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Group Decision Making with Uncertain Outcomes: Unpacking Child-Parent Choices of High School Tracks*

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Abstract

Predicting group decisions with uncertain outcomes involves the empirically difficult task of disentangling individual decision makers' beliefs and preferences over outcomes' states from the group's decision rule. This paper addresses the problem within the context of a consequential family decision concerning the high school track of adolescent children in presence of curricular stratification. The paper combines novel data on children's and parents' probabilistic beliefs, their stated choice preferences, and families' decision rules with standard data on actual choices to estimate a simple model of curriculum choice featuring both uncertainty and heterogeneous cooperative-type decisions. The model's estimates are used to quantify the impact on curriculum enrollment of policies affecting family members' expectations via "awareness" campaigns, publication of education statistics, and changes in curricular specialization and standards. The latter exercise reveals that identity of policy recipients–whether children, parents, or both–matters for enrollment response, and underlines the importance of incorporating information on decision makers' beliefs and decision rules when 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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"If one studies humanities in a general high school, but after 5 years he no longer wishes to go to university, what can he do? And after studying art in a general high school? Because when one is 14 he makes a choice, and thinks that, perhaps, he will go to college afterwards... But after 5 years he might change his mind. And if he is fed up with school, then he can go to work [if he attended a technical or vocational school, instead]*."* (a brother) (Istituto IARD, 2001, p.62)[1]

"As for the high school curriculum, she decided what to study. She chose the school, but only after we had talked together. Her father, for instance, preferred another [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 choices with *uncertain outcomes* and *multiple decision makers.* These choices span human capital investment, sexual behavior, crime behavior, and countless others. For instance, members of criminal gangs choose whether to commit crimes with partial knowledge of their probability of being arrested; sexually active partners make contraceptive choices with partial knowledge of effectiveness and side effects; family members select curricular tracks for their children with partial knowledge of children's tastes, ability, and future opportunities and choices. However, predicting any of these behaviors to inform policy requires disentangling decision makers' beliefs and preferences over outcomes' states from the group's decision rule. This is because there will generally exist several configurations of beliefs, preferences, and decision rules that are compatible with the *same observed choice* and have *different implications for policy.*

In this paper, I focus on choice of high school curriculum with curricular tracking, and I address the identification problem of empirically distinguishing how children's and parents' beliefs and preferences over choice-related outcomes drive curriculum choice via heterogeneous rules of child-parent decision making. Nonetheless, while substantively my analysis is relevant both for the debate on intergenerational transmission of beliefs and preferences from parents to children (e.g., Bisin and Verdier (2001) and Doepke and Zilibotti (2008)) and for understanding the role of preferences and information in career-oriented school choices (e.g., Arcidiacono et al. (2011) and Zafar (2008))–and hence for educational policy–the framework I study is more general. It encompasses any choice situation featuring a small group of decision makers that face a *common* discrete choice with uncertain outcomes, hold *subjective beliefs* and *individual preferences* over outcomes' states, and employ a *cooperative*-type decision rule aggregating their preferences and beliefs and nesting more unilateral decisions as special cases.[2]

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

[2]From a theoretical perspective, the paper's setup may be thought of as an application of Savage (1954)'s framework and Harsanyi (1955)'s utilitarian aggregation combined, as recently conceptualized and discussed by Gilboa et al. (2004). An important feature of this framework is that unanimity of group members' preferences over alternatives does not imply that an individually preferred alternative is also socially preferred, since unanimity may be generated by different combinations of individual preferences and beliefs over states of nature (see Mongin (2005)'s in-depth discussion and Raiffa (1968)'s "Paretians-vs.-Bayesians" dramatization). In fact, while I assume that decision makers are individually rational–in the sense that they maximize expected utility–I do not assume *a priori* that they hold rational expectations nor I make any specific assumption about the manner in which they update their own beliefs based on information they receive from the other members of the

To illustrate, let us consider the choice faced by an adolescent child ("he") and his parent ("she"), both wishing to select the best curriculum for the child between art and math. For simplicity, let child and parent be only concerned with the child's taste for subjects and the program's difficulty level *given* child's ability, all of which are uncertain. Child and parent hold subjective probabilistic beliefs over realization of different taste and difficulty states and attach individual valuations to them. (Perhaps the child thinks he is an artist and should follow his talent, whereas his mother thinks he has got what it takes to become a brilliant mathematician!) Moreover, either the child makes curriculum choice individually or child and parent make a joint decision.

In this setting, being able to tell beliefs and preferences apart is important for policy makers, since expectation-driven choices may be affected by some policy, e.g., by provision of information about subjects and difficulty levels, while preference-driven choices may require a different policy, e.g., no policy. Furthermore, identifying the target–child, parent, or both?–of a policy that aims at affecting curriculum enrollment via information provision and assessing the potential effectiveness of such a policy via counterfactual analysis require uncovering the role played by each decision participant in the choice.

Thus far, insufficient prior knowledge and lack of adequate data on how individuals and groups make decisions with uncertain outcomes has rendered this identification problem hard to tackle empirically (Manski, 2004*a*, 2000). First, commonly available data are limited to decision makers' characteristics and some features of the alternatives. Second, any statistical analysis associating choices with decision makers' background characteristics usefully reveals "which individuals or groups choose what" but does not uncover the main decision-making channels nor can be used to answer counterfactual policy questions. Last but not least, while counterfactual analysis relies on structural modeling, identification and estimation of structural models from standard data requires strong non-testable assumptions.

My work addresses these issues directly by collecting new data on usually unobserved primitives of a family decision process and by showing how such data can be used in the estimation of a simple model of curriculum choice with uncertain outcomes and heterogeneous child-parent decision-makings to achieve identification and make inference on families' choices. The paper thus tackles some of the aims of existing research agendas on behavioral choice modeling (e.g., Ben-Akiva et al. (2002) and Adamowicz et al. (2008)), especially concerning decision making under uncertainty (e.g., Manski (2004*a*, 2000)) and within the family (e.g., Dauphin et al. (2010)).

In particular, I designed and conducted a survey gathering the following field data from a relatively large sample of Italian families:

(A) Children's and parents' probabilistic expectations before the choice, elicited on a 0-100

group. On the other hand, analysis of identification depends on the adopted framework.

scale, over several in-high-school and post-diploma outcomes;

(B) Children's and parents' stated choice preferences before the choice (SP);

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

(D) Self-reported family decision rules, including **(1)** unilateral decision by child (parents), **(2)** choice by child (parents) after listening to the parents (child), and **(3)** child-parents joint decision;[3]

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

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

Then, within the theoretical framework previously outlined, I demonstrate how joint use of these data can be employed to separately identify and estimate structural parameters capturing how children and parents trade off different choice-relevant outcomes (*preference* or *utility weights*) and parameters describing family decision rules (*aggregation* or *protocol weights*).[4]

Specifically, with actual choices **(C)** observed, identification of the empirical model works as follows. Under unilateral decisions (and under "unitary family" decision in the sense of Becker (1981)), heterogeneity in decision makers' probabilistic expectations **(A)** identifies utility parameters, in the same fashion as alternatives- and decision makers-specific characteristics do in standard random utility models with no uncertainty. Actual choices **(C)** and family members' expectations **(A)**, however, do not suffice to separately identify preference and aggregation parameters for families making a multilateral decision according to **(D)**. To solve this problem, I combine data **(A)** and **(C)** with family members' stated preferred alternatives **(B)**, within a stated preference-revealed preference (SP-RP) joint framework (e.g., Ben-Akiva et al. (1994) and Hensher et al. (1999)). Intuitively, given data on family members' choice preferences, *utility weights* are identified from heterogeneity in expectations (one SP individual choice model for each family member with an "active" decision-making role); whereas, *protocol weights* are identified from differences between family members' individual choice preferences and families' actual choices (one RP family model of multilateral decision making).

Thus, methodologically, my paper bridges an emerging literature in economics with a literature that has long developed mainly outside economics, in the fields of transportation, marketing, and resource economics. The former is a stream of works employing "right-hand side" probabilistic expectations data in models of individual choice under uncertainty to achieve or improve identification of structural preference parameters (e.g., Delavande (2008), Arcidiacono

[3]Rule **(1)** holds that the child chooses by maximizing his subjective expected utility formed by his own preferences and beliefs over outcomes' states. Rule **(2)** holds that the child chooses by maximizing a subjective expected utility formed by his own preferences over outcomes' states and by beliefs updated to account for parental beliefs. Rule **(3)** holds that child's and parent's preferences and beliefs over outcomes' states contribute to the final choice via linear aggregation of the corresponding expected utility components. A formal representation is provided in subsection 2.3.

[4]Notice that I can focus on curriculum demand because the Italian secondary system features open enrollment. That is, lack of selectivity from the school side eliminates potential identification problems from the interplay of demand and supply in producing observed choices.

et al. (2011), and Zafar (2008) for static choices, and Erdem et al. (2005) and Mahajan and Tarozzi (2011) for dynamic settings).[5] The latter, originating from Morikawa (1989)'s original work, suggests pooling SP and RP data together–a process called "data enrichment" or "data fusion"–in order to exploit SP data to help identify parameters that RP data could not and, thus, improve estimation efficiency (see Louviere et al. (2000)'s state-of-the-art review). Both streams of literature, however, have focused on unilateral decision making and, to the best of my knowledge, the latter has never been used for analyzing group decisions with uncertain outcomes.[6]

The empirical tool developed in this paper enables me to investigate the following descriptive and normative issues of curriculum choice:

(I) What are the most important determinants of curriculum choice among future outcomes–defined over children's "taste" for curricula, their ability and effort while in high school, and post-graduation opportunities and choices–that are uncertain at the moment of curriculum choice and are potentially relevant for it?

(II) *Conditional on* an interacted family decision rule, to what extent are parental beliefs transmitted to children *during* the decision, and to what extent do parental preferences affect the final choice?

(III) How does curriculum enrollment respond to policy-induced changes of decision makers' beliefs over outcomes' states? And is it important to account for child-parent decision making and heterogeneous family rules for counterfactual analysis of curriculum choice?

I find that preference or taste for curriculum core subjects is systematically the most valued factor by both children and parents and across families using different decision rules. Whereas the importance of other in-high-school outcomes relative to post-diploma ones (e.g., school achievement and effort relative to flexible college-work and college major choices) is heterogeneous across groups **(issue I)**.

Estimates of the model with heterogeneous decision rules reveal that children incorporate parents' beliefs into their own when making the choice at least partially and to an extent that varies across outcomes **(issue II, family rule 2)**. For instance, children appear to trust parental opinion regarding their ability better than their own, assigning a larger weight to the former. On the other hand, the aggregation weights on the flexibility that different curricula will provide in the subsequent choice of field in college and the aggregation weights on child's preference for subjects favor children's opinions, although equal weights cannot be rejected for the latter outcome.

[5] Other recent papers have used expectations data as equilibrium outcomes in discrete choice with social interactions (Li and Lee, 2009) and, on the "left-hand side," as a response variable for choice experiments under incomplete scenarios (Blass et al., 2010), to improve estimation efficiency (e.g., van der Klaauw (2000)), and to identify unobserved heterogeneity in dynamic settings (Pantano and Zheng, 2010).

[6] Dosman and Adamowicz (2006) are a partial exception in that they 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.

Comparison of children's and parents' stated choice preferences with actual choices for families in which child and parent(s) make a joint decision supports group rationality, with less than 5% of families selecting an individually dominated choice. Moreover, parameters' estimates for this group suggest a substantial influence of parental preferences on curriculum choice **(issue II, family rule 3)**. For instance, the weight on the child's expected utility component of taste for subjects is smaller than 1/3, and a weight of 1/2 is statistically rejected. That is, parents may be trying to prevent children from overweighting their own preferences for subjects in high school relative to other outcomes that will realize at a later time in their future. On the other hand, the aggregation weights on the flexibility that different curricula will provide when children face the college field choice and those concerning the possibility of finding a liked job after graduation favor children's preferences. Nonetheless, weights' heterogeneity across outcomes is not statistically significant, and a unique weight of approximately 1/3 on the child's expected utility cannot be rejected.

I use the models' estimates to simulate counterfactual scenarios in which changes in individuals' beliefs–generated by "awareness" campaigns, publication of education statistics, and policies altering curricular specialization and standards–affect curriculum enrollment **(issue III)**. For instance, simulation of a 0.1 increase in individuals' probabilities of enjoying math and science in the general scientific curriculum following an awareness campaign about those subjects shows that the large utility weight families attach to the child's taste for subjects implies a potentially large impact of this kind of policies on curriculum enrollment. Altering access to university based on children's graduation curriculum has also a large impact on response, as opposed to providing information on curriculum graduation rates and on subsequent college enrollment for previous cohorts.

As for heterogeneity of family decision rules, the unitary-family benchmark and the proposed model with heterogeneous rules generate intuitive and qualitatively similar predictions that, nonetheless, are quantitatively different. In particular, the counterfactual exercises reveal that identity of policy recipients matters for enrollment response and underlines the importance of incorporating decision makers' beliefs and decision rules when evaluating policies. 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; whereas a unitary model based on children's expectations generates much closer predictions. Moreover, counterfactual enrollment responses decomposed by decision-making rule and by targeted group suggest that publication of education statistics would have a larger impact on children reporting unilateral decision by self than on the other children, and that if parents only were aware of policies changing institutional features of tracking, the impact of such policies may 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–it should be clear nonetheless that the approach I explore with this work does not mean to nor can eliminate the need of assumptions altogether. Rather, it transfers their locus from things researchers do not know to be true nor can usually test, i.e., the behavioral process, to elements over which they may have some control or at least better information, i.e., the collection and properties of the data. Thus, for example, I take data on expectations and family decision rules at face value. Trusting the reader's patience and hoping to achieve greater transparency, however, I defer a more thorough discussion of these and related aspects, including potential limitations, to the body of the paper–where they can be more conveniently related to the formal setup–and to the concluding session–where I briefly summarize them and identify areas of future work.

The paper is organized as follows. Section 2 conceptualizes child, parent, and family choice problems, and illustrates the main identification and policy issues through a simplified example with two decision rules, two alternatives, and two binary outcomes. 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 literature. Conclusions follow.

