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

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(Running Head: Group Decision Making)

Abstract

Predicting group decisions under uncertainty requires disentangling individual members' utilities over the consequences of choice, their expectations for uncertain outcomes, and their choice process as a group. I estimate simple Bayesian models of child-parent choice of high school track with subjective risk and unilateral or bilateral, non-strategic decisions, by combining families' actual choices with novel survey information about children's and parents' subjective probabilities over choice consequences, their individually preferred choices, and their decision roles. A set of policy counterfactuals confirms the importance of introducing the beliefs and decision roles of individual members in models and policy analysis of group decisions.

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1 Introduction

A board of directors deciding to enter a new market or to develop a new product; a couple choosing a place to live or a contraceptive method; a patient and her doctor selecting a treatment; or an elderly parent and her children selecting a nursing home, are an assorted sample of consequential choices members of specific 'groups' make jointly and in the face of uncertainty. Revealed preference analysis of any such choice requires a strategy to separately identify (i) the utility valuations individual agents assign to the future outcomes or consequences of choice; (ii) agents' subjective probabilities over the uncertain states; and (iii) the decision process or protocol they use as a group. This is because multiple configurations of these components are likely to be observationally equivalent while carrying different implications for prediction and policy (e.g., Gilboa et al. (2008), Manski (2004, 2000)).[1]

Absent any information about the group decision process behind observed choices, the common approach thus far has been to treat the group as a 'black box' and to make strong assumptions about the expectations of its members. In this article, I present the first empirical application that simultaneously departs from treating the family as a monolithic decision maker and from making strong rationality assumptions about the relevant expectations for intra-family decision making under uncertainty. I present and estimate simple Bayesian models of child-parent choice of high school track with subjective risk and with unilateral or bilateral, non-strategic decision making, by combining observed enrollment into distinct tracks for a sample of Italian 9th graders, with novel survey information about the probabilistic expectations, individual choice preferences, and choice participation and roles of the students and their parents.[2] The parameters of interest are the utility weights the child and the parent individually attribute to

[1] By revealed preference analysis, I refer to the practice of inferring decision rules from data on observed choices, and of using those inferences to predict behavior in other settings. An example of a decision rule for choice under uncertainty is subjective expected utility maximization. By group decision process, or protocol, I mean whether and how the utility valuations and probabilistic beliefs of the individual group members enter and drive the decision of the group.

[2] Recent works point to heterogenous decision-making agency of adolescents across families and decision domains (e.g., Lundberg et al. (2009), Dauphin et al. (2011)).

the outcomes of choice and, for families whose members report making a bilateral decision, the weights the child and the parent jointly use to aggregate either their beliefs or their subjective expected utilities.

Family members hold subjective beliefs, which are directly defined over the consequences of track choice they use to maximize their subjective expected utilities. For example, the empirical specification of the child's and the parent's subjective expected utilities includes short-term outcomes such as the child's enjoyment, effort, and achievement in high school, and longer-term outcomes such as the child's opportunities and choices after high school.[3] This assumption is both cognitively and descriptively plausible (Gilboa and Schmeidler, 2004), and it eases belief elicitation. As a downside, it rules out any perceived interdependencies among the probabilities as well as the utilities of different outcomes.

The Bayesian paradigm of choice under uncertainty implies that decision makers act upon their beliefs as though the probabilities were known to them, ruling out ambiguity or higher order beliefs. Additionally, Bayesian group decision making requires that group members process and aggregate their beliefs and their utilities separately, one outcome at a time, and that they reveal their beliefs and utilities honestly to one another, thus excluding situations with conflict of interest among group members, risk sharing, or social planning (e.g., Hylland and Zeckhauser (1979), Keeney and Nau (2011)). Bayesian group decision making does not guarantee that the group choice is efficient in a Paretian sense (e.g., Raiffa (1968), Hylland and Zeckhauser (1979)). However, under some conditions it can be represented by a process where individual members aggregate their subjective expected utilities directly, yielding Pareto-efficient choices: an implication I test in the data (Keeney and Nau, 2011).[4]

Enrollment of Italian students into high school tracks – general, technical, or vocational, with additional sub-categories – occurs non-selectively ('open enrollment') by family choice at the end

[3] Recent works in economics of human capital suggest that academic achievement and monetary returns may not be the only or most important drivers of educational choices (e.g., Jacob and Lefgren (2007), Zafar (2013)).

[4] A choice is Pareto-efficient for the group if no other feasible choice would increase the subjective expected utility of at least one member of the group without decreasing those of the other members (Raiffa, 1968).

of 8th grade, aided by teachers' recommendations. Curricular specialization during secondary education or earlier makes track choice consequential and implies a greater uncertainty the younger the students at tracking. While curricular tracking is the norm among the OECD countries (see Betts (2011)'s review), its implementation and institutional features tend to vary across countries. Italian tracking has both 'rigid' and 'flexible' features. On the one hand, different tracks or curricula are generally offered in separate schools, and track-switching occurs infrequently and can be costly time wise. On the other hand, graduation certificates from the majority of curricula, including vocational ones, enable students to continue onto college, albeit at the cost of training and, hence, skill mismatch. These features make the Italian setting especially interesting for the analysis and the policy counterfactuals.

Substantively, this paper addresses three main questions. First, what are the most important determinants of high school track choice? This may be restated as a question about what outcomes (e.g., short- vs. long-term) are most valued by families in my sample as implied by their observed choices. Second, what roles do children and parents play in the decision? This may be restated as a question about separately identifying and estimating the child's and the parent's utility parameters from the weights they use to aggregate their beliefs or utilities under non-strategic joint decision making. Third, does identity of policy targets – and relatedly allowing for heterogeneous family protocols – matter for prediction and counterfactuals? The answers to these questions inform both an emerging economic literature on child-parent decision making and interactions (e.g., Attanasio and Kaufmann (2014), Bursztyn and Coffman (2012), and Cosconati (2011)), and more established research on educational choices under uncertainty (e.g., Altonji (1993), Arcidiacono et al. (2012), Stinebrickner and Stinebrickner (2013), and Wiswall and Zafar (2014)). It is important to clarify, however, that the paper's findings hold conditional on the observed family protocol. Hence, any form of family protocol selection related, for instance, to the probabilities or utility structures of individual members, will be built in the elicited beliefs and/or in the estimated utility or aggregation parameters for the corresponding protocol group.

Methodologically, this paper introduces two innovations. First, for the first time stated and revealed preference data and methods are used together to identify and estimate the parameters of a multilateral discrete choice model under uncertainty.[5] Second, for the first time 'right-hand-side' data on individual members' subjective probabilities are combined with 'left-hand-side' data on both actual and stated choices in order to model and identify the expected utilities of the group as well as those of the individual members. The paper thus expands a growing body of research in economics, which has used expectations data exclusively to model unilateral decisions under uncertainty from actual or, alternatively, stated choices (e.g., Delavande (2008), Zafar (2013)). Finally, the paper contributes to a small but growing set of papers analyzing population heterogeneity in decision protocols used by individuals or groups (e.g., Adams and Ferreira (2010), Del Boca and Flinn (2012)).

I find that the child's enjoyment of the curriculum is the most valued attribute across family members and decision protocols. The importance of other short-term outcomes (e.g., school achievement or effort) relative to longer-term ones (e.g., facing flexible college and work choices after graduation) is instead heterogeneous across family members and protocols. Separate estimation by family protocol shows that parental expectations have differential influence on the choice through different outcomes, whenever the child and the parent jointly aggregate their beliefs. For example, parental opinion about the child's achievement in high school matters more than the child's own opinion. Whereas, the opposite is true about post-graduation choice flexibility. The estimated aggregation parameters indicate a predominant parental role in those families where the child and the parent make the decision by jointly aggregating their subjective expected utilities, with (1/3, 2/3) weights on child and parent respectively.

I use the parameter estimates to simulate hypothetical policies which would affect curriculum enrollment by changing children's and/or parents' beliefs. A simulated 10-point increase in

[5] The empirical literature has employed stated and revealed preference methods to improve estimation efficiency of unilateral discrete choice models and/or to estimate hard-to-identify utility parameters (Morikawa, 1994). Recent works in marketing and transportation have begun using combined stated and revealed preference methods to examine intra-family decisions (O'Neill et al., 2013), typically with no attention to uncertainty. On the other hand, the economics of the family has long recognized the need to account for forms of interaction among family members (e.g., Basu (2006)), but has not employed the types of data and econometrics used in this paper.

students' chances of enjoying math in the general track – an example of 'math sensitization' – indicates that the large utility weight families attach to the child's enjoyment can yield a large impact on curriculum enrollment with relatively small movements in beliefs. Subjecting university access to graduation from specific tracks – an example of institutional policy tightening specialization – would also produces a large impact on curriculum enrollment in my sample. On the contrary, providing information about population graduation rates, or about college enrollment by graduation track, would be likely inconsequential. While this is partly due to a limited importance of the latter outcomes relative to child's enjoyment, it concords with direct evidence that families' expectations about these outcomes are on target already.

Separate estimation by family protocol generates additional insights for policy consideration. For example, taking the parent to be the representative decision maker overestimates the magnitude of enrollment response to the simulated sensitization campaigns. On the other hand, a decomposition by family protocol and by policy recipient indicates that publication of specific statistics would have the largest impact on the enrollment of children who report making the decision unilaterally. Finally, if parents alone were aware of institutional changes to tracking, the impact of such policies would be likely smaller than if children too were aware of them.

In sum, the counterfactuals illustrate the role and the importance of introducing both expectations and decision roles of specific family members in models and policy analysis of human capital decisions. More generally, the approach advanced by this paper could be fruitfully used to study a range of group choices under uncertainty, outside the family and human capital contexts. The paper proceeds as following. Section 2 presents a general framework of Bayesian group decision making under uncertainty, and illustrates the main identification and policy issues with a stylized example. Section 3 covers the study design and describes the samples used in the empirical analysis of sections 4 and 5. Section 6 presents the counterfactual policy exercises. Section 7 concludes. I will use the terms in each of the following pairs interchangeably throughout: decision and choice, process and protocol, consequences and outcomes.

2 Theoretical Framework and Identification Problem

Individual and Group Processes of Bayesian Decision Making Let us consider a population of groups, $g = 1, ..., G$, such as families, collections of friends, or boards of directors. Each group is made of two or more individuals, $i = 1, ..., I_g$, facing a choice among a common set of discrete alternatives, $j = 1, ..., J \in \mathcal{J}$. In my application, the groups are child-parent dyads, with the parental role represented through the primitives of a single ('representative' or 'relevant') parent. The choice alternatives are high school curricula.

The choice is static, with separable binary outcomes, $\{b_n \in \{0, 1\}\}_{n=1}^{N} \in \mathcal{B}$. Choice outcomes may affect the whole group (e.g., a group of friends going on a vacation together), a particular member (e.g., a patient undergoing surgery but making her treatment decisions jointly with her physician), or even a third party (e.g., the organization behind an executive committee). In my application, choice outcomes are the events over which children's and parents' subjective probabilities were elicited in the survey, including the child's future experience in high school (e.g., his enjoyment of the curriculum, study effort, or achievement), as well as his opportunities and choices after high school (e.g., being able to choose between college and work options).[6]

Individual group members are Bayesian subjective expected utility maximizers, as following:

$$\begin{aligned} \max_{j \in \mathcal{J}} SEU_{ij} &= \sum_{n=1}^{N} \left[P_{ijn} \cdot u^i(b_n = 1) + (1 - P_{ijn}) \cdot u^i(b_n = 0) \right] = \\ &= \sum_{n=1}^{N} P_{ijn} \cdot \Delta u_n^i + \sum_{n=1}^{N} u^i(b_n = 0). \end{aligned} \tag{1}$$

For each $j \in \mathcal{J}$ and $b_n \in \mathcal{B}$, $P_{ijn} = P_{ij}(b_n = 1)$ indicates member i's subjective probabilistic beliefs that outcome $b_n = 1$ would result if alternative j were chosen. Whereas, $\Delta u_n^i = u^i(b_n = 1) - u^i(b_n = 0)$ represents the difference in utility that member i would derive from $b_n = 1$ relative to $b_n = 0$, following any choice. $\sum_{n=1}^{N} u^i(b_n = 0)$ drops out of the choice, as it is constant across the alternatives.

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[6] This approach strikes a balance between credibility and tractability. Measuring subjective probabilities of separable binary outcomes only requires eliciting one marginal probability per outcome and choice alternative from each respondent, i.e., $P_{ij}(b_n = 1)$ for all (n, j) pairs, instead of joint belief distributions.

In my application, i is replaced by c for child and by p for parent. Hence, parents put themselves in their children's shoes by solving the same problem as their children do. But they do so through their own lenses, that is, through their own subjective probabilities and through the utilities they consider appropriate to make trade-offs among the relevant choice outcomes, thus echoing Bisin and Verdier (2001)'s assumption of parental 'imperfect empathy.'

