individual Percent Chances that "Child Attends College" Coincide with Realized Frequencies in a Previous Cohort[b] for All Curricula**									
Unitary Model (All)–Children's Exp.	-2.67	-11.17	+3.36	+0.64	-5.29	-5.89	+2.07	+0.98	+0.28	+3.17
Unitary Model (All)–Parents' Exp.	-5.69	-12.46	+2.96	-0.14	-3.23	-3.50	+3.15	+2.65	+1.59	+3.08
Rule 1 (SP-RP)–Children's Exp.	-10.68	-24.81	+5.88	+0.62	-20.15	-18.88	+13.43	+14.20	+4.47	+6.77
Rule 2–Children's Exp.	-0.39	-0.17	+0.28	-0.09	-0.74	-0.57	+0.23	+0.19	+0.23	+0.14
Rule 2–Parents' Exp.	+3.14	+1.19	-1.77	+1.90	+3.29	+3.90	-1.03	-1.27	-0.81	-1.91
Rule 2–Children's and Parents' Exp.	+2.79	+0.99	-1.52	+1.86	+2.54	+3.56	-0.88	-1.07	-0.55	-1.79
Rule 3–Children's Exp.	-1.70	-5.13	+2.11	+1.96	-1.10	-2.66	+0.61	-1.25	-1.62	+0.90
Rule 3–Parents' Exp.	-1.28	-3.16	+0.73	+0.23	-0.01	-1.79	+0.63	+0.22	+0.42	+0.66
Rule 3–Children's and Parents' Exp.	-3.04	-8.37	+2.92	+2.23	-1.11	-4.46	+1.19	-0.88	-1.33	+1.56

[a] Statistics are from AlmaDiploma (2007*a*): Voc Com-Soc=86%, Voc Ind=83%, Tech Com-Soc=86%, Tech Ind=80%, Tech Surv=84%, Art Educ=86%, Gen Hum=98%, Gen Lang=93%, Gen Educ-Soc=91%, Gen Math-Scie=95%.
[b] Statistics are from AlmaDiploma (2007*b*): Voc Com-Soc=41%, Voc Ind=24%, Tech Com-Soc=60%, Tech Ind=55%, Tech Surv=53%, Art Educ=57%, Gen Hum=97%, Gen Lang=89%, Gen Educ-Soc=86%, Gen Math-Scie=97%.

Table 18: Counterfactuals 5 and 6: Institutional Policies on Standards and Specialization