2 The Identification Problem, Idealized

2.1 Curriculum Choice under Uncertainty

Setup. The environment is populated with families, $f = 1, ..., F \in \mathcal{F}$, each one formed by one adolescent child, $c = c(f)$, and one parent, $p = p(f)$. Families face high school curriculum choice for their children over a common set of available alternatives, $j = 1, ..., J \in \mathcal{J}$, and wish to make an optimal child-curriculum match as follows:

$$\max_{j \in \mathcal{J}} \theta_{cj}, \tag{1}$$

where θ_{cj} is the quality of the match between child c and curriculum j. This parameter should be thought of as multidimensional, encompassing both quality of curriculum choice during high school and opportunities and choices after graduation. Examples are whether the child would enjoy the core subjects, how his academic performance would be, and which opportunities and choices would he face after graduation, should he enroll in curriculum j.

Families are likely to perceive most if not all components of θ_{cj} as uncertain at the moment of the choice. Assuming separability of θ_{cj}'s components yields a convenient representation of uncertainty as a set of binary outcomes, $\mathcal{B} = \{b_n \in \{0,1\}\}_{n=1}^{N}$, with corresponding *objective* ex-ante realization probabilities, $\{\Pi_{cj} (b_n \in \{0,1\})\}_{n=1,...,N;j=1,...,J}$, such that

$\Pi_{cj}(b_n = 1) = 1 - \Pi_{cj}(b_n = 0)$. Hence θ_{cj} can be expressed as a function of such probabilities, i.e., $\theta_{cj} = \theta\left(\{\Pi_{cjn}\}_{n=1}^{N}\right)$, with $j = 1, ..., J$. In fact, I assume that family members hold *subjective* probabilistic beliefs, $\{P_{ij}(b_n \in \{0,1\})\}_{n=1,...,N; j=1,...,J}$ with $i \in \{c, p\}$, which may or may not coincide with the objective ones and based on which they form estimates of θ_{cj}, i.e., $\hat{\theta}_{ij} = \theta\left(\{P_{ijn}\}_{n=1}^{N}\right)$. Hence, to clarify, $\Pi_{cjn} = \Pi_{cj}(b_n = 1)$ indicates the objective ex-ante probability that outcome $b_n = 1$ occurs if child c attends curriculum j; whereas, $P_{ijn} = P_{ij}(b_n = 1)$ indicates the subjective probability held by family member $i \in \{c, p\}$ for the same outcome.

Finally, in my notation, individuals' indices indicate individual-specific variables or parameters, when used as subscripts; they indicate variables or parameters specific to the class of individuals identified by the index, when used as superscripts.

Assumptions. Before moving to the example, I wish to make the assumptions underlying the described framework more transparent and to provide motivations for them. Whenever warranted, I will defer further discussions to later sections.

First, I assume dyadic families because data on beliefs and stated choice preferences were collected 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. Inclusion of both parents into the framework would be conceptually straightforward, as it will become clear in subsections 2.3 and 4.2.

Second, based on the institutional features relevant for the empirical analysis, the supply side is characterized **(1)** by curricular tracking with physically separate curricula (i.e., offered by different schools) and **(2)** by an open enrollment system in which the allocation mechanism of children to curricula and schools is family choice.[7] On the demand side, I assume **(3)** a hierarchical process of **(a)** selection of a family decision rule, **(b)** curriculum choice, and **(c)** school choice, as well as **(4)** separability of curriculum choice from other family choices. **(1)** and **(2)** allow me to focus on the demand side; **(3)** and **(4)** allow me to analyze curriculum choice in isolation. While I discuss separability of family decision rule and curriculum choice later in the paper, separability of curriculum choice from school choice is supported by the fairly homogeneous quality of Italian public schools, to which I restrict in the empirical analysis.

Third, I assume that all families face the same "universal set" of alternatives and that they use it as their choice set for curriculum choice. The former assumption is warranted for my empirical analysis, since the size of the area where the data were collected, the schools' location within the area, and the characteristics of the public transport network make all curricula available to everybody (see Giustinelli (2010, Chpt. 2) for details). On the other hand, the latter assumption–commonly made in empirical applications–excludes the possibility of heterogeneous non-compensatory processes of "consideration set" formation. Later I will identify this aspect

[7] See section 6 for a short summary about curricular stratification in Italy and other OECD countries or Giustinelli (2010, Chpt. 2) for a more detailed one.

as an interesting candidate for further work, as it constitutes an additional channel through which parents and teachers may affect children's curriculum choice.

Finally, choice of modeling uncertainty as a set of separable binary outcomes is purely dictated by feasibility of data collection so that, for each respondent $i \in \{c, p\}$, $\{P_{ij}(b_n = 1)\}_{n=1,...,N;j=1,...,J}$ are elicited in place of the more complicated objects $\{P_{ij}(b_1, ..., b_N)\}_{j=1,...,J}$. Notice also that if multiple discrete or continuous outcomes were included, multiple points of the respondents' distributions of beliefs should be elicited for each outcome and alternative.

A 2×2×2 Example. Throughout the section, I illustrate the framework and the identification problem via a simple example with 2 alternatives, 2 outcomes, 2 family decision rules or "protocols," and 1 family. The family must choose between the art curriculum, "Michelangelo" (M), and the math-and-science curriculum, "Galileo" (G), by weighing a "Difficulty" outcome (D)–that the child will graduate from high school in the regular time–and a "Flexibility" outcome (F)–that the training he receives in high school will allow him to choose among a wide range of fields in college. An M-diploma would be easier to obtain for this child than a G-diploma: $\Pi_{cMD} = 95 > \Pi_{cGD} = 70$ (math at Galileo is really hard!). However, an M-diploma would provide him with less flexibility than a G-diploma: $\Pi_{cMF} = 30 < \Pi_{cGF} = 90$ (Michelangelo's artistic training is somewhat narrow and suitable only for studying architecture or some art-related field in college). Family members hold subjective assessments, $\{(P_{iMD}, P_{iMF}); (P_{iGD}, P_{iGF})\}_{i\in\{c,p\}}$, of the objective probabilities, $\{(\Pi_{MD}, \Pi_{MF}); (\Pi_{GD}, \Pi_{GF})\} = \{(95, 30); (70, 90)\}$, and use the former within one of the following decision processes: either the child unilaterally chooses his own curriculum or child and parent make a joint decision.

2.2 The Individual Problem: Separating Preferences and Beliefs

Analysis of the *individual* curriculum choice problem–as faced by a single family member o by a unitary decision-making unit–introduces the challenge of empirically separating the decision maker's preferences from his/her beliefs.

The Child Problem. Faced with the curriculum choice problem, the child selects the curriculum that maximizes $\hat{\theta}_{cj}$ over $\mathcal{J}$, according to decision rule (1). I operationalize this idea by assuming that he maximizes the following linear, separable-in-outcomes, and subjective expected utility:

$$EU_{cj} = \sum_{n=1}^{N} \sum_{b_n \in \{0,1\}} P_{cj}(b_n) \cdot u(b_n, z_c) + x'_{cj}\delta(z_c) + \varepsilon_{cj} = \sum_{n=1}^{N} P_{cjn} \cdot \Delta u_n^c + \bar{U}^c + x'_{cj}\delta^c + \varepsilon_{cj}, \quad (2)$$

which is a function of the vector of uncertain outcomes, $b = (b_1, ..., b_N)$, of a $M \times 1$ vector of child-curriculum specific attributes not subject to uncertainty, $x_{cj} = (x_{cj1}, ..., x_{cjM})'$, of a vector of individual characteristics, z_c, and of a random term unobservable to the econometrician, ε_{cj}. Being constant over alternatives, $\bar{U}^c = \sum_{n=1}^{N} u(b_n = 0, z_c)$ drops out of the choice.

Each structural preference parameter, $\Delta u_n^c = u(b_n = 1, z_c) - u(b_n = 0, z_c)$, represents the difference in utility that a child with characteristics z_c derives from occurrence of outcome n (i.e., $b_n = 1$), relative to its non-occurrence (i.e., $b_n = 0$). Hence, these parameters combine within a simple compensatory framework the different components of θ_{cj}, and should not be confused with the child's "choice preference" (i.e., his preferred alternative as implied by his underlying utility) nor with his "preference or taste for subjects" (i.e., a specific component of his utility function). In particular, while the child may not perfectly know his taste for subjects beforehand–indeed he holds subjective beliefs about it–the compensatory rule he uses to trade off different outcomes reflects his preferences over outcomes' states at the moment of the choice.[8]

Linearity of expected utility implies risk-neutrality. However, sociological evidence suggests that some children prefer curricula that–they believe–will enable them to "insure" against the presently uncertain outcomes of their future college and work choices, i.e., to "postpone" those choices.[9] Indeed, 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). To account for this aspect, albeit in a somewhat "reduced form" fashion, in the empirical model I include children's perception of the degree of flexibility that different curricula would give to them in the future choices of college versus work and of college major.

Example (continued). Let us assume that the family is observed (by an econometrician) to choose alternative M. Furthermore, let us momentarily assume that the family decision protocol, e.g., unilateral decision by the child according to "$\underset{j \in \{M,G\}}{Max} \ EU_{cj} = P_{cjD} \cdot \Delta u_{cD} + P_{cjF} \cdot \Delta u_{cF}$," is also observed. Even within this simple setup, the researcher is faced with multiple competing explanations consistent with choice of M. The following two scenarios illustrate the identification problem and its relevance for policy.

- **Scenario I**: The child holds rational expectations, i.e., $\{(P_{cMD}, P_{cMF}); (P_{cGD}, P_{cGF})\} =$

[8] Of course, preferences for outcomes realizing far ahead in time may differ from current preferences because of 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. See Mahajan and Tarozzi (2011) for a recent paper using expectations data to identify time preferences with heterogeneous time inconsistency.

[9] *"I chose this school because beyond giving me this training* [learning some foreign languages] *... afterwards I would like to study law in college. But should anything happen to me,* [with this diploma] *I can still get a job in a travel agency... Not everything is lost! It* [this school] *will provide me with several job opportunities."* (a girl attending a vocational school for tourism) (Istituto IARD, 2001, p.38) And her mother agrees *"Perhaps, once A. has gotten her diploma she may change her mind, and decide she does not wish to go to college after all... Yet,* [thanks to this training] *she will hold a diploma that will enable her to find a job. A piece of paper is chased!"* (Istituto IARD, 2001, p.38) On the other hand, a boy confident that he will go to college comments *"I knew I would go to college and I could do well in any type of general high school. Then, they* [the parents] *said 'The scientific curriculum is better because you will have more options afterwards.' That is, it is a school that will enable me to choose among a large number of fields in college."* (Istituto IARD, 2001, p.39)

$\{(95, 30); (70, 90)\}$, and only cares about difficulty, e.g., $\{\Delta u_{cD}, \Delta u_{cF}\} = \{10, 0\}$. With a linear compensatory rule trading off difficulty and flexibility, this configuration of preferences and beliefs implies $EU_{cM} = 95 \cdot 10 + 30 \cdot 0 > EU_{cG} = 70 \cdot 10 + 90 \cdot 0$.

- **<u>Scenario II</u>**: The child holds rational expectations on difficulty, but he erroneously perceives the two alternatives as providing the same degree of flexibility, e.g., $\{(P_{cMD}, P_{cMF}); (P_{cGD}, P_{cGF})\} = \{(95, 90); (70, 90)\}$. Moreover, he equally cares about difficulty and flexibility, e.g., $\{\Delta u_{cD}, \Delta u_{cF}\} = \{5, 5\}$. This yields $EU_{cM} = 95 \cdot 5 + 90 \cdot 5 > EU_{cG} = 70 \cdot 5 + 90 \cdot 5$.

Under the standard assumption that individual preferences (i.e., the utility weights) are hardwired and cannot be manipulated, **scenario I** (a preference-driven choice) has different policy implications than **scenario II** (an expectation-driven choice). Specifically, if a policy maker were to intervene by providing the child with the correct information–optimistically assuming that the policy maker knows it–his policy would be potentially effective only under the second scenario. That is, if the now informed decision maker of **scenario II** were to "comply" and used the disclosed objective realization probabilities, he would switch to choice of G (since $95 \cdot 5 + 30 \cdot 5 < 70 \cdot 5 + 90 \cdot 5$). Under **scenario I**, instead, the decision maker will choose M even without holding rational expectations, as long as he does not value flexibility and he correctly perceives M as an easier alternative.

The Parent Problem. I assume that parents put themselves in their children's shoes–meaning that they solve the same problem as their children do–but do it through their own lenses–i.e., through their own subjective expectations and preference weights. This echoes Bisin and Verdier (2001)'s assumption of parental "imperfect empathy," and implies that the parental problem can be formalized as in (2), substituting the individual index c with p.

2.3 Group Decision Making: Separating Members' Preferences, Beliefs, and Decision Rule

The Family Problem. A family-level decision process for curriculum choice may consist of a unilateral decision by a single family member or may entail interactions among members.[10] Specifying a particular form of interaction requires knowledge or assumptions on whether, which, and how family members' beliefs and preferences enter the process, and on whether and

[10] Becker (1981, p. 298) reasons, *"Of course children (in modern times, especially adolescents) may believe that they do know enough and that their parents are out of touch with important changes (...) The conflict with older children is usually less severe, and altruistic parents are more willing simply to contribute dollars that children can spend as they wish (...) [This conflict] means that a common utility function for the family does not exist; different members maximize different utility functions."* For instance, a girl of the Istituto IARD (2001)'s study narrates, *"They never wished to influence me too much, I think because, should it turn out that the choice they imposed is a mistake, they would regret it! Hence, they let me free."* (Istituto IARD, 2001, p.63) While a mother says, *"I liked such a clear idea, and I agreed!"* (Istituto IARD, 2001, p. 59), with reference to the fact that her son provided a clear supporting argument for his choice. And yet, another girl explains, *"My mom wanted me to attend the artistic high school, and my father the accounting track. But I chose a school that will train me to become a teacher, instead. Thus, I gave them both the sack."* (Istituto IARD, 2001, p. 61)

how the choice set and other constraints are modified by the interaction itself.[11]

Set the latter issue aside, a fairly general formalization of a *cooperative* decision process under uncertainty, nesting unilateral decision and other collective processes as special cases, incorporates both revision of decision makers' expectations and negotiation over preferences as follows:

$$\underset{j\in\mathcal{J}}{Max}\ \Gamma^k_{fj} = \sum_{n=1}^{N}\phi^c_n\cdot\left\{\left[w^{c,k}_n\cdot P_{cjn}+(1-w^{c,k}_n)\cdot P_{pjn}\right]\cdot\Delta u^{c,k}_n\right\}+$$
$$+(1-\phi^c_n)\cdot\left\{\left[(1-w^{p,k}_n)\cdot P_{cjn}+w^{p,k}_n\cdot P_{pjn}\right]\cdot\Delta u^{p,k}_n\right\}+$$
$$+\sum_{m}^{M}\varphi^c_m\cdot\left[\delta^{c,k}\cdot x_{cjm}\right]+(1-\varphi^c_m)\cdot\left[\delta^{p,k}\cdot x_{pjm}\right]+\varepsilon^k_{fj}. \quad (3)$$

Hence, child and parent update their subjective beliefs, $\{\{\{P_{ijn}\}_{n=1}^{N}\}_{j=1}^{J}\}_{i\in\{c,p\}}$, to account for each other's opinions and information using outcome-specific weights, $\{w^{c,k}_n\}_{n=1}^N$ and $\{w^{p,k}_n\}_{n=1}^N$ respectively. And they maximize a weighted average of their thus updated subjective expected utilities, using a different set of outcome-level weights, $\{\phi^c_n\}_{n=1}^N$ and $\{\varphi^c_m\}_{m=1}^M$, that reflect how much "outcome-specific say" each member has in the choice. $\{\Delta u^i_n\}_{n=1}^N$ and $\{\delta^i_m\}_{m=1}^M$ denotes family members' preference over outcomes (dependence of the preference parameters on individual characteristics is suppressed for notational convenience), and $\{\varepsilon^k_{fj}\}_{m=1}^M$ is a random component capturing the observational difficulty of the econometrician.