It is important to observe that the individual problem is formulated directly in terms of those utilities and subjective marginal probabilities group members would individually use to choose among the available alternatives, thus dispensing with the whole Savage (1954)-type state space (e.g., Gilboa and Schmeidler (2004)). Additionally, individual members' beliefs may or may not coincide with the probabilities of the true stochastic process governing the outcomes. Hence, no rational expectations or other common assumptions are invoked here. Lastly, equation (1) assumes that the utility parameters Δu_n^i are homogenous within family member's type across the population (i.e., across children, but not between children and parents), and that they are choice independent.[7]

If group members are individually Bayesian, how would they choose as a group? The Bayesian paradigm requires them to decompose the problem into utilities and probabilities; then, to process and aggregate the two sets separately across members; and finally to select the alternative that maximizes the group's SEU based on the aggregated probabilities and utilities. That is,

$$\max_{j \in \mathcal{J}} SEU_{gj} = \sum_{n=1}^{N} P_{gjn} \cdot \Delta u_n^g = \sum_{n=1}^{N} \left[\left(\sum_{i=1}^{I_g} \varpi_n^i \cdot P_{ijn} \right) \cdot \left(\sum_{i=1}^{I_g} \varphi_n^i \Delta u_n^i \right) \right], \tag{2}$$

where ϖ_n^i and φ_n^i are the weights group members use to aggregate their beliefs and their utilities.

The Bayesian model in (2) yields group choices that may or may not be Pareto optimal. In

[7] Parameter homogeneity within family member's type can be easily relaxed empirically by allowing the utility weights to depend on a vector of individual observable characteristics, z_i (i.e., $\Delta u_n^i = \Delta u(b_n, z_i)$), or by treating them as random coefficients. In fact, posing one of the components of z_i equal to $P_{ij\tilde{n}}$, for some outcome $\tilde{n}$ hypothesized to be related to n, would be equivalent to introducing interaction effects in i's SEUs, thereby partly relaxing the full separability across outcomes. On the other hand, parameter homogeneity across choice alternatives is both reasonable and customary in empirical models of discrete choice, but that too could be relaxed with richer expectations data.

general, Pareto optimality fails when a feasible unchosen alternative – if chosen – would increase the SEU of some member without making the others worse off. However, Pareto optimality holds in special cases or models nested in (2). Two special cases are when members' probabilities, utilities, or both are perfectly aligned, or when different members contribute different inputs to the decision process.[8] Pareto optimality results also in Keeney and Nau (2011)'s model of efficient Bayesian group decision making, where the group preferences can be represented by a linear aggregation of the individual members' SEUs.

As both the variety of existing models of Bayesian group decision making and casual real-life observation suggest, different groups may address the problem differently. Important decisions may require that group members develop a common decision frame, gather and exchange information, create and discuss alternatives, compare probabilities and utilities, etc. This process may lead to some updating and some convergence. However, the updated probabilities and utilities of each member are still individual ones. And whether or not the members end up completely agreeing, either the group or one of its members still must make a final decision. Accordingly, I assume that families approach the choice in two stages and according to one of the following decision processes:

(PR1) Unilateral choice by one member If no systematic interaction takes place among the members in the first stage, one member makes a unilateral decision in the second stage, according to the standard rule of Bayesian individual decision making of eq. (1).

On the other hand, when the preliminary interaction occurs in the first stage, group members make a final choice according to one of the following two protocols of Bayesian multilateral decision making in the second stage.

(PR2) Linear pooling of members' beliefs and a single decision maker The group members engage in linear pooling of their subjective probabilities, but accept the utility struc-

[8] For example, in Karni (2009)'s model of medical decision making the physician provides the probabilities of the outcomes associated with different treatments and the patient provides his utilities. In a special version of Raiffa (1968)'s panel of experts problem, the experts provide the probabilities and the decision makers combines those with his own probabilities and utilities to make a final choice.

ture of one member, $\tilde{i}$,

$$\max_{j \in \mathcal{J}} SEU_{\tilde{i}j} = \sum_{n=1}^{N} P_{gjn} \cdot \Delta u_n^{\tilde{i}} = \sum_{n=1}^{N} \left[\sum_{i=1}^{I_g} \omega_n^i \cdot P_{ijn} \right] \cdot \Delta u_n^{\tilde{i}}, \tag{3}$$

where $\omega_n^i \geq 0$ for all $i = 1, ..., I_g$ and $\{b_n\}_{n=1}^N$, and $\sum_{i=1}^{I_g} \omega_n^i = 1$ for all $\{b_n\}_{n=1}^N$.[9]

(PR3) Efficient group choice, with linear aggregation of members' SEUs The group members directly aggregate their SEUs (Keeney and Nau, 2011),

$$\max_{j \in \mathcal{J}} SEU_{gj} = \sum_{i=1}^{I_g} \phi^i \cdot SEU_{ij} = \sum_{i=1}^{I_g} \phi^i \cdot \left[\sum_{n=1}^{N} P_{ijn} \cdot \Delta u_n^i \right], \tag{4}$$

where $\phi^i \geq 0$ for all $i = 1, ..., I_g$ and $\sum_{i=1}^{I_g} \phi^i = 1$.

It is useful to notice that the first process (PR1) is nested in (2), with $\varpi_n^i = 1$, $\varphi_n^i = 1$, and $\varpi_n^h = 0$ and $\varphi_n^h = 0$ for all $h \neq i$. The second process (PR2) is nested in (2), with $\varpi_n^i = \omega_n^i$ for all i, $\varphi_n^{\tilde{i}} = 1$, and $\varphi_n^i = 0$ for all $i \neq \tilde{i}$. Whereas, the third process (PR3) is not nested in (2).

Because my data correspond to the time of the final decision, I focus on stage 2 and take stage 1 as given. If information about the group members' probabilities, choice preferences, or interactions were available for both stages, one could use them to model the selection into group protocols and the final choice jointly, and to test their interdependence.[10]

Identification Problem and Policy Implications: A 2×2×2×2 Example Let us consider a child (C) and a parent (P), facing the choice between art (A) and math (M). They focus on two outcomes. The first is whether the child would enjoy the curriculum taught in each track, the 'like' outcome (L). And the second is whether the training provided by each

[9] An alternative interpretation is that one member is in charge of the decision, but assigns some weights to the opinions of the other members. Following Dietrich (2010)'s, I use linear pooling to model belief aggregation in stage 2, where any remaining divergence between family members is more likely due to differences in representation or interpretation of the available information, rather than to differences in information previously shared in stage 1.

[10] In fact, repeated observations of individual members' beliefs during the decision process would additionally enable one to test the assumption of linear aggregation and/or to allow for more general or heterogenous forms of aggregation. I thank an anonymous referee for suggesting this point.

track would enable the child to choose between both college and work options after high school, the 'flexibility' outcome (F). While not disliking math, the child has a distinct taste for art. Accordingly, he faces 95 and 70 percent chances of enjoying A and M, respectively. On the other hand, the art training is somewhat narrow and most suitable for majoring or working in the area of figurative arts. Hence, the child's actual chances of a flexible college-work choice would be substantially lower if he were to graduate from A, 30 percent, than from M, 90 percent.

The child and the parent of the example form their subjective assessments $\{P_{iAL}, P_{iAF}\}$ and $\{P_{iML}, P_{iMF}\}$, with $i \in \{C, P\}$, of the actual probabilities $\{95, 30\}$ and $\{70, 90\}$. And they assign utilities to the outcomes $\{\Delta u_{iL}, \Delta u_{iF}\}$, with $i \in \{C, P\}$. Then, either the child makes the choice individually according to PR1, or the child and the parent make a joint decision according to PR3. The child's observed choice is art (A).

Let us temporarily assume that the child is known to have made the choice unilaterally, according to $\max\limits_{j \in \{A,M\}} SEU_{Cj} = P_{CjL} \cdot \Delta u_{CL} + P_{CjF} \cdot \Delta u_{CF}$. A researcher interested in making inference on the choice of this or similar families is faced with multiple competing explanations consistent with choice of A, conditional on unilateral decision making. The following two scenarios illustrate the identification problem and its policy relevance.

(S1) Utilities-driven choice C holds rational expectations, i.e., $\{P_{CAL}, P_{CAF}\} = \{95, 30\}$ and $\{P_{CML}, P_{CMF}\} = \{70, 90\}$, but only cares about enjoying the curriculum, e.g., $\{\Delta u_{CL}, \Delta u_{CF}\} = \{10, 0\}$. This implies $SEU_{CA} = 95 \cdot 10 + 30 \cdot 0 > SEU_{CM} = 70 \cdot 10 + 90 \cdot 0$.

(S2) Expectations-driven choice C holds rational expectations about enjoyment, but he erroneously perceives both tracks as highly likely to provide flexibility, e.g., $\{P_{CAL}, P_{CAF}\} = \{95, 90\}$ and $\{P_{CML}, P_{CMF}\} = \{70, 90\}$. Moreover, he equally cares about enjoyment and flexibility, e.g., $\{\Delta u_{CL}, \Delta u_{CF}\} = \{5, 5\}$. This yields $SEU_{CA} = 95 \cdot 5 + 90 \cdot 5 > SEU_{CM} = 70 \cdot 5 + 90 \cdot 5$.

Under the standard assumption that utilities are hardwired and cannot be manipulated, the two scenarios carry different policy implications. Specifically, if a policy maker could and did provide the child with the correct information, her policy would be potentially effective only under the second scenario, where the child would switch to choosing M (since $95 \cdot 5 + 30 \cdot 5 < 70 \cdot 5 + 90 \cdot 5$).[11]

Let us now assume that the child and the parent of the example make the choice jointly, according to $\max_{j \in \{A,M\}} = SEU_{fj} = \phi_C \cdot SEU_{Cj} + \phi_P \cdot SEU_{Pj}$. It is easy to imagine a third scenario in which the child and the parent select once again A.

(S3) Process-driven choice The parent has more say than the child, e.g., $\{\phi_C, \phi_P\} = \{1/3, 2/3\}$. Moreover, both of them care equally about enjoyment and flexibility, e.g., $\{\Delta u_{CL}, \Delta u_{CF}\} \equiv \{\Delta u_{PL}, \Delta u_{PF}\} = \{5, 5\}$. However, while the child holds rational expectations, i.e., $\{P_{CAL}, P_{CAF}\} = \{95, 30\}$ and $\{P_{CML}, P_{CMF}\} = \{70, 90\}$, the parent erroneously perceives both A and M as highly likely to provide flexibility, e.g., $\{P_{PAL}, P_{PAF}\} = \{95, 90\}$ $\{P_{PML}, P_{PMF}\} = \{70, 90\}$. Together these imply that $SEU_{fA} = \dfrac{1}{3}[95 \cdot 5 + 30 \cdot 5] + \dfrac{2}{3}[95 \cdot 5 + 90 \cdot 5] > SEU_{fM} = \dfrac{1}{3}[70 \cdot 5 + 90 \cdot 5] + \dfrac{1}{3}[70 \cdot 5 + 90 \cdot 5]$.

In this case, the information should target the parent. Moreover, assessing whether the information would be effective, clearly requires knowledge of the decision makers' roles and preferences. In the third scenario, disclosure of actual probabilities about F would still induce a change in behavior, as under the second (since $1/3\,[95 \cdot 5 + 30 \cdot 5] + 2/3\,[95 \cdot 5 + 30 \cdot 5] < 1/3\,[70 \cdot 5 + 90 \cdot 5] + 2/3\,[70 \cdot 5 + 90 \cdot 5]$). This need not be the case in general, however.

3 Data Collection and Description

Sampling and Study Design Participating families were drawn via choice-based sampling from the population of the 9th graders attending any public high school of the Municipality of Verona (Italy) in September of 2007 and their parents (4,189 families in total). Choice-based sampling means that the sample is endogenously stratified along the dependent variable and,

[11] Two qualifications are in order. First, a policy maker may not know the stochastic process faced by each single individual. However, she may know current and past population realizations, which may induce decision makers to revise their self-beliefs if published (e.g., Wiswall and Zafar (2014)). Second, the identification arguments used here rely on the assumed separability between utilities and beliefs. In models where the latter are interdependent (e.g., Koszegi and Rabin (2006)), any policy affecting the decision makers' beliefs will generally influence their behavior both through the beliefs and the utilities. I thank an anonymous referee for pointing this out.

therefore, it is random within choices but need not preserve the population frequencies across choices. This can be seen by comparing the population enrollment shares for the school year 2007-2008 in the first column of Table 1, with the enrollment distributions in the estimation samples shown in the remaining columns. Choice-based sampling is a natural choice in my setting, since students are physically clustered in schools and, hence, in tracks.