	Voc Com-Soc ($j=1$)	**Voc Ind** ($j=2$)	**Tech Com-Soc** ($j=3$)	**Tech Ind** ($j=4$)	**Tech Surv** ($j=5$)	**Artistic Educ** ($j=6$)	**Gen Hum** ($j=7$)	**Gen Lang** ($j=8$)	**Gen Edu-Soc** ($j=9$)	**Gen Math-Scie** ($j=10$)
	Initial Predicted Probabilities of Choosing Curriculum j									
	7.64	7.42	17.71	12.44	6.80	4.23	9.43	4.01	7.88	22.44
	% Change in Predicted Probabilities of Choosing Curriculum j ***if***									
Policy 5–Lower Standards	**Everybody Is Guaranteed a Diploma in the Regular Time from Any Curriculum (I.e., Percent Chances that "Child Graduates in the Regular Time"=100 for All Curricula)**									
Unitary Model (All)–Children's Expectations	-2.35	-2.29	+0.57	+0.53	-2.63	-6.35	+1.62	+0.36	-0.59	+2.27
Unitary Model (All)–Parents' Expectations	-4.38	-3.78	+0.61	+0.63	+0.77	-3.66	+2.07	+2.30	-1.63	+1.66
Rule 1 (SP-RP)–Children's Expectations	-0.47	-5.11	-0.11	-0.57	-2.28	-7.40	+0.20	+2.20	-0.92	+4.19
Rule 2–Children's Expectations	+1.68	-0.15	-0.53	+0.08	+0.02	+0.19	-0.54	+0.08	+0.27	-0.07
Rule 2–Parents' Expectations	-4.25	-0.30	+1.42	+0.35	-1.01	-2.33	+0.74	+5.05	+0.88	-0.55
Rule 2–Children's and Parents' Exp.	-3.03	-0.50	+1.03	+0.47	-0.98	-1.94	+0.10	+5.13	+1.23	-0.60
Rule 3–Children's Expectations	-2.60	-2.65	+0.32	+2.43	-1.64	-2.52	+0.22	-2.12	+0.78	+1.15
Rule 3–Parents' Expectations	-6.00	-4.00	+0.35	+2.92	-0.56	-1.94	+0.54	+0.32	+1.74	+1.12
Rule 3–Children's and Parents' Exp.	-7.99	-6.16	+0.44	+5.06	-2.08	-4.47	+0.67	-1.52	+2.40	+2.23
Policy 6–More Rigid Tracking	**Vocational Diplomas Do Not Give Access to College (I.e., Percent Chances that "Child Attends College," "Child Makes a Flexible College-Work Choice," and "Child Makes a Flexible College Field Choice" =0 for All Vocational Curricula)**									
Unitary Model (All)–Children's Exp.	-63.20	-53.38	+23.53	+19.07	+5.30	+10.01	+2.08	+5.35	+4.46	+3.14
Unitary Model (All)–Parents' Exp.	-61.99	-56.56	+22.47	+20.70	+11.86	+6.91	+2.01	+4.44	+4.15	+2.61
Rule 1 (SP-RP)–Children's Exp.	-61.25	-40.16	+13.14	+15.31	+6.30	+13.30	+7.00	+7.65	+13.27	+1.89
Rule 2–Children's Exp.	-52.52	-31.16	+26.67	+ 8.79	+0.30	+4.96	+0.03	+5.69	-0.00	+0.21
Rule 2–Parents' Exp.	-17.38	-18.16	+6.50	+10.68	+0.22	-0.06	+0.02	+3.63	-0.00	+0.15
Rule 2–Children's and Parents' Exp.	-57.97	-60.86	+31.85	+20.60	+0.32	+10.15	+0.03	+5.71	+0.00	+0.26
Rule 3–Children's Exp.	-33.82	-23.40	+11.10	+11.84	+2.78	+0.70	+0.32	+0.47	+5.37	+0.85
Rule 3–Parents' Exp.	-44.97	-45.97	+17.58	+20.86	+5.14	+0.91	+0.49	+0.68	+5.51	+1.08
Rule 3–Children's and Parents' Exp.	-72.03	-61.61	+29.49	+25.74	+6.70	+1.13	+0.56	+0.89	+9.64	+1.33

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A Choice-Based Sampling and the WESML Estimator

Likelihood function. Let us define $P(\tilde{j}|x,\theta)$ to be the conditional probability that alternative $\tilde{j} \in \mathcal{J}$ is selected given covariates $x \in X$; it specifies the behavioral choice model up to a parameter vector $\theta \in \Theta$ to be estimated. Additionally, $p(x)$ denotes the marginal distribution of attributes, $Q(\tilde{j})$ the population share of response $\tilde{j}$, and $H(\tilde{j})$ the corresponding sampling probability. Following Manski and McFadden (1981), the likelihood of observing the generic attributes-choice combination $(x,\tilde{j})$ under choice-based sampling can be written as

$$\lambda_{cb}(x,\tilde{j}) = p(x|\tilde{j})H(\tilde{j}) = \frac{P(\tilde{j}|x;\theta)p(x)}{Q(\tilde{j})}H(\tilde{j}) = \lambda_r(\tilde{j}|x)p(x)\frac{H(\tilde{j})}{Q(\tilde{j})}, \tag{8}$$

with

$$Q(\tilde{j}) = \int_X P(\tilde{j}|x;\theta)p(x)dx. \tag{9}$$

Hence, under choice-based sampling the kernel of the likelihood, $\left[P(\tilde{j}|x,\theta)/Q(\tilde{j})\right]$, depends on the true θ via $Q(\tilde{j})$, which therefore needs to be accounted for in estimation. This differs from the case of random sampling, where the kernel would simply be $P(\tilde{j}|x,\theta)$.