Example (continued). For the sake of the example let us now assume that whenever child and parent make a collective decision, they solve

$$\max_{j\in\{M,G\}}\ \phi^c\cdot\left[P_{cjD}\cdot\Delta u_{cD}+P_{cjF}\cdot\Delta u_{cF}\right]+\phi^p\cdot\left[P_{pjD}\cdot\Delta u_{pD}+P_{pjF}\cdot\Delta u_{pF}\right].$$

This process is nested in problem (3), with $\{w^{c,k}_n, w^{p,k}_n\}\equiv\{1,1\}$, $\phi^c_n\equiv\phi^c\ \forall n$, and $\phi^p=1-\phi^c$. It is then easy to concoct a third scenario in which, choosing according to this rule, child and parent select once again M.

- **Scenario III**: The parent has more say than the child in the choice, e.g., $\{\phi^c,\phi^p\}=\{1/3,2/3\}$. They both care equally about difficulty and flexibility, e.g., $\{\Delta u_{cD},\Delta u_{cF}\}\equiv\{\Delta u_{pD},\Delta u_{pF}\}=\{5,5\}$. The child has rational expectations, i.e., $\{(P_{cMD},P_{cMF});(P_{cGD},P_{cGF})\}=\{(95,30);(70,90)\}$, while the parent erroneously perceives M and G as providing the same degree of flexibility, e.g., $\{(P_{pMD},P_{pMF});(P_{pGD},P_{pGF})\}=\{(95,90);(70,90)\}$. Together these imply

$$EU_{fM}=\frac{1}{3}\left[95\cdot5+30\cdot5\right]+\frac{2}{3}\left[95\cdot5+90\cdot5\right]>EU_{fG}=\frac{1}{3}\left[70\cdot5+90\cdot5\right]+\frac{1}{3}\left[70\cdot5+90\cdot5\right].$$

[11] For example, in Cosconati (2011)'s model of parenting style and human capital formation the parent places constraints on the child's leisure time, thereby affecting his effort's possibility set in doing homework.

The latter example shows how knowledge of decision process dynamics, like presence or absence of interpersonal interactions, is also fundamental to inform policy. In this case, for information provision to be meaningful in the first place, it should target the parent. Furthermore, assessing whether disclosing certain information may be at all effective and to what extent–which a policy maker may wish to know given that information provision is generally costly–requires knowledge of the relative importance of each participant and of her/his preferences. For instance, in **scenario III** protocol and preference weights are such that disclosure of the objective probabilities on flexibility, if feasible, may effectively induce a change in behavior, since

$$\frac{1}{3}\left[95 \cdot 5 + 30 \cdot 5\right] + \frac{2}{3}\left[95 \cdot 5 + 30 \cdot 5\right] < \frac{1}{3}\left[70 \cdot 5 + 90 \cdot 5\right] + \frac{2}{3}\left[70 \cdot 5 + 90 \cdot 5\right].$$

But this need not be the case in general.

Let us finally consider a situation in which child and parent are perfectly aligned and both prefer M, based on the wrong perception that it provides the same degree of flexibility as G, i.e., $\{\Delta u_{cD}, \Delta u_{cF}\} \equiv \{\Delta u_{pD}, \Delta u_{pF}\} = \{5, 5\}$ and $\{(P_{cMD}, P_{cMF}); (P_{cGD}, P_{cGF})\} \equiv \{(P_{pMD}, P_{pMF}); (P_{pGD}, P_{pGF})\} = \{(95, 90); (70, 90)\}$. Hence, they should be "indifferent" among different decision rules–at least within the class of models satisfying unanimity–since any family decision rule linearly combining their expected utilities, including $\{0, 1\}$ and $\{1, 0\}$, would result in choice of M given the primitives. Nevertheless, knowing which rule is employed in the choice will generally be important for a policy maker. Assume he does not. Then, if the family decision process is such that the child chooses unilaterally (as in **scenario II**), providing the correct information may be useful. If, instead, the process entails weighting child's and parent's expected utilities with weights 1/3 and 2/3 (as in **scenario III**), targeting the child alone would not be effective, since

$$\frac{1}{3}\left[95 \cdot 5 + 30 \cdot 5\right] + \frac{2}{3}\left[95 \cdot 5 + 90 \cdot 5\right] > \frac{1}{3}\left[70 \cdot 5 + 90 \cdot 5\right] + \frac{2}{3}\left[70 \cdot 5 + 90 \cdot 5\right];$$

however, targeting the parent alone or both may be, e.g.,

$$\frac{1}{3}\left[95 \cdot 5 + 90 \cdot 5\right] + \frac{2}{3}\left[95 \cdot 5 + 30 \cdot 5\right] < \frac{1}{3}\left[70 \cdot 5 + 90 \cdot 5\right] + \frac{2}{3}\left[70 \cdot 5 + 90 \cdot 5\right].$$

Heterogeneous Family Protocols. In the empirical application, I focus on the following three main family rules observed in my data, all nested in (3).

- **Child chooses unilaterally ($k = 1$).** When a child chooses individually without major interactions with his parents, the family criterion function, Γ^1, coincides with the child's expected utility (2). This protocol includes the possibility that the child interacts with any person or listens to any source different from his parents, and is nested in (3) with $w_n^{c,1} = 1$ and $\phi_n^c = 1 \; \forall n$.

- **Child chooses after listening to the parent ($k = 2$).** I formalize this rule as one in which the child maximizes an expected utility function based on his own preferences, $\{\Delta u_n^{c,2}\}_{n=1}^N$ and $\{\delta_m^{c,2}\}_{m=1}^M$, and on updated expectations that incorporate parental opinions via weights $\{w_n^{c,2}\}_{n=1}^N$. This process is also nested in (3) with $\phi_n^c = 1\ \forall n$. In turn, it nests protocol $k = 1$ with $w_n^{c,2} = 1\ \forall n$.
- **Child and parent make a joint decision ($k = 3$).** This process is a special case of (3) with $w_n^{c,3} = 1$ and $w_n^{p,3} = 1$ for all n, i.e., a joint decision involving by-outcome negotiation with no explicit expectations' revision. However, in the special case in which $\Delta u_n^{c,3} = \Delta u_n^{p,3}\ \forall n$, $k = 3$ does nest $k = 2$. In such a case ϕ_n^c are effectively weights incorporating parental expectations, i.e., $\phi_n^c = w_n^{c,3}$ for all n.

As a final note, it should be made clear that without an explicit model of family rule's selection interpretation of the protocol weights is not univocal. For instance, while weights $\{1 - w_n^{c,2}\}_{n=1}^N$ in protocol 2 will generally capture child's internalization of parental opinions and suggestions, such parameters may in turn depend on aspects of parental socialization decisions and style (see Bisin et al. (2004) and references therein for relevant discussions).

3 Survey and Data

3.1 Study Design and Sample Characteristics

Study participants were sampled with a choice-based design, i.e., randomly within choices (see, e.g., Manski and McFadden (1981)), from the population of all 9th graders entering any public high school of the Municipality of Verona, Italy in September 2007 and their parents (4,189 families in total). Children's participation reached almost 100% of the targeted sample, for a total of 1,215 students. Albeit lower as expected ($\approx$ 60%), parental participation was good for this type of surveys.[12] In the empirical analysis I focus on the 1,029 participating families whose children had just enrolled in high school for the first time when the survey took place. Tables 1 and 2 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 (for a detailed description of the original samples see Giustinelli (2010, Chpt. 2)).

Children completed a paper-and-pencil questionnaire in school during a class time slot ($\approx$ 50-60 minutes), assisted by an interviewer and the teacher of the subject scheduled for that class. The parent questionnaire, also paper-and-pencil, was instead self administered at home

[12] Average parental participation, however, masks some differences across parents' groups. For instance, participation rates among parents of children that reported unilateral decision by self are lower than average. That is, whatever the underlying reason for these parents not to participate in their children's choice–either a deliberate parenting style or disengagement– they also appear to be the same parents that did not participate in the survey. This is not problematic here, since parental expectations and stated choice preferences are used only for estimation of $k = 2$ and $k = 3$ models, whose subsamples have the highest parental participation (up to 80%). On the other hand, this response pattern would indeed be troublesome if one wished to use the data to analyze family rule selection.

during the following 7-10 days and returned to the school in a sealed envelope for collection. The format and administration modes were chosen to maximize participation and facilitate administration inside the schools.

Two important design features were collection of field (as opposed to "experimental") data and use of a retrospective (as opposed to a prospective) approach. Choice of the former was grounded on the high-stakes and once-and-for-all nature of curriculum choice that could be hardly simulated or manipulated experimentally (see Dosman and Adamowicz (2006) for a general discussion). As for the retrospective approach, it is the only sensible one within the context of a cross-sectional data collection. First and foremost, actual choices are observed by design and can thus be combined with expectations data. Second, respondents can provide their probabilistic expectations and stated choice preferences with reference to the most relevant point in time–a relatively recent past before the decision was made–that is likely to vary across families and would therefore be hard to capture for everybody within a prospective framework. The obvious downside is that this approach relies on respondents' capability to unbiasedly recall their expectations and choice preferences before the choice. (For further details on design decisions and for complete English translations of child and parent questionnaires see Giustinelli (2010, Chpt. 2).)

3.2 Subjective Data

Reported Family Decision Rules. Child and parent perceptions of their family decision rule were elicited by means of the following question, here directed to the child. In the actual survey, however, in order to minimize any influence on respondents' recall and report of their beliefs and choice preferences, the battery of questions concerning the roles of family members in the choice were placed after the expectations and stated preference battery.

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

(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 <u>Indicate who decided</u>:	
(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:	○

The design is similar to that of analogous questions in existing large-scale surveys. Indeed, this kind of information can be usefully incorporated in economic models of intra-household behaviors (Friedberg and Webb (2006) and Cosconati (2011) are recent examples using the Health and Retirement Study (HRS) and the National Longitudinal Survey of Youth 1997 (NLSY97) respectively), although it is subject to the criticism that response categories are somewhat stylized and prone to subjective interpretation. Alternatively, numeric measures of "decision-making influence" are commonly used outside economics (e.g., Aribarg et al. (2002) elicit influence from respondents using a 0-100 scale). However, it is not necessarily obvious that qualitative differences between group decision processes can be mapped directly into quantitative differences and elicited as such.

Answers to the decision protocol question and to a follow-up question eliciting identities of the persons the decision maker talked to were then used to classify reported family rules into the three processes formalized in subsection 2.3.[13] Table 1 shows the sample distribution of family decision rules reported by children: either the child chose unilaterally ($\approx$ 27%), or he chose after listening to his parent(s) ($\approx$ 35%), or 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.[14]

Insofar as parents are generally thought to play a substantial role in curriculum choice, these numbers may look surprising. However, a comparison of children's and parents' stated choice preferences with the actual choices made by families reveals that only 14% of children did not have their own way versus 40% of parents (see tables 3 and 4). This is consistent with recent evidence on parenting and children's decision-making development that scholars have interpreted as an instance of the more general shift of Western parenting style in the

[13] Child chooses unilaterally ($k = 1$) includes the case in which he 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 ($k = 2$) covers part of **(C)**. Child and parent make a joint decision ($k = 3$) includes **(A)** and **(B)**. Parent chooses after listening to the child (say, $k = 4$) includes part of **(D)** and **(E)**. Parent chooses unilaterally (say, $k = 5$) includes the case in which she talked to any person different from the child (part of **(D)** and **(E)**) and that in which she chooses without any major interactions with others (**(H)** and **(I)**). Additionally, when either **(A)** or **(B)** was selected, the respondent was asked a follow-up question eliciting the identity of the "threat decision maker," i.e., the decision maker in the counterfactual situation in which no agreement or compromise could be reached. Answers to this question and other information were used to define the "relevant" or "representative" parent.

[14] Following empirical studies of parenting in developmental psychology and economics, I base my analysis on children's reports of family decision rule. In my case this choice is especially warranted by the fact that administration of the student questionnaire was interviewer-assisted (as opposed to the parent questionnaire that was self-administered) and enables me to avoid issues related to selection in parental participation.

last few decades towards a more open "affective and supportive" approach than the previous "prescriptive and rigid" one (Provantini and Arcari, 2009). Alternatively, parents–especially those with a higher socio-economic background and education–may just be "nudging" their children's choices in more subtle ways (similar to the rearing style of American middle-class parents according to Lareau (2003)).

Stated Preferences and Junior High School Orientation. Respondents' stated preferences were elicited by means of the following question, here reported with the wording used for the child questionnaire. With the aim of making their individual pre-decision beliefs salient to respondents when answering this question, in the actual questionnaire the question was placed immediately after the battery of expectations questions used to estimate the behavioral models (described in the paragraph "Probabilistic Expectations" below).