Sampled children (approx. 30% of the population) were invited to complete a 50 minutes paper-and-pencil questionnaire in class during the first 10 days of school. Their parents were mailed the questionnaire at home. They were asked to answer it without consulting with the children and to return it to the school in a sealed envelope for collection within 10 days. Nearly 100% of the sampled children and 60% of their parents returned the survey. While the latter is a satisfactory rate of participation for mailed surveys, the average rate masks substantial differences across reported family decision protocols, ranging from a 40% participation by parents of the children reporting making the decision unilaterally to almost 80% participation by parents of the children reporting a multilateral family decision. As long as family protocol selection and curriculum choice are separable, this is not particulary problematic for the empirical analysis, since I use parental beliefs and choice preferences only to estimate the choice models of the families making the decision multilaterally, according to either PR2 or PR3. On the other hand, low survey participation of parents whose children report making the decision unilaterally with respect to their parents, represents the main obstacle to empirically modeling selection into protocols, and it suggests low parental engagement behind PR1.

(TABLE 1 APPROX. HERE)

The choice of a retrospective approach was made as a compromise between the necessity to observe families' actual choices and individual members' choice preferences and subjective probabilities, and the impossibility for this particular study to survey families multiple times during the decision process. The main downside of this approach is that it relies on retrospective reports of beliefs and preferences. Necessary conditions to obtain unbiased estimates are (i) that respondents do not receive additional relevant information about choice consequences between the decision and the survey (or that any new information does not bias their reports), and (ii) that respondents do not experience cognitive dissonance or ex-post rationalization during the survey. Previous studies of college major choice in the U.S. have found no evidence of cognitive dissonance in students' retrospective reports (e.g., Zafar (2011), Arcidiacono et al. (2012)). I discuss this issues more formally in the web appendix. A final downside is the impossibility of modeling belief formation and aggregation between family members during the decision process, corresponding to the first stage of the model of Section 2.

In the empirical analysis, I focus on the 1,029 families whose children were in 9th grade for the first time at the time of the survey. Additionally, I drop the observations with item non-response to the questions used to construct the key variables, i.e., respondents' subjective probabilities, their choice preferences, and the reported family protocol. This leaves me in Table 1 with a sample of 998 children and with one of 565 child-parent matched pairs, after dropping 3% and 7% of the observations in the children's sample and in the matched child-parent sample respectively. (Sample background characteristics are shown in Table A2 of the online appendix).

Actual Choices, Stated Preferences, and Decision Protocols Actual choices by families are observed by design. The individual preferences of family members were elicited with the following question (worded as in the student instrument), asking the respondents to rank a list of alternatives available to them in the Municipality.[12]

Think about your situation during the past school year, when you were facing the choice of the high school track and just before making a final decision. Please rank the following curricula from the one you like the best to the one you like the least for yourself, considering the factors you thought were important for choosing among them. Start by assigning 1 to your favorite curriculum, then proceed by increments of 1 until you reach your least preferred one. The same number may not be assigned to two different curricula. (Curricula were listed by row in the first column; while the empty cells of the second column were used for ranking.)

The family decision process was elicited by means of the following question (worded as in the student instrument), adapted from existing questions of individual or household large-scale

[12] In reality, the survey started by eliciting respondents' subjective expectations, followed by their individual choice preference, the decision protocol used in their family, and a number of additional questions covering the orientation suggestion by the child's teachers in junior high school and basic background characteristics of the children and their families. The order of the question has been changed here for purpose of exposition.

surveys, about the modes of inter-spouses or child-parent decision making or interactions.

Which one of the following statements best describe the way in which the choice of high school track for you was made within your family? Please mark one only.

(A) We realized pretty soon that in our family we had the same idea about the choice.	○
(B) We discussed within our family until we reached a common decision based on a compromise.	○
A single member of our family made the final decision, after exchanging information and/or opinions with others. Indicate who decided:	
(C) Myself	○
(D) My father	○
(E) My mother	○
(F) Other person, specify:	○
A single member of our family made the final decision, without discussing with anyone else. Indicate who decided:	
(G) Myself	○
(H) My father	○
(I) My mother	○
(L) Other person, specify:	○

Answers to this question, and to a follow-up question eliciting identities of all persons the decision maker talked to, were used to classify the reported family decision processes. 'Child chooses unilaterally' (PR1) includes the case in which the child talked to any person different from his parents and, hence, it groups part of (C) and all of (G) answers. 'Child chooses with parental input' (PR2) covers part of (C) answers. 'Child and parent make a joint decision' (PR3) includes (A) and (B) answers. 'Parent chooses with the child input' and 'Parent chooses unilaterally' were constructed symmetrically, but not used in the empirical analysis because few such cases were observed in the data. Finally, when either (A) or (B) were selected, respondents were asked a follow-up question eliciting the identity of the decision maker in the counterfactual situation in which no agreement or compromise would be reached. Answers to this question and additional survey information were used to define the 'relevant' or 'representative' parent.

In the bottom portion of Table 1, the observed family choice (RP for 'revealed preference') is compared with the individually preferred choice of each member (SP), both in the matched child-parent sample (3rd column) and disaggregated by family decision protocol (4th-6th columns). There are two main takeaways from this table. First and foremost, in only a little over 50% of the sampled families, the child's and the parent's stated-preferred choices do coincide with each other, and with the actual choice, as of the time of the final decision. This is remarkable, as the displayed snapshot follows the likely interaction and convergence of the first stage described in Section 2 (in fact, 14 years of parental socialization), and it uses the child-parent matched sample where any interaction and convergence is more likely to have occurred. Second, in over two thirds of the families where the child's and the parent's stated-preferred choices are not aligned (over a third of the whole matched sample), the observed choice coincides with the child's stated-preferred alternative but not with the parent's.

As those figures are disaggregated by reported family protocol, an expected pattern emerges. The fraction of families where the child's and the parent's stated-preferred choices coincide with each other, and with the actual choice, is higher conditional on a multilateral protocol, especially PR3. The fraction of families where the actual choice coincides with the stated-preferred alternative of the child but not with that of the parent is substantially lower conditional on a multilateral protocol.

Conditional on a child-parent joint decision (PR3) and on SP reports, approximately 8% of actual choices are inconsistent with Pareto optimality (bottom-right cell), suggesting that Keeney and Nau (2011)'s model of efficient Bayesian group decision making is a reasonable approximation for this sub-sample. On the other hand, the observed choice and the child's stated-preferred alternative do not coincide in 13% of families where the child reports choosing independently of the parents. Taking the reported family protocols at face value, this pattern may be explained by existence of some factors or constraints that affected the actual decision but were not factored in the reported SPs. In the empirical sections 4-5, I investigate the possibility that children did tend to report their choice preferences net of their teachers' suggestions. A comparison of the observed choice, the child's stated-preferred alternative, and the teachers' suggested curriculum for the PR1 sub-sample in Table A1 of the online appendix generates figures consistent with this possibility.

Subjective Probabilities as Percent Chances of Choice Outcomes Based on existing qualitative evidence on high school track choice (e.g., Istituto IARD (2001), Istituto CISEM-

IARD (2009)), I created a list of choice outcomes families would likely consider when making the choice, including the main inputs into children's achievement while in high school (group A), the main choices or outcomes children face after high school (group B), and child-parent interdependent preferences and peers' interdependent choices (group C).

Outcome	**Description**
Group A	*Outcomes while in high school*
$b_1 = 1$	**Like:** The child will enjoy the curriculum content
$b_2 = 1$	**Study Effort:** The child will spend $\geq$ 2.5h a day studying or doing homework
$b_3 = 1$	**Performance I:** The child will graduate in any length of time
$b_4 = 1$	**Performance II:** The child will graduate in the regular time
$b_5 = 1$	**Performance III:** The child will graduate in the regular time and with a GPA $\geq$ 7.5
Group B	*Outcomes following high school*
$b_6 = 1$	**Flexibility I:** The curriculum training will enable the child to choose among both college fields and liked jobs
$b_7 = 1$	**Going to College:** The child will go to college after high school
$b_8 = 1$	**Flexibility II:** The curriculum training will enable the child to choose among many university fields
$b_9 = 1$	**Liked Job:** The child will find a liked job after high school
e_1	**Expected earnings I:** The expected earnings the child will make at 30 with a high school diploma but no college
e_2	**Expected earnings II:** The expected earnings the child will make at 30 with a high school diploma and a college degree
Group C	*Outcomes capturing interdependent choices or preferences*
$b_{10} = 1$	**Peers:** The child will be in school with his closest friends
$b_{11} = 1$	**Happy Parents:** The child will please his parents (for children only)

School achievement ($\{b_n = 1\}_{n\in\{3,4,5\}}$) can be thought of as the output of a simple human capital production function, where innate ability, study effort, and previously acquired skills produce new skills over time (e.g., Todd and Wolpin (2003)). While study effort ($b_2 = 1$) is costly in general, the child's interest in and enjoyment of the curriculum content ($b_1 = 1$) may balance his disutility of effort. On the one hand, children might believe that they would exert lower effort in curricula they perceive they may be less good at and/or less likely to enjoy. On the other hand, the opposite may result if children value school performance in general, or if they are ability constrained (e.g., Stinebrickner and Stinebrickner (2013)).

Inclusion of the flexibility outcomes ($\{b_n = 1\}_{n\in\{6,8\}}$), above and beyond college enrollment and finding a liked job ($\{b_n = 1\}_{n\in\{7,9\}}$) is motivated by existing evidence suggesting that families value curricula that enable the child to hedge current uncertainty about future college and work choices by postponing those choices (Istituto IARD, 2001).[13]

An attempt was also made to elicit expected child's earnings at the age of 30, under the two alternative scenarios (i) of reaching a high school diploma from each curriculum without further enrolling in college (e_1), or (ii) of obtaining a college degree following graduation from each curriculum (e_2). While the high rates of item non-response to this question ($\approx$ 65% among children) prevented the use of expected earnings in the empirical model, the answers and feedback to these questions were nonetheless informative. In particular, most children admitted that they had no idea about what the magnitude of a monthly salary may be; whereas, a minority of them reported either the information they had received from the school counselors or their parents' earnings. Some parents, in turn, left written notes on the survey, expressing their perceived difficulty of providing any meaningful forecast, and stating that they did not regard future earnings as an important factor for this decision.

Subjective expectations were elicited by asking respondents to assign a number between 0 and 100 to the likelihood that each one of the listed outcomes would occur, should the child attend each curriculum available in their Municipality, that is, Vocational-Commerce ($j = 1$), Vocational-Industrial ($j = 2$), Technical-Commerce or Social ($j = 3$), Technical-Industrial ($j = 4$), Technical-Surveyors ($j = 5$), Art Track ($j = 6$), General-Humanities ($j = 7$), General-Languages ($j = 8$), General-Education or Social Sciences ($j = 9$), General-Math and Science ($j = 10$). The battery of subjective probability questions was preceded by an introductory section, explaining the use of the 0-100 percent chance scale and engaging respondents with three warm-up questions.[14] The following question, eliciting the child's subjective probabilities

[13] As risk aversion can generate preference for flexibility (Ficco and Karamychev, 2009), inclusion of these outcomes may also help mitigating the implicit assumption of risk neutrality implied by the linear SEUs.

[14] The introductory section included some examples of the mapping between the numerical 0-100 percent chance scale and verbal probability statements such as 'Impossible/Certain,' '(Un)Likely,' or 'Even chances.' Children were walked through the instructions and the warm-up questions by an interviewer assigned to their class. Children's warm-up questions asked, *1. What do you think is the percent chance that you will eat pizza for dinner sometime next week? 2. What do you think is the percent chance that you will get the flu sometime during the winter? 3. What do you think is the percent chance that you will get the flu in January?* The first question was replaced by *1'. What do you think is the percent chance that it will rain*

of the outcome 'Like' ($b_1 = 1$) conditional on each choice, provides an illustration.

Think about your situation during the past school year, when you were facing the choice of the high school track and just before making a final decision. What did you think would be the chances out of 100 that you would enjoy the content of the following curricula, should you enroll in each one them? (Curricula were listed by row in the first column; while the empty cells of the second column were used for the percent chance.)

Given the retrospective design, how should one think of the survey task for this question? Let us consider a child who made the choice with parental input, according to process PR2. The question asks him to retrieve and provide his subjective probabilities of the outcomes and his ranking of the curricula corresponding to those probabilities at the time immediately preceding the final decision (i.e., between the first and the second stage of the model introduced in Section 2). This is a weaker and more plausible requirement than asking respondents to report their beliefs at the beginning of stage 1. More important, it should be noted that while these questions did follow the actual choice, they did not follow the realization of the outcomes over which respondents' probabilities were elicited.