Estimation. A number of different estimators have been proposed to estimate θ in (8), depending on a researcher's knowledge of p and Q (see Cosslett (1993)'s review). Manski and Lerman (1977)'s weighted exogenous maximum likelihood estimator (WESML) is a pseudo-maximum likelihood approach that starts from the likelihood function appropriate under exogenously stratified sampling and re-weights the data to achieve consistency, with weights equal to $[H(j)/Q(j)]^{-1}$. Hence, knowledge of $\{Q(j)\}_{j=1}^{J}$ is required, but not that of $p(x)$. I use the WESML estimator because of its tractability and its best-predictor interpretation under misspecification of the logit model (Xie and Manski, 1989). The random sampling maximum likelihood estimator (RSMLE) with the intercepts' correction proposed by McFadden (see Manski and Lerman (1977) for details) is, in fact, a more popular and efficient alternative, but it relies on the logit assumption being correct.

Ex-post conditioning. In Giustinelli (2010, Chpt. 2) I formally show that, similar to the case of random sampling, ex-post conditioning does not affect estimation under choice-based sampling. Hence, the WESML estimator can be used without modifications to consistently estimate the RP component of the model separately for each family decision rule.

Multiple sources of preference data. The likelihood in (8) can be rewritten for the case with multiple sources of preference data as follows:

$$\lambda_{cb}(x, j, y, h) = p(x, y, h|j)H(j) = \frac{P(j, y, h|x; \theta)p(x)}{Q(j)}H(j), \tag{10}$$

where j indexes families' actual choices, y indexes children's stated-preferred alternatives, and h indexes parents' stated-preferred alternatives, with $j, y, h \in \mathcal{J}$. If the different sources of data are treated as independent conditional on the observables, the likelihood function is simply equal to the product of their contributions

$$\begin{aligned}\lambda_{cb}(x, j, y, h) =& P(y|x^y, j; \theta^y)P(h|x^h, j; \theta^h)P(j|x^j; \theta^j)p(x)\frac{H(j)}{Q(j)} = \\ =& \lambda_r(y|x^y)\lambda_r(h|x^h)\lambda_r(j|x^j)p(x)\frac{H(j)}{Q(j)},\end{aligned} \tag{11}$$

with

$$Q(j) = \int_{X^j} P(j|x^j; \theta^j)p(x^j)dx^j.$$

x^j, x^y and x^h, and θ^j, θ^y and θ^h, may overlap, and their unions are equal to the vectors x and θ, respectively. Possible relationships or restrictions between covariates and parameters across data sources are specified by the structural model. In this case, only the RP component, j, needs to be corrected by the usual factor $H(j)/Q(j)$. In appendix B.2.2 I discuss issues involving the extension of this framework to address the possibility of persistent (across data sources) unobservable heterogeneity while simultaneously accounting for choice-based sampling of RP.

B Robustness Checks and Discussions

B.1 Statistical Inference

Statistical inference is based on the robust asymptotic variance-covariance matrix derived by Manski and Lerman (1977) for the WESML estimator. Because sample size is modest for the rule-specific models, as a robustness check I also calculated 95% bias-corrected bootstrap confidence intervals (not shown for reasons of space, but available upon request). These bootstrap estimates are virtually identical to the asymptotic ones for the unitary models and somewhat larger than the latter for the heterogenous models. However, significance levels of coefficients remain mostly unchanged and qualitative patterns are identical.

Accounting for the fact that students are physically clustered in classrooms may be an additional desirable check. Unfortunately, the small number of classes *within* choices in my data makes it infeasible to perform. This is because with endogenous stratification the bootstrap must be applied in a manner that preserves the original data structure; hence, observations (classes in place of individuals) would need to be drawn from the choice subsamples rather than from the whole sample. Institutional arguments, however, help relaxing major concerns on inference. First, conditional on the attended curriculum, the assumption that extracting classes within schools is equivalent to extracting individuals within schools is warranted by commonly applied rules for determination of class composition. Second, common factors faced by students at the class level (e.g., teachers) should not play a relevant role given that students were interviewed during the first week of school. Third, some concern would be justified if children copied from one another when filling in the questionnaire in class. However, presence of the interviewer and of the teacher and my own personal observation of class dynamics during administration of the survey renders this potential concern rather weak.