Try and think about your situation last year, when you where still attending your third year of junior high school. [In the common introductory paragraph to expectations and stated preference questions.] ***Please, RANK the following curricula from YOUR most preferred one to the one you like the least, considering only YOUR preferences, expectations, and 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, for example, the survey task of a $k = 2$ child would entail retrieving his probabilistic beliefs *and* his curriculum ranking (corresponding to those beliefs) before the choice, i.e., net of any updating based on parental inputs.

In fact, set measurement issues aside, child and parent stated choice preferences will generally not coincide with the family actual choices due to child-parent interaction in decision making. In table 3, the proportion of families in which the final choice 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 decision rules (columns 4 and 5). On the other hand, actual choices and parents' stated choice preferences do not coincide in 40% of families (table 4). This percentage is, once again intuitively, highest among families in which children reported making a unilateral choice and decreases conditional on more cooperative protocols.

Admittedly, actual choices and children's stated top-ranked alternatives do not coincide even for the 11% of families whose children reported unilateral (self) decision (see table 3). Taking the reported choice protocols at face value, this pattern may be explained by the existence of some factors or constraints that affected the actual decision but were not accounted for in the stated preference task (called "prominence" in the literature). For instance, figures in table 5 show that in about 60% of the cases in which child's SP and RP do not coincide, the latter does coincide with the orientation suggestion provided by junior high school teachers of the child. Hence, one possibility is that, when reporting their choice preferences, some children abstracted from the role that such a suggestion had in their choice. In the empirical analysis of section 4 I explore this possibility.

A separate interesting question is whether families employing joint decision making select undominated alternatives, given individual members' choice preferences. Table 6 shows that cooperative families fail to select an undominated alternative in less than 5% of cases in my sample, thereby supporting "group rationality."

Probabilistic Expectations. From anecdotal and sociological evidence on curriculum choice in Italy (Istituto IARD, 2001, 2005), I identified a set of outcomes, listed in the table below, potentially important for this choice. Hence, after being prompted to think back to the previous year before a final discussion and a final choice had been made, respondents were asked to report on a 0-100 percent chance scale their subjective probabilities, $\{P_{ijn}\}_{i\in\{c,p\}}$, that outcomes $n = 1, ..., N$ would realize under the alternative scenarios that the child were to attend each curriculum $j = 1, ..., J$ of his choice set.[15]

[15] An additional question attempted to elicit children's expected earnings at age 30 under the two alternative scenarios that they would start working immediately after graduation and that they would first obtain a college degree. However, response rates for these question were low, especially among children. Many of them did admit that they had no sense whatsoever of the order of magnitude of a monthly salary. A minority provided answers based either on information received during orientation in junior high school or on their knowledge of their parents' earnings. As for parents, a number of them 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 the choice. Be as it may, low response rates for these questions prevented inclusion of expected income in the empirical specification of child's and parent's expected utility functions.

Outcome	Description
$b_{j1} = 1$	"Like": The child will enjoy the core subjects of curriculum j.
$b_{j2} = 1$	"Ability-Effort I": In curriculum j the child will spend $\geq$ 2.5h a day studying or doing homework.
$b_{j3} = 1$	"Ability-Effort II": The child will graduate from curriculum j in any length of time.
$b_{j4} = 1$	"Ability-Effort III": The child will graduate from curriculum j in the regular time.
$b_{j5} = 1$	"Ability-Effort IV": The child will graduate from curriculum j in the regular time *and* with a yearly GPA $\geq$ 7.5.
$b_{j6} = 1$	"Peers": Attending curriculum j will enable the child to be in school with his best friend(s).
$b_{j7} = 1$	"Flexibility I": Attending curriculum j will enable the child to face a flexible college-work choice by providing him with a suitable training both for some university field(s) and for work in some liked occupation(s).
$b_{j8} = 1$	"College": The child will enroll in college, conditional on graduating from curriculum j.
$b_{j9} = 1$	"Flexibility II": Attending curriculum j will enable the child to face a flexible choice of field in college, i.e., to choose among a wide range of fields, conditional on graduating from j *and* on going to college.
$b_{j10} = 1$	"Work": The child will find an acceptable and liked job after graduating from curriculum j.
$b_{j11} = 1$	"Parent(s)": The child will make his parent(s) happy by attending curriculum j. (Asked to the child only.)

As an illustration, I focus on the "objective outcome" b_{j5}, which is one of special interest since respondents' probabilistic beliefs about its realization can be taken as their estimates of the child's curriculum j-specific ability combined with his effort.

For each curriculum listed below, please, answer the following percent chance question: Last year, when you were still attending your third year of junior high school, what did you think would be your percent chances of maintaining an YEARLY GPA of 7.5 or HIGHER during your educational career, had you decided to attend that curriculum?

Figure 1 shows the distributions of responses for the vocational commerce and the general math-and-science curricula in different estimation samples. As it is indeed observed in actuality (i.e, based on realized students' GPAs, though not on their passing and graduation rates), children perceive the general math curriculum as more difficult than the vocational commerce one. This can be seen by comparing the two top histograms, as low probabilities of obtaining a high GPA in general math feature higher response frequencies than the corresponding ones for vocational commerce, and viceversa. Moreover, higher frequencies for probabilities above equal chances in the parental distribution of beliefs for general math (bottom right histogram) than in their children's distribution (bottom left histogram) are consistent with the common finding that parents tend to be more optimistic regarding youths' future (positive) outcomes than youths are (e.g., Fischhoff et al. (2000), Dominitz et al. (2001), and Attanasio and Kaufmann (2010)).

A complete statistical description of expectations data is beyond the scope and space of this paper, and can be found in Giustinelli (2010, Chpt. 2) for the original samples. There, I compare moments of the sample distributions of probabilistic beliefs with local population statistics (and with statistics from other studies) for outcomes for which such statistics are available (i.e., b_2, b_4, b_5, and b_{10}). Despite substantial heterogeneity of beliefs across respondents and some evidence of rounding and bunching at multiples of 5%, the mean and median responses match up fairly well with the statistics used as comparisons, another typical finding in the literature employing expectations data.

Unfortunately, beliefs on taste for subjects and on flexibility of future choices cannot be easily related to objective statistics. Nonetheless, for the flexibility outcome b_9 I was able to compare respondents' subjective beliefs with enrollment rates in different groups of fields by graduation curriculum, where I take high school curricula followed by more disperse enrollment distributions across college fields as those providing more choice in the college field decision. Remarkably, subjective beliefs and statistics concord in identifying high school curricula that provide more flexibility: the general math-and-science curriculum and, independent of the track, any technology-oriented curriculum.[16]

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" benchmark model of curriculum choice. In the first, the child is the representative or relevant decision maker (i.e., $i \equiv c(f)$); in the second, such a role is taken by the parent (i.e., $i \equiv p(f)$).

Assuming i.i.d. type-I extreme value random terms, the probability of observing child c from family f attending curriculum $\tilde{j}$ is

$$P\left(\tilde{j}|\{\{P_{ijn}\}_{n=1}^{N}\}_{j=1}^{10};\{\{\alpha_j^i\}_{j=1}^{9},\{\Delta u_n^i\}_{n=1}^{N}\}\right) = \frac{exp\left(\mu^i\left[\alpha_{\tilde{j}}^i+\sum_{n=1}^{N}P_{i\tilde{j}n}\cdot\Delta u_n^i\right]\right)}{\sum_{j=1}^{10}exp\left(\mu^i\left[\alpha_j^i+\sum_{n=1}^{N}P_{ijn}\cdot\Delta u_n^i\right]\right)}, \quad (4)$$

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.

[16]While this exercise reveals that flexibility and preferences for flexibility are modeled in a somewhat reduced-form manner (see Barberà et al. (2004) for the theory), eliciting subjective probabilistic beliefs over all possible study and work paths following graduation from each high school curriculum in the choice set would have imposed an excessive response burden on respondents in the context of the current study.

In practice, statistical identification of utility parameters relies on heterogeneity of decision makers' beliefs that function as alternative- and individual-specific attributes of the conditional logit. Alternatively, under rational expectations, one could simply replace individual probabilistic expectations with population averages disaggregated by individual characteristics, if available. In fact, while estimation results from subjective expectations data could be easily compared with those obtained imposing the assumption of rational expectations, the comparison would not provide a proper test for rational expectations, since there exist several reasons why respondents may have expectations that differ from mean realizations in some population or sub-population of reference. For instance, they may hold rational expectations but their process may simply differ from the one characterizing the population taken as a reference by the econometrician.[17]

Estimation of (4) 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 (4) using children's and parents' stated preferences (SP data) as response variables and compare the estimates thus obtained with those based on actual choices.[18] 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 basic case without persistent heterogeneity across choice situations and for sole purpose of parameters' estimation–as opposed to other population quantities whose recovery would still require reweighting–data from choice situations other than the interception can be treated in estimation as if the sampling were random.[19] 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

[17]Delavande (2008) provides an illustration and further discussion on this point. On the other hand, Li and Lee (2009) are able to test and reject rational expectations in the context of political voting with social interactions, where voters' expectations are defined over the voting behaviors of the members of their reference group, demonstrating once again usefulness of expectations data.

[18]It is important to clarify that estimates from the SP model should not necessarily be interpreted as strictly providing the trade-offs children and parents will respectively make under unilateral decision making, for this would require that members of families employing multilateral decision rules (and non-decision makers of families using a unilateral rule) were presented with a *counterfactual* stated choice scenario explicitly worded in terms of individual decision-making. And it would also require that decision makers of families employing a unilateral decision rule were presented with a stated choice scenario making explicit reference to the actual choice situation. Yet, since children's and parents' SPs were elicited through a task that encouraged respondents to recall their beliefs and preferences before the family choice process took place, SP data will contain useful information on individual preference structures of children and parents over outcomes' states.

[19]Notice also that because existing empirical evidence on SP models using 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 estimate the SP models using as an outcome variable the highest ranked curriculum only rather than the complete ranking of alternatives.

multiple data sources presented in appendix A.

Revealed Preferences. Estimates of preference parameters for the basic benchmark model with actual choices are shown in table 7. Significance levels are based on robust ("sandwich") asymptotic standard errors derived by Manski and Lerman (1977). (I discuss their validity for statistical inference with my data 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 the parameters' 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 "average daily homework $\geq$ 2.5h" (b_2), whose utility coefficient may rather be hypothesized to be negative. The most important outcome is "child likes the subjects" (b_1), whose coefficient is approximately 2.5 times larger than that of "face a flexible college field's choice" (b_9), 3.5 times larger than that of "graduate in the regular time" (b_4), and approximately 5 times larger than those of "find a liked job after graduation" (b_{10}), "attend college" (b_8), and "face a flexible college-work choice" (b_7). Preference parameters for these outcomes are all significant at 1%, as opposed to that for "being in school with friends" (b_6) which, somewhat surprisingly, is barely significant.[20]

Qualitative results do not change when "make parent happy" (b_{11}) is introduced in column 3, although the outcome itself turns out to be the third most important one after "child likes the subjects" and "face a flexible college field choice." Similarly, inclusion of a dummy capturing the orientation suggestion by junior high school teachers (columns 4 and 5) induces only marginal changes in the estimates, mostly by making the coefficient of the homework time's outcome not significant.[21] However, the corresponding utility coefficient is significant and approximately 4 times smaller in magnitude than that of "child likes the subjects." This is true despite the fact that the information content of junior high school orientation suggestions should be incorporated in decision makers' expectations. Hence, it is possible that orientation suggestions affect curriculum choice through additional channels, e.g., indirectly, through choice set formation or, directly, through preferences over outcomes.[22]

[20]Notice that while beliefs about friends' choice behavior seems a potentially important variable to incorporate in a model of curriculum choice, my model does not structurally allow for social interactions in the sense of Brock and Durlauf (2001).

[21]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 version constraining the 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 results identical to the ones shown. Sample size of columns 4 and 5 is lower than that of columns 2 and 3 because of item non-response on the orientation question.

[22]In fact, if the orientation suggestion consists of one or more specific alternatives a child may successfully pursue but lacks detailed supporting motivations, families face an inferential problem similar to that faced by an econometrician trying to

Columns 6-7 display estimates from analogous specifications estimated using parental expectations. This model implies the same preference ranking over the most valued outcomes as the model estimated using children's expectations, thereby confirming 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' preference 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. Since the estimated coefficients measure the product of preference weights, $\{\Delta u_n^i\}_{n=1}^N$, and scale parameter, μ^i, a quick way to check whether preference weights are likely to be 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.[23] 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 had a more important role in the choice. 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.

Stated Preferences. Table 8 shows estimation results from SP data. A comparison with the corresponding estimates based on RP data (e.g., columns 5 of tables 7 and 8) reveals that the relative importance of different outcomes implied by children's stated choice preferences 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 making parents happy and on the orientation suggestion.

For parents, too, the relative importance that the child will find a liked job upon graduation and that he will face a flexible college-work choice are higher based on stated preferences (e.g., columns 7 of tables 8 and 7), while that of the orientation suggestion is lower. The coefficient on homework time is now intuitively negative but, curiously, only among parents (although 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.

recover decision makers' beliefs and preference parameters from choices. On the one hand, this implies that family members may have only noisy measures of teachers' opinions available to update their own beliefs. On the other hand, if teachers were to base their suggestions not only on children's abilities and aptitudes but also on children's intentions and choice preferences inclusion of the orientation dummy would be problematic to start with.

[23]Estimates of preference parameters from children's and parents' expectations and for different samples 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 requests. On the other hand, high non-response rates to the expected earnings' questions prevent me from including that variable and from making willingness-to-pay calculations based on its utility coefficient.

Overall, ratios of preference parameters for pairs of outcomes display some variability both between children and parents and across data sources, suggesting that the corresponding differences in estimated coefficients are not a pure artifact of heterogeneous variance of unobserved factors across groups and data sources. Put differently, under the assumption of no bias in SP responses (discussed in appendix B.2.1), it seems reasonable to hypothesize that utility parameters estimated from actual choices and children's (or parents') expectations will capture both preferences and decision-making interactions.

Moreover, as discussed in subsection 2.3, even when children and parents are aligned in theirs beliefs, preferences, or both, prediction and counterfactual analysis still require that family decisions be analyzed through a model that specifies the correct decision-making unit and protocol. Therefore, motivated by this idea, in the next subsections I pool RP and SP data together, and I exploit their distinct information contents together with information on family decision rules to gain identification power and separate parameters describing the latter from children's and parents' utility weights. Specifically, I estimate a distinct discrete choice model for each observed family decision rule, thus making the conceptual framework presented in subsection 2.3 operational.