The top and middle panel of Table 2 display the means, standard deviations, and main quantiles of the children's and parents' answers to the Like ($b_1 = 1$) and the Flexibility I ($b_6 = 1$) expectation questions for Art ($j = 6$) and Math ($j = 10$), reminiscent of the illustration presented in Section 2.[15] The bottom panel shows the main features of the corresponding distributions of the within-family differences in beliefs between the child and the parent. On average, children and parents display similar beliefs as of the time of the final decision, thereby the mean and median differences are very small or zero, especially about child's enjoyment. Their standard deviations and extreme quantiles, however, indicate the existence of a fair amount of variation in those differences across families. Based on a Wilcoxon matched-pairs signed-ranks test, the null hypothesis of expectations equality between the child-parent matched pairs cannot be accepted for the majority of curricula and outcomes.

tomorrow? in the parent questionnaire.

[15] Table A3 in the online appendix shows the underlying empirical distributions. Answers feature some typical rounding and corresponding bunching at multiples of 5 and 10. This notwithstanding, respondents used the full 0-100 scale, especially the children (col.1-4).

(TABLE 2 APPROX. HERE)

The main features of the empirical beliefs' distributions for the remaining outcomes, are shown in Tables A4 through A12 of the online appendix, in the interest of space. The main patterns resemble those shown in Table 2 of the paper; nonetheless, outcomes' specificities also emerge. For instance, parents tend to be more optimistic about the child's performance than children are, consistent with existing evidence (e.g., Fischhoff et al. (2000), Attanasio and Kaufmann (2014)). Moreover, parents expect on average smaller differences in the child's effort and performance across tracks and curricula.

The belief heterogeneity across children (parents) and across curricula, shown in the top (middle) panel of Table 2, provides identification of children's (parents') utility weights (i.e., $\{\Delta u_n^i\}_{n=1}^N$ in eq. (1)) in the empirical analysis of the next two sections. Whereas, the heterogeneity in within-family differences between the child's and the parent's beliefs (in the bottom panel of Table 2), that explains within-family differences among the child's and the parent's SPs and the RP (in the bottom portion of Table 1), provides identification of the parameters capturing the aggregation of child's and parent's beliefs or SEUs under multilateral decision making (i.e., $\{\omega_n^i\}_{n=1}^N$ in eq. (3) or ϕ^i in eq. (4)).

4 Baselines: Individual Members and the 'Unitary Family'

Econometric Implementation First, I estimate a baseline model that alternatively takes the child or the parent as the 'representative' decision maker of the choice ($i \in \{c, p\}$). The model corresponds to that of Bayesian individual decision making in eq. (1) of Section 2. I implement it econometrically within a standard random utility framework, where the components of the decision makers' SEUs unobserved to the econometrician are captured by additive random errors, $\{\varepsilon_j\}_{j=1}^J$, which I assume to be i.i.d. and type-I extreme value for all i.

Under these assumptions, the probability of observing a child attend a specific curriculum

$\tilde{j}$ can be expressed as

$$P\left(\tilde{j}|\{\{P_{ijn}\}_{n=1}^{N}\}_{j=1}^{J};\{\{\alpha_j^i\}_{j=1}^{J},\{\Delta u_n^i\}_{n=1}^{N}\}\right)=\frac{exp\left(\mu^i\left[\alpha_{\tilde{j}}^i+\sum_{n=1}^{N}P_{i\tilde{j}n}\cdot\Delta u_n^i\right]\right)}{\sum_{j=1}^{J}exp\left(\mu^i\left[\alpha_j^i+\sum_{n=1}^{N}P_{ijn}\cdot\Delta u_n^i\right]\right)}. \quad (5)$$

In equation (5), the term $\sum_{n=1}^{N}P_{ijn}\cdot\Delta u_n^i$ represents the systematic component of the decision maker i's SEU from the jth alternative, which is observed by the econometrician up to the parameter vector $\{\Delta u_n^i\}_{n=1}^{N}$, to be estimated. The interpretation of each P_{ijn} and Δu_n^i components are as provided in Section 2. The terms $\{\alpha_j^i\}_{j=1}^{J}$ are alternative-specific constants that measure the average effect of $\{\varepsilon_j\}_{j=1}^{J}$ and are also to be estimated. Finally, μ^i is a scale parameter inversely related to the variance of the error terms.

Given the parametric assumptions on the random terms, and after setting $\alpha_J^i=0$ as a location normalization, the model's parameters, $\{\alpha_j^i\}_{j=1}^{J-1}$ and $\{\Delta u_n^i\}_{n=1}^{N}$ are identified up to the scale factor, μ^i, by variation in the observed subjective probabilities of the choice outcomes ($\{\{\{P_{ijn}\}_{j=1}^{J}\}_{n=1}^{N}\}_{i=1}^{I}$), across the alternatives ($j=1,...,J$) and decision makers ($I=1,...,I$). In practice, I use families' actual choices (RP) as my dependent variable, and elicited children's, or alternatively parents', subjective probabilities over the choice outcomes ($\{\{P_{ijn}\}_{j=1}^{J}\}_{n=1}^{N}$ with $i\in\{c,p\}$) as main explanatory variables. Hence, the subjective probabilities of survey participants function as alternative- and individual-specific attributes of the conditional logit model of eq. (5).

I estimate the model using the Manski and Lerman (1977)'s weighted exogenous sampling maximum likelihood (WESML) estimator to correct for choice-based sampling.[16] Its implementation requires knowledge of curriculum enrollment in the population, in order to calculate the weights that make the likelihood function behave asymptotically as under random sampling. Table 1 displays the curriculum choice distributions in the population (col.1) and in the estimation samples (remaining columns).

For comparison, I also estimate (5) from children's or parents' stated choice preferences

[16] The WESML is computationally tractable and yields a constrained best predictor of the discrete response even when the logit assumption is not correct (Xie and Manski 1989). I provide a formal description in the online appendix.

(SPs), used as alternative response variables. 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 the purpose of parameter estimation, data from choice situations other than the interception can be treated as if sampling were random.[17]

RP Estimates The columns in the left panel of Table 3 display the estimates of the utility parameters in eq. (5), obtained using RP data and different specifications of the latent SEUs. Because the utility weights ($\{\Delta u_n^i\}_{n=1}^N$) and the scale factor (μ^i) are not separately identified, each parameter estimate corresponding to a different choice outcome (by row), is equal to the product of the two. Significance levels are based on robust asymptotic standard errors derived in Manski and Lerman (1977).[18]

All specifications include alternative-specific constants, whose overall significance is confirmed by a Likelihood Ratio (LR) test. The adjusted Likelihood Ratio (LR) index reported in the bottom row of the table measures the percent increase in the value of the log-likelihood calculated at the parameter estimates, relative to its value under equal chances (i.e., no model). It can be used as a goodness-of-fit indicator, and for a comparison of specifications estimated on the same data and with the same set of alternatives. However, it should neither be interpreted as the R^2 of a linear regression, nor used to compare models that are not estimated on the same sample of data (Train, 2009).

The first four specifications (S1-S4) use the children's subjective probabilities as explanatory variables. The estimated coefficients feature the expected (positive) signs, with the exception of study effort (b_2), hypothesized to be negative. Because the ratio of the estimated utility coefficients for any pair of outcomes is scale free (as $(\Delta u_{n''}^i \cdot \mu^i)/(\Delta u_{n'}^i \cdot \mu^i) = \Delta u_{n''}^i / \Delta u_{n'}^i$ for

[17] This also applies to the joint SP&RP models estimated later, as discussed in the online appendix. On the other hand, cases with persistent heterogeneity across choice situations, or those requiring recovery of population quantities other than the underlying parameters, would still require re-weighting. These cases are highly problematic, as the relevant population SP shares are unobservable.

[18] I provide a discussion and a comparison with bootstrap standard errors in the online appendix.

any $b_{n'}$, $b_{n''}$), I discuss parameter estimates in terms of the outcomes' 'relative importance.' Estimates of the utility weights across specifications and samples can be also evaluated and compared free of scaling issues, in terms of the change they imply in predicted choice probabilities when beliefs of specific outcomes are changed marginally (e.g., Train (2009) and Long (2009)). Some of these calculations are shown in Table 7 of the main text and in Table A21 of the online appendix, and they are discussed in the counterfactuals Section 6.[19]

The most weighted outcome is child's enjoyment of the curriculum (b_1), whose utility weight is approximately 2.5 times larger than the weight on facing a flexible college field choice (b_8), 3.5 times larger than that on graduating in the regular time (b_4), and approximately 5 times larger than those on finding a liked job after graduation (b_9), on attending college (b_7), and on facing a flexible college-work choice (b_6). Parameter estimates for these outcomes are all significant at 1%, as opposed to the coefficient of being in school with friends (b_{10}), which is barely significant.

Qualitative results do not change when pleasing one's parents (b_{11}) is introduced in the second specification (S2), although this outcome turns out to be the third most weighted one after child's enjoyment and flexibility of the college field choice. Similarly, inclusion of a dummy capturing the orientation suggestion by the child's teachers in the third and fourth specifications (S3-S4), induces only marginal changes in the estimates, mostly by making the coefficient of study effort not significant.[20] Its own utility weight, on the other hand, is significant and approximately 4 times smaller in magnitude than the weight attached to the child's enjoyment. This is true despite the fact that the information content of the teachers' suggestion should already be incorporated in children's beliefs. It is thus possible that teachers' counseling affects

[19] Additional ones are available upon request. The impossibility of including expected earnings, however, prevents use of willingness-to-pay calculations to map 'utils' into Euros.

[20] The orientation dummy is equal to 0 either when no suggestion was provided or when a track was suggested but no particular curriculum within the suggested track was specified, and is equal to 1 otherwise. A specification constraining the utility coefficient of the suggestion dummy to 0 when the child indicated that the suggestion was not considered in the choice, produced identical results. Sample sizes for specifications S3 and S4 decrease slightly due to some non-responses to the survey question eliciting teachers' suggestion.

curriculum choice through additional channels, above and beyond children's information and beliefs; perhaps, through their consideration set and/or their utility ranking of the outcomes.[21]

Estimation of S1 and S3 from RP data and from parents' subjective probabilities as explanatory variables, generates similar importance rankings over outcomes to those obtained using children's probabilities (i.e., given $\Delta u^i_{n'} > \Delta u^i_{n''} > \Delta u^i_{n'''}$ for some $b_{n'}$, $b_{n''}$, and $b_{n'''}$, the latter holds for both $i = c$ and $i = p$), consistent with the similarity of their belief distributions.[22] The utility coefficients associated to children's expectations, however, have higher significance levels when the latter are used to predict actual choices than the utility coefficients associated to parental expectations, consistent with the descriptive evidence presented in Section 3 that children play a more important role in the choice.[23]

(TABLE 3 APPROX. HERE)

SP Estimates The columns in the right panel of Table 3 display estimates of model (5) for the same SEUs' specifications as in the corresponding columns of the left panel, but now replacing the actual choices with the children's (parents') highest-ranked choice, whenever the children's (parents') beliefs are used as explanatory variables. Inspection of the comparable specifications reveals that the utility rankings over choice outcomes implied by the children's beliefs and stated choice preferences (SP) and by the parents' beliefs and stated preferences, differ both from each other and from those implied by the observed choices (RP).

For example, when used to rationalize the observed choices, sample variation in children's

[21] For instance, a teacher may advise her students to follow their own interests and inclinations, rather than their friends'. If not explicitly modeled, the latter would be conflated in the estimated utility weights.

[22] Comparing ratios of the estimated coefficients for any two outcomes between children and parents provides a quick and easy way to compare the magnitudes of the implied utility weights (i.e., $\Delta u^c_{n''}/\Delta u^c_{n'}$ vs. $\Delta u^p_{n''}/\Delta u^p_{n'}$). To further ease the comparison, I estimate specifications S1 and S3 using the matched child-parent sample, shown in Table A13 of the online appendix. However, I refrain from a formal test of equality of the estimated coefficients, since cumbersome and likely not meaningful in practice (e.g., Long (2009)).

[23] At least in stage 2 of the model; parental socialization would operate, arguably more indirectly, during stage 1 or earlier. The higher significance levels of children's beliefs for almost all outcomes may additionally or alternatively suggest a greater underlying heterogeneity in utilities among children.

beliefs implies higher utility ranks for shorter-term outcomes such as study effort and school achievement, than when used to rationalize children's stated preferences. Results for post-graduation outcomes are instead mixed. In particular, actual choices imply a relatively more pronounced preference for flexibility of future study and work choices, than the children's stated preferences do. The opposite is true for going to college and for finding a liked job. Additionally, the children's SPs imply a positive and significant utility weight on being in school with one's friends–insignificant or even negative based on RP data–but relatively smaller weights on pleasing one's parents and on following the teachers' suggestion.