B.2 Data Measurement and Model Specification

B.2.1 Stated Choice Preferences and Retrospective Elicitation

In an influential paper concerned with ex-post rationalization by parents asked to retrospectively report their ex-ante wantedness of their newly born children, Rosenzweig and Wolpin (1993) found that parents' retrospective statements were significantly influenced by children's actual traits. This example provides a neat illustration of the most natural concern about validity of stated intention and stated preference data elicited after actual choices have been made. The design of the NLSY79 pregnancy roster used by Rosenzweig and Wolpin (1993) and that of my data, however, feature two fundamental differences. First, at the time of interview none of the outcomes (with the exception of being in school with friends) had realized nor it is likely that any new significant information had become available, as children had experienced only about 7-10 days of high school and had never been tested during that period. Second, respondents were never inquired about whether they wanted to choose the curricula children eventually enrolled in. Rather, they were presented with the universal set of alternatives and were asked to rank them according to their preferences, their expectations, and the criteria they individually thought were important for the choice during the previous year.

The SP literature has long recognized a tendency among respondents to report stated choice preferences that coincide with actual choices ("justification bias") and has attributed such a bias to some form of "inertia." A recent paper by Chen and Risen (2010), however, shows analytically and experimentally that if people's ratings or rankings are imperfect measures of their preferences, and their choices are at least partially guided by their preferences, observed spreading (between their stated preferences elicited before and after the choice) may not be unambiguosly taken as evidence of choice-induced change in preference attitudes, since such a spreading will generally occur even with stable preferences.

If, nonetheless, when asked to state their choice preferences, respondents do tend to report more often those alternatives they previously selected in a real choice situation, this tendency would induces state dependence of stated preferences on actual choices. Following Morikawa (1994), the empirical SP-RP literature has attempted to address the problem by including RP or "inertia" dummies in specification of SP utilities. In tables 13-15 I present "d" specifications including inertia dummies in the SP utility functions. (Results for the unitary SP-RP model are not presented for reasons of space but are available upon request. On the other hand, no inertia specification was run for the (R1) group, since logically incorrect under the model's assumptions.) While such dummies feature mostly significant coefficients (not shown), their inclusion does not change qualitative results for the structural parameters.

Inclusion of inertia dummies, however, may induce estimates' bias and inconsistency if there exists also unobserved underspecified correlation between the SP and RP error terms. For instance, if some common variable were omitted from the deterministic components of both of the SP and RP utility functions, this omission would generate correlation between the error terms of the SP utility functions and the RP dummies. On the other hand, the extensive Montecarlo evidence provided by Abramson et al. (2000) indicates that only the coefficient of the variable capturing state dependence would be severely biased in presence of underspecified serial correlation (and only for extreme values of the latter), and identifies serial correlation as the least worrisome (for parameter bias and prediction) source of unobserved heterogeneity relative to others, such as choice set effects, residual taste heterogeneity, and state dependence.

B.2.2 Unobserved SP-RP Correlation

At least since Morikawa (1994), the SP-RP literature has exerted substantial effort to develop models that build in, and methods that can deal with, forms of dependence between multiple sources of preference data generated by different designs of stated preference experiments (e.g., Train and Wilson (2008)). Despite this and despite the large volume of empirical literature pooling SP and RP data, with the latter collected through a choice-based sampling protocol, complications arising when introduction of unobserved SP-RP correlation is combined with complex non-random survey designs seem to have been largely ignored. The only exception I am aware of is McFadden (1996), which shows that in the context of an "intercept&follow" sampling design no natural extension to the WESML estimator exists for the case of unobserved heterogenity. On the other hand, a natural extension to endogenous stratification may be possible for a more specific form of unobservable persistence between SP and RP data, similar to that analyzed by Train and Wilson (2008) for SP-off-RP designs. Its development, however, is beyond the scope of this paper and left for future work.