Heterogeneity. While I do necessarily impose restrictions on preference parameters between SP and RP models *within* family decision protocols, I do not impose any restriction on preference parameters *across* models describing different protocols. 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 protocols and actual choices in the data.[24]

Preference heterogeneity between children and parents and across decision rules are the only forms of systematic or observed heterogeneity I explore in this paper. Of course, it is possible that preferences over outcomes' states 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 assuming a functional form that specifies how individual characteristics enter the structural parameters, because of the relatively small sample sizes available for estimation of the protocol-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 provide in itself indirect evidence about preference heterogeneity across the latter.[25]

[24] In fact, imposing homogeneous preferences for children and parents across decision protocols would actually strengthen identification, possibly allowing me to analyze empirically the more general model in (3). In such a case preference parameters would be identified from variation in children's and parents' beliefs from $k = 1$ families, whereas beliefs' and preferences' aggregation parameters would be respectively identified from differences between stated preferences and actual choices of $k = 2$ and $k = 3$ families. An obstacle to this approach, however, is that response rate is low among $k = 1$ parents.

[25] A discrete choice model may additionally feature forms of unobserved heterogeneity that, if present, will generate correla-

4.2 Heterogeneous Decision Protocols

4.2.1 Econometric Models

Child Chooses Unilaterally (k = 1). Taking information of family decision rules at face value, if a child reports making curriculum choice without any interactions with his parents, only his expectations and preferences are relevant for the final choice. Hence, a first natural approach is to estimate children's preference parameters from their expectations and actual choices (or/and stated preferences), as follows.

- **Model with One Data Source.** This model is formally equivalent to the unitary benchmark in (4), with $i \equiv c(f)$, but is estimated on the subsample of children that reported making a unilateral choice. That is,

$$\max_{j \in \mathcal{J}} \Gamma^1_{fj} \equiv EU^{t,1}_{cj} = \alpha^{t,1}_j + \sum_{n=1}^{N} P_{cjn} \cdot \Delta u^{c,t,1}_n + \varepsilon^{t,1}_{cj}, \tag{5}$$

  where $\varepsilon^{t,1}_{cj}$ is i.i.d. type-I extreme value, with scale parameters $\mu^{t,1}$ and $t \in \{\mathrm{RP}, \mathrm{SP}\}$.

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

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

$$\begin{cases} (RP, 1): \quad \Gamma^1_{fj} \equiv EU^{RP,1}_{cj} = \alpha^{RP,1}_j + \sum_{n=1}^{N} P_{cjn} \cdot \Delta u^{c,1}_n + \varepsilon^{RP,1}_{fj} \\ \\ (SP, 1): \quad EU^{SP,1}_{cy} = \alpha^{SP,1}_y + \sum_{n=1}^{N} P_{cyn} \cdot \Delta u^{c,1}_n + \varepsilon^{SP,1}_{cy}, \end{cases} \tag{6}$$

  where j indexes actual choices (RP) and y indexes stated choice preferences (SP), with $j, y \in \mathcal{J}$. $\varepsilon^{RP,1}_{fj}$ and $\varepsilon^{SP,1}_{cy}$ are 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 (shown in appendix A).

The main difference between (6) and (5) is that the common component of the systematic portions of RP and SP utilities (i.e., $\sum_n P_{cjn} \cdot \Delta u^{c,1}_n$) enables identification and estimation of the SP-RP scales' ratio, $\mu^1 = \mu^{c,SP,1}/\mu^{RP,1}$. Specifically, because $\mathrm{Var}(\varepsilon^{RP,1}_{fj}) = (\mu^1)^2 \cdot \mathrm{Var}(\varepsilon^{SP,1}_{cy})$, 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.

tion across the alternatives' random utility components and cause the i.i.d. assumption to fail. In appendix B.2.2 I discuss a potential source of unobserved heterogeneity that is specific of SP-RP (and repeated SP and other logitudinal) settings, i.e., unobservable persistence across data sources.

Child Chooses After Listening to the Parent (k = 2). The system of latent expected utilities is now

$$\begin{cases} (RP,2): \quad \Gamma^2_{fj} \equiv EU^{RP,2}_{cj} = \alpha^{RP,2}_j + \sum_{n=1}^N \left[w^{c,2}_n \cdot P_{cjn} + (1 - w^{c,2}_n) \cdot P_{pjn} \right] \cdot \Delta u^{c,2}_n + \varepsilon^{RP,2}_{fj} \\ (c\text{-}SP,2): \quad EU^{SP,2}_{cy} = \alpha^{SP,2}_y + \sum_{n=1}^N P_{cyn} \cdot \Delta u^{c,2}_n + \varepsilon^{SP,2}_{cy}, \end{cases} \tag{7}$$

where $j, y \in \mathcal{J}$ and $\varepsilon^{RP,2}_{fj}$ 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 preferences, instead, are estimated from a standard SP model,

$$(p\text{-}SP,2): EU^{SP,2}_{ph} = \alpha^{SP,2}_h + \sum_{n=1}^N P_{phn} \cdot \Delta u^{p,2}_n + \varepsilon^{SP,2}_{ph}, \tag{8}$$

with $h \in \mathcal{J}$.

Children's preference weights, $\{\Delta u^{c,2}_n\}_{n=1}^N$, are identified from variation in children's expectations, through the SP component of the model (c-SP,2). The equality constraints on preference parameters between (c-SP,2) and (RP,2) and the add-to-one restrictions on the aggregation weights for each outcome allow one to back up the latter set of parameters, $\{w^{c,2}_n\}_{n=1}^N$, from the RP model.[26] In fact, whether one is able to pin these weights down with some precision will generally depend on how much variability exists both in child-parent expectations' differences and between children's stated preferences and observed choices 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 (k = 3). In this model child and parent aggregate their expected utilities outcome by outcome but without distinction between expectations' revision and negotiation over preferences. That is,

$$\begin{cases} (RP,3): \quad \Gamma^3_{fj} \equiv EU^{RP,3}_{cj} = \alpha^{RP,3}_j + \sum_{n=1}^N \phi^{c,3}_n \cdot \left[P_{cjn} \cdot \Delta u^{c,3}_n \right] + (1 - \phi^{c,3}_n) \cdot \left[P_{pjn} \cdot \Delta u^{p,3}_n \right] + \varepsilon^{RP,3}_{fj} \\ (c\text{-}SP,3): \quad EU^{SP,3}_{cy} = \alpha^{c,SP,3}_y + \sum_{n=1}^N P_{cyn} \cdot \Delta u^{c,3}_n + \varepsilon^{SP,3}_{cy} \\ (p\text{-}SP,3): \quad EU^{SP,3}_{ph} = \alpha^{p,SP,3}_h + \sum_{n=1}^N P_{phn} \cdot \Delta u^{p,3}_n + \varepsilon^{SP,3}_{ph}, \end{cases} \tag{9}$$

with $j, y, h \in \mathcal{J}$. $\varepsilon^{RP,2}_{fj}$, $\varepsilon^{SP,3}_{cy}$ 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 (9) is analogous to that of (7), but it requires the additional restriction of equal relative scales for (c-SP,3) and (p-SP,3).

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

4.2.2 Estimation Results

Children's preferences are displayed by decision protocol in tables 9, 10, and 12 and 13, which also include estimates of the protocol weights. Whereas parents' preferences, shown in tables 11, 12, and 13, are estimated for groups $k \in \{2, 3\}$ only, because of low participation of $k = 1$ parents.

Preference weights. Starting with the in-high-school outcomes, taste or preference for subjects is confirmed to be the most valued outcome by both children and parents, as well as across decision protocol groups and data sources.

The difference in utility generated by the prospect of having to study and to do homework for at least 2.5 hours daily versus not having to is negative for the $k = 1$ children and positive, but not significant, for the other two groups. This coefficient is negative also among $k \in \{2, 3\}$ parents, but it is not significant. Because the $k = 1$ subsample is more populated by male children attending curricula with longer school hours, less homework and home study time, and more manual laboratory classes (e.g., the vocational and technical industrial and the artistic tracks), this pattern is suggestive of differential preferences for these kinds of schedule and activities as well as gender differences.

The importance rank of graduating in the regular time, between 3rd and 5th among all outcomes, is fairly stable across protocol groups; however, its relative magnitude (with respect to taste for subjects) is highest in the $k = 2$ group and lowest in the $k = 1$ group. Again, this may be capturing differential preferences for a regular path among high ability students and girls, more represented in the $k = 2$ group (see table 2). 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 for being in school with friends, its utility weight is positive among children and negative among parents for most specifications, but it is never significant. Finally, when the outcome "make (the relevant) parent happy" is introduced, qualitative results do not change and, as for the benchmark model, the coefficient for this outcome is always positive and usually significant. Its relative importance, however, vary across protocol groups, being substantially higher among $k = 1$ children. Hence, to the extent that children have some knowledge, albeit imperfect, of their parents' preferences, this suggests that even $k = 1$ parents are likely to play a relevant role in their children's choice, perhaps more indirectly.

Moving to outcomes capturing choices and opportunities after graduation from high school, $k = 2$ children display a relatively strong preference for being able to make a flexible college field choice, second most important outcome to them after like the subjects, followed by find a liked job after graduation and make a flexible college-work choice. $k = 3$ 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 seems 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 2). 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 $k = 1$ 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. When combining SP and RP data and letting 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 (b_9) and finding a liked job after graduation (b_{10}). Hence, in columns 11 and 13 of table 9 (specifications S5 and S6 respectively) I allow coefficients of both b_9 and b_{10} 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.[27]

Another difference between RP and SP for group $k = 1$ concerns the orientation suggestion. As suggested by the descriptive evidence shown in subsection 3.2, 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. Even larger differences are observed for the other two groups ($k \in \{2, 3\}$), 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 the existence of an additional channel, beyond that of expectations, through which the orientation suggestion affect actual choices but not stated preferences. As previously mentioned, this channel could be preferences directly or could be a separate stage of choice set formation. The former may occur if, for instance, teachers publicize "institutionally approved" criteria of curriculum choice (e.g., "children should focus on their attitudes without letting themselves being influenced by their friends' choices"), thereby offering second-order preferences that children can adopt through a process of alignment of their first-order preferences to them. Of course this requires relaxation of the assumption that individuals' preference structures are

[27] 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 than the "inertia or justification bias" generated, e.g., by mechanisms of ex-post rationalization (discussed in appendix B.2.1).

hardwired and cannot be manipulated via policies enacted by socialization agents (see Karniol (2010) for a theory of socialization that develops this idea). The latter may occur if teachers' opinions and recommendations affect choice sets used by families in the choice by inducing them to consider alternatives that they would not consider otherwise or to drop alternatives that they would seriously consider in the choice.[28]

Differences between the data generating processes of SP and RP can be further investigated by inspection of the SP/RP scale parameter and of the alternative-specific constants of the two models. On the one hand, for the $k = 1$ group I cannot reject the hypothesis that $\mu^1 = 1$ nor a model with the RP and SP constants 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 choice under a hypothetical, it is possible that the additional noise is indeed related to the mental process of recall and abstraction respondents were required to perform. (For related issues concerning sp-off-rp experiments see also Train and Wilson (2008).)

Protocol weights. Inspection of the top panel of table 10 reveals that variability of child-parent expectations' differences pins down child's weights on parental expectations, $\{\widehat{1 - w_n^{c,2}}\}_{n=1}^N$, with some precision only for few outcomes. For instance, children assign a greater weight on their parents' opinions than on their own about graduating in the regular time, thereby trusting parental assessments of their ability and effort better than theirs. The estimated weight 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 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

[28]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 occur at least for the $k \in \{2, 3\}$ groups.

for all specifications. The weight on making a flexible college field choice, instead, favors child'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.

Estimates for the $k = 3$ group in top panel of table 12 refer to the weights on children's utility components, $\{\widehat{\phi_n^{c,3}}\}_{n=1}^N$. The weight on child likes the subjects ranges between 0.15 and 0.3. A weight of 0 is rejected for all specifications, and similarly for any weight greater or equal to 0.5. On the contrary, weights on making a flexible college field choice and on finding a liked job after graduation are favor the child; however, only values close to 0 can be rejected, given estimates' precision. Estimated weights for the remaining outcomes are imprecise and compatible with a large range of values, including 0 and 1.

For this group I cannot reject the null hypothesis of a unique weight aggregating child's and parent's expected utilities. Estimates for the constrained model are shown in table 13. The estimated weight on child's utility, which ranges between 0.295 and 0.370, is fairly precise; both 0 and values of 0.5 or above are rejected. This confirm the important explicit role of the $k = 3$ 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 misspecifications, I test the multilateral decision models against the unilateral model and against one another. Since the unilateral model is nested in both multilateral models, I perform LR tests for whether all weights on parental beliefs are equal 0 in table 10 and for whether the weight on child's expected utility is equal 1 in table 13. The null hypothesis is rejected in both cases.

I finally estimate the specification in which the child chooses after listening to the parent on the $k = 3$ subsample and I compare it with the child-parent joint decision model, and viceversa for the $k = 2$ subsample. Since the two models are not nested, I use the test presented in Ben-Akiva and Lerman (1985, p. 171-174) that compares 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 specification in which the child chooses after listening to the parent is found to be statistically superior for both $k = 2$ and $k = 3$ groups.[29]

[29] In fact, a comparison of reported family decision rules by children and by parents reveals less agreement (and hence higher risk of missclassification) in distinguishing between rules 2 and 3 than between rule 1 versus the others (see Giustinelli (2010, Chpt. 2) for more details).

5 Counterfactual Analysis

Galileo and Michelangelo, Resumed. In this paper I maintain the standard assumption that preferences used to trade off different outcomes' states are hardwired and cannot be manipulated by policies. On the contrary, tastes or preferences for curricula's core subjects are uncertain in the model, and individuals hold subjective beliefs on them. It is therefore possible that "awareness" or "desensitization" campaigns can influence choice behavior by affecting beliefs on taste. Hence, in table 14 I simulate two scenarios in which individual subjective probabilities that the child will like the subjects of a specific curriculum change by a *fixed* amount.

Specifically, in the top panel I calculate the percent changes in predicted enrollment shares following a 0.1 increase in the subjective probabilities (of children, parents, and both) that the child would enjoy the core subjects of the math-and-sciences curriculum **(policy 1)**. Whereas, in the bottom panel I report the corresponding changes following a 0.1 drop in the probabilities that the child would like the subjects of the artistic curriculum **(policy 2)**. Calculations are done separately for the pooled samples (unitary models) and for the different decision protocol groups (protocol-specific models).