When used to rationalize parents' SPs, sample variation in their beliefs implies higher utility ranks for some of the post-graduation outcomes (e.g., facing a flexible college-work choice and finding a liked job after high school), than when used to rationalize the observed choices. The opposite is instead true for the child's effort, his achievement, and also for the teachers' suggestion. Interestingly, the utility coefficient on the child's study effort is implied to be negative by the parents' beliefs, but not by the children's. On the other hand, the possibility that the child attends the same school as his friends does not appear to be of much relevance according to the parents' beliefs and stated preferences.

Implications and Next Step I have used the child's or the parent's subjective probabilities to alternatively rationalize the observed family choice (RP) or the individually preferred choice of each family member (SP). And I have derived estimates of the utility weights for each model. This exercise has generated two main findings. First, the differences between the child's and parent's SPs within families – observed in the bottom part of Table 1 – are mainly attributable to differences in the estimated utility weights rather than to differences in the child's and the parent's subjective probabilities. Indeed, the latter are close to each other, also according to the figures shown in Table 2 of the paper and in Tables A4-A12 of the online appendix. Second, the difference between the utility weights estimated from the child's (or the parent's) probabilities and SP, and the utility weights estimated from the observed choice, suggests that the latter conflate the former and 'something else'; that is, the topic of the next section.

In the next section, I estimate an extension of model (5) with two main features. First, the model explicitly recognizes that in each family the child and the parent may have both distinct beliefs and utility weights over outcomes. Second, the model rationalizes observed within-family differences among the observed choice, the child's stated preferred alternative, and the parent's stated preferred alternative, not only as a function of the heterogeneous beliefs and/or utility weights of the individual members, but also as a function of the family decision protocol subsuming those components.[24]

5 Piecing It All Together: Heterogeneous Family Processes

Econometric Implementation Each of the following models is separately estimated on the sub-sample of families correspondingly classified as using protocol PR1, PR2, and PR3, based on children's reports in the survey.[25]

(PR1) Child Chooses Unilaterally I estimate a joint RP-SP model,

$$\begin{cases} SEU_{cj}^{RP,1} = \alpha_j^{RP,1} + \sum_{n=1}^{N} P_{cjn} \cdot \Delta u_n^{c,1} + \varepsilon_{cj}^{RP,1} \\ SEU_{cy}^{SP,1} = \alpha_y^{SP,1} + \sum_{n=1}^{N} P_{cyn} \cdot \Delta u_n^{c,1} + \varepsilon_{cy}^{SP,1}, \end{cases} \tag{6}$$

where j indexes the RP and y indexes the child's SP, with $j, y \in \mathcal{J}$. $\varepsilon_{cj}^{RP,1}$ and $\varepsilon_{cy}^{SP,1}$ are assumed i.i.d. type-I extreme value, with scale parameters $\mu^{RP,1}$ and $\mu^{c,SP,1}$. Under no serial correlation between the SP and the RP, the log-likelihood of observing any RP-SP pair (j, y) equals the

[24] Heterogeneous utility weights between children and parents, and across family protocols, are the only forms of systematic parameter heterogeneity in this paper. There would neither be conceptual or computational difficulties in allowing for additional dimensions of heterogeneity, e.g., by specifying a functional form for how individual characteristics, probabilistic beliefs, or other variables enter utility parameters. Nonetheless, because of the relatively small size of the protocol-specific samples, I prefer not to pursue this line. On the other hand, allowing for unobserved forms of heterogeneity in this setting (e.g., serial correlation between SPs and RP) presents specific difficulties under choice-based sampling, which I discuss in the web appendix.

[25] This follows existing studies of parenting in developmental psychology and economics (e.g., Bumpus et al. (2001) and Cosconati (2011)). In my setting it avoids issues related to parental selection into survey participation.

sum of the log-likelihoods of j and y, the former corrected for choice-based sampling.

Combination of RP and SP increases estimation precision relative to the use of one data source. Additionally, it enables the investigation of possible differences between the RP and SP data generating processes. Specifically, the common component between the SP and RP SEUs, $\sum_n P_{cjn} \cdot \Delta u_n^{c,1}$, enables identification and estimation of the SP/RP scale ratio, $\mu^1 = \mu^{c,SP,1}/\mu^{RP,1}$. Because $\mathrm{Var}(\varepsilon_{cj}^{RP,1}) = (\mu^1)^2 \cdot \mathrm{Var}(\varepsilon_{cy}^{SP,1})$, the estimated μ^1 can be used to investigate whether the SP and the RP contain the same amount of random noise, by testing $\mu^1 = 1$. In turn, testing the equality of the RP and SP alternative-specific constants (i.e., $\alpha_j^{RP,1} = \alpha_j^{SP,1}$ for all j), provides additional useful information about the relationship between the RP and SP unobservables, as they capture the average effects of all unobserved factors.

(PR2) Child Chooses with Parental Input The system of latent SEUs for the child is

$$\begin{cases} SEU_{fj}^{RP,2} = \alpha_j^{RP,2} + \sum_{n=1}^{N} \left[w_n^{p,2} \cdot P_{pjn} + (1 - w_n^{p,2}) \cdot P_{cjn} \right] \cdot \Delta u_n^{c,2} + \varepsilon_{fj}^{RP,2} \\ SEU_{cy}^{SP,2} = \alpha_y^{c,SP,2} + \sum_{n=1}^{N} P_{cyn} \cdot \Delta u_n^{c,2} + \varepsilon_{cy}^{SP,2}, \end{cases} \tag{7}$$

with $j, y \in \mathcal{J}$. $\varepsilon_{fj}^{RP,2}$ and $\varepsilon_{cy}^{SP,2}$ are assumed to be i.i.d. type-I extreme value, with scale parameters $\mu^{RP,2}$ and $\mu^{c,SP,2}$ and no serial correlation. Whereas, the parents' utility weights can be separately estimated from SP data, according to model (5).

The child's utility weights ($\{\Delta u_n^{c,2}\}_{n=1}^{N}$) are identified by belief heterogeneity across children and alternatives through the SP equation. The equality restriction on the utility weights between the SP and the RP equations, combined with the add-to-one restriction on the aggregation weights for each outcome ($\{w_n^{p,2}\}_{n=1}^{N}$), yields identification of the latter from the RP SEUs. The statistical precision of these estimates, however, will ultimately depend on whether there exists enough variation in within-family differences between the child's and the parent's beliefs across families, that explains the variation in the observed differences between the RP and the child's SP. Finally, combining SP and RP provides identification of μ^2.[26]

The structure of the RP equation in the PR2 model makes it transparent why explicitly allowing for child-parent interactions constitutes an important improvement over the unitary baseline model. In particular, estimating a unitary or unilateral model (PR1) on a sub-sample of families that have made the choice multilaterally will yield biased estimates of the utility parameters. This is because the unspecified parental contribution to the decision will get subsumed into the error terms, thereby inducing a correlation between the observed and the unobserved components of the model (a formal derivation is provided in the web appendix).

(PR3) Child and Parent Make a Joint Decision The family system is

$$\begin{cases} SEU_{fj}^{RP,3} = \alpha_j^{RP,3} + \phi^{c,3} \sum_{n=1}^{N} \left[P_{cjn} \cdot \Delta u_n^{c,3} \right] + (1 - \phi^{c,3}) \sum_{n=1}^{N} \left[P_{pjn} \cdot \Delta u_n^{p,3} \right] + \varepsilon_{fj}^{RP,3} \\ SEU_{cy}^{SP,3} = \alpha_y^{c,SP,3} + \sum_{n=1}^{N} P_{cyn} \cdot \Delta u_n^{c,3} + \varepsilon_{cy}^{SP,3} \\ SEU_{ph}^{SP,3} = \alpha_h^{p,SP,3} + \sum_{n=1}^{N} P_{phn} \cdot \Delta u_n^{p,3} + \varepsilon_{ph}^{SP,3}, \end{cases} \tag{8}$$

with $j, y, h \in \mathcal{J}$. $\varepsilon_{fj}^{RP,3}$, $\varepsilon_{cy}^{SP,3}$, and $\varepsilon_{ph}^{SP,3}$ are i.i.d. type-I extreme value, with scale parameters $\mu^{RP,3}$, $\mu^{c,SP,3}$, and $\mu^{p,SP,3}$, and with no serial correlation across data sources. The identification argument for (8) is analogous to that of (7), but it requires the additional restriction of equal relative scales for the two SP equations.

Utility weights estimates Parameter estimates of the child's utilities are displayed by family decision protocol in Table 4 (for PR1), Table 5 (for PR2), and Table 6 (for PR3). The latter two tables also include estimates of the family aggregation weights (described below). Finally, Table 6 shows estimated parameters of the parent's utilities for protocol PR3. Specification labels are

[26] Mechanically, identification of the aggregation weights is obtained as follows. Taking ratios of the SP and RP coefficients separates $\{w_n^{p,2} \cdot \mu^2\}_{n=1}^N$ and $\{(1 - w_n^{p,2}) \cdot \mu^2\}_{n=1}^N$ from $\{\Delta u_n^{c,2}\}_{n=1}^N$. Further taking ratios between $\{w_n^{p,2} \cdot \mu^2\}_{n=1}^N$ and $\{(1 - w_n^{p,2}) \cdot \mu^2\}_{n=1}^N$ for each outcome isolates $\{w_n^{p,2}\}_{n=1}^N$. This argument applies to the current framework, as both utility and aggregation weights are left unrestricted across family protocols. Imposing homogeneous utility weights of the individual family members across decision protocols would likely strengthen identification and would potentially enable estimation of more general protocols of child-parent decision making or interaction.

consistent with those used for the unitary models in Table 3 unless specified otherwise.[27]

To start with the shorter-term outcomes, curriculum enjoyment is confirmed to be the most weighted factor by both children and parents, and across all three decision protocols (see 1st or 3rd columns of Table 4 and any column of Tables 5 and 6). The utility difference assigned to a high versus a low study effort, on the other hand, varies across groups. It is negative among the PR1 children in Table 4, positive but not significant among the PR2 and PR3 children in Tables 5 and 6, and negative but not significant among the PR2 and PR3 parents. (Estimates for RP2 parents are shown in Table A16 of the web appendix.) The utility weight attached to experiencing a regular path in high school makes this factor rank stably as the third to fifth most valued one. Its relative magnitude (with respect to the child's enjoyment) is nonetheless highest among the PR1 children and lowest among the PR2 children. This coefficient is never significantly different from 0 for all parent sub-samples and specifications.

(TABLE 4 APPROX. HERE)

Children attach a positive utility to the event of going to school with their closest friends, whereas parents seem to value it negatively. However, these coefficients are never significant. Finally, when pleasing one's parents is explicitly included as an argument of the child's SEUs, its positive and usually significant estimated coefficient points toward interdependent child-parent utilities, even on the child's side. Its relative importance, however, varies across protocols and is remarkably higher among the PR1 children. Hence, to the extent that children have some, albeit imperfect, knowledge of their parents' choice preferences, this finding suggests that even the PR1 parents are likely to play a role in their children's choice, perhaps more indirectly.[28]

Moving to the post-graduation choices and outcomes, the PR2 children of Table 5 display a relatively strong preference for facing a flexible college field choice, which is the second most important outcome to them after enjoying the curriculum content, and is followed by finding

[27] Estimates from alternative specifications or robustness checks are reported in the online appendix.

[28] Table A19 of the web appendix provides evidence about children's knowledge of their parents' choice preference for them, and viceversa. Parents appear to know their children's choice preferences better than viceversa on average, but the PR1 parents are less knowledgeable than the other two groups of parents. On the other hand, the PR1 children do not seem less knowledgeable than the PR2-PR3 children, conditional on parental participation in the survey.

an enjoyable job after graduation and facing a flexible college-work choice. In Table 6, the PR3 children too place a high weight on making a flexible college field choice, whose utility coefficient is twice as large as that on attending college, and is comparable in magnitude to the coefficient on finding a liked job after graduation. Similarly, the PR3 parents display relatively sizeable and statistically significant preferences for flexibility, especially of the child's field choice in college. The PR2 parents, on the other hand, attach a relatively higher importance to the child's satisfaction of the job than to the remaining post-graduation outcomes (as shown in Table A16 of the web appendix).

(TABLE 5 APPROX. HERE)

Things look more complex for the PR1 children. Separate estimation of the unilateral model (6), alternatively using SP and RP as dependent variables, points to somewhat different utility structures (as shown in Table A14 of the web appendix). That is, the utility coefficients estimated from the SP data imply a strong preference for finding an enjoyable job after graduation for this group, whereas the estimated coefficients implied by the RP data emphasize the importance of attending college and of facing a flexible college-work choice.

To shed light on these differences, I estimate the joint SP&RP model (5) letting the utility coefficients vary between the two data sources, one outcome at a time. I test their equality using an LR test, instead of imposing it. Reassuringly, I cannot reject the null hypothesis of equal SP and RP coefficients for most outcomes. However, the test does reject the fully constrained model (specification S2 of Table 4), in favor of a specification that lets the coefficients on facing a flexible college field choice and on finding an enjoyable job after graduation differ across data sources (specification S2').[29]

Finally, when an indicator for the teacher's suggestion is included in the PR1 specification, its coefficient too differs across data sources. As hypothesized in Section 3, the RP data imply a stronger role for the orientation dummy, whose coefficient is approximately twice as large as

[29] A potential explanation is what the literature calls 'prominence,' or the respondents' tendency to focus on few most important attributes and/or to fail to take situational constraints into account, when answering SP questions. If present, this bias would go into the opposite direction than the 'inertia or justification bias' I discuss in the online appendix.

that implied by children's SPs. Even larger differences are observed for the other two groups, where the orientation dummy is not significant in the SP equations.

(TABLE 6 APPROX. HERE)

Testing the SP and RP data processes Differences between the SP and RP data generating processes can be further investigated by inspecting the SP/RP scale parameter and the alternative-specific constants. For the PR1 group, I cannot reject the null hypothesis that $\mu^1 = 1$, nor a model with $\alpha_j^{RP,1} = \alpha_j^{SP,1}$ for all j. This says that the unobservable processes underlying the RP and the SP data are reassuringly similar for this group, thereby providing a first validation of the information about children's decision role for the PR1 sample.

On the other hand, μ^2 and μ^3 are significantly different from 1 in all specifications. Their values range from 0.45 to 0.65, meaning that the variance of the unobserved components is between 2.5 and 5 times larger in the SP equation than in the RP one. A larger SP variance is a common finding in the SP&RP literature (Morikawa, 1994), which attributes it to the fact that respondents participating in SP tasks under hypothetical scenarios generally use or have only a subset of the information they would use or have in actual choice situations (e.g., Manski (1999)). While in my setting the SP task is more one of recall than one of hypothetical choice, it is possible that the additional noise is indeed related to the required process of recollection and abstraction.

Aggregation weights estimates Inspection of Table 5 (top panel) reveals that existing within-family differences between the child's and parent's beliefs, and their variation across families, pin down the aggregation weights ($\{w_n^{p,2}\}_{n=1}^N$) with some precision only for some of the outcomes. For example, the parental opinion about the child's achievement in high school matters more than the child's own opinion. The estimated weight on the parent's belief for this outcome ranges from 0.626 to 1.120, depending on the specification; however, all values between 0.5 and 1 are compatible with the estimates, and for some specifications even a weight of 0 cannot be rejected. The weight on the parent's belief about the child's enjoyment is

estimated precisely and lies between 0.411 and 0.457. The hypothesis of equal weights cannot be rejected, while 0 and 1 are rejected for all specifications. The weight on facing a flexible college field choice, instead, favors the 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. This notwithstanding, a model imposing equal weights across outcomes can be rejected for all specifications.

In the top panel of Table 6, weights on the child's SEUs ($\{\phi_n^{c,3}\}_{n=1}^N$) range between 0.295 and 0.370, and are precisely estimated. Both 0 and values of 0.5 or above are rejected. This is consistent with the important explicit role that PR3 parents are reported by their children to play in the choice.

Testing family protocols specifications The above estimates rely on a correct specification of the family decision protocol. To shed some light on potential misspecifications and to provide some validation for the survey information about the family protocols, I test the two bilateral models against the unilateral model and against one another. Since PR1 is nested in both PR2 and PR3, I perform an LR test for whether all weights on the parent's beliefs are equal to 0 in Table 5, and for whether the child's weight is equal to 1 in Table 6. The null hypothesis is rejected in both cases.

Finally, I estimate the PR2 model on the PR3 sample and I compare its estimates with those from the PR3 model, and vice versa for the PR2 sample. Since the two models are not nested, I use the Ben-Akiva and Lerman (1985, p. 171-174) test comparing the adjusted LR indices 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 PR2 specification in which the child chooses with parental input, is found to be statistically superior in both the PR2 and PR3 samples. On the other hand, an alternative specification of the child-parent joint decision model PR3 featuring outcome-specific weights (shown in Table A17 of the web appendix), is rejected in favor of the basic PR3 model with a single weight.

6 Counterfactual Analysis

The Math&Art Example Resumed My framework maintains that the utilities of outcomes – like how important it is for the child to enjoy the curriculum content versus failing to do so – are hardwired and known to the decision maker. On the other end, whether the child would enjoy the curriculum content of any specific curriculum is ex-ante uncertain to the decision maker, who holds subjective beliefs about the likelihood of this and related events. The Italian Ministry of Education has recently implemented a 'sensitization' campaign to promote mathematics and technology, especially among girls. By emphasizing the importance of mathematics and science, such a policy may induce children to change their beliefs about the likelihood that they would enjoy the math curriculum or that they would find a good job after taking math. Such changes in beliefs may, in turn, influence children's choice of track.

In the top panel of Table 7, I simulate a policy that boosts by 10 percent-chance points the subjective probability of the children, of the parents, or of both, that the child would enjoy the math curriculum (policy 1). Calculations are done separately for the pooled samples (unitary models) and for the sub-samples of families using different decision protocols. This hypothetical shift in beliefs generates an intuitive increase in the enrollment probability for the mathematics curriculum in all groups and models, and a corresponding decrease for all the other curricula. Such changes, however, are heterogeneous across policy recipients and models, emphasizing the importance of explicitly taking the latter into account. For instance, assuming a unitary model with the parent as a representative decision maker and a policy target sizeably overestimates the magnitude of the enrollment response to the promotion campaign implied by the protocol-specific models ($\mathbf{+18.93}$ vs. $\{\mathbf{0}, \mathbf{+5.06}, \mathbf{+8.50}\}$). A unitary model based on the children's beliefs generates a closer, albeit still somewhat high, prediction (*+11.16* vs. $\{$*+7.04*, *+6.74*, *+6.41*$\}$).

In Table A20 of the web appendix I calculate the response of enrollment probabilities to an hypothetical drop of 10 percent-chance points in the respondents' subjective likelihoods that the child would enjoy the art curriculum (policy 4). An additional interpretation of these calculations is that they provide scale- and unit-free measures of the importance of the 'like' outcome, in terms of the change in predicted choice probabilities implied by a marginal change in individuals' belief about that outcome.

(TABLE 7 APPROX. HERE)

Tracking and Specialization In the middle panel of Table 7, I simulate the effect of a change in the beliefs of children, parents, or both, generated by a policy that strengthens tracking by preventing access to university following any diploma of the vocational type (policy 2). This policy mimics a main feature of the Italian secondary system before the reform of 1969 that opened university access to the students graduating from technical and vocational schools. In practice, I set the subjective probabilities of the targeted group to 0 for the three outcomes 'attend college,' 'flexible college-work choice,' and 'flexible college field' and the two vocational curricula ($j \in \{1, 2\}$).

This policy induces a huge drop in vocational enrollment, mostly in favor of the technical curricula. The result is intuitive: those children who value the possibility of going to college after graduation, but would enroll in a vocational curriculum if the restriction were not in place, would now switch to curricula of the 'lowest' track ensuring eligibility for college enrollment. Finally, a decomposition by decision protocol shows that if the parents only were aware of the policy, its impact would be smaller than if the children also were informed (e.g., $\{\mathbf{0}, \mathbf{-17.38}, \mathbf{-44.97}\}$ vs. $\{\textit{-61.25}, \textit{-57.97}, \textit{-72.03}\}$ for the vocational-commerce curriculum, but the pattern is analogous for the vocational-industrial curriculum).[30]

Publication of Education Statistics Finally, I calculate the changes in predicted enrollment probabilities following disclosure of national statistics about college enrollment in 2006-2007, disaggregated by graduation curriculum (policy 3). These statistics are the most recent

[30] In Table A20 of the online appendix, I additionally simulate a policy that lowers educational standards and equalizes them across curricula, by guaranteeing all students to pass all grades on the first try (policy 5). This simulation captures some of the features temporarily introduced by the Law 425-1997, which 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.

ones that could have been made available to the families in my sample, whose children entered high school in the Fall of 2007. This policy generates an intuitive though moderate increase in predicted enrollment for general curricula, especially the humanities and math ones, and a corresponding drop in predicted enrollment for the vocational and the artistic curricula. A decomposition of the counterfactual enrollment response by family protocol shows that publication of education statistics would have a larger impact on children reporting making a unilateral decision. While not unambiguous, this signals that these children may have less precise beliefs. For example, families where parents have a greater involvement in their children's choice may be relying more on statistics and on other 'hard' information from teachers, schools, and orientation in stage 1.[31]

An obvious shortcoming of these calculations is their reliance on the assumption that families would use these statistics at the face value. That is, even though families would likely update their beliefs, there is no reason to believe that they would slavishly use population probabilities in place of individual-specific ones, as confirmed by existing evidence from experiments with U.S. college students (Wiswall and Zafar, 2014). A useful alternative interpretation of these counterfactuals is that they provide an estimate of the prediction error made by an econometrician who assumes common priors across (and within) families for these outcomes, by setting decision makers' beliefs equal to the average of past population realizations.

7 Conclusion

This paper introduces subjective risk and multiple processes of child-parent decision making into a simple model of high school track choice. It simultaneously departs from treating the family as a unit and from making strong rationality assumptions about the relevant expectations for intra-family decision making under uncertainty. Methodologically, it combines data on actual choices with novel survey information about children's and parents' probabilistic expectations,

[31] In Table A20 of the online appendix, I additionally show the changes in predicted enrollment probabilities induced by publication of the 2006 graduation rates by curriculum (conditional on a regular path), based on the statistics of AlmaDiploma (2007*a*) (policy 6).

choice preferences, and decision roles, separately elicited from each family member. Use of multiple sources of data enables me to separately identify parameters capturing how children and parents individually make trade-offs among the choice outcomes, and parameters describing different protocols of child-parent decision making. This approach may be applied to other group decisions as well, especially within the household (e.g., saving and investing, labor supply and retirement, long-term care decisions, etc.).

The paper's general message is that disentangling the group members' probabilities and utilities from the group's decision protocol, is fundamental for prediction and policy analysis of group decisions under uncertainty. Within its specific application, the paper's findings indicate that the economics of the family needs to provide explicit accommodation of adolescents' decision-making, and that the economics of education needs to explicitly take into account the channels through which parents affect children's human capital decisions.

Direct measurement of the family members' probabilities and decision roles is a main feature and strength of the analysis. Nevertheless, this work does still rely on substantial simplifications regarding both the theoretical framework and the data. Validity of the counterfactuals, for example, requires that the family decision protocols are correctly specified and remain unchanged following the hypothesized policies. The empirical analysis provides some evidence of the ability of the family protocol indicator to discriminate among different models of family decision-making. However, neither alternative forms of family interaction (e.g., strategic ones), nor selection into family decision protocols are addressed in this paper. Finally, both the theoretical framework and the data maintain the Bayesian agnosticism about how beliefs are formed and about the potential role of ambiguity.

Substantial progress can be made by collecting a panel of beliefs, by relaxing risk neutrality, by eliciting joint or conditional beliefs, by allowing respondents to provide ranges as a way to express ambiguity. Future efforts should additionally extend the current approach to modeling and analyzing selection into family choice protocols and choices jointly. Large representative studies such as the National Longitudinal Survey of Youth, the Panel Study of Income Dynamics, or the Health and Retirement Study, have collected high-quality longitudinal data for decades, but have focused on families' or specific members' choices and outcomes, their background characteristics, their social context, and to a lesser extent on subjective point-expectations. To improve our understanding of why families use certain decision styles and make the choices we observe, it would be fruitful to augment existing surveys with new information from multiple members, including individual members' preferences and beliefs as well as the constraints or incentives they pose to one another. Such data would inform economic models of family behavior by suggesting more credible assumptions and specifications of family decision-making and interactions, and it would enable identification of a richer set of structural parameters and corresponding policy counterfactuals when used within econometric models of family choice.