These 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 decision-making protocol 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.[30] Specifically, in the top panel of table 15 I calculate the percent changes in predicted enrollment probabilities following publication of the 2006 high school graduation rates by curriculum of graduation (conditional on a regular path) based on Al-

[30] This is similar in spirit to existing works in economics of education that analyze the effect on parents' school choices of disclosure of information on school-level characteristics, such as school test scores (see Hastings and Weinstein (2008) for an application exploiting both a natural and a field experiments). Indeed, most high schools in Verona, and in Italy more generally, have public web-pages where some of them post, among other information, school-level statistics for previous cohorts (e.g., passing rates between grades) and post-graduation outcomes (e.g., college enrollment by field and job placement by sector). Of course, while statistics summarizing outcomes of previous cohorts by chosen action constitute in principle useful information, in practice decision makers attempting to use such information face, as econometricians would, the identification problem known as selection (see analysis by Manski (2004*b*)).

maDiploma (2007*a*)'s statistics **(policy 3)**.[31] And in the top panel of Table 16 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 5)**. 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.

Policy 3 generates a moderate increase in predicted enrollment in general curricula, especially the humanities and math, and a drop in predicted enrollment in the vocational and artistic curricula. While this pattern is suggestive of a potential overstatement of the difficulty levels of general curricula, the protocol-specific predictions show an intuitive attenuated pattern for the $k = 2$ group, especially the children, which is probably due to selection of girls and higher socio-economic background/higher ability children into this group (see table 2). In turn, **policy 5** generates qualitatively similar predictions, this time suggesting a potential underestimation of the "costs" of going to college after receiving a not fully suitable training.[32]

Last but not least, decomposition of counterfactual enrollment responses by decision-making rule for these experiments shows that publication of education statistics would have a larger impact on the group of children reporting unilateral decision by self. While this cannot be necessarily taken as a sign that these children have less precise beliefs, this is indeed one possibility. Of course this may be either due to differential observable or unobservable characteristics of children across protocol groups (such as ability or access to information) or to the very decision protocol (or to both). In particular, 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 (see Adams and Ferreira (2010) for a similar argument about individual vs. multilateral decision, but in a different context).

Institutional Policies. In the bottom panels of tables 15 and 16 I simulate the effects of changes in families' beliefs generated by two institutional-type policies. **Policy 4** lowers educational standards and equalizes them across curricula by guaranteeing all children a pass in all grades through the diploma for all curricula.[33] In practice, I assume that individuals hold subjective probabilities that the child will graduate in the regular time equal to 1 for all curricula, keeping expectations for the other outcomes fixed.

[31] 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.almadiploma.it).

[32] A limitation of this counterfactual experiment is that, although these statistics are curriculum specific, they are not disaggregated by individuals' characteristics, such as gender or academic ability (see Sartarelli (2011) for an argument in favor of disclosure of *conditional* statistics in the context of college major choice). More generally, the exercise assumes that disclosed statistics are taken and used by decision makers at face value, since no model of expectations' formation and updating is specified and estimated.

[33] While taken literally this policy may appear unrealistic and probably 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 individuals hold zero subjective probabilities of going to college, of facing a flexible college-work choice, and of facing a flexible choice of field in college after graduating from any vocational curriculum.

As expected, the first intervention tends to stimulate enrollment in general curricula and in some technical curricula while depressing enrollment in vocational and artistic curricula. But responses do not seem large. Once again the pattern is attenuated, and in some cases reversed, among the $k = 2$ children who are likely the least "ability constrained." In turn, the second intervention induces a huge drop in vocational enrollment, mostly in favor of technical schools. The latter result is intuitive: children who value the possibility of going to college after graduation, but that would enroll in a vocational curriculum if the restriction were not in place, would now switch to curricula of the "lowest" track that ensures eligibility for enrolling in college. Finally, the decomposition by decision protocol shows that if parents only were aware of policies changing institutional features of tracking, the impact of such policies may be much 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 (as in the U.S.), curricular, or a combination of the two (as in many European countries). The distinctive purpose of the latter 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.[34] 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 one side, the earlier the child's age at

[34]There exists a sizeable literature in economics of education concerned with how institutional features of a stratified schooling system affects its efficiency (e.g., Ariga et al. (2010)) and equity (e.g., Brunello and Checchi (2007)). Prominent issues analyzed by this literature are the tension between breadth and depth of education and the determination of the optimal time of tracking (e.g., Brunello et al. (2007)). In the OECD group, for instance, the age of first tracking ranges from 10 in Austria and Germany to 18 in Canada and the U.S., and 15-16 are modal (Brunello and Checchi, 2007). In fact, the American system is considered to be de-tracked curricular-wise, though recently some states have experienced specialization shifts, such as the Florida requirement that 9th graders declare a major (I thank David Figlio for pointing this out). As for the sorting mechanism, typical ones are testing (e.g., in Germany) and family choice (e.g., in Italy). As for the degree of rigidity, a fully rigid stratification (as in 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.

tracking the longer the future that must be anticipated and the less the accumulated history of past school performance that can be used to form expectations on the child's tastes, ability, and future outcomes. On the other side, the stronger and more rigid is specialization the more difficult are "wrong choices" to be costlessly corrected or corrected at all.

The Italian system considered in this paper constitutes an interesting hybrid characterized by a relative early tracking (at entry in high school) that is, in principle, mitigated 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. Based on anecdotal and sociological evidence (e.g., Istituto IARD (2001, 2005)), however, Italian families (especially the children) seem to believe that a wrong training in high school will generally carry a "cost" in 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.

As a matter of fact, tracking during compulsory education renders curriculum choice a (early) career decision that, 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) and Arcidiacono (2004)). 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-related outcomes (see Manski (1993) and references therein). Moreover, such a structural albeit simple framework enables me to perform novel counterfactual exercises simulating the effects on curriculum enrollment of policies involving publication of information aiming at reducing families' uncertainty and modification of variables regulating rigidity and standards of stratification.

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 their 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, the main contribution of the data collection and the empirical analysis carried by this work is clearly to provide new and more rigorous and detailed evidence on some these issues.[35]

[35] Saez-Marti and Zilibotti (2008) review the cultural transmission-endogenous preference literature and summarize the two

6.2 Parenting and Decision Making by Children

As just mentioned, the literature on curriculum choice posits a crucial role of family background (Checchi and Flabbi, 2007). Despite this, to the best of my knowledge no existing study has explicitly modeled the roles of children and parents in the choice. For instance, Arcidiacono et al. (2011) and Zafar (2008) estimate models of college major choice under uncertainty using measures of subjective probabilities and counterfactuals from students of two top American universities. Both works assume that college students are the main decision makers of their major, which appears sensible given the latter's age. And yet, based on data on perceived (by students) parental approval and expectations, Zafar (2008, 2011) finds evidence of a likely strong parental influence in the choice. In turn, 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 child-parent interaction 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 (see Lundberg et al. (2009) and reference therein from developmental psychology). It seems, therefore, natural to hypothesize existence of heterogeneous decision rules across families, ranging from unilateral to more interacted protocols.

Despite this fact, to date only a recent handful of studies, such as Bursztyn and Coffman (2011) and Berry (2010), have challenged the unitary view of household behavior (Becker, 1981) in the context of educational choices. These works develop non-cooperative models of child-parent interactions with moral hazard motivating empirical applications on children's school attendance (or achievement) using data from field experiments in developing countries. Specifically, Bursztyn and Coffman (2011) analyze 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 (2010) tests whether identity of

main modeling approaches. In the paternalistic model parents use their own preferences to evaluate their children's utility and, with some effort, seek to transmit their preference trait to the latter (as in Bisin and Verdier (2001)). Whereas, in the non-paternalistic model (e.g., Doepke and Zilibotti (2008)), parents choose their children's preferences to maximize children's well-being by making a costly investment, but without necessarily trying to install their own cultural variant. My framework incorporates both non-paternalistic and paternalistic features. On the one hand, parents and children share the same objective function, i.e., choosing the curriculum that matches the child best while accounting for both early and later future consequences of this choice. And, with this very purpose, parents may try to affect children's choice (and future) via the channels of beliefs' transmission or of a negotiated choice. On the other hand, parents' intervention is based on their own beliefs and preferences over future states, which are allowed to differ from those of their children.

recipients (i.e., children or parents) of cash incentives for school achievement (e.g., enrollment and attendance) in India affects their effectiveness.[36]

My paper contributes to this stream of works by analyzing a different schooling choice margin (i.e., "quality" vs. "quantity" of human capital, although the two are clearly related in a stratified context) and by explicitly modeling child-parent decision making with heterogeneous cooperative-type rules. The latter choice is justified by the fact that in my setting children and parents are assumed to solve the very same problem. Thus, even though in this paper I do not model family selection into decision rules, which I take as exogenously given, the underlying idea is that cooperation exists whenever communication of opinions, information, and preferences can improve quality of choice.[37]

7 Conclusions

In this paper I study the empirical identification of a framework of static decision making under uncertainty with multiple decision makers and no strategic interactions that combines elements of Savage (1954)'s setup, Harsanyi (1955)'s utilitarian aggregation, and Raiffa (1968)'s experts problem. The identification problem is one of distinguishing how decision makers' beliefs and preferences over outcomes' states and their decision rule determine actual choices.

I use this framework to analyze high school curriculum choice with curricular stratification, conceptualized as a choice with uncertain child's taste, ability, and future opportunities and choices, and one in which child's and parents' decision-making roles may vary across families. I employ purposely collected data on families' actual choices and decision rules together with children's and parents' stated choice preferences and probabilistic beliefs over outcomes' states to unpack the determinants of this choice and to estimate structural parameters capturing children's and parents' trade-offs among different outcomes' states and parameters describing family rules.

Estimates of two unitary-family models (Becker, 1981), alternatively assuming that children and parents are the representative decision makers, suggest that children and parents hold

[36]These papers and mine fit in with an emerging literature studying child-parent interactions and decision-making dynamics and their consequences on children's outcomes (e.g., Weinberg (2001), Burton et al. (2002), Hao et al. (2008), Lizzeri and Siniscalchi (2008), and Cosconati (2011), among others). 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) for a discussion).

[37]In fact, modeling this aspect explicitly would require confronting the issue of how certain are individuals about the probabilities for, to the extent that child and parent disagree about some of them, one may have better information than the other (I thank Peter Arcidiacono for articulating this point). While this seems beyond the scope of this paper and the possibilities of my data–since the survey asked respondents to provide point probabilities without encouraging them to express their potential ambiguity through ranges or second order beliefs–it did, nonetheless, ask them to express on a 0-100 scale how sure they had felt *ex ante* that their favorite curriculum would be their best option. (And, if such a probability was less than 100, it asked respondents to split the remaining amount among the curricula they thought would alternatively be their best option.) Assuming fixed preferences, the latter variable may be interpreted as an aggregate (i.e., not outcome-specific) measure of how certain are individuals about their beliefs. The interested reader can find a descriptive analysis of this measure in relationship to the family decision rules in Giustinelli (2010, Chpt. 3).

similar beliefs and preferences over outcomes' states. Nevertheless, differences in the relative magnitude of preference parameters between the two groups, a stronger explanatory power of children's expectations on actual choices, and direct information on families' decision rules all point to a prominent role played by children. In fact, accounting for decision rule heterogeneity reveals that children reporting own decision after listening to their parents trust parental opinion better than their own for some outcomes (e.g., those concerning their ability, but not those regarding their preferences for subjects). And estimates of the joint decision-making model support a substantial influence of parental preferences on the final choice for the corresponding group of families, with approximate relative weights of $\{1/3, 2/3\}$ in favor of parents.

I use the estimates to simulate response of curriculum enrollment to changes in individual expectations generated by "awareness" campaigns, provision of information on outcomes of previous cohorts, and institutional policies affecting curricular standards and specialization. I find that the unitary-family benchmark and the model with heterogeneous decision rules generate intuitive and qualitatively similar predictions that, nonetheless, are quantitatively different. In particular, identity of policy recipients–whether children, parents, or both–matters for enrollment response, implying that accounting for decision makers' beliefs and decision rule heterogeneity is important for policy analysis.

Taken altogether, the results suggest that it is important that the economics of the family provides a formal accommodation for the role of adolescents in family decision-making and that the economics of education takes into account the channels and degree in which parents transmit their beliefs and preferences to their children–whether because they want to make them in their own image or, on the contrary, because they wish to help them make better choices and face better future opportunities.

Inevitably, this work relies on simplifications and assumptions concerning both the theoretical framework and the study design. On the theoretical side, separability of uncertain outcomes **(i)** and of beliefs and utility valuations over outcomes' states **(ii)** follow directly from the adopted Bayesian-type framework à la Gilboa et al. (2004). In turn, exogeneity of decision makers' beliefs with respect to choice preferences **(iii)** posits an imperfect information model of randomness that allows decision makers to measure attributes (i.e., the objective realization probabilities) with error, but assumes that such errors do not affect decision making. (E.g., this assumption would be violated if decision makers were aware of their errors, were risk averse, and had differential information across alternatives.)

As for exogeneity of family decision protocols with respect to choice preferences **(iv)**, while the former appear to be statistically related with actual choices in my data, it remains to be established whether such a relationship is structural in nature, as it would be if, e.g., selection of a family decision rule for curriculum choice were dependent on child's and parent's beliefs and preferences structures. Indeed, this may due to gains and costs from cooperation (as in

Del Boca and Flinn (2011)), a deliberate parental behavior (as in Bisin and Verdier (2001) and Doepke and Zilibotti (2008)), or some other reasons. And if any of these were true, quantifying the effects of a policy targeting family members' expectations would require a joint model of decision rule selection *and* curriculum choice, since that policy would affect curriculum choice both directly *and* through the channel of decision rule selection.

Finally, I decided to focus on cooperative family processes **(v)** because of a main feature curriculum choice shares with the Raiffa (1968)'s panel-of-experts problem, in which aggregation of family members' preferences and beliefs is implicitly motivated by the wish of making a better choice than the one a single member would make individually. Nonetheless, it is clear that the typical nature of child-parent interactions suggests exploring also non-cooperative, agency-type avenues (e.g., Cosconati (2011)).