Table 1: Population and Sample Enrollment Distributions, and A Comparison of Actual Choices (RP) with Individual Members' Stated Choice Preferences (SP)

Curriculum	(1) Population[a] (%)[b]	(2) 'Unitary' Model All Sample[c]	(3) 'Unitary' Model Matched Smpl.[d]	(4) PR 1 as Reported by Child[e]	(5) PR 2 Reported by Child[f]	(6) PR 3 as Reported by Child[g]
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 Track	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 Track	1548 (36.9)	281 (28.16)	179 (31.08)	65 (38.23)	48 (21.92)	83 (34.86)
Total Artistic Track	177 (4.2)	76 (7.62)	15 (2.60)	18 (10.59)	5 (2.28)	5 (2.10)
General - Humanities	395 (9.43)	172 (17.23)	123 (21.35)	16 (9.41)	52 (23.74)	52 (21.85)
General - Languages	168 (4.01)	59 (5.91)	33 (5.73)	6 (3.53)	22 (10.05)	8 (3.36)
General - Education-Social Scie.	330 (7.89)	100 (10.02)	57 (9.90)	18 (10.59)	29 (13.24)	21 (8.82)
General - Math and Science	940 (22.43)	173 (17.33)	116 (20.14)	22 (12.94)	47 (21.46)	50 (21.01)
Total General Track	1833 (43.8)	504 (50.49)	329 (57.12)	62 (36.47)	150 (68.49)	131 (55.04)
Total All Tracks	4189 (100)	998 (100)	576 (100)	170 (100)	219 (100)	238 (100)
% Families Where the Actual Choice Equals		**Child's&Parent's SPs**	54.13	51.78[h]	52.56	57.98
		Child's SP Only	33.03	40.17[i]	35.81	28.99
		Parent's SP Only	5.87	1.79	6.51	5.04
		Neither	6.97	5.36	5.12	7.98[j]
		N (%)	565 (100)	112 (19.82)	215 (38.05)	238 (42.13%)

Notes:

[a]: Source: Provincial Agency for Education of Verona (Italy). [b]: Percentages in parentheses.

[c]: After dropping children repeating 9th grade or with any item non-response in the key variables (SP, probabilities, and family protocol). Sample used to estimate the baseline model without heterogeneous decision roles ('unitary family').

[d]: Same as [c], but applied to the child-parent matched pairs.

[e]: Same as [c], but applied to the subset of children reporting making a unilateral choice (PR1)

[f]: Same as [d], but applied to the subset of families where children reported making the choice with parental input (PR2).

[g]: Same as [d], but applied to the subset of families where children reported making a joint choice with their parents (PR3).

[h] is likely an upper bound, and [i] a lower bound, due to higher non-participation of PR1 parents.

[j] Cases violating Pareto optimality.

Table 2: Percent Chance of 'Like'[a] and 'Flex. I'[b]–Main Features of the Empirical Beliefs Distributions Across Curricula and Samples

	Like								Flexibility I							
	Children (N=998)[c]															
	0.10-Q[e]	0.25-Q	0.50-Q	0.75-Q	0.90-Q	Mean	Std. Dev.		0.10-Q	0.25-Q	0.50-Q	0.75-Q	0.90-Q	Mean	Std. Dev.	
Voc., Comm.	0	0	17.5	45	75	26.839	28.804		1	15	50	80	100	46.970	33.319	
Voc., Indust.	0	0	10	37	67	22.265	27.121		1	15	50	72	96	45.432	32.598	
Tech., Comm.	0	5	20	50	80	29.960	29.782		10	30	50	83	100	53.993	32.447	
Tech., Indust.	0	0	11	50	80	27.229	31.038		10	29	56	82	100	55.019	32.236	
Tech., Surv.	0	1	20	53	86	32.026	33.059		10	40	65	90	100	60.951	31.204	
Art Track	0	1	20	65	90	35.048	35.041		0	10	40	70	94	41.897	32.527	
Gen., Hum.	0	0	16.5	62	92	32.814	36.137		0	20	59.5	93	100	54.966	37.316	
Gen., Lang.	0	0	30	65	90	36.083	35.150		2	21	64	90	100	57.746	35.260	
Gen., Educ.	0	2	30	70	90	37.567	34.697		0	20	50	83	100	52.222	34.518	
Gen., Math	0	3	40	80	97	43.093	36.645		1	20	69	95	100	58.539	36.830	
	Parents (N=576)[d]															
	0.10-Q	0.25-Q	0.50-Q	0.75-Q	0.90-Q	Mean	Std. Dev.		0.10-Q	0.25-Q	0.50-Q	0.75-Q	0.90-Q	Mean	Std. Dev.	
Voc., Comm.	0	5	20	48.5	70	27.729	27.118		5	21.50	50	80	100	53.115	32.494	
Voc., Indust.	0	5	20	40	70	26.479	26.722		5	27.50	50	80	100	52.043	32.093	
Tech., Comm.	0	10	30	50	80	32.625	27.785		15	40	60	85	100	60.686	29.344	
Tech., Indust.	0	5	20	50	70	30.337	28.163		20	50	70	90	100	63.283	28.437	
Tech., Surv.	0	1	20	50	80	29.481	30.010		20	50	69	85	100	63.102	27.994	
Art Track	0	5	30	60	80	33.997	30.742		5	20	40	60	90	42.309	29.786	
Gen., Hum.	0	10	40	70	90	40.816	34.015		10	26.75	57.5	90	100	55.832	33.913	
Gen., Lang.	0	10	40	70	90	40.519	31.918		10	40	70	90	100	62.986	30.261	
Gen., Educ.	0	10	40	70	81	40.174	31.412		10	30	55	80	100	54.856	30.901	
Gen., Math	0	10	50	74	90	46.819	31.937		10	30	60	90	100	59.101	32.335	
	Child-Parent Difference (N=576)[d,f]															
	0.10-Q	0.25-Q	0.50-Q	0.75-Q	0.90-Q	Mean	Std. Dev.	P > $\|z\|$[g]	0.10-Q	0.25-Q	0.50-Q	0.75-Q	0.90-Q	Mean	Std. Dev.	P> $\|z\|$[g]
Voc., Comm.	-37	-20	0	10	33	-2.306	27.842	0.0146	-60	-40	-10	20	40	-9.083	40.806	0.0000
Voc., Indust.	-42	-20	-5	9	30	-6.606	28.588	0.0000	-60	-40	-10	19.5	40	-9.516	39.774	0.0000
Tech., Comm.	-40	-20	0	12	38	-2.870	29.841	0.0148	-60	-40	-10	20	40	-8.878	39.577	0.0000
Tech., Indust.	-40	-20	0	12	31	-3.352	29.377	0.0083	-56	-37	-8	15.5	40	-8.887	37.175	0.0000
Tech., Surv.	-30	-10	0	20	42	3.439	30.299	0.0054	-50	-28.5	0	20	41	-2.681	37.358	0.1559
Art Track	-40	-20	0	12	37	-2.234	30.381	0.0449	-55	-30	-1	20	50	-4.189	39.626	0.0118
Gen., Hum.	-40	-20	0	10	30	-3.670	29.445	0.0181	-70	-37	0	30	62	-2.074	47.511	0.4297
Gen., Lang.	-40	-20	0	10	35	-3.239	29.536	0.0044	-60	-32	-2	20	50	-6.776	41.686	0.0004
Gen., Educ.	-40	-20	0	20	40	-1	31.497	0.5215	-60	-30	0	25	50	-3.630	41.498	0.0749
Gen., Math	-33	-14.5	0	19.5	40	1.758	29.701	0.1148	-66	-34	0	30	60	-1.910	46.544	0.4962

[a]: The child will enjoy the curriculum content. [b]: The curriculum training will enable the child to choose among both college fields and liked jobs.
[c]: Whole children sample. [d]: Matched child-parent sample.
[e]: α-Q is the α quantile of the empirical beliefs' distribution for the corresponding outcome Like and curriculum (by row), with $\alpha \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$.
[f]: Difference between child's and parent's beliefs over outcomes 'Like' and 'Flexibility I' in different curricula.
[g]: Wilcoxon matched-pairs signed-ranks test. Null hypothesis of equality of child-parent matched beliefs. Prob > $|z|$ gives the confidence level at which the null hypothesis of equality cannot be accepted.

Table 3: 'Unitary Family' Baseline–RP and SP Models–'All' Samples

	RP Data						SP Data					
	Child's Beliefs				Parent's Beliefs		Child's Beliefs and SP				Parent's Beliefs and SP	
Outcomes	**(S1)**	**(S2)**	**(S3)**	**(S4)**	**(S1)**	**(S3)**	**(S1)**	**(S2)**	**(S3)**	**(S4)**	**(S1)**	**(S3)**
Like Curriculum Content (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)	7.11^{***} (0.53)	6.71^{***} (0.53)	7.22^{***} (0.62)	6.89^{***} (0.64)	4.08^{***} (0.29)	3.79^{***} (0.31)
Daily Homework ≥ 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)	0.79^{*} (0.46)	0.64 (0.47)	0.50 (0.50)	0.32 (0.52)	−0.21 (0.42)	−0.20 (0.43)
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)	1.66^{***} (0.47)	1.54^{***} (0.48)	1.33^{**} (0.52)	1.25^{**} (0.53)	−0.12 (0.45)	−0.18 (0.48)
In School with Friend(s) (b_{10})	0.36 (0.24)	0.11 (0.25)	0.20 (0.28)	−0.05 (0.29)	0.69 (0.42)	0.69 (0.49)	0.64^{***} (0.22)	0.49^{**} (0.24)	0.66^{***} (0.23)	0.52^{**} (0.25)	0.09 (0.31)	−0.02 (0.33)
Flexible College-Work Choice (b_6)	1.05^{***} (0.32)	0.96^{***} (0.32)	1.36^{***} (0.37)	1.21^{***} (0.39)	0.87^{*} (0.45)	0.99^{*} (0.53)	0.70^{*} (0.38)	0.55 (0.38)	0.57 (0.37)	0.42 (0.38)	1.05^{***} (0.35)	1.13^{***} (0.38)
Attend College (b_7)	1.13^{***} (0.43)	0.92^{**} (0.46)	1.31^{**} (0.52)	1.22^{**} (0.56)	0.70 (0.65)	1.14 (0.78)	2.01^{***} (0.46)	1.95^{***} (0.48)	1.58^{***} (0.47)	1.57^{***} (0.49)	0.37 (0.38)	0.39 (0.40)
Flexible College Field Choice (b_8)	2.40^{***} (0.47)	2.11^{***} (0.48)	2.58^{***} (0.64)	2.19^{***} (0.67)	2.64^{***} (0.62)	1.94^{***} (0.75)	2.52^{***} (0.52)	2.29^{***} (0.52)	2.35^{***} (0.54)	2.15^{***} (0.54)	1.29^{***} (0.46)	1.22^{***} (0.47)
Liked Job after Graduation (b_9)	1.16^{***} (0.30)	1.05^{***} (0.31)	1.09^{***} (0.36)	0.98^{***} (0.37)	1.18^{***} (0.47)	1.16^{**} (0.50)	2.26^{***} (0.34)	2.30^{***} (0.35)	2.23^{***} (0.37)	2.26^{***} (0.38)	1.87^{***} (0.34)	1.94^{***} (0.37)
Happy Parents (b_{11})	–	1.74^{***} (0.39)	–	1.74^{***} (0.49)	–	–	–	1.57^{***} (0.41)	–	1.32^{***} (0.42)	–	–
Teachers' Suggestion	–	–	1.59^{***} (0.19)	1.49^{***} (0.20)	–	1.90^{***} (0.21)	–	–	0.38^{**} (0.15)	0.31^{**} (0.16)	–	0.64^{***} (0.16)
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	-515.229	-503.288	-433.089	-426.189	-709.581	-646.179
Adjusted Likelihood Ratio Index ($\bar{\rho}^2$)	0.718	0.726	0.767	0.773	0.651	0.686	0.762	0.767	0.766	0.769	0.433	0.447
Sample Size	998		857		588	550	971		836		557	522

***: 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 4: 'Child Chooses Unilaterally' (PR1)–Child's Utility Weights–SP&RP Model

Outcomes	SP&RP Model (S2)	(S2')	(S4)	(S4')
Like Curriculum Content (b_1)	5.98*** (1.13)	6.55*** (1.13)	5.72*** (1.19)	6.57*** (1.23)
Daily Homework $\geq$ **2.5h** (b_2)	−0.66 (0.84)	−0.73 (0.89)	−1.77* (1.04)	−2.06* (1.12)
Graduate in Regular Time (b_4)	2.30*** (0.78)	2.59*** (0.85)	1.89** (0.87)	2.21** (1.00)
In School with Friend(s) (b_{10})	0.35 (0.46)	0.42 (0.50)	0.36 (0.59)	0.48 (0.64)
Flexible College-Work Choice (b_6)	0.95 (0.71)	1.14 (0.77)	1.74** (0.87)	2.08** (0.94)
Attend College (b_7)	3.20*** (0.92)	3.49*** (1.01)	3.48** (1.39)	4.02** (1.59)
Flexible College Field Choice (b_8)**–RP**	1.36 (0.88)	0.42 (0.97)	0.34 (0.82)	−1.08 (0.96)
Flexible College Field Choice (b_8)**–SP**	–	2.87** (1.41)	–	1.65 (1.28)
Liked Job after Graduation (b_{10})**–RP**	1.81*** (0.69)	0.87 (0.77)	2.28*** (0.72)	1.23 (0.89)
Liked Job after Graduation (b_{10})**–SP**	–	3.55*** (1.12)	–	4.14*** (1.12)
Happy Parents (b_{11})	2.84*** (1.09)	3.22*** (1.18)	3.08*** (1.13)	3.65*** (1.28)
Teachers' Suggestion–RP	–	–	2.33*** (0.64)	2.26*** (0.63)
Teachers' Suggestion–SP	–	–	1.11** (0.48)	1.50** (0.61)
SP/RP Scale	1.008*** (0.120)	0.845*** (0.096)	1.010*** (0.134)	0.813*** (0.103)
Constants	Yes	Yes	Yes	Yes
Log-likelihood ($LL(\hat{\theta})$)	-178.309	-174.317	-131.176	-127.823
Adjusted Likelihood Ratio Index ($\bar{\rho}^2$)	0.736	0.739	0.757	0.759
Sample Size	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 5: 'Child Chooses with Parental Input' (PR2)–Aggregation Weights and Child's Utility Weights