Additional modeling simplifications, such as the non-structural (or not fully structural) treatment **(vi)** of formation of children's choice set (possibly shaped by parents and teachers), **(vii)** of the role of friends ("peer or network effects"), and **(viii)** of preferences for flexibility in the subsequent work and college choices, were mostly dictated by constraints on the study design. I consider this work to be a first step; points **(iv)**-through-**(viii)** are in progress within a new prospective and longitudinal (during-the-choice) study.

8 Tables and Figures

Table 1: OBSERVED CHOICES AND REPORTED DECISION PROTOCOLS

Curriculum	**Population**[a] (%)[b]	**"Unitary"**[c] **Model All**	**"Unitary"**[d] **Model Matched**	**Protocol 1**[c] **Reported by Child**	**Protocol 2**[e] **Reported by Child**	**Protocol 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 Sciences	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)
Reported Decision Protocol				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 2: Background Characteristics

Background Characteristics	Unitary Model Sample	Protocol 1 Sample	Protocol 2 Sample	Protocol 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 3: COMPARING FAMILY REVEALED PREFERENCE (RP) AND CHILD STATED PREFERENCE (C'S SP)

	Unitary Model All	**Unitary Model Matched**	**Protocol 1 Reported by Child**	**Protocol 2 Reported by Child**	**Protocol 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 4: COMPARING 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 3
are due to higher item non-response rates to the SP question among parents.

Table 5: Family RP, Child's SP, and Junior High School Suggestion - $k = 1$ Group

	RP $\equiv$ JH	**RP $\neq$ JH**	**Marginals**
RP $\equiv$ Child's SP	68 (55.74)	37 (30.33)	105 (86.07)
RP $\neq$ 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 6: Family RP, Child's SP, Parent's SP, and "Group Rationality" (P.O.) - $k = 3$ Group

	RP P.O.	**RP $\neg$P.O.**	**Marginals**
RP$\equiv$C's SP$\equiv$P's SP	138 (57.98)	0 (0)	138 (57.98)
RP$\equiv$C's SP$\neq$P's SP	69 (28.99)	0 (0)	69 (28.99)
RP$\equiv$P's SP$\neq$C's SP	12 (5.04)	0 (0)	12 (5.04)
RP$\neq$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.

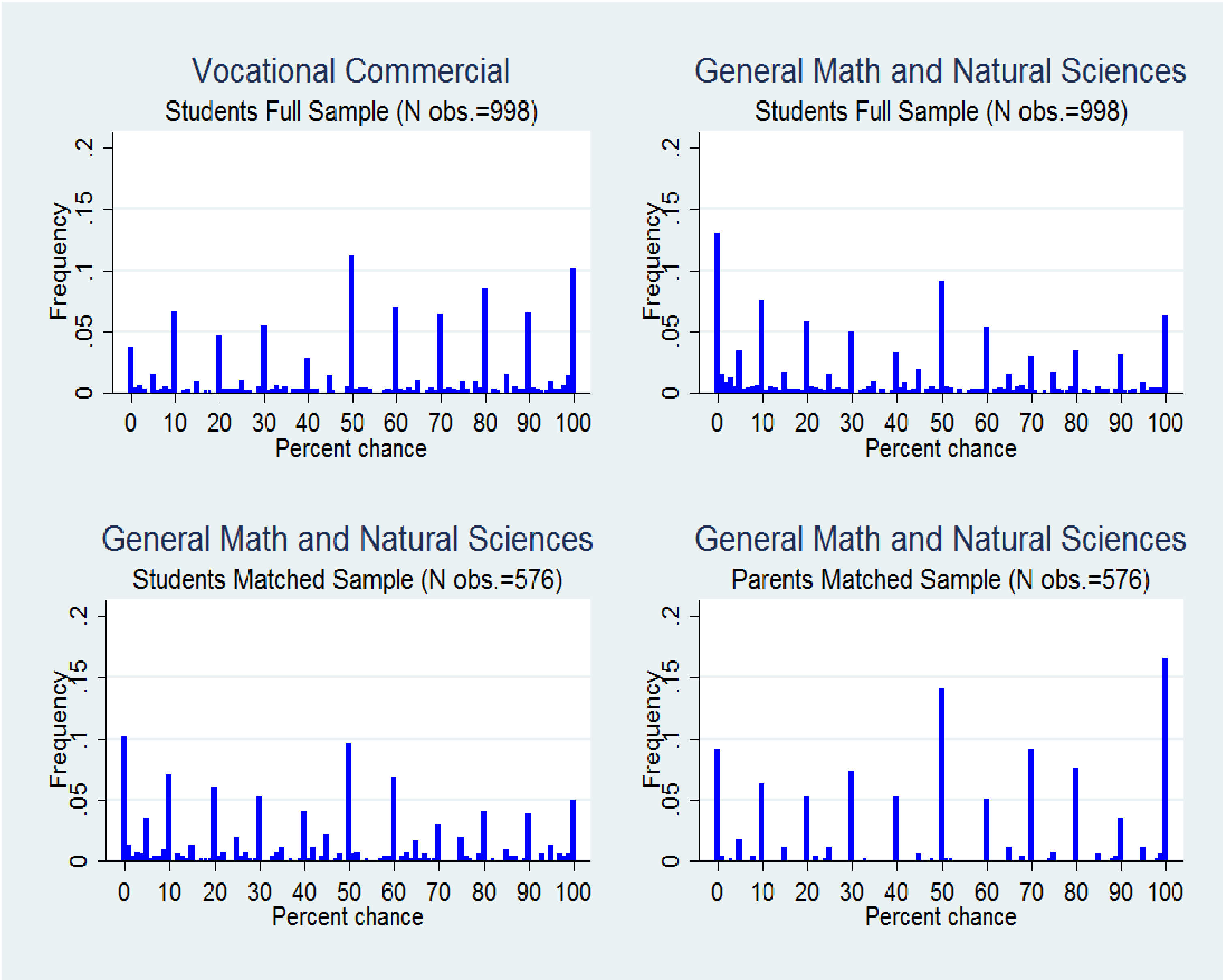

Figure 1: Respondents' Use of the 0-100 Scale: Percent Chances that the Child Graduates in the Regular Time with an Yearly GPA ≥ 7.5.

Table 7: "Unitary Model" 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_6)	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_7)	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_8)	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_9)	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_{10})	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)	–	–
Junior High School 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 8: Children's and Parents' 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_6)	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_7)	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_8)	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_9)	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_{10})	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)	–	–
Junior High School 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 9: "Child Chooses Unilaterally"

Variables	RP Model (S1)	RP Model (S2)	RP Model (S3)	RP Model (S4)	SP Model (S1)	SP Model (S2)	SP Model (S3)	SP Model (S4)	SP-RP Model (S2)	SP-RP Model (S5)	SP-RP Model (S4)	SP-RP Model (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_6)	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_7)	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_8)	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_9) **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_9) **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)
Junior High School Suggestion RP	–	–	2.38*** (0.64)	2.32*** (0.64)	–	–	–	–	–	–	2.33*** (0.64)	2.26*** (0.63)
Junior High School Suggestion SP	–	–	–	–	–	–	1.26*** (0.45)	1.14*** (0.44)	–	–	1.11** (0.48)	1.50** (0.61)
Constants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SP Scale	–	–	–	–	–	–	–	–	1.008*** (0.120)	0.845*** (0.096)	1.010*** (0.134)	0.813*** (0.103)
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 10: "Child Chooses After Listening to the Parent" – Children's SP-RP Model

Variables	(S1)	(S2)	(S2d)	(S3)	(S4)	(S4d)
Weights on Parent's Expectations						
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_6)	−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_7)	−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_8)	−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_9)	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_{10})	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's 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_6)	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_7)	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_8)	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_9)	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_{10})	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)
Junior High School Suggestion RP	–	–	–	3.13*** (3.05)	3.08 (2.12)	3.30 (3.16)
Junior High School Suggestion SP	–	–	–	0.51 (2.05)	0.35** (1.79)	−4.33** (2.57)
Constants	Yes	Yes	Yes	Yes	Yes	Yes
RP Dummies	No	No	Yes	No	No	Yes
SP 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)
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 11: "Child Chooses After Listening to the Parent" – Parents' SP Model

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_6)	0.03 (0.44)	0.04 (0.42)	−0.15 (0.48)	−0.12 (0.41)
Flexible College-Work Choice (b_7)	1.37** (0.55)	1.34** (0.55)	1.50*** (0.57)	1.56*** (0.56)
Attend College (b_8)	0.20 (0.64)	−0.06 (0.59)	0.22 (0.66)	−0.16 (0.62)
Flexible College Field Choice (b_9)	1.56** (0.75)	1.55** (0.72)	1.52** (0.73)	1.47** (0.71)
Liked Job after Graduation (b_{10})	2.34*** (0.58)	2.35*** (0.58)	2.33*** (0.61)	2.30*** (0.60)
Junior High School Suggestion	–	–	0.42* (0.23)	0.02 (0.29)
Constants	Yes	Yes	Yes	Yes
RP Dummies	No	Yes	No	Yes
Log-likelihood ($LL(\hat{\theta})$)	-268.705	-244.8485	-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 12: "Child and Parent Make a Joint Decision" – Outcome-Specific Weights

Variables	(S1)	(S2)	(S2d)	(S3)	(S4)	(S4d)
Child's Weights						
Like Subjects (b_1)	0.243***	0.287***	0.196***	0.209***	0.194**	0.161**
	(0.067)	(0.074)	(0.075)	(0.072)	(0.084)	(0.068)
Daily Homework $\geq$ **2.5h** (b_2)	0.711	1.183	0.656	0.799	1.309	0.865
	(1.031)	(1.123)	(0.435)	(1.330)	(1.581)	(0.701)
Graduate in Regular Time (b_4)	0.551	6.451	0.572	0.356	0.673	0.423
	(0.548)	(15.207)	(0.486)	(0.496)	(1.029)	(0.284)
In School with Friend(s) (b_6)	0.480	0.322	1.060	0.404	0.231	0.352
	(0.794)	(1.998)	(3.300)	(0.491)	(0.724)	(0.463)
Flexible College-Work Choice (b_7)	0.307	-1.038	-0.559	0.235	-1.000	-0.180
	(0.360)	(1.817)	(1.167)	(0.472)	(2.192)	(1.138)
Attend College (b_8)	0.070	0.063	0.016	-0.049	-0.147	-0.040
	(0.149)	(0.063)	(0.106)	(0.190)	(0.225)	(0.137)
Flexible College Field Choice (b_9)	0.686**	1.021**	0.618***	0.721	0.879**	0.685***
	(0.356)	(1.021)	(0.220)	(0.445)	(0.387)	(0.245)
Liked Job after Graduation (b_{10})	0.979**	0.334	1.032***	0.876	0.461	0.932***
	(0.514)	(0.334)	(0.187)	(0.756)	(0.387)	(0.308)
Child's Preferences						
Like Subjects (b_1)	15.95***	11.53***	17.98***	17.63**	13.91***	19.75***
	(5.09)	(2.69)	(6.83)	(7.38)	(4.38)	(7.57)
Daily Homework $\geq$ **2.5h** (b_2)	1.38	1.21	1.47	1.11	1.22	1.35
	(1.37)	(0.91)	(1.43)	(1.51)	(1.08)	(1.25)
Graduate in Regular Time (b_4)	4.37	0.52	3.75	3.79	3.26	3.30
	(2.73)	(1.33)	(2.90)	(2.34)	(2.56)	(2.62)
In School with Friend(s) (b_6)	1.12	0.43	-0.22	1.61	0.86	0.89
	(1.06)	(0.89)	(1.26)	(1.13)	(1.07)	(1.61)
Flexible College-Work Choice (b_7)	1.55	-0.55	-1.31	1.16	-0.43	0.84
	(1.59)	(0.52)	(2.38)	(1.93)	(0.57)	(5.26)
Attend College (b_8)	4.51**	3.76***	7.06*	4.07*	3.69**	5.73
	(1.93)	(1.31)	(3.67)	(2.26)	(1.67)	(3.65)
Flexible College Field Choice (b_9)	5.58**	3.84**	5.38**	5.02*	3.83**	4.70**
	(2.40)	(1.53)	(2.29)	(2.70)	(1.91)	(2.12)
Liked Job after Graduation (b_{10})	1.64	3.98*	1.21	2.25	4.22	2.06
	(1.80)	(2.11)	(1.04)	(2.98)	(3.07)	(1.98)
Parent Happy (b_{11})	–	2.29**	1.91*	–	2.70**	2.38*
		(0.94)	(1.00)		(1.17)	(1.36)
Junior High School Suggestion RP	–	–	–	2.90**	1.16***	1.11**
				(1.19)	(0.42)	(0.49)
Junior High School Suggestion SP	–	–	–	-1.48	0.04	-3.01**
				(2.11)	(0.52)	(1.86)
Parent's Preferences						
Like Subjects (b_1)	8.80***	7.23***	8.89***	8.01***	7.21	7.86***
	(2.00)	(1.39)	(1.73)	(2.19)	(1.54)	(1.49)
Daily Homework $\geq$ **2.5h** (b_2)	-1.50	-0.90	-2.69	-0.79	-1.00	-2.37
	(1.85)	(1.45)	(2.03)	(1.23)	(1.89)	(2.48)
Graduate in Regular Time (b_4)	1.79	-0.39	2.64	1.82	1.57	4.02
	(2.98)	(0.74)	(3.73)	(1.38)	(4.16)	(2.72)
In School with Friend(s) (b_6)	-0.33	-0.11	-0.40	-0.72	-0.49	-1.44
	(1.16)	(0.93)	(1.16)	(1.30)	(0.92)	(1.21)
Flexible College-Work Choice (b_7)	1.97	0.96	1.41	3.38	1.07	2.18
	(1.23)	(1.02)	(1.31)	(2.34)	(1.32)	(2.04)
Attend College (b_8)	0.79	0.79	0.28	0.41	0.52	0.35
	(1.20)	(0.88)	(1.26)	(0.77)	(0.90)	(1.36)
Flexible College Field Choice (b_9)	3.32	2.07	4.80*	1.22**	2.62	4.79*
	(2.03)	(1.45)	(2.48)	(0.50)	(1.88)	(2.53)
Liked Job after Graduation (b_{10})	3.95**	2.63***	6.38***	3.17*	3.08**	6.11**
	(1.84)	(0.96)	(2.61)	(1.63)	(1.33)	(2.87)
Junior High School Suggestion SP	–	–	–	2.21**	1.84**	2.48*
				(1.11)	(0.72)	(1.28)
Constants	Yes	Yes	Yes	Yes	Yes	Yes
RP Dummies	No	No	Yes	No	No	Yes
SP Scale (Child≡Parent)	0.478***	0.635***	0.285***	0.451***	0.532***	0.280***
	(0.133)	(0.113)	(0.088)	(0.163)	(0.140)	(0.086)
Log-likelihood ($LL(\hat{\theta})$)	-502.383	-494.693	-437.941	-457.802	-450.630	-401.005
Adjusted Likelihood Ratio Index ($\bar{\rho}^2$)	0.663	0.667	0.689	0.667	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 13: "Child and Parent Make a Joint Decision" – Single Weight

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

	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 of Subjective Prob. of "Child Likes the Subjects" of General Math-Scie by 0.1**									
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
Protocol $k=1$ (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
Protocol $k=2$–Children's Expectations	-0.30	-0.14	-1.09	-3.64	-1.42	-0.20	-5.44	-3.93	-0.71	+6.74
Protocol $k=2$–Parents' Expectations	-0.23	-0.10	-0.83	-2.71	-1.02	-0.18	-4.17	-2.90	-0.50	+5.06
Protocol $k=2$–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
Protocol $k=3$ (1 weight)–Children's Expectations	-0.73	-0.54	-0.40	-0.76	-1.12	-2.93	-4.94	-7.33	-2.75	+6.41
Protocol $k=3$ (1 weight)–Parents' Expectations	-0.94	-0.73	-0.55	-0.98	-1.43	-3.85	-6.61	-9.71	-3.67	+8.50
Protocol $k=3$ (1 weight)–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	**An Decrease of Subjective Prob. of "Child Likes the Subjects" of Artistic Educ by 0.1**									
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
Protocol $k=1$ (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
Protocol $k=2$–Children's Expectations	+0.01	+0.06	+0.06	-0.02	+0.13	-6.20	+1.80	+0.23	+0.80	-0.01
Protocol $k=2$–Parents' Expectations	+0.00	+0.06	+0.06	-0.03	+0.11	-4.70	+1.33	+0.16	+0.64	-0.01
Protocol $k=2$–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
Protocol $k=3$ (1 weight)–Children's Expectations	+0.12	+0.11	+0.12	+0.01	+0.72	-6.13	+0.31	+0.31	+0.18	+0.52
Protocol $k=3$ (1 weight)–Parents' Expectations	+0.17	+0.12	+0.13	+0.02	+0.94	-7.86	+0.39	+0.43	+0.21	+0.67
Protocol $k=3$ (1 weight)–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 15: POLICY EXPERIMENTS (CONTINUED)

	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 Subjective Prob. of "Child Graduates in the Regular Time" Coincide with the Realized Ones 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
Protocol $k=1$ (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
Protocol $k=2$–Children's Expectations	-1.73	-0.17	-0.50	+0.38	+0.16	+0.41	-0.85	+0.12	+0.27	-0.23
Protocol $k=2$–Parents' Expectations	-4.30	-0.12	+1.06	-2.94	-2.23	-5.10	+3.93	+4.12	+0.64	+1.32
Protocol $k=2$–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
Protocol $k=3$ (1 weight)–Children's Expectations	-2.48	-2.88	+0.22	+1.47	-1.89	-3.39	+1.28	-2.63	+0.79	+1.68
Protocol $k=3$ (1 weight)–Parents' Expectations	-5.74	-4.57	+0.09	+0.75	-1.19	-3.64	+2.86	-0.70	+1.80	+2.31
Protocol $k=3$ (1 weight)–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–Lower Standards	**Everybody Is Guaranteed a Diploma in the Regular Time from Any Curriculum (I.e., Subjective Prob. of "Child Graduates in the Regular Time"=1 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
Protocol $k=1$ (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
Protocol $k=2$–Children's Expectations	+1.68	-0.15	-0.53	+0.08	+0.02	+0.19	-0.54	+0.08	+0.27	-0.07
Protocol $k=2$–Parents' Expectations	-4.25	-0.30	+1.42	+0.35	-1.01	-2.33	+0.74	+5.05	+0.88	-0.55
Protocol $k=2$–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
Protocol $k=3$ (1 weight)–Children's Expectations	-2.60	-2.65	+0.32	+2.43	-1.64	-2.52	+0.22	-2.12	+0.78	+1.15
Protocol $k=3$ (1 weight)–Parents' Expectations	-6.00	-4.00	+0.35	+2.92	-0.56	-1.94	+0.54	+0.32	+1.74	+1.12
Protocol $k=3$ (1 weight)–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

[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%.

Table 16: Policy Experiments (Continued)

	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–Info Provision of College Enrollment Stats.	**Individual Subjective Prob. of "Child Attends College" Coincide with the Realized Ones in a Previous Cohort[a] 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
Protocol $k=1$ (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
Protocol $k=2$–Children's Exp.	-0.39	-0.17	+0.28	-0.09	-0.74	-0.57	+0.23	+0.19	+0.23	+0.14
Protocol $k=2$–Parents' Exp.	+3.14	+1.19	-1.77	+1.90	+3.29	+3.90	-1.03	-1.27	-0.81	-1.91
Protocol $k=2$–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
Protocol $k=3$ (1 weight)–Children's Exp.	-1.70	-5.13	+2.11	+1.96	-1.10	-2.66	+0.61	-1.25	-1.62	+0.90
Protocol $k=3$ (1 weight)–Parents' Exp.	-1.28	-3.16	+0.73	+0.23	-0.01	-1.79	+0.63	+0.22	+0.42	+0.66
Protocol $k=3$ (1 weight)–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
Policy 6–More Rigid Tracking	**Vocational Diplomas Do Not Give Access to College (I.e., Subjective Prob. of "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
Protocol $k=1$ (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
Protocol $k=2$–Children's Exp.	-52.52	-31.16	+26.67	+ 8.79	+0.30	+4.96	+0.03	+5.69	-0.00	+0.21
Protocol $k=2$–Parents' Exp.	-17.38	-18.16	+6.50	+10.68	+0.22	-0.06	+0.02	+3.63	-0.00	+0.15
Protocol $k=2$–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
Protocol $k=3$ (1 weight)–Children's Exp.	-33.82	-23.40	+11.10	+11.84	+2.78	+0.70	+0.32	+0.47	+5.37	+0.85
Protocol $k=3$ (1 weight)–Parents' Exp.	-44.97	-45.97	+17.58	+20.86	+5.14	+0.91	+0.49	+0.68	+5.51	+1.08
Protocol $k=3$ (1 weight)–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

[a] 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%.

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A Choice-Based Sampling and the WESML Estimator

Likelihood function. Let us first 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 pair $(x,\tilde{j})$ under choice-based sampling can then be written as

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

with

$$Q(\tilde{j}) = \int_X P(\tilde{j}|x;\theta)p(x)dx. \tag{11}$$

The important point here is that 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 (10), 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 components of) the protocol-specific models.

Multiple sources of preference data. The likelihood in (10) can be easily rewritten for the case with multiple sources of preference data,

$$\lambda_{cb}(x,j,y,h) = p(x,y,h|j)H(j) = \frac{P(j,y,h|x;\theta)p(x)}{Q(j)}H(j), \tag{12}$$

where j indexes families' actual choices, y indexes children's stated-preferred alternatives, and h indexes parents' stated-preferred alternatives, with $j, y, h \in \mathcal{J}$. It is then clear that 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

$$\begin{aligned}\lambda_{cb}(x,j,y,h) =& P(y|x^y,j;\theta^y)P(h|x^h,j;\theta^h)P(j|x^j;\theta^j)p(x)\frac{H(j)}{Q(j)} = \\ =& \lambda_r(y|x^y)\lambda_r(h|x^h)\lambda_r(j|x^j)p(x)\frac{H(j)}{Q(j)},\end{aligned} \tag{13}$$

with

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

and where x^j, x^y and x^h, as well as 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 the extension of this framework to account for persistent (across data sources) unobservable heterogeneity while accounting for choice-based sampling of RP.

B Robustness Checks and Discussions

B.1 Statistical Inference

Statistical inference is based on the robust ("sandwich") asymptotic variance-covariance matrix derived by Manski and Lerman (1977) for the WESML estimator. Because sample size is modest for the protocol-specific models, as a robustness check I additionally 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 protocol-specific models. However, coefficients' significance levels remain mostly unchanged and qualitative patterns are identical.

While econometric theory and simulation evidence suggest that the bootstrap may be superior, especially if applied to pivotal statistics such as confidence intervals (see Horowitz (2001) for details), assessing superiority of the bootstrap for this particular application would require an ad-hoc Montecarlo study, which is left for a separate work. More specifically, existing simulations for the logit model provide evidence that in small samples bootstrap standard errors tend to outperform the asymptotic ones while overestimating the true values (e.g., Teebagy and Chatterjee (1989)); nonetheless, standard errors are not asymptotically pivotal statistics, and evidence is lacking for non-random samples.

Finally, calculating confidence intervals that account for the fact that students are physically clustered in classrooms may be a desirable additional check. Unfortunately, the small number of classes *within* choices makes it infeasible to perform with my data. This is because with endogenous stratification the bootstrap must be applied in a manner that preserves the original data structure, i.e., by drawing observations–in this case classes in place of individuals as above–from choice subsamples rather than from the whole sample. Nevertheless, two institutional arguments should 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 existing 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, a concern would arise if children had copied from one another when filling in the questionnaire in class.[38] However, presence of the interviewer and of the teacher and my own personal observation (as an interviewer) of class dynamics during administration of the survey makes this 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 retrospectively reporting ex-ante wantedness of their newly born children, Rosenzweig and Wolpin (1993) found that wantedness stated after children had been born was significantly influenced by children's 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. In fact, the design of the NLSY79 pregnancy roster used by Rosenzweig and Wolpin (1993) and that of my data feature two fundamental differences. First, at the time of the survey none of the outcomes relevant for curriculum choice (with the exception of being in school with friends) had realized nor significant information had become available for families to update their expectations (e.g., children had experienced only about 7-10 days of high school and had never been tested during that period). Hence, respondents could not have updated their choice preferences based on realized outcomes' states or new information on outcomes' realization probabilities. Second, respondents were never inquired about whether they wanted to choose the curricula children had actually enrolled in. Rather, they were presented with the universal set of curricula available in the Verona Municipality 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, in turn, names respondents' tendency to report stated choice preferences that coincide with actual choices "justification bias" and attributes such a bias to some form of "inertia." In fact, a recent paper by Chen and Risen (2010) 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 attitude change due to cognitive dissonance and ex-post rationalization, since it will generally occur even with stable preferences. This notwithstanding, if when asked to state their choice preferences respondents do tend to report more often the alternatives they did previously select in a real choice situation, such a tendency induces state dependence of stated preferences on actual choices. Indeed, following Morikawa (1994), empirical works in the SP-RP literature have included RP or "inertia" dummies in specification of SP utilities to deal with state dependence.

In tables 10-13 I myself run "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 $k = 1$ group, since logically incorrect under the model's assumptions.) While such dummies have mostly significant coefficients (not shown for reasons of space but available upon request), their inclusion does not change qualitative results for the structural parameters.

These results should be interpreted cautiously, however, for the inclusion of inertia dummies may induce estimates' bias and inconsistency if there exists also unobserved underspecified correlation between

[38] I thank Aviv Nevo for pointing this out.

the SP and RP error terms. For instance, if something is omitted from the deterministic components of SP and RP utility functions (e.g., see in equations (7) and (9)), then such an omission will generate correlation between the error terms of the SP utility functions and the RP dummies that are, therefore, endogenous. 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 tractable methods that can deal with) forms of dependence between multiple sources of preference data generated by different designs of the stated preference or stated choice experiments (see Train and Wilson (2008) for the econometrics of some state-of-the-art SP designs). Despite this and despite the large volume of literature, especially in transportation, using combined SP and RP data with the latter collected through a choice-based sampling protocol, the complications arising when introduction of unobserved SP-RP correlation is combined with complex non-random survey designs seem to have been largely ignored.

As an exception, in the context of an "intercept & follow" sampling design McFadden (1996) shows that no natural extension to the WESML estimator exists for the case of unobserved heterogenity, since the correction factor needed for this case will generally not be available in form of auxiliary data nor could be calculated from the model without one knowing the parameters. However, 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, a natural extension to endogenous stratification may be possible. Exploration and validation of such a possibility are in progress in a companion work. This would be especially interesting with heterogeneous unilateral and multilateral decision rules since, as shown in Giustinelli (2010, Chpt. 2), the particular error structure capturing correlation across data sources will generally depend on the nature of the decision rule.

B.2.3 Probabilistic Expectations and the Retrospective Elicitation

Finally, I briefly discuss potential issues related to retrospective elicitation of expectations data, while abstracting from issues like rounding, approximation, or bunching at "focal values" (e.g., see Manski and Molinari (2010)). Specifically, I consider the case in which–whether due to recall bias or to lack of effort–respondents report their post-choice expectations instead of their pre-choice expectations.[39] (These two types of expectations may be seen as the two polar cases, of "no recall" and "perfect recall" respectively, of a model of recall where retrospectively reported expectations are mixtures of the pre-choice and the post-choice expectations.) Conditional on the decision protocol variable being error free and on arguments developed in section B.2.1, retrospective elicitation is potentially problematic only for $k \in \{2, 3\}$ families. Intuitively, the closer reported probabilistic beliefs are to decision makers' ex-post expectations the less variability will generally exist between children's and parents' reported beliefs among the former protocol groups implying, at the minimum, less precise estimates of protocol parameters. More formally, assuming that children report their expectations already updated to account for their parents' beliefs (and viceversa) and using the relationship between observed ex-post expectations and ex-ante unobserved expectations (known up to the updating parameters), one could write down the misspecified model in terms of the true variables and protocol parameters (available upon request). Usefulness of this exercise, however, is limited to making transparent that the implied measurement error is non-classical and induces heteroskedastic errors (see also the discussion in Bound et al. (2001)). In particular, this together with lack of closed form for the estimator makes it difficult to predict the direction of the potential bias.

[39] In the context of unilateral decision making, Zafar (2010)'s findings are positively reassuring. By analyzing patterns of beliefs' updating, he is able to rule out cognitive dissonance being of serious concern nor does he find evidence of systematic (non-classical) measurement error in the reporting of beliefs.