Outcomes	(S1)	(S2)	(S3)	(S4)
Aggregation Weights (on the Parent's Beliefs)				
Like Curriculum Content (b_1)	0.433*** (0.047)	0.450*** (0.051)	0.411*** (0.056)	0.434*** (0.059)
Daily Homework ≥ 2.5h (b_2)	1.282 (2.534)	1.440 (2.470)	−0.073 (3.248)	−0.984 (13.953)
Graduate in Regular Time (b_4)	0.626 (0.481)	0.669 (0.534)	1.021*** (0.343)	1.120** (0.447)
In School with Friend(s) (b_{10})	−0.167 (1.141)	0.057 (1.174)	0.113 (1.167)	0.710 (1.088)
Flexible College-Work Choice (b_6)	−0.113 (0.484)	0.099 (0.430)	0.047 (0.526)	0.296 (0.470)
Attend College (b_7)	−0.403 (1.905)	16.132 (37.568)	2.180 (7.317)	1.131 (2.058)
Flexible College Field Choice (b_8)	0.204 (0.174)	0.249 (0.173)	0.231 (0.178)	0.229 (0.159)
Liked Job after Graduation (b_9)	0.545* (0.247)	0.494** (0.245)	0.411 (0.304)	0.281 (0.371)
Child's Utility Weights				
Like Curriculum Content (b_1)	12.64*** (2.24)	12.43*** (2.36)	15.16*** (3.05)	15.38*** (3.56)
Daily Homework ≥ 2.5h (b_2)	0.80 (1.54)	0.90 (1.57)	0.72 (2.05)	0.30 (2.12)
Graduate in Regular Time (b_4)	3.33** (1.57)	2.94* (1.53)	4.29** (2.05)	3.52* (1.79)
In School with Friend(s) (b_{10})	0.81 (0.84)	0.68 (0.90)	1.04 (0.91)	0.86 (0.94)
Flexible College-Work Choice (b_6)	2.44** (1.32)	2.66** (1.31)	3.41** (1.59)	3.67* (1.87)
Attend College (b_7)	0.78 (1.68)	−0.08 (1.77)	−0.59 (1.67)	−1.42 (1.74)
Flexible College Field Choice (b_8)	7.70*** (1.83)	7.88*** (2.01)	9.23*** (2.47)	9.12*** (2.63)
Liked Job after Graduation (b_9)	3.40*** (1.01)	3.25*** (1.01)	3.83*** (1.39)	3.58** (1.40)
Happy Parents (b_{11})	–	2.53** (1.10)	–	3.43** (1.54)
Teachers' Suggestion–RP	–	–	3.13*** (3.05)	3.08 (2.12)
Teachers' Suggestion–SP	–	–	0.51 (2.05)	0.35* (0.179)
RP Dummies	No	No	No	No
SP/RP Scale	0.608*** (0.122)	0.586*** (0.124)	0.511*** (0.120)	0.488*** (0.126)
Constants	Yes	Yes	Yes	Yes
Log-likelihood ($LL(\hat{\theta})$)	-161.119	-156.909	-132.824	-128.487
Adjusted Likelihood Ratio Index ($\bar{\rho}^2$)	0.806	0.807	0.820	0.824
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 6: 'Child and Parent Make a Joint Decision' (PR3)

Outcomes	(S1)	(S2)	(S3)	(S4)
Aggregation Weight (on Child's SEUs)	0.344*** (0.085)	0.357*** (0.078)	0.295*** (0.075)	0.307*** (0.069)
Child's Utility Weights				
Like Curriculum Content (b_1)	13.33*** (3.09)	12.13*** (2.79)	14.90*** (3.97)	13.58*** (3.58)
Daily Homework ≥ 2.5h (b_2)	1.48 (1.88)	1.86 (1.77)	1.18 (2.38)	1.60 (2.30)
Graduate in Regular Time (b_4)	4.27** (2.47)	3.88** (2.35)	3.37* (2.25)	3.10* (2.09)
In School with Friend(s) (b_{10})	1.11 (1.07)	0.52 (1.13)	1.65* (1.16)	1.10 (1.16)
Flexible College-Work Choice (b_6)	1.48* (1.14)	1.04 (1.26)	1.12 (1.27)	0.86 (1.42)
Attend College (b_7)	3.27** (1.61)	2.88** (1.46)	2.83* (1.81)	2.71* (1.68)
Flexible College Field Choice (b_8)	6.37*** (2.44)	5.49*** (2.26)	6.00** (2.84)	5.18** (2.56)
Liked Job after Graduation (b_9)	3.74*** (1.53)	3.98*** (1.61)	4.56** (2.13)	4.72** (2.19)
Happy Parents (b_{11})	–	3.56** (1.67)	–	4.18** (2.03)
Teachers' Suggestion–RP	–	–	1.20*** (0.45)	1.13*** (0.45)
Teachers' Suggestion–SP	–	–	0.17 (0.56)	−0.04 (0.55)
Parent's Utility Weights				
Like Curriculum Content (b_1)	8.49*** (1.54)	8.46*** (1.56)	7.94*** (1.66)	7.97*** (1.68)
Daily Homework ≥ 2.5h (b_2)	−1.39 (1.17)	−1.31 (1.16)	−1.33 (1.23)	−1.23 (1.22)
Graduate in Regular Time (b_4)	2.52 (2.10)	2.35 (1.98)	3.34* (2.27)	3.18* (2.16)
In School with Friend(s) (b_{10})	−0.37 (0.86)	−0.38 (0.86)	−0.70 (0.97)	−0.73 (0.97)
Flexible College-Work Choice (b_6)	2.14** (1.09)	2.20** (1.12)	2.04** (1.12)	2.15** (1.15)
Attend College (b_7)	0.92 (1.06)	0.88 (1.07)	0.84 (1.13)	0.81 (1.14)
Flexible College Field Choice (b_8)	2.99*** (1.19)	2.96*** (1.21)	2.98*** (1.21)	2.96*** (1.23)
Liked Job after Graduation (b_9)	1.74** (0.99)	1.84** (0.96)	1.66* (1.04)	1.78** (1.03)
Teachers' Suggestion–SP	–	–	2.00*** (0.70)	2.01*** (0.71)
RP Dummies	No	No	No	No
SP/RP Scale (Child≡Par)	0.523*** (0.093)	0.524*** (0.093)	0.488*** (0.103)	0.486*** (0.102)
Constants	Yes	Yes	Yes	Yes
Log-likelihood ($LL(\hat{\theta})$)	-507.4697	-501.9089	-463.1923	-457.8141
Adjusted LR Index ($\bar{\rho}^2$)	0.664	0.667	0.668	0.671
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 7: Counterfactuals: % Change in Predicted Probabilities of Choosing Curriculum j Following...

	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
Policy 1–Math 'Promotion':	**...A 10 Points Increase in the Percent Chance that the Child Will Enjoy Math in General-Math**									
Unitary (All)–Child's Beliefs	-1.29	-1.73	-1.38	-2.27	-3.97	-1.99	-8.40	-7.61	-3.78	*+11.16*
Unitary (All)–Parent's Beliefs	-2.53	-3.05	-3.50	-5.04	-4.63	-3.47	-11.58	-12.36	-6.76	**+18.93**
PR1 (SP&RP)–Child's Beliefs	-1.28	-0.84	-0.26	-1.76	-3.51	-2.01	-4.78	-1.58	-4.02	*+7.04*
PR2–Child's Beliefs	-0.30	-0.14	-1.09	-3.64	-1.42	-0.20	-5.44	-3.93	-0.71	*+6.74*
PR2–Parent's Beliefs	-0.23	-0.10	-0.83	-2.71	-1.02	-0.18	-4.17	-2.90	-0.50	**+5.06**
PR2–Child's and Parent's Beliefs	-0.50	-0.24	-2.02	-6.95	-3.16	-0.28	-9.63	-7.99	-1.58	+12.73
PR3–Child's Beliefs	-0.73	-0.54	-0.40	-0.76	-1.12	-2.93	-4.94	-7.33	-2.75	*+6.41*
PR3–Parent's Beliefs	-0.94	-0.73	-0.55	-0.98	-1.43	-3.85	-6.61	-9.71	-3.67	**+8.50**
PR3–Child's and Parent's Beliefs	-1.49	-1.34	-1.00	-1.68	-2.29	-6.62	-11.89	-17.20	-6.66	+15.03
Policy 2–More Rigid Tracking:	**...Vocational Diplomas Stop Giving Access to College**[a]									
Unitary (All)–Child's Beliefs	-63.20	-53.38	+23.53	+19.07	+5.30	+10.01	+2.08	+5.35	+4.46	+3.14
Unitary (All)–Parent' Beliefs	-61.99	-56.56	+22.47	+20.70	+11.86	+6.91	+2.01	+4.44	+4.15	+2.61
PR1 (SP&RP)–Child's Beliefs	*-61.25*	-40.16	+13.14	+15.31	+6.30	+13.30	+7.00	+7.65	+13.27	+1.89
PR2–Child's Beliefs	-52.52	-31.16	+26.67	+ 8.79	+0.30	+4.96	+0.03	+5.69	-0.00	+0.21
PR2–Parent's Beliefs	**-17.38**	-18.16	+6.50	+10.68	+0.22	-0.06	+0.02	+3.63	-0.00	+0.15
PR2–Child's and Parent's Beliefs	*-57.97*	-60.86	+31.85	+20.60	+0.32	+10.15	+0.03	+5.71	+0.00	+0.26
PR3–Child's Beliefs	-33.82	-23.40	+11.10	+11.84	+2.78	+0.70	+0.32	+0.47	+5.37	+0.85
PR3–Parent's Beliefs	**-44.97**	-45.97	+17.58	+20.86	+5.14	+0.91	+0.49	+0.68	+5.51	+1.08
PR3–Child's and Parent's Beliefs	*-72.03*	-61.61	+29.49	+25.74	+6.70	+1.13	+0.56	+0.89	+9.64	+1.33
Policy 3–Publication of College Enrollment Stats:	**...Beliefs about 'Attend College' (b_7) Coincide with Past Realized Frequencies**[b] **for All Tracks**									
Unitary (All)–Child's Beliefs	-2.67	-11.17	+3.36	+0.64	-5.29	-5.89	+2.07	+0.98	+0.28	+3.17
Unitary (All)–Parent's Beliefs	-5.69	-12.46	+2.96	-0.14	-3.23	-3.50	+3.15	+2.65	+1.59	+3.08
PR1 (SP&RP)–Child's Beliefs	-10.68	-24.81	+5.88	+0.62	-20.15	-18.88	+13.43	+14.20	+4.47	+6.77
PR2–Child's Beliefs	-0.39	-0.17	+0.28	-0.09	-0.74	-0.57	+0.23	+0.19	+0.23	+0.14
PR2–Parent's Beliefs	+3.14	+1.19	-1.77	+1.90	+3.29	+3.90	-1.03	-1.27	-0.81	-1.91
PR2–Child's and Parent's Beliefs	+2.79	+0.99	-1.52	+1.86	+2.54	+3.56	-0.88	-1.07	-0.55	-1.79
PR3–Child's Beliefs	-1.70	-5.13	+2.11	+1.96	-1.10	-2.66	+0.61	-1.25	-1.62	+0.90
PR3–Parent's Beliefs	-1.28	-3.16	+0.73	+0.23	-0.01	-1.79	+0.63	+0.22	+0.42	+0.66
PR3–Child's and Parent's Beliefs	-3.04	-8.37	+2.92	+2.23	-1.11	-4.46	+1.19	-0.88	-1.33	+1.56

[a]: The percent chance of 'Attend college' (b_7), 'Flexible College-Work Choice' (b_6), and 'Flexible College Field Choice' (b_8) =0 for the vocational curricula ($j \in \{1, 2\}$)

[b]: Statistics from AlmaDiploma (2007*b*):[c] 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%.

[c]: AlmaLaurea/Diploma is a consortium that collects data on attainment, college, and labor market outcomes of high school graduates in Italy (http://www.almalaurea.it).

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